A NOVEL APPROACH TO INVESTIGATE PEDESTRIAN SAFETY IN NON-SIGNALIZED CROSSWALK ENVIRONMENTS AND RELATED TREATMENTS USING TRAJECTORY DATA

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Dedication

To my lovely wife **Danqing Ruan** *for her love, companionship and support*

To my parents **Yequn Fu** *&* **Caiying Zhou** *for their selfless and unconditional love and support*

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LIST OF SYMBOLS AND ABBREVIATIONS

AASHTO American Association of State Highway and Transportation Officials. 195, 213

ATR automatic traffic recorder. 31

BC MOT British Columbia Ministry of Transportation. 23

CA crosswalk area. 40

CDF cumulative distribution functions. 112 118 120

CIA crosswalk influence area. 40

DOT Department of Transportation. 31, 184

DRS deceleration required to stop. 142, 143, 147, 153-156, 167-169, 172, 173, 188, 189, 191, 193-197, 211, 242-244

DV framework distance-velocity framework. 10-12, 127, 129, 134, 137-146, 148, 150-152, 154-156, 161, 163, 164, 167-169, 171, 172, 174, 175, 177, 182, 183, 185-189, 191, 192, 202, 203, 209-214, 234, 237, 240, 242

EB Empirical Bayes. 29

FHWA Federal Highway Administration. 22, 23

GHG greenhouse gas. 2, 181

GT gap time. 106, 131

HERG Highway Engineering Research Group. 34

HOG histogram of oriented gradients. 78, 79, 91

HVC high-visibility crosswalk. 41

ITS intelligent transportation system. 71

LPET lane-based post-encroachment time. 37

MOT measure of tracking accuracy. 75

MRE mean relative error. 83, 93, 95, 96

MTO Ministry of Transportation of Ontario. 22, 23

NHTSA National Highway Traffic Safety Administration. 3, 6, 23, 104, 130, 180, 210

NSERC Natural Sciences and Engineering Research Council. xxiv, 98, 123, 156, 203

PET post-encroachment time. 6, 11, 25, 34, 37, 103, 105, 106, 110-113, 118-121, 123, 131-134, 156, 182, 208

PHB pedestrian hybrid beacon. 43

PRI pedestrian risk index. 37

RAE relative accuracy error. 83, 93-96

ROC receiver operating characteristic. 74, 98

RPE relative precision error. 83, 93-96

RRFB rectangular rapid flash beacon. 43, 132, 214, 216-218

RRSR Quebec Road Safety Research Network. xxiv

SCM single chip microcomputer. 75, 76

SMoS surrogate measure of safety (also surrogate safety measure, SSM). 4, 7, 11, 21, 22, 24-26, 30, 33, 47, 50, 51, 127, 208, 210, 211, 213

StBA Statistisches Bundesamt (Federal Statistical Office of Germany). 181

SVM support vector machine. 74, 78, 79, 91

SYG strong yellow green sign. 32, 48

TC time-to-crossing. 142, 143, 147, 153-156, 168, 169, 172, 173, 188, 191, 193, 194

TCT traffic conflict technique. 6

TTC time-to-collision. 6, 25, 34, 36, 37, 131, 132, 156, 182

UIIG ITE Unsignalized Intersection Improvement Guide. 21

WHO World Health Organization. 3, 22, 31

GLOSSARY

classification error An error made in identifying the classification of the target. Here, it means a false classification result in which a road user is wrongly classified when applying the classification algorithm. 80

collision course An instantaneous situation where two or more road users have a non-zero likelihood to collide in a short time. 36, 37, 44, 188

computer vision A field of computer science that focuses on obtaining useful information from digital images or videos. 11, 70, 72, 74, 82, 111, 113, 115, 132, 212

conflict severity Conflict severity has two dimensions which include both the proximity to a crash and severity of its potential consequences. 34, 50, 106

confusion matrix A table used to describe and visualize the performance of a classification algorithm/model. In the general case with N classes, the confusion matrix is an NxN matrix that contains in each cell c_{ij}, the number of objects of true class i predicted as class j. 74, 81, 82

crash data-based approach An approach which investigates road safety using the crash data-based method, which relies on crash data to study road safety (s). xix, 4, 5, 11, 25, 27, 23

crash risk The possibility of a crash and its potential consequence (the severity). 26-29, 39, 40, 184, 217

crash severity The severity of personal injury or property damage resulting from a traffic crash, also defined as crash outcome severity. 30

dangerous pedestrian crossing A crossing decision made by a pedestrian getting into a dangerous situation where the vehicle cannot yield during the interaction of interest. 129, 141, 154, 167, 172, 173, 175, 188, 194-197, 242, 244

deceleration rate required to stop The constant deceleration rate required for the vehicle to stop. 135, 142, 179, 209

detection miss A detection error in which a road user who should be detected is not. 73

detection over-segmentation A detection error in which one road user is detected as multiple road users when applying a vision-based tracking technique. 78

detection over-grouping A detection error in which multiple road users are detected as one road user when applying a vision-based tracking technique. 78, 82

Distance-Velocity framework A newly-proposed framework which investigates pedestrian safety by considering pedestrian-vehicle interactions when pedestrians cross the street and road user behavior during such interactions. 10, 127, 129, 134, 135, 137, 178-181

human error A mistake made by a person due to an unintentional action or a decision. Human error in the context of road traffic generally refers to mistakes made or violations conducted by road users. 6

interaction of interest (for pedestrian-vehicle interaction) A situation where a vehicle approaches a crosswalk and a pedestrian is either already moving to cross or is present in a position showing willingness to cross. 136, 141, 145, 146, 163, 164, 166-169, 211, 213

marked crosswalk A pedestrian crosswalk that is regulated by crosswalk markings assigning right-of-way to pedestrians. Accordingly, **unmarked crosswalk** is a pedestrian crosswalk without any crosswalk marking. xx, 9, 12, 29, 32, 36, 43, 48, 104, 127, 137, 161, 164-175, 189, 190, 192, 193, 195, 198, 202, 209, 210, 217, 219-221, 223, 229, 237, 238, 242

method based on surrogate measure of safety A methodology that relies on surrogate measures of safety to learn road safety. 4, 25, 130

non-signalized crosswalk A pedestrian crosswalk where there are not traffic lights controlling the traffic. xix, xx, 2-9, 10-12, 19-25, 27-29, 31-33, 35, 37-41, 43, 48, 49, 51, 52, 68, 101-104, 108, 110, 127-134, 143, 155, 164, 167, 175, 177, 214, 216

pedestrian occurrence The moment when a pedestrian arrives close to the beginning of the crosswalk. In this dissertation, it is defined as the pedestrian arriving within a cross-section distance of 1 m from the beginning of the crosswalk and showing the intention to cross the street by either facing the road or turning their head toward the road, unless his/her behavior obviously implies they do not intend to cross the street (e.g. standing and talking, squatting, or staying in this area for specific purposes such as equipment installation and etc.). 9, 50, 135, 136, 138, 142, 143, 145-147, 152, 153, 155, 163, 168, 169, 171, 179, 185, 191, 199, 212, 213, 235, 238, 241

pedestrian crossing decision The action when a pedestrian decides to cross the street, regardless if he/she is later forced to retreat by non-yielding vehicles. This includes actual crossing attempts which may happen when a pedestrian keeps a constant walking speed to cross without waiting or starts to cross after waiting. 9-12, 21, 25, 38-46, 129, 132, 133, 135, 136, 138, 139, 141-143, 145-147, 153-156, 163, 164, 167, 169, 172-175, 179, 180, 182-185, 187, 188, 191-198, 209, 212, 213, 235, 238, 241-244

pedestrian crossing after vehicle passage A crossing decision made by the pedestrian, who gives up his/her right-of-way, to pass after the vehicle passage during the interaction of interest. 136, 164, 167, 172, 182, 192-197, 242-243

post-encroachment time Time between the departure of the first road user and the arrival of the second road user at the crossing zone where their trajectories overlap. 6, 25, 37, 103, 182

receiver operating characteristic curve A method that uses a graphical plot to validate the performance of a binary classifier. 74

risky pedestrian crossing A crossing decision made by a pedestrian getting in a risky situation where the vehicle may not have enough time to react and yield during the interaction of interest. 42, 129, 141, 167, 172, 188, 195-197, 242-243

road user Anyone, such as a pedestrian, cyclist or motorist, who uses the road infrastructure for transportation purposes. xix, xx, 2-6, 9, 11, 21, 24-26, 28, 33, 34, 36-38, 41, 46-48, 50, 52, 68, 71, 72, 74, 77-84, 87, 89, 91, 93, 96-98, 103, 104, 106, 108-117, 116, 118, 123, 127, 130, 133, 135, 143-145, 155, 156, 166, 177, 180-183, 189, 191, 202, 208, 211, 212, 214

safe pedestrian crossing A crossing decision made by the pedestrian where the vehicle has enough time to react and yield during the interaction of interest. 38, 42, 129, 142, 154, 167, 172, 187, 188, 191, 195-197, 142, 143, 144

safety analysis approach A methodological approach to analyse road safety. xix, 4, 10, 11, 22, 24, 25, 50, 52, 208

staged pedestrian A pedestrian who stops and waits at the edge of the curb to cross the street. Accordingly, an **unstaged pedestrian** is a pedestrian who takes a few steps into the vehicle lane, making himself more visible to drivers to cross the street. 43, 44

stop sign controlled crosswalk (stop-controlled) A pedestrian crosswalk which has a stop sign upstream requiring all vehicles to stop before the crosswalk, crossing the street without waiting. xx, 12, 145, 150-155, 161, 164, 166-175, 232, 240, 241

support vector machine A supervised learning model used for classification or regression analysis. 74

surrogate measure of safety A proactive measure which, instead of relying on historical crash data, uses other measures (e.g. speed etc.) or events (e.g. conflicts) to describe the road safety condition. 4, 21, 22, 101, 105, 106, 107, 132, 142, 143, 155, 156, 168, 181, 216-223

surrogate safety approach An approach to analyze road safety using one or more surrogate safety methods. Based on the categories of methods in SMoS, this dissertation classifies surrogate safety approaches into four: the traffic data approach, the conflict approach, the behavior approach, and the perception approach. xix, 50

thermal camera A camera which detects infrared radiation from objects and records the detection as visualized heat zone images and videos. xix, xx, 9-11, 68, 72, 74-77, 85, 87-98, 101, 103, 108, 109, 116, 123, 161, 208, 212

time-to-collision Time remaining for two road users to collide if they continue their present trajectory on the collision course. 6, 25, 36, 131, 182

time to crossing Time remaining for the vehicle to reach the pedestrian crossing path if it continues along its present trajectory. 129, 143, 188

traffic crash An incident when a vehicle collides with another vehicle, pedestrian, or another object in the road traffic environment. 8, 51, 72

traffic conflict A traffic event involving two road users approaching each other where there is a risk of crash unless at least one of them changes his/her movement. 4-6, 21, 24, 33, 34, 36, 54, 122, 183

traffic conflict technique The most commonly-used method based on SMoS, which relies on collecting traffic conflict data to estimate road safety. 6, 7, 107, 132, 155

trajectory A series of positions of an object over time. Vision-based tracking techniques work as a practical tool to extract road user trajectory from videos collected from the road environment. 6, 9, 32, 36, 51, 71, 77, 80, 105-115, 132, 143-146, 155, 166, 189, 191, 208, 211, 212

uncontrolled crosswalk A pedestrian crosswalk that is not controlled by any type of signs or markings. xx, 9, 12, 20-23, 42, 127, 130, 161, 164-175, 209, 226, 234, 235, 243

vehicle yielding behavior Behavior of the driver in response to the occurrence of a pedestrian showing intent to cross the road and the vehicle path during an interaction of interest. Vehicle yielding behavior includes both yielding and non-yielding maneuvers. 7-12, 21, 25, 43, 46, 116, 122, 129, 131-139, 179-184, 188-197, 209, 212-214, 242-244

vehicle yielding maneuver The maneuver by the driver who gives the right-of-way to the pedestrian during an interaction of interest. 38, 43, 116, 129, 133, 135, 140-143, 150, 155, 167, 172, 179, 182, 188, 193-197, 212, 242-244

vehicle non-infraction non-yielding A non-yielding maneuver by the driver who is unable to stop after the pedestrian occurrence during an interaction of interest. 43, 129, 139, 152, 167, 188, 191, 195-197, 242-244

vehicle uncertain non-yielding maneuver A non-yielding maneuver by the driver who may or may not be able to react in time to stop after the pedestrian occurrence during an interaction of interest. 43, 129, 139, 152, 167, 188, 191, 195-197, 242-244

vehicle non-yielding violation A non-yielding maneuver by the driver, with enough time to react and brake, who chooses not to yield after the pedestrian occurrence during an interaction of interest. 43, 129, 139, 152, 167, 188, 191, 195-197, 242-244

visible spectrum camera A camera which detects and records objects in the portion of the electromagnetic spectrum that is visible to the human eye. xix, xx, 11 51, 68, 89, 101, 208

vision-based tracking A process of tracking objects over time using video cameras and computer vision techniques. xix, 5, 6, 211

vulnerable road user A road user who faces a high probability of injury in a collision with a vehicle and should be given increased attention. Pedestrians and cyclists are vulnerable road users because of their unprotected, or less-protected, state when using the road. 24, 130, 180

yield-controlled crosswalk A pedestrian crosswalk regulated by signs or markings assigning right-of-way to pedestrians. 23

yielding rate The proportion of vehicles that yield to pedestrians among all the interactions of interest. 40-44, 50, 122, 129, 132, 140, 141, 151, 152, 155, 167, 169, 170, 175, 188, 192, 194-197, 209, 211, 242-244

yielding compliance The proportion of vehicles that yield to pedestrians among the interactions where vehicles that are physically able to yield to crossing pedestrians. 7, 11, 44, 50, 103, 105, 106, 116, 118, 119, 122, 129, 131-135, 138, 140, 143, 151-156, 167, 169, 170, 175, 179, 180, 183, 188, 192-197, 202, 203, 208-210, 242-244

ABSTRACT

Pedestrian safety is a topic that concerns everyone. Not only does it concern researchers and practitioners who dedicate themselves to improve road safety, it also concerns all road users, as everyone is a pedestrian at some point in the transportation system. The high frequency of pedestrian crash injuries and the great possibility of fatal consequences have made pedestrian safety a great focus in road safety research. Pedestrian safety becomes even more of a problem at non-signalized locations when compared to signalized crosswalk locations, due to the absence of traffic lights controlling the traffic. Different methods have been proposed and empirical studies have been conducted to investigate pedestrian safety. Despite the extensive literature on investigating pedestrian safety at non-signalized crosswalk locations, much remains to be done, especially in studying interactions between the pedestrian and vehicles and their behavior during those interactions. Therefore, this dissertation aims to improve data collection methods for pedestrian safety analysis and to develop a methodological framework to investigate pedestrian safety at non-signalized crosswalk locations and implement such a framework using video data collected from different crosswalk locations with the help from vision-based tracking technology.

The work of the dissertation started with reviewing methodologies and data collection methods in previous studies. Methods used in past studies were classified into five different approaches. These are the crash data approach and four surrogate safety approaches, namely, the traffic data approach, the conflict event approach, the behavioral analysis approach, and the perception analysis approach. Issues in the use of terms and definitions, methodologies applied, and data used in previous studies were summarized. Some preliminary data collection work had indicated the limitations of using regular visible spectrum cameras in low visibility conditions. To overcome the limitations that regular visible spectrum cameras have encountered during the data collection process, the thermal camera was introduced and its performance in road user detection, classification, and speed measurement was validated through its comparison to the use of the regular camera. Validation results showed an evidently better performance from thermal camera for low visibility and shadow conditions, particularly when tracking pedestrians and

cyclists. However, the regular camera narrowly outperformed the thermal camera during daytime. For speed measurements, the thermal camera was consistently more accurate than the regular camera at daytime and nighttime. To evaluate existing measures in investigating pedestrian-vehicle interactions at non-signalized crosswalk locations, a study was conducted to investigate pedestrian safety at nighttime. Although, the methodology applied in the study performed well in looking at pedestrian-vehicle interactions, further limitations of using safety measure methods were discovered upon the completion of the study. A novel framework, which evaluates pedestrian safety by looking at the interaction between the pedestrian and the vehicle, and their behavior during the interactions, was proposed and illustrated through a case study. The framework was further tested through a study to compare the performance of three main non-signalized crosswalk types, including uncontrolled, marked, and stop sign controlled crosswalks, on pedestrian safety using data collected from different sites in Montreal. Among the three types of non-signalized crosswalks, stop sign controlled crosswalks had the best performance in protecting pedestrians while uncontrolled crosswalks performed the worst. To explore the extensive applications of the framework, the investigation of cyclist-pedestrian interactions was introduced as it has been a major road safety problem but underestimated in previous research. Marked crosswalks alone fail to protect pedestrians from passing cyclists. Besides, pedestrian safety at crossings on cycling facilities with downhill grades was found to be a great issue.

In brief, the dissertation will: 1) provide a comprehensive literature review that acts as a practical reference to investigating pedestrian safety at non-signalized crosswalk locations, 2) introduce a promising alternative, the use of the thermal camera, to overcome the limitations of using the visible spectrum camera for automated traffic data collection, 3) propose a new framework that describes pedestrian-vehicle interactions more precisely, compared to previous studies. This framework is promising for different purposes in road safety on various topics, such as the analysis of interactions between different types of road users, the simulation of road user interactions, validations of safety treatments, and the performance evaluations of autonomous vehicles.

RÉSUMÉ

La sécurité des piétons est un sujet qui concerne tout le monde, non seulement les chercheurs et les praticiens qui se consacrent à l'amélioration de la sécurité routière, elle concerne également tous les usagers de la route, car chacun est un piéton dans le système de transport. La fréquence élevée des accidents impliquant des piétons et le grand risque de conséquences mortelles ont fait de la sécurité des piétons un élément central de la recherche sur la sécurité routière. La sécurité des piétons devient encore plus problématique aux emplacements non signalés, en raison de l'absence de feux de circulation contrôlant le trafic, par rapport aux emplacements de passages pour piétons signalés. Différentes méthodes de contrôle de la circulation ont été proposées et différentes études ont été menées pour améliorer la sécurité des piétons. Malgré la littérature abondante sur la sécurité des piétons aux passages pour piétons non signalés, il reste encore beaucoup à faire, en particulier pour étudier les interactions entre les piétons et les véhicules et leur comportement au cours de ces interactions. Par conséquent, cette thèse visait à améliorer les méthodes de collecte de données pour l'analyse de la sécurité des piétons et développer un cadre méthodologique pour étudier la sécurité des piétons aux emplacements de passages pour piétons non signalés et à mettre en œuvre un tel cadre en utilisant des données vidéo recueillies à partir de différents emplacements de passages pour piétons avec l'aide de la technologie de suivi basée sur la vision.

Le travail de la thèse a commencé par la révision des méthodologies et des méthodes de collecte de données dans les études précédentes. Les méthodes utilisées dans les études antérieures ont été classées en cinq approches différentes, notamment l'approche par les données sur les accidents et quatre approches de sécurité indirectes, à savoir l'approche par les données du trafic, l'approche par conflit, l'approche par analyse comportementale et l'approche par analyse de la perception. Les problèmes d'utilisation des termes et définitions, des méthodologies appliquées et des données utilisées dans les études précédentes ont été résumés. Pour évaluer les mesures existantes en matière d'enquête sur les interactions entre piétons et véhicules aux emplacements de passages pour piétons non signalés, une étude a été menée sur la sécurité des

piétons la nuit. Certains travaux préliminaires de collecte de données avaient montré les limites de l'utilisation de caméras à spectre visible classiques dans des conditions de faible visibilité. Bien que la méthodologie appliquée dans l'étude ait donné de bons résultats en examinant les interactions entre piétons et véhicules, des limitations supplémentaires de l'utilisation de méthodes de mesure de sécurité ont été découvertes à la fin de l'étude. Pour surmonter les limitations rencontrées par les caméras à spectre visible classiques lors du processus de collecte de données, la caméra thermique a été introduite et ses performances en matière de détection, de classification et de mesure de la vitesse des usagers de la route ont été validées par comparaison avec l'utilisation de la caméra classique. Les résultats de validation ont montré que la caméra thermique offrait manifestement de meilleures performances dans les conditions de faible visibilité et d'ombre, en particulier lors du suivi des piétons et des cyclistes, bien que la caméra ordinaire surperforme de près la caméra thermique pendant la journée. Pour les mesures de vitesse, la caméra thermique était toujours plus précise que la caméra normale jour et nuit. Un nouveau cadre, qui apprend la sécurité des piétons en examinant l'interaction entre les piétons et les véhicules et leur comportement au cours des interactions, a été proposé et illustré à travers une étude de cas. Le cadre a ensuite été testé dans le cadre d'une étude comparant les performances de trois types de passages pour piétons non signalés, notamment les passages pour piétons incontrôlés, balisés et contrôlés par des panneaux de signalisation, en matière de sécurité des piétons à l'aide de données recueillies sur différents sites de Montréal. Parmi les trois types de passages pour piétons non signalés, les passages pour piétons contrôlés par panneaux de signalisation ont la meilleure performance en matière de protection des piétons, tandis que les passages pour piétons non contrôlés ont le pire. Pour explorer les applications étendues du cadre, il a été introduit pour étudier les interactions cyclistes-piétons qui constituaient un problème majeur de sécurité routière mais sous-estimé dans les recherches précédentes. Les passages pour piétons marqués ne permettent pas à eux seuls de protéger les piétons des cyclistes de passage. En outre, la sécurité des piétons aux passages à niveau sur des installations cyclables avec des pentes en descente s'est avérée être un problème majeur.

En résumé, la thèse devrait: 1) fournir une littérature complète qui fonctionne comme une référence pratique pour enquêter sur la sécurité des piétons sur les passages pour piétons non signalés, 2) présenter une alternative prometteuse consistant à utiliser la caméra thermique pour surmonter les limitations de l'utilisation du spectre visible caméra pour la collecte automatisée de données sur la circulation, 3) propose un nouveau cadre décrivant plus précisément les interactions entre piétons et véhicules par rapport aux études précédentes et offrant des perspectives prometteuses en matière de sécurité routière sur divers sujets tels que l'analyse des interactions entre différents types de routes. Utilisateurs, la simulation des interactions des usagers de la route, la validation des traitements de sécurité et l'évaluation des performances des véhicules autonomes.

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CONTRIBUTIONS OF AUTHORS

This dissertation report is a manuscript-based report consisting of five journal manuscripts. Among the five manuscripts, three have been published and the other two are under review. Details of the publications are presented below. I would like to declare that I am the first and sole author, among the co-authors. My contributions to the articles include conducting the research studies, collecting and preparing the data, proposing the model, analyzing the data, and writing the manuscripts. The author's supervisors, Prof. Luis Miranda-Moreno and Prof. Nicolas Saunier, provided guidance, comments, and editorial revisions throughout the entire process. The other co-authors contributed by helping in data collection, providing comments, and editing the papers.

T. Fu*, J. Stipancic, L. Miranda-Moreno, & N. Saunier. Methodologies and Key Findings on Pedestrian Crosswalk Performance Evaluation at Non-signalized Locations: A Literature Review, in preparation for Transport Reviews.

T. Fu*, J. Stipancic, L. Miranda-Moreno, S. Zangenehpour, & N. Saunier. Automatic Traffic Data Collection under Varying Lighting and Temperature Conditions in Multimodal Environments: Thermal VS Visible Spectrum Video-based Systems, Journal of Advanced Transportation, No. 2017, 2017.

T. Fu*, L. F. Miranda-Moreno, and N. Saunier. Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime using Thermal Video Data and Surrogate Safety Measures, Transportation Research Record, No. 2586, 2016, pp 90-99.

T. Fu*, L. Miranda-Moreno, and N. Saunier. A Novel Framework to Evaluate Pedestrian Safety at Non-signalized Locations, Accident Analysis & Prevention, Volume 111, 2018, pp 23-33.

T. Fu*, D. Beitel, B. Navarro, L. Miranda-Moreno, & N. Saunier. Investigating Cyclist-Pedestrian Interactions and Cyclist & Pedestrian Behavior using a Novel Distance-Velocity Model, submitted to Journal of Transport & Health, 2019.

Chapter 1.

Introduction

Chapter 1 Introduction

This chapter presents the introduction of the dissertation including the motivation and context of the research on pedestrian road safety at non-signalized crosswalks, a discussion of missing gaps in the literature related to this topic, the objectives of this research work, and the organization of the dissertation.

1.1 MOTIVATION AND CONTEXT

Walking is a key component of the transportation system, especially in urban areas. It is the transportation mode that people take most frequently every day. Walking acts either as the primary or as the ancillary transportation mode in one’s daily life. All road users are pedestrians as walking is part of any trip, regardless of whether the primary mode of this trip is walking or not (Peterniak, 2015). For instance, even if someone drives all the time for most of his/her daily trips, that person, if able-bodied, will still need to walk to and from his parking lot, walk to a grocery store for daily purchases, or walk across the street to get a coffee from a coffee shop on the other side of the street.

As an important part of active transportation and sustainable mobility, the promotion of walking has increased in recent years. Walking provides individual benefits such as improved health, increased likelihood of social interactions, and can save both money and time for commuters (Public Health Agency of Canada, 2014). Additionally, there are societal benefits associated with walking, including reduced emissions of Greenhouse Gas (GHG) and other pollutants. Therefore, walking has been promoted by many cities to meet their sustainability goals and to improve their citizens’ quality of life. In spite of the benefits, active transportation also faces some challenges and barriers, road safety being one of them.

Given the dimension of the issue, pedestrian safety has become a priority for many cities due to the increased awareness of pedestrians' vulnerability compared to other road users. In 2013 in the US, 14 % of total road crash fatalities were pedestrians (NHTSA, 2015). Also in 2013 in Canada, 15.6 % of road crash fatalities were pedestrians (Transport Canada, 2015). The issue is even worse in developing countries. For instance, the report from WHO shows that around 40 % of road crash fatalities were pedestrians in countries such as Albania, Armenia, and Chile (WHO, 2009). Over 50 % of road crash fatalities were pedestrians in countries such as Bangladesh, Ethiopia, and Mozambique in 2007 (WHO, 2009). Globally, almost one out of five road crash fatalities were pedestrians according to data from 2010 (WHO, 2013).

Most crashes happen when pedestrians are exposed to motorized traffic, mostly, when they are crossing the streets. Around 4700 pedestrians were killed and over 165000 pedestrians were injured when crossing the street between 1999 and 2014 in Canada (Transport Canada, 2015). Pedestrians are vulnerable at locations with signalized and non-signalized crossings (crossings without traffic light). Hunter et al. found that 40 % of intersection crashes and 93 % of midblock crashes occurred at non-signalized locations (Hunter, et al., 1996). Police reports from Arkhangelsk, Russia show that 79 % of pedestrian-vehicle crashes between 2005 and 2010 occurred at non-signalized crosswalks (Kudryavtsev, et al., 2012).

The numerical evidence shows that the safety of pedestrians at non-signalized crossings is an important public health problem. Thus, transportation agencies and other practitioners are spending more efforts in prioritizing pedestrian safety. Given the importance of pedestrian safety in research and practice, different studies have been conducted and treatments have been evaluated (Huang, et al., 2000; Nabavi Niaki, et al., 2016), however, more research and empirical evidences are still needed.

1.2 LITERATURE AND RESEARCH GAPS

This section provides a general description of the five methodological approaches used in previous studies on pedestrian-vehicle interactions, as well as the literature gaps. Details on the literature review work are included in ***Chapter 2***.

1.2.1 Literature Summary

1.2.1.1 Methodological Approaches

Road safety analysis methods can be categorized into crash-data based and surrogate measures of safety (SMoS). Traditionally, road safety studies make use of historical crash data, focusing on crash frequency and severity as direct measures of safety (Abdel-Aty & Haleem, 2010; Nabavi Niaki, et al., 2016). In investigating pedestrian safety at non-signalized crosswalk locations, many studies have also relied on using historical crash data (Campbell, 1997; Chu, 2006; Chu, et al., 2008; Ellis & Van Houten, 2009; Gibby, et al., 1994; Jones & Tomcheck, 2000; Liu, et al., 2011; Pfortmueller, et al., 2014; Zegeer, et al., 2001). However, it is known by researchers and practitioners that the crash-data based approach depends on the quality and availability of the data (Fu, et al., 2016; Tarko, et al., 2009). Besides, long periods (multiple years) of observation are required to obtain data in sufficiently large quantities, making inefficient the evaluation of treatments (St-Aubin, et al., 2013). This has also been criticized for being a reactive approach. To overcome these issues of using crash data, proactive methods relying on SMoS (or surrogate safety measures, SSM) have emerged without waiting for crashes to happen to gather the data. These methods based on SMoS, i.e. safety diagnosis methods that rely on SMoS, investigate pedestrian safety mainly through four approaches[1]: i) the traffic data approach based on traffic data (speed, volume, etc.), ii) the traffic conflict approach, iii) the behavioral analysis approach based on road user behavior, and iv) the perception analysis approach based on road user perception (Fu, et al., 2018).

[1] According to its definition, SMoS should satisfy the conditions of being both observable non-crash events and being statistically related to crashes in terms of frequency and/or severity (Tarko, et al., 2009). They include SMoS or SMoS candidates, SMoS of which relationship with crashes is not statistically proved, but which have been applied for safety analysis purposes in past studies.

Different sources of data and approaches have been proposed for pedestrian safety studies at non-signalized crosswalks. The crash data-based approach has relied on crash reports from the police, government organizations, and sometimes ambulance or in-/outpatient records from hospitals (Diogenes & Lindau, 2010; Ellis & Van Houten, 2009; Ivan, et al., 2012; Jones & Tomcheck, 2000; Olszewski, et al., 2015; Pfortmueller, et al., 2014). In the traffic data-based approach, traffic information such as speed and volume have been collected using different methods including speed guns, loop detectors, magnetic plates and video data (Antov, et al., 2007; Boyce & Van Derlofske, 2002; Fu, et al., 2016; Gitelman, et al., 2016a; Gitelman, et al., 2016b; Liu, et al., 2011; Wang, et al., 2017). Data in the conflict event-based approach has been collected through manual field observations (Brumfield & Pulugurtha, 2011; Clark, et al., 1996; Mitman, et al., 2010; Nteziyaremye, 2013; Van Houten, et al., 2001), and video data both processed manually or automatically with the help of vision-based tracking technologies (Almodfer, et al., 2016; Cafiso, et al., 2011; Gómez, et al., 2011). Different tools and data sources including video, field observations, speed guns, naturalistic driving data and driving or pedestrian simulations have been applied in collecting data for the behavior analysis approach (Brumfield & Pulugurtha, 2011; Bungum, et al., 2005; Fitzpatrick, et al., 2007; Harrison, 2017; Jiang, 2012; Shi, et al., 2007a; Shi, et al., 2007b). The perception analysis approach has most commonly relied on surveys (Boyce & Van Derlofske, 2002; Chai & Zhao, 2016; Dhar & Woodin, 1995; Mitman & Ragland, 2007; Johansson & Leden, 2007; Zhuang & Wu, 2014).

1.2.1.2 Pedestrian-Vehicle Interaction Studies

The occurrence of pedestrian-vehicle interactions is the necessary condition for the occurrence of pedestrian-vehicle crashes. In the context of pedestrian safety at crosswalk locations, a pedestrian-vehicle interaction is a situation where both the pedestrian and the vehicle arrive close in time and risk a chance of a crash at the crosswalk location. Learning how pedestrian-vehicle interactions are formed and unfold has been a focus in studying pedestrian safety at non-signalized crosswalk locations. In previous studies, pedestrian-vehicle interactions have been mostly investigated through the study of traffic conflicts and behavioral analysis – interactions result from the behavior and choice of actions of road users and conflicts are the outcome of interactions.

Traffic conflict analysis has adopted traffic conflict techniques (TCT), e.g. the Swedish TCT, to predict the outcome of interactions. Time-to-collision (TTC) and post-encroachment time (PET) are the most common measures for identifying conflicts in general (Almodfer, et al., 2016). Different researchers have used TTC and PET for pedestrian safety analysis (Almodfer, et al., 2016; Cafiso, et al., 2010; Tang & Nakamura, 2009). Pedestrian-vehicle conflicts can be divided into discrete severity levels based on different PET and TTC thresholds (Ismail, et al., 2011; Malkhamah, et al., 2005).

Given the fact that human error is found to be one of the reasons for approximately 95 % of road crashes (NHTSA, 2008), the behavior analysis approach is popularly applied in studies investigating pedestrian safety at non-signalized intersections. Different studies have looked at safety-related behaviors including yielding (Bella & Silvestri, 2015; Crowley-Koch & Van Houten, 2011; Fitzpatrick, et al., 2011; Mitman & Ragland, 2008; Pulugurtha, 2015; Xiang, et al., 2016), crossing movements, (Boroujerdian & Nemati, 2016; Brewer, et al., 2006; Jiang, 2012; Jiang, et al., 2015; Kadali & Perumal, 2016; Kadali, et al., 2014; Nteziyaremye, 2013; Pawar & Patil, 2015; Schroeder, et al., 2014; Sun, et al., 2003) and pedestrian and vehicle checking behavior to investigate pedestrian safety at non-signalized crosswalk locations (Fisher & Garay-Vega, 2012; Gómez, et al., 2011; Gómez, et al., 2014; Harrison, 2017; Knoblauch, et al., 2001; Nteziyaremye, 2013), and etc.

Many studies investigating pedestrian-vehicle interactions have relied on direct (manual) field observations (Brumfield & Pulugurtha, 2011; Bungum, et al., 2005; Hakkert, et al., 2002; Ismail, et al., 2011; Knoblauch, et al., 2001; Li & Ming, 2016; Mitman, et al., 2010; Van Houten, et al., 2002) or from video data recordings (Boyce & Van Derlofske, 2002; Dobbs, 2009; Fitzpatrick, et al., 2007; Harrison, 2017; Ibrahim, et al., 2005; Shi, et al., 2007a; Shi, et al., 2007b; Sisiopiku & Akin, 2003; Van Derlofske, et al., 2003). Recently, vision-based tracking techniques have become available to extract detailed traffic data, such as road user trajectories (Cafiso, et al., 2011; Saunier, n.d.; Saunier & Sayed, 2006). The recent development of video-based techniques has brought about the possibility of investigating pedestrian-vehicle interactions in a more precise and microscopic way, for example in (Boroujerdian & Nemati, 2016; Fu, et al., 2018; Jiang, 2012; Jiang, et al., 2015).

1.2.2 Limitations and Gaps in Previous Studies

Despite the research efforts on pedestrian safety at non-signalized crosswalk locations, some limitations exist in the current literature:

- Despite the promise of the different methods used for evaluating non-signalized crosswalk safety, a comprehensive review of these methods is missing. Many of the published work does not include a systematic investigation on all related methods. Therefore, a detailed literature review study will help and will provide a guideline for the application of existing methods, and the development of new approaches.

- For investigating pedestrian-vehicle interactions, a comprehensive framework, which considers both the development of interactions (e.g. pedestrian and vehicle behaviors) and the outcome of events, (e.g. the measurements based on traffic conflict techniques) is promising. However, most previous studies have only focused on one of the two.

- Despite frequent usage, behavior analysis approaches require improvements, considering the complex dynamics of pedestrian and vehicle behaviors and attitudes during the development of an interaction. Research on vehicle yielding behavior is limited as the definition of yielding compliance is ambiguous. Some situations have not been explicitly discussed, for example where it is impossible for the vehicle to yield due to their speed and proximity to the crosswalk. Considering such situations as non-compliance is far-fetched. Meanwhile, the definition of non-yielding maneuver is unclear – determining when a pedestrian arrives at the beginning of the crosswalk and should be noticed and yielded by the driver is often subjective.

- Data issues are common in studies that investigate pedestrian safety at non-signalized crosswalks. The quality and quantity of crash data have been often limited. Data used in SMoS are usually collected using short-term data collection methods such as field observation and video data collection (Laureshyn, et al., 2016). Most studies relied on data from a limited number of sites due to the amount of work needed (setting up equipment, manually labeling and extracting information, or conducting surveys) or due to the difficulty in obtaining permission for videotaping or collecting personal information. Data quality may also be challenged especially from manual observations or surveys which can be highly subjective.

- The benefits of vision-based techniques notwithstanding, there are critical limitations associated with using regular video cameras for traffic data collection. Regular cameras are sensitive to lighting conditions and fail to perform well in adverse weather, low light conditions and darkness. Meanwhile, shadows and glare in the daytime also degrade the accuracy of the regular cameras. In other words, regular cameras do not work under all conditions, especially at nighttime when increased injury risk leads to more severe road traffic crashes (Plainis, et al., 2006; Tyrrell, et al., 2016). Alternatives need to be explored for using this type of technology.

In general, limitations and gaps still exist in the methodologies. The research work in this thesis aims at addressing these limitations and gaps.

1.3 OBJECTIVES OF THE RESEARCH

The ***general objective*** of the research is to investigate pedestrian-vehicle interactions in pedestrian crossings by proposing and validating new data collection methods and a theoretical model. The proposed methods are validated using video data at various Montreal crosswalk environments with different geometric and lighting conditions. The ***specific objectives*** are described as follows.

A) **To conduct an extensive literature review work related to methodologies for pedestrian safety diagnosis at non-signalized crosswalks**.

B) To study issues with data collection using a regular spectrum camera under different lighting conditions and to investigate the performance of thermal video-camera sensors – Aiming to solve the issues found in using video data for extracting road user trajectory under poor visibility conditions, the thermal camera is introduced as an alternative for traffic data collection, in particular to investigate pedestrian safety during nighttime. The performance of using this type of sensing technology is validated through a comparison to a regular camera.

C) To propose a novel pedestrian-vehicle interaction framework to investigate pedestrian safety at crosswalks – The framework considers the development of pedestrian-vehicle interactions over time, and allows the investigation of road user behaviors critical to the outcome of crashes: vehicle yielding behaviors, pedestrian occurrence and crossing decisions.

D) To test the framework through the performance evaluation of different types of crosswalk facilities on pedestrian safety – The framework is tested based on data from different traffic environments. Data is collected from three main types of crosswalk facilities. These are uncontrolled (crosswalks not controlled by any type of signs or markings), marked (crosswalks with markings assigning right-of-way to pedestrians) and stop sign controlled crosswalks (crosswalks with a stop sign requiring all vehicles to stop before the crossing location).

E) To explore the application of the proposed methodology for cyclist-pedestrian interactions – The framework can be applied in exploring different road safety issues, for example cyclist-pedestrian interactions, which have not previously been investigated.

1.4 CONTRIBUTIONS

The key contributions of this dissertation are summarized as follows:

- This thesis provides a comprehensive review of the methodological approaches and data collection methods used in the existing literature on pedestrian safety at non-signalized crosswalk locations. Researchers and practitioners can use this literature-review work as a useful reference. Meanwhile, the identification of the limitations and gaps in the existing literature can motivate future research in better understanding pedestrian-vehicle interactions.

- From the data collection methods, this work integrates and validates data collection method using a thermal video sensor and demonstrates that this solution can meet the requirements of an around-the-clock tool for traffic data collection and safety analysis under all weather and lighting conditions. Besides, the dissertation applies the thermal camera system for investigating pedestrian safety in low visibility conditions when pedestrians face a higher risk of crash and few data collection tools are available to study their safety.

- It proposes a new framework for pedestrian safety at non-signalized crosswalks, referred to as the distance-velocity (DV) model. This novel method gives insights about pedestrian-vehicle interactions by considering the development of interactions and behavioral factors such as vehicle yielding behavior and pedestrian crossing decisions that are critical to the outcome of a crash.

- This work explores the safety of pedestrians in their interactions with cyclists, which has been rarely studied in the past. This work is expected to attract more research and practices focused on the topic of cyclist-pedestrian interactions, which is important in the context of the promotion of active transportation. This relies on the application of the DV framework to another road safety problem.

1.5 ORGANIZATION OF THE DISSERTATION

The dissertation is structured into eight chapters including the introduction. As being manuscript-based, the remainder of the dissertation includes one manuscript in preparation for a submission to a peer-reviewed journal (***Chapter 2***), four refereed journal papers (***Chapter 3-5,*** *7*), an additional chapter about the work in testing the framework (***Chapter 6***), and the conclusion (***Chapter 8***).

Chapter 2 provides a comprehensive review of the existing literature on pedestrian safety at non-signalized crosswalk locations. Key methodologies as well as their advantages, limitations in the past three decades (from the year of 1987) are reviewed and discussed. These methodological approaches are summarized into five main categories (the crash data approach and four approaches relying on SMoS). Details of the data collection and safety methods are clearly documented in each main category.

Chapter 3 introduces the thermal camera system and presents the validation of its performance in traffic data collection under various conditions. For validation purposes, existing computer vision methods for automated data processing are integrated. The performance of using thermal cameras for collecting road user information, including detection, classification and speed measurements, under varying lighting and temperature conditions across multiple sites is validated, and is compared to the performance of a visible spectrum camera.

Chapter 4 proposes a methodology that relies on several existing and applicable SMoS in exploring pedestrian safety at non-signalized crosswalks at nighttime based on data collected using the thermal camera system. The methodology used several SMoS indicators including vehicle approaching speed, PET, yielding compliances, and conflict rates. The methodology is applied to evaluate pedestrian safety at non-signalized crosswalks at nighttime.

Chapter 5 introduces a new methodological framework, the DV model, for investigating pedestrian safety at non-signalized crosswalk locations. Assumptions, some practical definitions, and the detailed explanation of the model, along with the derived measures, are presented. The model classifies interactions between approaching vehicles and pedestrians showing the intention to cross in different categories. The framework is demonstrated through a case study involving three non-signalized crosswalks including a marked crosswalk, an uncontrolled crosswalk, and a stop sign controlled crosswalk.

Chapter 6 aims at validating the applicability of the proposed DV model in a study involving 15 different crosswalk locations in Montreal. Pedestrian safety at the three types of crosswalks, marked, uncontrolled, and stop sign controlled, is analyzed and compared using the framework. The occurrences of interactions, vehicle yielding behavior, pedestrian crossing decisions, and the observation of evasive maneuvers are investigated. Results in this chapter suggest that the framework describes pedestrian-vehicle interactions at non-signalized crosswalk locations in a proper way with correct assumptions and parameters.

Chapter 7 investigates the applicability of the proposed methodology and the DV model to study pedestrian-cyclist interactions in urban areas. The case study deals with crosswalks at non-signalized intersections and crosswalks at bus stops along segregated cycle tracks.

Finally, ***Chapter 8*** concludes and summarizes the key findings and contributions in this dissertation, and discusses the limitations, implications of the DV model and future research in the field of pedestrian safety.

1.6 REFERENCES

Abdel-Aty, M. & Haleem, K., 2010. *Analysis of the Safety Characteristics of Unsignalized Intersections.* Lisbon, Portugal.

Almodfer, R. et al., 2016. Quantitative Analysis of Lane-based Pedestrian-vehicle Conflict at a Non-signalized Marked Crosswalk. *Transportation Research Part F: Traffic Psychology and Behaviour,* Volume 42, pp. 468-478.

Antov, D., Rõivas, T. & Rõuk, H., 2007. Investigating Drivers' Behaviour at Non-Signalised Pedestrian Crossings. *Baltic Journal of Road and Bridge Engineering,* 2(3), pp. 111-118.

Boroujerdian, A. M. & Nemati, M., 2016. Pedestrian Gap Acceptance Logit Model in Unsignalized Crosswalks Conflict Zone. *International Journal of Transportation Engineering,* August, 4(2), pp. 87-96.

Boyce, P. & Van Derlofske, J., 2002. *Pedestrian Crosswalk Safety: Evaluating In-Pavement, Flashing Warning Lights,* New Jersey.

Brumfield, R. & Pulugurtha, S. S., 2011. *When Distracted Road Users Cross Paths,* Washington DC: Public Roads.

Bungum, T. J., Day, C. & Henry, L. J., 2005. The association of Distraction and Caution Displayed by Pedestrians at A Lighted Crosswalk. *Journal of Community Health,* August, 30(4), pp. 269-279.

Cafiso, S., Garcia, A., Cavarra, R. & Rojas, M. A. R., 2010. *Pedestrian Crossing Safety Improvements: Before and After Study using Traffic Conflict Techniques.*, pp. 2-5.

Cafiso, S., García, A. G., Cavarra, R. & Romero Rojas, M. A., 2011. *Crosswalk Safety Evaluation using a Pedestrian Risk Index as Traffic Conflict Measure.* Italy.

Campbell, B. J., 1997. *Marked Crosswalks and Safety,* Chapel Hill, North Carolina.

Chai, J. & Zhao, G., 2016. Effect of Exposure to Aggressive Stimuli on Aggressive Driving Behavior at Pedestrian Crossings at Unmarked Roadways. *Accident Analysis & Prevention,* Volume 88, pp. 159-168.

Chu, X., 2006. *Pedestrian Safety at Midblock Locations,* Tallanassee, FL, US.

Chu, X., Lin, P.-S. & Kourtellis, A., 2008. *Safety Effects and Guideline Development for Uncontrolled Midblock Crosswalks.* Miami, FL, USA.

Clark, K., Hummer, J. & Dutt, N., 1996. Field Evaluation of Fluorescent Strong Yellow-Green Pedestrian Warning Signs. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1538, pp. 39-46.

Dhar, S. & Woodin, D. C., 1995. *Fluorescent Strong Yellow-green Signs for Pedestrian/School/Bicycle Crossings: Results of a New York State Study,* Albany, NY, US.

Diogenes, M. C. & Lindau, L. A., 2010. Evaluation of Pedestrian Safety at Midblock Crossings, Porto Alegre, Brazil. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2193, pp. 37-43.

Ellis, R. & Van Houten, R., 2009. Reduction of Pedestrian Fatalities, Injuries, Conflicts, and Other Surrogate Measures in Miami–Dade, Florida: Results of Large-Scale FHWA Project. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2140, pp. 55-62.

Fitzpatrick, K., Turner, S. & Brewer, M. A., 2007. Improving Pedestrian Safety at Unsignalized Intersections. *ITS Journal,* May, 77(5), pp. 34-41.

Fitzpatrick, K. et al., 2011. *Evaluation of Pedestrian and Bicycle Engineering Countermeasures: Rectangular Rapid-Flashing Beacons, HAWKs, Sharrows, Crosswalk Markings, and the Development of an Evaluation Methods Report*, Texas: s.n.

Fu, T., Miranda-Moreno, L. F. & Saunier, N., 2016. Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime: Use of Thermal Video Data and Surrogate Safety Measures. *Transportation Research Record: Journal of the Transportation Research Board,* Volume 2586, pp. 90-99.

Fu, T., Stipancic, J., Miranda-Moreno, L. & Saunier, N., 2018. Methodological Approaches to Evaluating Pedestrian Safety at Non-signalized Crossing Locations: A Literature Review. *submitted to Transport Reviews.*

Gibby, A. R., Stiles, J. L., Thurgood, G. S. & Ferrara, T. C., 1994. *Evaluation of Marked and Unmarked Crosswalks at Intersections in California,* Chico, CA.

Gitelman[a], V., Carmel, R., Pesahov, F. & Chen, S., 2016. Changes in Road-user Behaviors Following the Installation of Raised Pedestrian Crosswalks Combined with Preceding Speed Humps, on Urban Arterials. *Transportation Research Part F: Traffic Psychology and Behaviour.*

Gitelman[b], V., Carmel, R., Pesahov, F. & Hakkert, S., 2016. An Examination of the Influence of Crosswalk Marking Removal on Pedestrian Safety as Reflected in Road User Behaviours. *Transportation Research Part F: Traffic Psychology and Behaviour.*

Gómez, R. A. et al., 2011. Do Advance Yield Markings Increase Safe Driver Behaviors at Unsignalized, Marked Midblock Crosswalks? Driving Simulator Study. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2264, pp. 27-33.

Gómez, R. A. et al., 2014. Mitigation of Pedestrian–Vehicle Conflicts at Stop-Controlled T-Intersections. *Transportation Research Record: Journal of the Transportation Research Board*, Issue 2464, pp. 20-28.

Hakkert, A. S., Gitelman, V. & Ben-Shabat, E., 2002. An Evaluation of Crosswalk Warning Systems: Effects on Pedestrian and Vehicle Behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, pp. 275-292.

Harrison, D., 2017. *Study of Distracted Pedestrians' Behavior when Using Crosswalks,* Mississippi State, US.

Huang, H., Zegeer, C. & Nassi, R., 2000. Effects of Innovative Pedestrian Signs at Unsignalized Locations: Three Treatments. *Transportation Research Record: Journal of the Transportation Research Board,* pp. 43-52.

Hunter, W. W., Stutts, J. C., Pein, W. E. & Cox, C. L., 1996. *Pedestrian and Bicycle Crash Types of Early 1990's.*

Hydén, C., 1987. *The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique,* Lund.

Ismail, K., Sayed, T. & Saunier, N., 2011. Methodologies for Aggregating Indicators of Traffic Conflict. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2237, pp. 10-19.

Ivan, J. N., Ravishanker, N., Islam, M. S. & Serhiyenko, V., 2012. *Evaluation of Surrogate Measures for Pedestrian Safety in Various Road and Roadside Environments,* Storrs, CT, US.

Jiang, X., 2012. *Intercultural Comparison of Road User Behavior Centred Vehicle-Pedestrian Conflict in Urban Traffic.*

Jiang, X., Wang, W., Bengler, K. & Guo, W., 2015. Analyses of Pedestrian Behavior on Mid-block Unsignalized Crosswalk comparing Chinese and German Cases. *Advances in Mechanical Engineering,* 7(11), pp. 1-7.

Johansson, C. & Leden, L., 2007. Short-term Effects of Countermeasures for Improved Safety and Mobility at Marked pedestrian Crosswalks in Borås, Sweden. *Accident Analysis & Prevention,* May, 39(3), pp. 500-509.

Jones, T. & Tomcheck, P., 2000. Pedestrian Accidents in Marked and Unmarked Crosswalks: A Quantitative Study. *ITE Journal,* September, 70(9), pp. 42-46.

Kadali, B. R., Rathi, N. & Perumal, V., 2014. Evaluation of Pedestrian Mid-block Road Crossing Behaviour using Artificial Neural Network. *Journal of Traffic and Transportation Engineering,* 1(2), pp. 111-119.

Kadali, B. R. & Perumal, V., 2016. Analysis of Critical Gap based on Pedestrian Behaviour during Peak Traffic Hours at Unprotected Mid-block Crosswalks. *Asian Transport Studies*, 4(1), pp. 261-277.

Kudryavtsev, A. V. et al., 2012. Explaining Reduction of Pedestrian Motor Vehicle Crashes in Arkhangelsk, Russia, in 2005-2010. *International Journal of Circumpolar Health,* September, 71(19107), pp. 1-8.

Kwayu, K. M., 2016. *Improved Methodology for Developing Non-Motorized Safety Perfomance Functions*, s.l.: Western Michigan University.

Liu, P., Huang, J., Wang, W. & Xu, C., 2011. Effects of Transverse Rumble Strips on Safety of Pedestrian Crosswalks on Rural Roads in China. *Accident Analysis & Prevention,* 43(6), pp. 1947-1954.

Li, M. & Ming, X., 2016. *Study on the Effect of Distraction for Pedestrian Crossing*.

Laureshyn, A. et al., 2016. *Review of Current Study Methods for VRU Safety: Appendix 6: Scoping Review: Surrogate Measures of Safety in Site-based Road Traffic Observations*, Poland: Warsaw University of Technology, Poland.

Malkhamah, S., Tight, M. & Montgomery, F., 2005. The Development of an Automatic Method of Safety Monitoring at Pelicen Crossings. *Accident Analysis & Prevention,* 37(5), pp. 938-946.

Mitman, M. F. & Ragland, D. R., 2007. Crosswalk Confusion More Evidence Why Pedestrian and Driver Knowledge of the Vehicle Code Should Not Be Assumed. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2002, pp. 55-63.

Mitman, M. F. & Ragland, D. R., 2008. *Driver/Pedestrian Understanding and Behavior at Marked and Unmarked Crosswalks*, s.l.: s.n.

Mitman, M. F., Cooper, D. & DuBose, B., 2010. Driver and Pedestrian Behavior at Uncontrolled Crosswalks in Tahoe Basin Recreation Area of California. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2198, pp. 23-31.

Nabavi Niaki, M. et al., 2016. Effects of Road Lighting on Bicycle and Pedestrian Accident Frequency: Case Study in Montreal, Canada. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2555, pp. 86-94.

NHTSA, 2008. *National Motor Vehicle Crash Causation Survey,* Virginia, US: National Highway Traffic Safety Administration.

NHTSA, 2015. *Traffic Safety Facts 2013 Data.*

Nteziyaremye, P., 2013. *Understanding Pedestrian Crossing Behaviour: A Case Study in the Western Cape, South Africa.*

Olszewski, P., Szagała, P., Wolanski, M. & Zielinska, A., 2015. Pedestrian Fatality Risk in Accidents at Unsignalized Zebra Crosswalks in Poland. *Accident Analysis & Prevention,* Issue 84, pp. 83-91.

Peterniak, R., 2015. *Pedestrian Crossing Safety and Accommodation at Signalized Intersections in San Jose, Costa Rica,* Winnipeg, Manitoba, Canada: University of Manitoba.

Pfortmueller, C. A. et al., 2014. Injury Severity and Mortality of Adult Zebra Crosswalk and Non-Zebra Crosswalk Road Crossing Accidents: A Cross-Sectional Analysis. *Plos One,* 9(3), pp. 1-6.

Plainis, S., Murray , I. J. & Pallikaris, I. G., 2006. Road Traffic Casualties: Understanding the Night-time Death Toll. *Injury Prevention*, 12(2), pp. 125-128.

Public Heath Agency of Canada, 2014. *What is Active Transportation.* [Online] Available at: http://www.phac-aspc.gc.ca/hp-ps/hl-mvs/pa-ap/at-ta-eng.php

Robert, K., 2009. *Night-Time Traffic Surveillance A Robust Framework for Multi-Vehicle Detection, Classification and Tracking.*, pp. 1-6.

Saunier, N. & Sayed, T., 2006. *A Feature-based Tracking Algorithm for Vehicles in Intersections.*

Schroeder, B. et al., 2014. *Empirically-Based Performance Assessment and Simulation of Pedestrian Behavior at Unsignalized Crossings,* Gainesville, FL, US.

Shi, J., Chen, Y., Ren, F. & Rong, J., 2007a. Research on Pedestrian Behavior and Traffic Characteristics at Unsignalized Midblock Crosswalk: Case Study in Beijing. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2038, pp. 23-33.

Shi, J., Wang, Z. & Chen, Y., 2007b. *Analysis on Behaviours and Safety of VRUs at Unsignalized Roadway Crosswalk.* Beijing, China.

St-Aubin, P., Miranda-Moreno, L. F. & Saunier, N., 2013. An Automated Surrogate Safety Analysis at Protected Highway Ramps using Cross-Sectional and Before-after Video Data. *Transportation Research Part C: Emerging Technologies,* Volume 36, pp. 284-295.

Sun, D., Ukkusuri, S. V., Benekohal, R. F. & Waller, S. T., 2003. *Modeling of Motorist-Pedestrian Interaction at Uncontrolled Mid-block Crosswalks.* Washington DC.

Tang, K. & Nakamura, H., 2009. Safety Evaluation for Intergreen Intervals at Signalized Intersections based on Probabilistic Methodology. *Transportation Research Record: Journal of Transportation Research Board,* Issue 2128, p. 226–235.

Tarko, A. et al., 2009. *White Paper: Surrogate Measures of safety.*

Transport Canada, 2015. *Canadian Motor Vehicle Traffic Collision Statistics 2013.*

Tyrrell, R. et al., 2016. The Conspicuity of Pedestrians at Night: a Review. *Clinical and Experimental Optometry,* 99(5), pp. 425-434.

Van Houten, R., Malenfant, L. & McCusker, D., 2001. Advance Yield Markings: Reducing Motor Vehicle–Pedestrian Conflicts at Multilane Crosswalks with Uncontrolled Approach. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1773, pp. 69-74.

Van Houten, R. et al., 2002. Advance Yield Markings and Fluorescent Yellow-Green RA 4 Signs at Crosswalks with Uncontrolled Approaches. *Transportation Research Record: Journal of the Transportation Research Board*, Issue 1818, pp. 119-124.

Wang, C., Ye, Z., Wang, X. & Li, W., 2017. Effects of Speed-control Measures on the Safety of Unsignalized Midblock Street. *Traffic Injury Prevention,* pp. 1-6.

WHO, 2009. *Global Status Report on Road Safety: Time for Action,* Switzerland: World Health Organization.

WHO, 2013. *Global Status Report on Road Safety 2013: Supporting a Decade of Action,* Switzerland: World Health Organization.

Ye, Z., Zhang, Y. & Lord, D., 2013. Goodness-of-fit Testing for Accident Models with Low Means. *Accident Analysis & Prevention*, Volume 61, pp. 78-86.

Zegeer, C. V., Stewart, R., Huang, H. & Lagerwey, P., 2001. Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations: Analysis of Pedestrian Crashes in 30 Cities. *Transportation Research Record: Journal of Transportation Research Board,* Volume 1773, pp. 56-68.

Zhuang, X. & Wu, C., 2014. Pedestrian Gestures Increase Driver Yielding at Uncontrolled Mid-block Road Crossings. *Accident Analysis & Prevention*, Issue 70, pp. 235-244.

Chapter 2

A Literature Review: Methodological Approaches to Evaluating Pedestrian Safety at Non-signalized Crossing Locations

Chapter 2 A Literature Review: Methodological Approaches to Evaluating Pedestrian Safety at Non-Signalized Crossing Locations

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In presentation for Transport Reviews

2.1 INTRODUCTION

2.1.1 Background

The safety of pedestrians at non-signalized crossings (crossings without traffic light) has become a great concern in road safety (Makarova, et al., 2016; Olszewski, et al., 2015). In Canada, around 4700 pedestrians were killed and over 165000 were injured when crossing the street between 1999 and 2014 (Transport Canada, 2015). Over 62 % of pedestrian deaths and injuries occurred at non-signalized locations. Note that the terms "non-signalized" (or "unsignalized") and "uncontrolled" are unfortunately used interchangeably in the existing literature to describe crosswalk locations without traffic lights. These terms describe different situations; non-signalized crosswalks are locations without traffic lights, while uncontrolled crosswalks are without any traffic control devices (no signs, no markings, and also no traffic light). Recent attempts to correct the interchangeable use of these words have added to the conceptual confusion (Elefteriadou, 2014; McGee, et al., 2015). While the ITE Unsignalized Intersection

Improvement Guide (UIIG) properly defines non-signalized intersections as intersections not "controlled by a traffic signal" (McGee, et al., 2015), it does not include crossing locations that are not at intersections. The UIIG (McGee, et al., 2015) nevertheless states that non-signalized crossings may be classified as: 1) uncontrolled, for crossings without any type of signs or markings. This chapter reviews previous work on non-signalized crosswalk safety based on the above definitions.

Recognizing the risk for pedestrians at non-signalized crosswalk locations, practitioners have made pedestrian safety a major design factor and have prioritized pedestrians when constructing non-signalized crossings by proposing and implementing treatments including road infrastructure, signage, and pavement marking improvements (Mead, et al., 2014). Researchers have likewise investigated safety issues and sought solutions to improve pedestrian safety at non-signalized crosswalk locations. Safety, along with the efficiency of several designs and safety countermeasures has been investigated in several studies (Cafiso, et al., 2011; Huang, et al., 1999; Jones & Tomcheck, 2000; Sisiopiku & Akin, 2003; Smith, et al., 2009; Van Houten, 1988). Safety studies have typically relied on crash data, although crash data samples are often insufficient due to low vehicle traffic and pedestrian activity. This results in a low frequency of crashes (low mean problem) leading to long periods of data collection and then poor fit and accuracy of derived statistical models (Fu, et al., 2016; Lord & Miranda-Moreno, 2008). Methodologies based on crash data are time-inefficient, requiring many years of data, making it difficult to evaluate recently developed treatments (St-Aubin, et al., 2013). In many cases, crash data is limited or is inadequately detailed to explore safety problems such as road user non-compliance and pedestrian misjudgement of gaps in traffic among others (McGee, et al., 2015). Instead, many researchers have used surrogate measures of safety (SMoS). Some have considered vehicle approach speed to investigate the effectiveness of safety treatments (Bentley, 2015; Fu, et al., 2016; Hakkert, et al., 2002), while others have relied on exposure measures (Molen, 1981; Mitman, et al., 2008) or traffic conflicts (Cafiso, et al., 2011; Svensson & Hydén, 2006). Driver and pedestrian behaviors, such as yielding behavior and crossing decisions, and their contributions to pedestrian-vehicle crashes, have also been explored (Brumfield & Pulugurtha, 2011; Jiang, 2012; Mitman & Ragland, 2008).

Despite the promise of these methods, many have been proposed without a systematic investigation of related work. Additionally, utilized variables vary among the studies, and different thresholds or "rules" have been applied to the same measure. Many national and provincial projects and standards across Canada (Delphi MRC, 2010; Highway Safety Branch, Ministry of Transportation and Highways, 1994; MTO, 2016) and the US (Fitzpatrick, et al., 2006; FHWA, 2009; Zegeer, et al., 2005) have relied on safety measures without a detailed review to justify why the measures were initially adopted. A comprehensive review of existing and state-of-the-art methods for evaluating non-signalized crosswalk safety is essential, providing a guide of feasible methodologies for the future development of safety approaches, including those exploring new surrogate measures of safety.

The primary goal of this work is to provide a systematic literature review of the alternative methods for investigating pedestrian safety at non-signalized crosswalks. This document reviews the research literature on this topic from the previous 30 years, from 1987 to 2017, highlighting key studies with a focus on implemented methods. The considered studies use either traditional approaches for evaluating safety based on crash data analysis or newer SMoS. The studies are identified through a series of searches of several publication databases, which included Google Scholar, TRIS, TRANSDOC, ITRD, and SafetyLit (Google, 2018; Transportation Research Board, 2018; Ovid Technologies, 2018; WHO, 2018). Additional studies were identified using the citations within the papers found in these databases. Approximately 150 reports and peer-reviewed papers were included in this review. Based on this literature, the methodologies are classified into five distinct approaches. This document defines each methodological approach, summarizing commonly used measures, data, and collection methods. Finally, this work discusses the limitations and challenges of each approach with respect to methods and data, identifying research gaps to be further explored.

2.1.2 Brief History of Previous Work

Although crosswalks existed in ancient Rome over 2000 years ago (Bennett & Van Houten, 2016), the first signalized crossing was built in London in 1868 (The Times, 1868). Most non-signalized crossings were uncontrolled until the early 1910s, when stop signs were first implemented in Detroit, Michigan (Greenbaum & Rubinstein, 2011). As stop signs often increase delay, most non-signalized sites remained uncontrolled. Different markings and signs for protecting pedestrians were first trialed in the 1920s and 1930s (Ishaque & Noland, 2012), and these crossings became the earliest versions of yield-controlled crosswalks. The first zebra crossing was implemented in the UK in 1951 and proved to be the most effective marking pattern for protecting pedestrian crossings (Road Research Laboratory, 1963). Despite debate on its efficiency (Campbell, 1997; Gibby, et al., 1994; Herms, 1972; Mitman, et al., 2008; Zegeer, et al., 2005), the zebra crossing remains to be the countermeasure that has been the most frequently used (BC MOT, 1994; FHWA, 2001).

Thanks to advances in traffic engineering and the development of lighting, sensing, and material technologies, new countermeasures for pedestrian safety at non-signalized crosswalks have emerged in recent decades. Most of these literature reviews on crosswalk safety and the efficiency of pedestrian countermeasures have summarized previous practices and innovations mostly within Europe (Davies, 1999; Draskóczy & Hydén, 1994; Fizpatrick, et al., 2007; Mead, et al., 2014; Tan & Zegeer, 1995; Gitelman, et al., 2012; Tan & Zegeer, 1995). Some cities have also published guidelines for pedestrian safety countermeasures: for instance, Delphi MRC, 2010; MTO, 2016. Mead et al. (2014) comprehensively reviewed existing research on pedestrian safety countermeasures, summarizing countermeasures into six categories: 1) marking and sign enhancements, 2) curb extensions, 3) crossing islands, 4) raised crosswalks, 5) street lighting improvements, and 6) automated pedestrian detection systems.

Additionally, some past studies have provided an overview regarding the methodologies used for safety analysis (Campbell, et al., 2004; Karsch, et al., 2012; Nemeth, et al., 2014; Van Houten & Malenfant, 1999). Reviews have also been undertaken on specific topics related to pedestrian safety. For example, Martin (2006) reviewed research exploring factors influencing pedestrian safety and Papadimitriou et al. (2009) conducted an assessment of pedestrian behavior models proposed in earlier studies with a focus on crossing behavior. The US NHTSA conducted a review of literature on child pedestrian education and possible child pedestrian programs (Percer, 2009). Though these reviews did not aim to cover non-signalized crosswalks, they did provide important references for research on non-signalized crosswalks. In a recent European

Union project, researchers reviewed and summarized current safety studies for vulnerable road users such as pedestrians and cyclists (Olszewski, et al., 2016). The report categorized existing studies as epidemiological studies based on accident data, naturalistic driving studies, behavioral observation studies, traffic conflict (SMoS) studies, and studies based on self-reported accidents. Despite this work, to the best of our knowledge, no document has summarized the methods for studying pedestrian safety at non-signalized crosswalk locations applied in past studies.

2.2 STUDIES AND METHODOLOGICAL APPROACHES

2.2.1 Summary of Studies

A summary of studies is provided in APPENDIX I, including country of origin, topic investigated, methodological approaches and data source or type. A total of 134 references are summarized in the table including 84 peer-reviewed journal papers, 36 reports, and 14 papers in conference proceedings. Over half of the studies are from North America (76 from the US and 14 from Canada), 26 in Asia with 13 from China and the rest from Israel (5), India (4), Malaysia, (3) and Iran (1). 11 of these studies are based on European data, and a small number of studies are from Africa (2), South America (1) and Oceania (2). Two studies were conducted jointly by German and Chinese Institutes.

From APPENDIX I, studies on pedestrian safety at non-signalized crosswalks generally fall into the following main topics (ordered by the number of studies on each topic):

Performance evaluation: Evaluating the performance of pedestrian safety treatments and countermeasures (84 studies)

Behavior or Perception analysis: Analyzing road user behavior or response through habits, maneuver patterns, and motives, and their associated impact on safety; investigating road user perceptions and their general understanding of safety; or the use of both behavior and perceptions in the same study (33 studies)

Methods: Proposing or validating new safety analysis methods (9 studies)

Interaction modeling/simulation: Modelling or simulating pedestrian-vehicle interactions (5 studies); this topic also includes the analysis of interactions between autonomous vehicles and pedestrians (2 out of the 5 studies)

Safety factors: Evaluating the impact of geometric design, environmental conditions, pedestrian facilities, and other factors on safety (3 studies)

2.2.2 Methodological Approaches

Our review of previous work shows that no document has revised the methods for evaluating pedestrian safety at non-signalized crosswalks in a comprehensive manner. Though the mechanisms or methodological details often differ from the methods used in other road environments, they do fall within the wide scope of road safety and meet the general framework of safety studies presented in **FIGURE 2-1**. Methods can be classified as either 1) reactive methods based on historical crash data, or 2) proactive methods based on SMoS, i.e. non-crash measures that are physically and predictably related to crashes (Tarko, et al., 2009). Here, the approaches proposed in the literature for safety analysis are classified as:

Crash data approach: this approach relies on historical crash data from police reports, government reports, and hospital and ambulance data.

Traffic data approach: this approach relies on SMoS based on traffic parameters, mainly vehicle speed and volumes.

Conflict approach: this approach makes use of SMoS based on near-crash events. Some typical measures for conflicts include the famous Time-to-Collision (TTC) and Post-Encroachment Time (PET).

Behavioral approach: this approach is based on measures derived from road user behaviors such as driver yielding behaviors, pedestrian gap acceptance, crossing decisions, user distraction, etc.

Perception approach: this approach relies on road user perceptions, including the perception of safety, awareness and knowledge of signalization and crossing treatments.

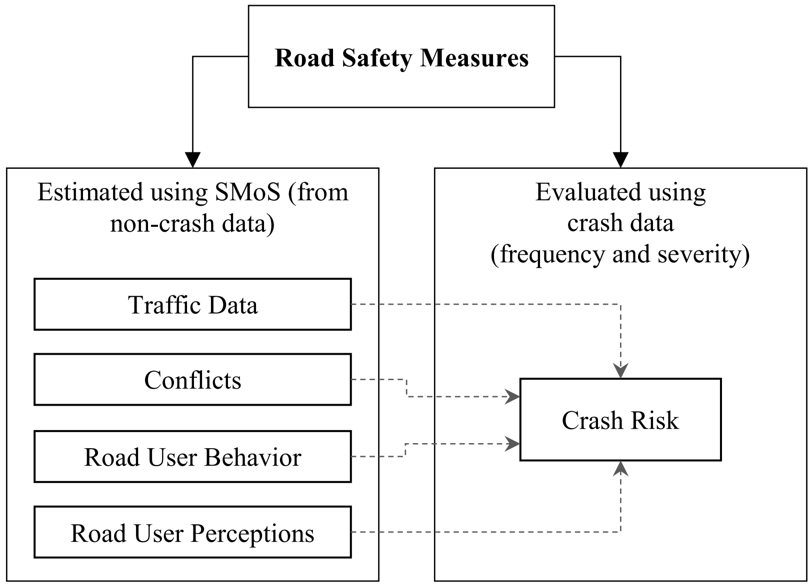

FIGURE 2-1 General Framework of Road Safety Measures

2.3 CRASH DATA APPROACH

Traditional road safety studies rely on historical crash data, to characterize safety in terms of crash frequency, rate, and severity. Crash-based analysis supports the road safety management process through hotspot or network screen analysis, identification of crash contributing factors (traffic, geometry, and built environment features) influencing safety and evaluation of countermeasures. Crash studies can be either aggregate or disaggregate (Yu, 2012; Postorino, 2003; Cai, et al., 2018). Aggregate studies consider the safety performance of a discrete area, using measures such as crash frequency per site, and uncover impacts of "mobility characteristics, the transport system, and the socio-economic characteristics of the area itself" (Postorino, 2003). Aggregate crash-based studies include those conducting network screening, also referred to hotspot identification (Dobbs, 2009), investigating the relationship of traffic and road geometric factors with pedestrian safety, (Diogenes & Lindau, 2010; Gårder, 2004; Islam, et al., 2014; Ivan, et al., 2001; Ivan, et al., 2012; Keall, 1995; Koepsell, et al., 2002; Kudryavtsev, et al., 2012), and evaluating treatments by comparative analysis and modeling (Campbell, 1997; Chu, 2006; Chu, et al., 2008; Ellis & Van Houten, 2009; Gibby, et al., 1994; Jones & Tomcheck, 2000; Liu, et al., 2011; Pfortmueller, et al., 2014; Zegeer, et al., 2001). Disaggregate studies investigate safety at the event level by analyzing each crash individually and model the possibility and severity of a potential crash based on event factors (such as weather conditions, behavior, and socio-demographics). The disaggregate safety models are also called "real-time crash risk evaluation models" which can be used "in monitoring crash hazardousness with the real-time field data fed in" (Yu, 2012). However, most studies investigating pedestrian safety at non-signalized crosswalk locations have been aggregate.

2.3.1 Data Collection Methods

Crash data are normally compiled from police reports (Chu, 2006; Chu, et al., 2008; Kudryavtsev, et al., 2012; Olszewski, et al., 2015; Pfortmueller, et al., 2014; Zegeer, et al., 2001) or transportation organizations (Diogenes & Lindau, 2010; Dobbs, 2009; Ellis & Van Houten, 2009; Gårder, 2004; Gibby, et al., 1994; Islam, et al., 2014; Ivan, et al., 2001; Ivan, et al., 2012; Jones & Tomcheck, 2000; Keall, 1995), though some have relied on medical and ambulance records for data extraction. For instance, Strauss et al. (2014) used ambulance data to investigate multimodal injury risk at signalized and non-signalized intersections. Pfortmueller et al. (2014) used medical and ambulance records in addition to police reports to obtain sufficient data. This approach requires high-quality information on crashes, their severity, and their location. Yet in many cases, crash data is known to be incomplete (underreporting issue), with inaccurate locations, or misclassifications (Fu, et al., 2016). Moreover, the low mean problem (sparse nature of the crash data) can present a statistical issue, especially low-volume sites such as pedestrian crosswalks. This explains why few studies have used crash data to investigate crosswalk safety and the fit of statistical models were either low or unreported. In some cases, information related to crash data can be confidential, or otherwise exempt from disclosure under policy or laws, increasing the difficulty of obtaining sufficient data for safety analysis (CDMV, 2015). Some studies have relied on driving simulation (Waizman, et al., 2014) or traffic simulation experiments (Gómez, et al., 2011; Gómez, et al., 2014) to generate crash data.

2.3.2 Methods and Measures

Ranking, case-control and before-after analysis methods are most frequently used. These methods focus on comparing frequencies or crash risks, either across sites or over time.

2.3.2.1 Ranking Methods

Some studies used methods that rank different locations either based on or considering crash frequency or crash risk as one of the key criterions, normally to identify crash black spots. For example, Dobbs (2009) used the total number of crashes per crossing location, as a variable in ranking the safety performance of different non-signalized crosswalk locations to prioritize sites for improvement.

2.3.2.2 Case-Control Methods

The case-control method is used to evaluate the effectiveness of treatments or other factors such as the built environment or road user characteristics, as can be seen in many studies (Campbell, 1997; Gibby, et al., 1994; Pfortmueller, et al., 2014; Zegeer, et al., 2001; Koepsell, et al., 2002). Case-control studies compare crash risks between sites of interest and other sites used as control. Some existing studies used case-control analysis to investigate the performance of crosswalk markings by comparing the crash risk at marked crosswalks to unmarked crosswalks. Campbell (1997) and Zegeer et al. (2001) found that crash frequency was higher at marked crosswalks. Pfortmueller et al. (2014) also found crashes were more common at marked crosswalks, though injury severity was significantly reduced.

2.3.2.3 Before-After Analysis Methods

Before-after methods investigate the effectiveness of site modifications by evaluating changes in the crash risk before and after changes to facilities or the implementation of countermeasures (Chen, 2010). Based on the comparison techniques, before-after analysis can be categorized into before-after comparative methods (including the "naïve" before-after and before-after with comparison group) and before-after with Empirical Bayes (EB) (Hauer, et al., 2002). Jones & Tomcheck (2000) compared the number of crashes before and after painted crosswalks were removed from both signalized and non-signalized intersections, finding that crosswalk removal reduced crashes significantly at the non-signalized sites. Liu et al. (2011) conducted an observational before-after study using a comparison group and the EB method, estimating that transverse rumble strips reduced crashes by 25 % at rural non-signalized pedestrian crosswalks in Guangdong, China.

Some before-after studies also implement statistical models to predict the impact of the built environment, traffic, law enforcement, and population on crash risk (Dobbs, 2009; Kudryavtsev, et al., 2012). Regression modeling is used to investigate factors related to road safety to identify key issues, find potential solutions, and make improvements (Diogenes & Lindau, 2010; Ivan, et al., 2001; Olszewski, et al., 2015). Diogenes & Lindau (2010) used a Poisson regression model to evaluate the probability of pedestrian crashes at midblock crosswalks with and without traffic signals. Important factors contributing to crash risk included the presence of bus stops, the number of traffic lanes, and the distance to the closest marked crossing, while factors mediating risk included the presence of marked crosswalk and traffic signals, the average sidewalk width, and the hourly vehicle volume. Olszewsky et al. (2015) used a binary logit model to investigate the effect of various factors on pedestrian fatality probability. The study found that darkness, two-way roads, non-built-up area, and mid-block crossings increased the probability of pedestrian deaths.

2.4 TRAFFIC DATA APPROACH

The traffic data approach refers to methods that rely on macroscopic traffic variables like volume, density, mean speed, and average headway/gap as predictors of safety, in the sense of SMoS (Yan, et al., 2008). All traffic data approaches have mainly been implemented to investigate pedestrian exposure to motorized traffic, crash severity, and vehicle headways or gaps for crossing (Huang, 2000). The traffic data approach is considered an aggregate analysis, investigating road safety using macroscopic traffic information rather than individual events. Existing studies have shown significant relationships between traffic variables and crash frequency and probability (Gårder, 2004; Islam, et al., 2014; Ivan, et al., 2001; Olszewski, et al., 2015; Stipancic, et al., 2018; Zegeer, et al., 2005).

Studies using the traffic data approach have largely focused on speed and volume measures. Although other traffic variables such as vehicle headway/gap and density might be used as safety measures, quite a few existing studies adopting these measures could be found (Schroeder, et al., 2010).

2.4.1 Data Collection Methods

Speed and volume data have been measured in numerous ways. Speed information has been collected using more conventional tools including laser and radar guns (Gitelman, et al., 2016a; Gitelman, et al., 2016b; Hakkert, et al., 2002; Johansson & Leden, 2007; Liu, et al., 2011) and more advanced technologies including video cameras, LiDAR guns, and naturalistic driving data (mainly GPS). Video cameras can record and save rich traffic information, making it an efficient data collection method in the field of transportation. Wang et al. (2017) manually measured vehicle speeds from collected video data. Fu et al. (2016) used automated video-based tracking technology to obtain vehicle crossing speeds at non-signalized crosswalk locations. Boyce & Van Derlofske (2002) also relied on video data, though the collection and processing of the video data was not explained. Naturalistic driving data is another promising data collection method for rich positional and speed information collected using GPS devices, cameras, and other in-vehicle sensors. Antov et al. (2007) and Bentley (2015) used naturalistic driving data to obtain vehicle speeds at pedestrian crossings. Dougald et al. (2012) used a LiDAR gun, which provides very accurate speed measurements, and mentioned the use of automatic traffic recorders (ATRs) without providing more detail. Other studies did not provide or clearly explain their methods for collecting speed data (Burritt, et al., 1990; Dhar & Woodin, 1995; Huang, et al., 1999; Karkee, et al., 2010; Pécheux, et al., 2009).

Traffic volume data is fundamental in the field of transportation. Traffic sensors, including inductive loops, video cameras, and magnetic plates have been widely used to collect volume data more efficiently than manual counts by on-site observers (Iowa DOT, 2002; Leduc, 2008). Among the studies using traffic volume as a safety measure, Chi (2007) collected vehicle volume information by manually reviewing collected video footage. Fu et al. (2016) relied on automated video-based tracking technology to extract volumes of vehicles and pedestrians to investigate pedestrian exposure to motorized traffic. Dhar & Woodin (1995) used traffic volume as a safety measure but the data collection method is not described in the study. Given the limited work conducted, it is not possible to draw further conclusions on methods in collecting volume data applied in previous studies.

2.4.2 Methods and Measures

2.4.2.1 Vehicular Speed Method

Based on the principle of work and kinetic energy, a higher vehicle speed leads to an increase in energy release if a crash happens, which brings up the probability of severe injuries or even fatalities. Studies using vehicle speed as a safety measure have shown a strong relation between speed, crash likelihood, and severity (WHO, 2004; European Commission, 2017; Kloeden, et al., 1997; Gårder, 2004; Nemeth, et al., 2014; Olszewski, et al., 2015). Various speed measures have been explored, including the driving speed at pedestrian crosswalk (Antov, et al., 2007), the speed at a sight distance reference point (where the driver is able to see the crosswalk and stop before the crosswalk, given the speed limit and a reaction time of 2.5 sec) (Bentley, 2015), and the approach speed (Boyce & Van Derlofske, 2002; Van Derlofske, et al., 2003). The definitions of these measures are often unclear if provided at all. The approach speed is measured at a certain location before the crosswalk and has been applied by several researchers (Bentley, 2015; Boyce & Van Derlofske, 2002; Gitelman, et al., 2016a; Hakkert, et al., 2002; Liu, et al., 2011; Pécheux, et al., 2009). The passing speed is measured at the crosswalk (for example, the crossing area defined by road markings) and has likewise been investigated thoroughly (Antov, et al., 2007; Bentley, 2015; Dougald, et al., 2012; Fu, et al., 2016; Hakkert, et al., 2002; Wang, et al., 2017). Other studies fail to state the way and the location of the speed measurement (Burritt, et al., 1990; Dhar & Woodin, 1995; Gitelman, et al., 2016b; Huang, et al., 1999; Johansson & Leden, 2007; Karkee, et al., 2010; Wallberg & Wisenbord, 2000).

In APPENDIX I, most of the studies using vehicle speed have focused on the evaluation of countermeasures, designs, and facilities. Antov et al. (2007) found that average passing speeds at non-signalized crosswalks in Estonia were generally unaffected by pavement markings, with 60% of drivers going over the speed limit. Bentley (2015) used both approach and passing speed to show that both high-visibility crosswalks and crossing signs decreased the speed at the sight distance reference point and the crosswalk. Boyce & Van Derlofske (2002) found that clear striping did not reduce the mean approach speed, while an in-pavement flashing warning system did initially reduce mean speed, though the effect diminished over time (Boyce & Van Derlofske, 2002; Van Derlofske, et al., 2003). Fu et al. (2016) used vehicle passing speed to compare the safety performance of non-signalized crosswalks during day and at night conditions. Without explaining the speed measure used, Burritt et al. (1990) found that flashing beacons failed to reduce vehicle speeds at school crossings, Dhar & Woodin (1995) found that fluorescent strong yellow-green signs (SYG) at marked crosswalks reduce vehicle speeds significantly, and Karkee et al. (2010) observed that the average speed was significantly lower after installation of an in-pavement flashing light system at marked crosswalks.

2.4.2.2 Traffic Volume Method

In road safety, traffic volume is one key element affecting crash occurrence. Traffic volume determines “the exposure to risk that pedestrians are facing when they cross the road” (Ivan, et al., 2012). The positive correlation between exposure and crash likelihood has been demonstrated in previous studies (Islam, et al., 2014; Ivan, et al., 2001). Volume is the most common exposure measure. The measures applied in volume-based methods include either vehicle volume or pedestrian volume, or some combination of both (for instance, their product). Several existing studies utilizing the volume method are identified in APPENDIX I. Schroeder et al. (2010) used the traffic volume as the safety measure to compare between two non-signalized crosswalks at roundabouts, and suggested that the site with lower vehicle volume is safer with the reduced likelihood of encountering a vehicle in the pedestrian crossing. Chi (2007) found that adding crosswalk painting at the studied locations was associated with an increase in both pedestrian and vehicle volumes. Fu et al. (2016) found that exposure was much higher during the day than at night at several non-signalized crosswalk locations. Dhar & Woodin (1995) looked at the volume before and after the installation of fluorescent yellow-green signs and found that road user volumes did not change after the installation. Traffic volume was used as a safety measure (exposure to motorized traffic) though not being clearly explained in that paper (Dhar & Woodin, 1995). According to Tarko et al. (2009), although traffic volume and flow are “necessary for crashes to happen” (Tarko, et al., 2009), they may be difficult to study as “most of the safety treatments do not affect traffic volume” (Tarko, et al., 2009). This may explain why few studies have used SMoS based on traffic volume to validate treatment performance.

2.5 CONFLICT APPROACH

The conflict approach, likely the oldest and most common safety diagnosis approach relying on SMoS, considers traffic conflicts, interactions between road users, or evasive maneuvers (Sayed, et al., 2013). The general conflict definition is “an observable situation in which road users approach each other to such an extent that there is a risk of collision if their movements remain unchanged” (Tarko, et al., 2009). Islam et al. (2014) and Ivan et al. (2012) showed that conflicts were significant in predicting crashes occurring at non-signalized crosswalk locations, and suggested conflicts “may be a good surrogate for crashes in analyzing pedestrian safety”. *Conflict frequency* and *severity* are analyzed in both aggregate and disaggregate ways for the purpose of safety evaluation. Conflict severity is about the probability of a crash and the severity of the potential crash (Laureshyn, et al., 2017) which is determined using different measures such as PET and TTC.

2.5.1 Data Collection Methods

Traffic conflict data can be collected manually, in the field, or from video recordings. Alternatively, automated video-based tracking technology can extract positional and speed information of road users, making it a more efficient approach. Most existing studies based on evasive maneuvers have relied on field observations (Brumfield & Pulugurtha, 2011; Clark, et al., 1996; Hakkert, et al., 2002; Islam, et al., 2014; Ivan, et al., 2012; Mitman, et al., 2010; Van Houten & Malenfant, 1992; Van Houten, 1988; Van Houten, et al., 1998; Van Houten, et al., 2001; Van Houten, et al., 2002). Other researchers manually post-processed collected video data (Boyce & Van Derlofske, 2002; Dobbs, 2009; Fitzpatrick, et al., 2006; Gitelman, et al., 2016a; Gitelman, et al., 2016b; Nteziyaremye, 2013; Van Derlofske, et al., 2003).

Most time-based studies use video data collection, with some extracting information manually (Johansson & Leden, 2007). As with conflict methods, researchers have used video-based tracking to extract data more efficiently. Cafiso et al. (2011) used the Highway Engineering Research Group (HERG) software and Fu et al. (2016) used Traffic Intelligence (Jackson, et al., 2013). One study recorded information (Bella & Silvestri, 2015). Other studies, using video data, did not describe the tool used for extracting information (Almodfer, et al., 2016; Sun & Lu, 2011).

2.5.2 Methods and Measures

Conflicts can be measured using human observation of evasive maneuvers, including urgent evasive maneuvers (such as rushing to complete or swerving) and less urgent ones (e.g. reducing the speed or waiting to cross) made either by the pedestrian or the driver to avoid a crash

(Perkins & Harris, 1968; Hughes, et al., 2001), time-based measurements which quantify the proximity of the pedestrian and vehicle in term of time (Hydén, 1987; Svensson & Hydén, 2006), or acceleration or deceleration noise (Shoarian-Sattari & Powell, 1987).

2.5.2.1 Methods based on Evasive Maneuvers

A large number of past studies have focussed on conflicts, interactions where at least one user must make some predefined evasive maneuver to avoid a crash (Dobbs, 2009; Clark, et al., 1996; Dhar & Woodin, 1995; Fitzpatrick, et al., 2006; Gitelman, et al., 2016a; Gitelman, et al., 2016b; Gómez, et al., 2011; Hakkert, et al., 2002; Jiang, 2012; Jiang, et al., 2015; Van Houten, 1988; Van Houten & Malenfant, 1992; Van Houten, et al., 1998; Van Houten & Malenfant, 1999; Van Houten, et al., 2001; Van Houten, et al., 2002). Evasive maneuvers include reactions such as rushing to complete or aborting a crossing (for pedestrians) and swerving, lane changing, or braking (for drivers). Dhar & Woodin (1995) defined pedestrian-vehicle conflicts as involving "swerving or sudden braking" and found that the number of conflicts at non-signalized crosswalks decreased after installing fluorescent yellow-green signs. Brumfield & Pulugurtha (2011) considered six different conflict situations including sudden braking or swerving, lane changing, and several pedestrian movements. The study found that distracted drivers were four times more likely to be involved in conflicts. Fitzpatrick et al. (2006) defined conflicts as interactions where either a pedestrian or vehicle takes evasive action, though they observed only one such conflict. Gitelman et al. (2016a) used conflicts defined as situations involving evasive maneuvers (sudden changes in speed or the direction to avoid a crash) to show that a raised pedestrian crosswalk with preceding speed humps reduced the number of pedestrian-vehicle conflicts. The same method was used to show that removing crosswalk markings at non-signalized crossings reduced rates of pedestrian-vehicle conflicts on multilane divided urban roads (Gitelman, et al., 2016b). Using both crash and near-crash data from driving simulation experiments, Gómez et al. (2011) found that advanced yielding signs reduced crashes and near crashes by 50 % at intersections. Hakkert et al. (2002) found a significant reduction in the conflict rate (number of conflicts per pedestrian at the crosswalk) after the implementation of a pedestrian-detecting crosswalk warning system.

A few studies relied on less urgent and more frequent evasive maneuvers, such as reducing the speed or standing and waiting to cross. Huang et al. (1999) defined conflicts as having occurred when a motorist slowed or stopped to avoid hitting a pedestrian or when a pedestrian changed speed or stopped to avoid being struck by a vehicle. The authors found that pedestrians crossing at the flashing crosswalk experienced fewer conflicts than those who crossed elsewhere. Boyce & Van Derlofske (2002) described conflicts as "an occasion when a driver moves over the crosswalk while a pedestrian is on the crosswalk, the vehicle passing either in front or behind the pedestrian", which were reduced with in-pavement flashing warning lights. Mitman et al. (2010) used "multiple-threat opportunities as a safety measure, defined as "the number of times in which a driver yielded in one lane (the first lane encountered in the crossing direction of the pedestrian), whereas a driver in the adjacent lane of the same direction of travel (the next lane encountered) did not yield". Multiple-threat opportunities should be considered conflicts since they are "observable situation[s] in which road users approach each other to such an extent that there is a risk of collision if their movements remain unchanged". The authors showed that the probability of being involved in multiple-threat opportunities at marked crosswalks was higher than at unmarked crosswalks on multi-lane roads. Wang & Fang (2008) proposed using pedestrian walking speed to measure pedestrian evasions. Conflicts were categorized, using crossing speeds of 0.8-1.4 m/sec in front of approaching vehicles to represent safe conditions, 1.4-1.6 m/sec to represent slight conflicts, above 1.6 m/sec to represent serious conflicts, and highly abnormal or inconsistent pedestrian gaits to indicate extreme conflicts.

2.5.2.2 Methods Using Time-Based Measurements

Probably the most mature and most widely-used conflict analyses use time-based measurements to define and evaluate traffic conflicts (Zhang, et al., 2014). Conflicts between pedestrians and vehicles are often classified into discrete severity levels according to different time thresholds of the given time-based measurement.

One common time-based measurement for pedestrian-vehicle interactions is Time-to-collision (TTC). TTC is defined as the expected time for two road users to collide if they continue their trajectories on a collision course (St-Aubin, 2016). TTC between two road users on a collision course is measured based on their current states (such as the speed and the acceleration) and locations, and their potential motions after (St-Aubin, 2016). The simplest, and most classic, hypothesis in motion prediction for TTC is motion prediction at constant velocity, where TTC is defined as "the expected time for two road users to collide if they remain at their present speed, direction, and on the same trajectory" (Hayward, 1971). An Italian study proposed the Pedestrian Risk Index (PRI) based on the TTC and vehicle speeds to link both the probability of collision and the severity of the consequences (Cafiso, et al., 2011). The study found that traffic calming techniques of speed humps and raised crosswalks reduced the severity of conflicts compared to traditional crosswalk markings. Johansson & Leden's (2007) used time-to-accident (TA), which is the TTC when one of the road users starts an evasive action (Svensson, 1998). Yet, limited studies investigating pedestrian safety at non-signalized crosswalks have used TTC, perhaps due to *1)* the less-predictable pedestrian motion that differs from simple constant velocity; and *2)* the higher complexity of TTC measures using advanced motion prediction methods (Mohamed & Saunier, 2013) for pedestrian-vehicle interactions.

Post-Encroachment Time (PET) is another popular time-based measurement. PET is defined as "the time between the moment that the first road user leaves the virtual collision zone and the moment the second road user reaches it". PET is of a completely different nature from TTC which is continuous and relies on motion prediction methods (Várhelyi, 1998). Fu et al. (2016) defined conflicts as pedestrian-vehicle interactions with a PET of less than 5 seconds and dangerous conflicts as interactions with a PET of less than 1.5 seconds. The proportion of dangerous conflicts was found to be higher at night than during the day. Almodfer et al. (2016) proposed the concept of the lane-based PET (LPET) which regards the collision zone as a width of the travel lane, instead of the width of the vehicle as normally used in PET measures, to identity pedestrian-vehicle conflicts.

Other indicators such as vehicle acceleration/deceleration or rotation information (Olszewski, et al., 2016) can also been used to represent the severity of pedestrian conflicts. However, nothing has been found in previous studies.

2.6 BEHAVIORAL APPROACH

Crash reconstruction and witness accounts have shown the strong relationship between crashes and behavior at non-signalized crosswalk locations (Cottrell & Mu, 2005). This may explain why the behavioral analysis approach, which considers road user behavior as a safety indicator, is the most popular among the reviewed studies (nearly 70 %). Although vehicles are required to yield to pedestrians at non-signalized crosswalks, they may not comply and pedestrians need to pay attention to passing vehicles to make safe crossing decisions. Safety-related behaviors include yielding, crossing movements, and pedestrian and vehicle checking behavior (Cinnamon, et al., 2011), and are typically studied at the microscopic level (for each interaction).

2.6.1 Methods and Measures

The behavior of a road user is either active or reactive. Active behavior includes pedestrian and driver behaviors determined by intrinsic movement patterns and habits, such as distraction, checking habits, and pedestrian walking patterns of speed and crossing location, or other behaviors not triggered by a threat from the road environment. Reactive behaviors, including yielding maneuvers, pedestrian crossing decisions, or gap acceptance, are actions taken in response to external triggers from the road environment (potential collisions).

2.6.1.1 Active Behavior Methods

Different studies have used active behaviors to investigate pedestrian safety at non-signalized crosswalks (Bentley, 2015; Brewer, et al., 2015; Brumfield & Pulugurtha, 2011). The following sections summarize studies focused on behavior and studies using behavior as a measure for safety analysis. Pedestrian active behaviors include distraction, gaze behavior, and walking patterns, while driver active behaviors include distraction, glancing behavior, and speed adaptation.

(1) **Pedestrian Distraction**

At crosswalks, pedestrian distraction refers to situations in which pedestrians focus on something other than crossing the street. Distractions include "wearing headphones, talking on a cell phone, eating, drinking, smoking or talking" (Bungum, et al., 2005). Several studies have focused on pedestrian distractions (Brumfield & Pulugurtha, 2011; Bungum, et al., 2005; Harrison, 2017; Li & Ming, 2016; Pulugurtha, et al., 2011; Solah, et al., 2016). In a study conducted on the campus of University of North Carolina at Charlotte involving seven different non-signalized crosswalk locations, Brumfield & Pulugurtha (2011) found that 29 % of pedestrians were noticeably distracted as they crossed the street. Brumfield & Pulugurtha found that drivers yielded more to distracted pedestrians; however, careless and aggressive crossing decisions by pedestrians associated with distraction increased the crash risk for pedestrians (Brumfield & Pulugurtha, 2011). Bungum et al. (2005) found that about 20 % of pedestrians were distracted when crossing under the white "walk" signal based on observations from a T intersection in Las Vegas, Nevada. According to Harrison (2017), 45 % of pedestrians were distracted by their cell phone at two different crosswalks on the campus of Mississippi State University.

(2) **Pedestrian Gaze Behavior**

Pedestrian gaze is required for pedestrians to check for oncoming vehicles, important for ensuring safe passage, as considered in several studies (Harrison, 2017; Knoblauch, et al., 2001; Nteziyaremye, 2013). Knoblauch et al. (2001) considered "pedestrian looking behavior" using the percentage of pedestrians who performed gaze maneuvers as a measure of effectiveness and found an increase in gaze maneuvers after marking the crosswalk. Others investigated the number of looks made by crossing pedestrians (Harrison, 2017) or average head movements before and during crossing (Nteziyaremye, 2013).

(3) **Pedestrian Crossing Patterns**

Pedestrian crossing patterns refer to the ways in which pedestrians behave when they approach and cross the street without response to external influence (interactions). Pedestrian crossing patterns found in past studies mainly consider the crossing speed (Fitzpatrick, et al., 2006; Goh, et al., 2012; Jiang, 2012; Jiang, et al., 2015; Nteziyaremye, 2013; Shi, et al., 2007a; Shi, et al., 2007b) and compliance in using the designated crosswalk area (Fitzpatrick, et al., 2006; Gitelman, et al., 2016a; Hakkert, et al., 2002; Knoblauch, et al., 2001; Sisiopiku & Akin, 2003). Fitzpatrick et al. (2006) studied transit rider safety at non-signalized crosswalks by considering the speed of pedestrians crossing to reach a bus. Goh et al. (2012) found that pedestrians at non-signalized crosswalks have significantly higher crossing speeds compared to those at signalized crosswalks. Huang & Cynecki (2001) used the share of pedestrians crossing within the crosswalk boundaries to investigate the performance of the raised intersection treatment, finding an improvement from 11 % to 38 %. Gitelman et al. (2016a) also reported an increase in the share of pedestrians crossing within the boundaries of raised pedestrian crosswalks combined with preceding speed humps. Sisiopiku & Akin (2003) defined the crossing compliance rate as the number of pedestrians crossing at the crosswalk area (CA), defined as the area within 3 m from both sides of the crosswalk painting, over the number of pedestrians in the larger crosswalk influence area (CIA), in a period of time.

(4) **Driver Distraction**

Like pedestrian distraction, driver distraction refers to situations in which drivers focus on something other than paying attention to pedestrians and navigating the crossing. Driver distractions such as talking on the phone or texting have been normally investigated (Brumfield & Pulugurtha, 2011; Pulugurtha, et al., 2011). Brumfield & Pulugurtha (2011) found that 18 % of drivers were noticeably distracted with 9% talking on the phone and 3% texting, and that distracted drivers were about 15 times less likely to yield to pedestrians. Believing yielding rate was "an indicator of the relative safety" (Brumfield & Pulugurtha, 2011), the authors concluded that crash risks are higher for distracted drivers: Pulugurtha et al. (2011) found that distracted drivers were four times more likely to be involved in a conflict.

(5) **Glancing Behavior**

Driver glancing is required for drivers to check for pedestrians who intend to cross the street. Several authors who studied driver glancing behavior at non-signalized crosswalk locations (Fisher & Garay-Vega, 2012; Gómez, et al., 2011; Gómez, et al., 2014). Fisher & Garay-Vega (2012) found that advanced yielding markings and prompt signs increased the likelihood that a driver glances towards pedestrians and increases the distance of the first glance towards the pedestrian. Gómez et al. (2011) showed that at advanced yielding markings, 54 % of drivers glanced toward pedestrians, compared to 40 % at standard crossing markings. (Van Houten, et al., 2001).

(6) **Active Speed Adaptation**

Unlike speed measures discussed in the traffic data approach, speed adaptation focuses on maneuvers drivers take to avoid dangerous situations, measured as a speed reduction or deceleration rate. Active behaviorr studies consider that vehicles crossing a pedestrian crosswalk often change speed independently of pedestrian presence. Antov et al. (2007) found minor changes in speed near zebra crosswalks. Bentley (2015) used acceleration rate and gas pedal position to evaluate the effectiveness of high-visibility crosswalks (HVC) and pedestrian crossing signs. The study found that HVCs increase the magnitude of the vehicle deceleration regardless of pedestrian presence. Smith et al. (2009) used deceleration rate to show similar driver behavior at active and passive warning systems at non-signalized intersections and mid-block crossings.

2.6.1.2 Reactive Behavior Methods

Reactive behavior methods consider pedestrian and driver behaviors undertaken in response to other road user actions and are more common than active behavior methods in crosswalk safety studies. Common pedestrian reactive behaviors include waiting behavior (time) and crossing decisions (gap acceptance), while vehicle reactive behaviors include yielding (yielding rates and the choice of the stopping distance to crosswalk) and speed adaptation behaviors (acceleration/deceleration maneuvers).

(1) **Waiting Behavior**

Pedestrian waiting behaviors include the decision to wait (Jiang, 2012; Jiang, et al., 2015) and the time spent waiting (Jiang, 2012; Jiang, et al., 2015; Shi, et al., 2007a; Shi, et al., 2007b; Ibrahim, et al., 2005). Upon arrival at a crossing, pedestrians decide whether to wait for approaching vehicles. An alert pedestrian will stop and wait until the oncoming vehicle shows the intention to yield. Jiang (2012) compared waiting decisions in China and Germany and found that over 80 % of pedestrians in China stopped at the roadside and waited to cross in China, compared to 30 % in Germany. Further results were published in Jiang et al. (2015). Pedestrian waiting time also affects pedestrian safety. Extended waiting times could increase exposure to approaching vehicles and result in lost patience and risky crossing attempts, as also illustrated in (Brosseau, et al., 2013). Shi et al. (2007a) found pedestrians were willing to accept shorter gaps after longer waiting times. Other studies (Pécheux, et al., 2009; Pulugurtha, 2015) used observations of stranded pedestrians who had to wait for "a significantly long time" before being able to cross safely (Pécheux, et al., 2009).

(2) **Crossing Decisions**

During pedestrian-vehicle interactions, decisions made by pedestrians are one of the key elements to be considered. Safe crossing decisions reduce the risk of collision, while risky decisions (very short gaps) could result in dangerous situations involving hard vehicle braking, near-misses, or even crashes. Accepted gap is the most common measure used to describe pedestrian crossing decisions (Boroujerdian & Nemati, 2016; Brewer, et al., 2006; Jiang, 2012; Jiang, et al., 2015; Kadali & Perumal, 2016; Kadali, et al., 2014; Nteziyaremye, 2013; Pawar & Patil, 2015; Schroeder, et al., 2014; Sun, et al., 2003). Brewer et al. (2006) explored pedestrian gap acceptance at uncontrolled mid-block crosswalks and found that the 85th centile of the accepted gaps ranged from 5.3 to 9.4 s. Jiang (2012) and Jiang et al. (2015) found that pedestrians in China had a slightly smaller acceptable gap than those in Germany, recommending a critical gap of 5.0 seconds for both Chinese and Germany pedestrians. Statistical techniques (Boroujerdian & Nemati, 2016; Kadali & Perumal, 2016; Schroeder, et al., 2014; Sun, et al., 2003) and machine learning methods (Kadali, et al., 2014) have been used to model pedestrian gap acceptance and explore factors contributing to gap acceptance. Other than gap acceptance, Fu et al. (2018) investigated pedestrian crossing decisions based on the status of the approaching vehicle measured using time-to-crossing and required deceleration rate. Xiang et al. (2016) applied Monte-Carlo simulation to evaluate pedestrian safety considering both pedestrian gap acceptance and waiting time.

(3) **Yielding Behavior**

Vehicle yielding behavior is believed to be one of the most important indicators of pedestrian safety at non-signalized crosswalks and has therefore been most widely studied within behavioral approaches. Many studies (around 30 studies included in this paper) used yielding rates as a measure of effectiveness to validate the performance of pedestrian treatments or countermeasures at non-signalized crosswalks. For instance, Brewer et al. (2015) found the installation of pedestrian hybrid beacon (PHB) or rectangular rapid flash beacon (RRFB) treatments improved yielding rates substantially and that yielding rates were higher for pedestrians waiting in the vehicle lane (unstaged) compared to pedestrians who waited on the curb (staged). Gitelman et al. (2016a) found that raised pedestrian crosswalks and preceding speed humps improved yielding rates. Chi (2007), Knoblauch et al. (2001), Mitman et al. (2008), and Mitman & Ragland (2008) compared yielding rates at marked and unmarked crosswalks. Brewer et al. (2015), Domarad et al. (2013), Fitzpatrick et al. (2011), Shurbutt & Van Houten (2010), Fitzpatrick et al. (2016a), and Fitzpatrick et al. (2016b) explored the efficiency of the RRFB sign in protecting pedestrians at crosswalks based on yielding rates of vehicles. Other studies considered yielding rates with respect to pedestrians who were distracted (Brumfield & Pulugurtha, 2011), considering variations across ethnicity (Coughenour, et al., 2017; Goddard, et al., 2014), staged and unstaged (Brewer, et al., 2015; Dulaski & Liu, 2013), different ages and gender (Rosenbloom, et al., 2006; Wa, 1993), with disabilities (Schroeder, et al., 2010; Schroeder, et al., 2014), and with different gestures (Zhuang & Wu, 2014).

Some studies specially investigate vehicle yielding behavior during pedestrian-vehicle interactions (Chai & Zhao, 2016; Jiang, 2012; Jiang, et al., 2015; Ibrahim, et al., 2005; Várhelyi, 1998) or model vehicle yielding behavior and investigate factors related to vehicle yielding (Antov, et al., 2007; Schroeder, 2008; Schroeder & Rouphail, 2011; Sun, et al., 2003). Millard-Ball (2016) used game theory to analyze relationships between pedestrians and autonomous vehicles based on yielding. Fu et al. (2016) compared vehicle yielding behavior in daytime conditions to nighttime conditions at non-signalized crosswalks. Fu et al. (2018) proposed a new framework to deal with limitations of simple yielding rates based on the status of approaching vehicles and their ability to conduct a successful yielding maneuver. Non-yielding maneuvers were classified as non-yielding violation, uncertain non-yielding maneuver, and non-infraction non-yielding, and yielding rate and yielding compliance were redefined. Some studies have also looked at yielding distance from the crosswalk (Karkee, et al., 2010) or "the distance that motorists stopped before the crosswalk when yielding to pedestrian" (Van Houten & Malenfant, 1992; Van Houten, 1988; Van Houten, et al., 1998; Van Houten, et al., 2001; Van Houten, et al., 2002).

(4) **Reactive Speed Adaptation**

Different from active speed adaptations which occur independently from pedestrian presence, reactive speed adaptations are changes in vehicle speed when approaching pedestrians who are crossing or intend to cross the street. Knoblauch & Raymond (2000) compared vehicle speed reductions before and after adding the crosswalk marking, under three pedestrian presence conditions (no pedestrian, pedestrian looking, and pedestrian not looking). The pedestrian presence was defined as the presence of staged pedestrians. The study found that the vehicle speed reduction was much smaller when pedestrians were looking at approaching vehicles (0.28 km/h), compared to when pedestrians were not looking (2.61 km/h) and when there were no pedestrians (3.32 km/h). Várhelyi (1998) investigated vehicle speed adaptations during encounters and non-encounters with pedestrians[2], and speed adaptations without pedestrian presence. Most vehicles did not adapt their speed or yield the right-of-way. Other studies specifically considered vehicle decelerations to investigate pedestrian-vehicle interactions (Jiang, 2012).

2.6.2 Data Collection Methods

In general, behavioral analysis studies have used data collected from video cameras, field observations, and other sensors (LiDAR and radar). Other studies have used naturalistic driving data and driving or pedestrian simulation.

[2] In this study, situations with pedestrian presence are defined as "situations when an approaching car is within 70 m from the zebra crossing and there is a pedestrian presence (pedestrian approaching or crossing) at the zebra crossing" (Várhelyi, 1998). Situations with pedestrian presence are further classified as encounters and non-encounters. Encounters are defined as "situations in which the approaching car and the pedestrian could theoretically arrive at the meeting point at the same time (they are on a collision course)" (Várhelyi, 1998). The rest of the situations with pedestrian presence are non-encounters. One can refer to the study for more details.

2.6.2.1 Active Behavior Methods

Pedestrian distraction has been studied using manual field observations (Brumfield & Pulugurtha, 2011; Bungum, et al., 2005; Li & Ming, 2016) and video data, or some combination thereof (Harrison, 2017; Solah, et al., 2016). For pedestrian gaze behavior, Knoblauch et al. (2001) manually collected data from field observations, Harrison (2017) manually extracted information from video data, and Nteziyaremye (2013) combined both video data collection and field observation methods. For pedestrian crossing behavior, most studies relied on data extracted manually from videos (Fitzpatrick, et al., 2006; Fizpatrick, et al., 2007; Gitelman, et al., 2016a; Huang, et al., 2000; Ibrahim, et al., 2005; Shi, et al., 2007a; Shi, et al., 2007b; Sisiopiku & Akin, 2003), semi-automatically using computer-based tools (Jiang, 2012; Jiang, et al., 2015), collected using field observations (Goh, et al., 2012), or a combination of video and field work (Nteziyaremye, 2013).

Driver distraction is mainly studied using only field observations (Brumfield & Pulugurtha, 2011; Pulugurtha, et al., 2011). Most studies exploring driver glancing behavior used driving simulation experiments with eye trackers or cameras (Fisher & Garay-Vega, 2012; Gómez, et al., 2011; Gómez, et al., 2014). As an alternative, data for vehicle speed adaptations have been collected using naturalistic driving data (Antov, et al., 2007; Bentley, 2015) and automatically extracted from video (Smith, et al., 2009).

2.6.2.2 Reactive Behavior Methods

Pedestrian waiting behavior has largely been studied using video data and manual techniques, e.g. (Ibrahim, et al., 2005; Sisiopiku & Akin, 2003), though some have extracted data using computer-based tools, e.g. (Jiang, 2012; Jiang, et al., 2015). Likewise, crossing decisions have been studied manually (Brewer, et al., 2006; Kadali & Perumal, 2016; Sun, et al., 2003) and using computer-based tools (Boroujerdian & Nemati, 2016; Fu, et al., 2018; Jiang, 2012; Jiang, et al., 2015). Pawar & Patil (2015) and Schroeder et al. (2014) relied on field observations, while Nteziyaremye (2013) used both manual observations and video. A few studies have used experiments including simulators and picture- or video-based surveys (Granié, et al., 2014; Liu

& Tung, 2014; Oxley, et al., 2005). Xiang et al. (2016) simulated pedestrian crossing decisions and safety using the Monte Carlo simulation method.

Vehicle yielding behavior has generally been investigated using field-observed data (Brumfield & Pulugurtha, 2011; Cambridge, 2012; Hakkert, et al., 2002; Knoblauch, et al., 2001; Mitman & Ragland, 2008; Van Houten, et al., 2002; Zhuang & Wu, 2014) or data manually extracted from videos (Brewer, et al., 2015; Chi, 2007; Fitzpatrick, et al., 2006; Ibrahim, et al., 2005; Sun, et al., 2003). Chai & Zhao (2016) investigated vehicle yielding behaviors using driving simulators. Reactive speed adaptations have relied on video data collection and computer-based tools (Jiang, 2012) and field data collection using speed measuring devices (Várhelyi, 1998).

2.7 PERCEPTION APPROACH

Perceptions of safety and the road environment may have a substantial impact on safety as they influence road user behavior. Perception-based approaches investigate for example perceptual factors that may affect pedestrians' decisions to use a crosswalk. Studies have focused on different types of perceptions, including sense of safety, awareness, and knowledge of crossing treatments, and main concerns during crossing activities. Perception analysis has been used to extract road user requirements, to investigate their awareness and acceptance of various treatments, and to better understand the gap between perceptions and actual safety.

2.7.1 Data Collection Methods

Studies on perception analysis have most commonly used surveys through on-site questionnaires or face-to-face interviews (Boyce & Van Derlofske, 2002; Dhar & Woodin, 1995; Fitzpatrick, et al., 2004; Huang, et al., 1999; Ibrahim, et al., 2005; Mitman & Ragland, 2007). Chai & Zhao (2016) conducted an "on-site" questionnaire after driving simulation experiments involving 50 participants. Zhuang & Wu (2014) conducted a questionnaire by recruiting drivers for participation. To collect pedestrian perception information, Nteziyaremye (2013) used an on-street face-to-face interview. Johansson & Leden (2007) conducted a school survey for children about their safety perceptions. Some studies have distributed surveys electronically, including Sisiopiku & Akin (2003) and Dougald et al. (2012), who used both an on-site questionnaire and an electronically-distributed survey. Dutt et al. (1997) relied on physical surveys mailed or handed-out and surveys distributed via email. Traditional methods of distributing surveys by mail or by phone have seen limited use in recent years due to poor efficiency and return rates.

2.7.2 Methods and Measures

The different measures used in existing studies can be classified as: 1) focusing on perceived safety of drivers and pedestrians; 2) investigating road user knowledge and preferences; 3) exploring the concerns and suggestions of pedestrians, and; 4) investigating road user motives.

2.7.2.1 Methods Considering Perceived Safety

As perceptions of safety may mirror reality, they might be used as SMoS, as demonstrated in several studies (Boyce & Van Derlofske, 2002; Chai & Zhao, 2016; Dougald, et al., 2012; Fitzpatrick, et al., 2004; Ibrahim, et al., 2005; Johansson & Leden, 2007; Sisiopiku & Akin, 2003). Boyce & Van (2002) surveyed pedestrians about two crosswalk treatments: repainting crosswalk striping, and repainting with the installation of in-pavement flashing warning lights. Results showed that while pedestrians considered both crosswalks to be moderately safe, in-pavement flashing warning lights did not change their perceptions of safety. Chai & Zhao (2016) investigated the effect of exposure to aggressive stimuli (provocations from other vehicles including sustained honking and improper passing) on driver perceived risk. They found that perceived risks significantly increased after repeated provocations. Dougald et al. (2012) investigated the performance of zig-zag markings through pedestrian and driver surveys. 61% of drivers agreed that the markings increased their awareness or attention, and 56% of drivers agreed that the markings increased pedestrian and cyclist safety. 58% of pedestrians and cyclists thought zig-zag markings improved their safety.

2.7.2.2 Methods Considering Knowledge and Preference

Knowledge of and preferences towards crossing countermeasures and treatments should be considered in safety studies, as they may affect road user maneuvers, compliance, and safety. Several studies have considered road user knowledge and preference in investigating pedestrian safety at non-signalized crosswalk locations (Dhar & Woodin, 1995; Dougald, et al., 2012; Dutt, et al., 1997; Fitzpatrick, et al., 2004; Huang, et al., 1999; Mitman & Ragland, 2007; Sisiopiku & Akin, 2003; Zhuang & Wu, 2014). Dhar & Woodin (1995) conducted a survey of pedestrians, nearby residents, and passing motorists regarding their preferences towards the standard crosswalk sign and the strong yellow green (SYG) sign. 73% of participants preferred the SYG signs, while 6% preferred the standard option. Dutt et al. (1997) also found SYG signs were preferred in general. Fitzpatrick et al. (2004) looked at pedestrian preferences of several treatments (two marked crosswalks, an in-roadway light treatment, a Hawk treatment, two split midblock signal treatments, and a countdown pedestrian timer) across seven sites. Huang et al. (1999) explored pedestrians' understanding of the pedestrian crosswalk warning system with in-pavement flashing lights surrounding the crosswalk area, activated by pedestrians walking between sensors. Although the system was successfully activated by pedestrians in 75% of the cases, results showed that most pedestrians did not know how to activate the system. Zhuang & Wu (2014) summarized 11 types of pedestrian gestures signaling intent to cross at non-signalized crosswalk locations, and a survey was conducted to study driver understanding of pedestrian crossing intentions. Sisiopiku & Akin (2003) assessed pedestrian knowledge of right-of-way and their preference of different types of crosswalk. Mitman & Ragland (2007) explored pedestrian and driver knowledge of the right-of-way at marked and unmarked crosswalks. Results clearly showed the uncertainty about pedestrian right-of-way laws among both pedestrians and drivers.

2.7.2.3 Methods Considering Concerns and Suggestions

By understanding pedestrians' concerns and suggestions regarding safety factors and crossing activities, improvements to pedestrian perceptions of safety and actual safety are possible. Some studies have used pedestrian concerns and suggestions to find and solve safety issues (Fitzpatrick, et al., 2004; Sisiopiku & Akin, 2003). Fitzpatrick et al. (2004) collected suggestions on elements pedestrians found confusing and elements that could improve safety, finding that the unpredictability of drivers was a main concern. Sisiopiku & Akin (2003) asked for pedestrians' opinions on major problems at designated crosswalks, though responses were not clearly summarized.

2.7.2.4 Methods Considering Motives

A better knowledge of user motives (mainly pedestrians' willingness to use the crosswalk properly and drivers' willingness to yield right-of-way) improves the understanding of factors related to pedestrian safety. Sisiopiku & Akin (2003) considered the motives of pedestrians behind the spatial non-compliance behavior[3] (Nteziyaremye, 2013). A survey was designed to "reveal motivational factors determining the performed unsafe road-crossing behavior" (Nteziyaremye, 2013). Results from the survey showed that the spatial crossing compliance rate calculated through survey results was 59%, which was almost exactly equal to the crossing compliance rate calculated according to field observations (58.7%), indicating "the reliability of the perception data" (Sisiopiku & Akin, 2003).

2.8 ISSUES AND CHALLENGES IN NON-SIGNALIZED CROSSWALK SAFETY ANALYSIS

Despite the important efforts in pedestrian safety research at non-signalized crosswalk locations, some limitations and research gaps still exist. Specific issues are summarized in three areas: lack of consistency in the terms and definitions, methodological limitations, and data issues.

2.8.1 Terms and Definitions

In this research area, terms and definitions for different variables and indicators have varied or have been used interchangeably in different studies. For example, crash data studies (Dobbs, 2009; Gibby, et al., 1994; Olszewski, et al., 2015; Zegeer, et al., 2001) have used "risk", "rate",

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[3] Nteziyaremye (2013) categorized pedestrian non-compliance behavior as spatial non-compliance (pedestrian crossing out of the crosswalk area or jay-walking) or temporal non-compliance (red light violation).

and “probability” to present the probability of an outcome of a crash (e.g. number of crashes per 1 million people or vehicles, in a given location/area), while other studies (Kudryavtsev, et al., 2012; Chu, 2006; Chu, et al., 2008) used “rate” to refer to the proportion of a certain type of crash (e.g. fatal crashes, or crashes classified by types) among the total number of crashes. Traffic exposure most commonly refers to traffic volumes or average daily traffic estimates, though some studies have used exposure measures based on traffic conflicts (Fu, et al., 2016). In the behavior analysis approach, yielding compliance and yielding rates have been used interchangeably. Additionally, different parameters and thresholds have been applied in past studies. For instance, determining when a pedestrian arrives at the beginning of the crosswalk and should be noticed and yielded by the driver is relatively subjective – Van Houten et al. (1998) defined “pedestrian presence” as pedestrians positioned 30 cm from the curb facing the crosswalk, while Fu et al. (2018) used “pedestrian occurrence” and a threshold of 1 m. The use of different thresholds for determining conflict severity (serious conflicts) also lacks validation. Moreover, many studies included variables and indicators (such as yielding compliance and yielding rate) without definition or explanation, and terms remain unexplained and without a detailed account of how to implement them.

2.8.2 Methodological Limitations

Some methods introduced or applied in previous studies have limitations. One is that many methods relying on historical crash data and statistical modeling have poor fit and accuracy (Hummer, et al., 2000; Ye, et al., 2012). Approaches based on SMoS also have limitations. Traffic analysis considers the likelihood and severity of pedestrian crashes based on traffic conditions, but it does not take account of other factors that are closely associated with pedestrian safety such as behavioral factors. In other words, traffic analysis looks at pedestrian safety in a macroscopic way but does not consider factors that are microscopic and the direct cause of crashes, at the unit of individual road users or events.

In general, most, if not all, SMoS need to be further validated as “predictable and reliable” surrogates of crashes. Despite frequent usage, behavior analysis approaches require improvements, considering the complex dynamics in pedestrian and vehicle behaviors during the development of interactions. Lastly, perceived safety is different from actual road conditions and safety, and the gap between perceived and objective safety must be addressed further.

2.8.3 Data Issues

Data issues are common in road safety studies, especially in studies investigating pedestrian safety at non-signalized crosswalks. The limitations of crash data are well documented, as discussed earlier. Data used to compute SMoS are usually based on short-term data collection methods such as field observations and video data collection, which can provide detailed and time-efficient data for safety analysis. However, there are few guidelines regarding the number of locations and the duration of observations (to collect a sufficient number of observations, e.g. individual events) according to (Laureshyn, et al., 2016). Many studies collect data at a limited number of sites due to the high cost and labor required (setting up equipment, manually labeling information, or conducting surveys) or due to confidentiality (the sensitivity and difficulty to obtaining permission for videotaping or collecting personal information). An additional concern when collecting data on-site (both crash and SMoS data) is the safety of observers or data collectors who can be exposed to motorized traffic. Data quality may also be challenged especially when collected using manual observations or surveys which can be subjective.

While great benefits have been obtained using vision-based techniques, there are critical limitations. Regular visible spectrum cameras are sensitive to lighting conditions, thus the accuracy of using them to collect traffic data is limited. They fail to perform well in adverse weather, low light conditions, and darkness. Meanwhile, shadows and glare in the daytime also degrade the accuracy of the regular cameras when collecting traffic data. In other words, regular cameras do not work under all conditions, especially at nighttime and other low-visibility conditions when increased injury risk leads to more severe road traffic crashes (Plainis, et al., 2006). Alternatives need to be explored for using this type of technology. Besides, many studies rely on manual or semi-automated methods in extracting data from video recordings, which is normally time-consuming and strenuous. Developments of automated data processing methods/tools based on video trajectory data help reduce the workload involved when manually processing the data and avoid errors and the subjective nature of observer assessments.

In general, the occurrence of a crash does not have a single contributory factor but is due to a complex combination of the specific interaction, reactions and maneuvers, traffic environment, road characteristics, and the characteristics of road users and their vehicles. The greatest challenge in analyzing pedestrian safety at non-signalized crosswalk locations, which has been also the challenge in most road safety studies, is explaining these complex dynamics and designing methodological solutions to analyze safety.

2.9 CONCLUSIONS

The chapter reviewed methodologies and data collection methods used to study pedestrian safety at non-signalized crosswalk locations between 1987 and 2017. Methods used in past studies are classified into five approaches, which are the crash data approach, the traffic data approach, the conflict approach, the behavioral approach, and the perception approach. Definitions, methods used, related measures, and data collection methods for each approach are discussed. Limitations of the previous studies are summarized. Signalized and non-signalized crossings are obviously different due to the level of control and different standards that exist for them; and methods for investigating pedestrian safety should reflect these differences. As the key contribution, this paper systematically summarizes past research in pedestrian safety at non-signalized crosswalks based on the methodologies used, providing a practical reference for researchers and practitioners.

In the future, more effort is necessary to propose simple, comprehensive, and consistent terms and definitions, as well as a better justification or discussion of criteria and thresholds. Guidelines and standards should be developed for the applications of the methodologies. The complex dynamics of pedestrian-vehicle interactions, in terms of the multiple maneuvers they may make, different contributing factors that can affect their maneuvers or the outcomes, and their less-predictable outcomes after these maneuvers under the effect of the factors, must be thoroughly explained using an improved methodology to capture the outcome of an interaction.

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2.11 REFERENCES

Almodfer, R. et al., 2016. Quantitative Analysis of Lane-based Pedestrian-vehicle Conflict at a Non-signalized Marked Crosswalk. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42, 468-478.

Antov, D., Rõivas, T. & Rõuk, H., 2007. Investigating Drivers' Behaviour at Non-Signalised Pedestrian Crossings. *Baltic Journal of Road and Bridge Engineering*, 2(3), 111-118.

Arnold, E. D. & Landz, K. E., 2007. *Evaluation of Best Practices in Traffic Operations and Safety: Phase I: Flashing LED Stop Sign and Optical Speed Bars,* Richmond, VA.

Austin, J., Hackett, S., Gravina, N. & Lebbon, A., 2006. The Effects of Prompting and Feedback on Driver's Stopping at Stop Signs. *Journal of Applied Behavior Analysis,* 39(1), 117-121.

BC MOT, 1994. *Pedestrian Crossing Control Manual for British Columbia,* Victoria, BC: Ministry of Transportation and Highways, Province of British Columbia.

Beaubien, R. F., 1989. Controlling Speeds in Residential Streets. *ITE Journal,* April, 59(4), 37-39.

Bella, F. & Silvestri, M., 2015. Effects of Safety Measures on Driver's Speed Behavior at Pedestrian Crossings. *Accident Analysis & Prevention,* 83, 111-124.

Bennett, M. K. & Van Houten, R., 2016. Variables Influencing Efficacy of Gateway In-Street Sign Configuration on Yielding at Crosswalks. *Transportation Research Record: Journal of the Transportation Research Board,* 2586, 100-105.

Bentley, C., 2015. *Effectiveness of High-visibility Crosswalks on Pedestrian Safety Surrogates: An Exploratory Empirical Analysis using the SHRP 2 Naturalistic Driving Data.*

Bichicchi, A. et al., 2017. The Influence of Pedestrian Crossings Features on Driving Behavior and Road Safety. *Transport Infrastructure and Systems,* 741-746.

Boroujerdian, A. M. & Nemati, M., 2016. Pedestrian Gap Acceptance Logit Model in Unsignalized Crosswalks Conflict Zone. *International Journal of Transportation Engineering,* August, 4(2), 87-96.

Boyce, P. & Van Derlofske, J., 2002. *Pedestrian Crosswalk Safety: Evaluating In-Pavement, Flashing Warning Lights,* New Jersey.

Brewer, M. A., Fitzpatrick, K. & Avelar, R., 2015. Rectangular Rapid Flashing Beacons and Pedestrian Hybrid Beacons. *Transportation Research Record: Journal of the Transportation Research Board,* 2519, 1-9.

Brewer, M., Fitzpatrick, K., Whitacre, J. & Lord, D., 2006. Exploration of Pedestrian Gap-Acceptance Behavior at Selected Locations. *Transportation Research Record: Journal of the Transportation Research Board,* 1982, 132-140.

Britt, J. W., Bergman, A. B. & Moffat, J., 1995. Law Enforcement, Pedestrian Safety, and Driver Compliance with Crosswalk Laws: Evaluation of a Four-Year Campaign in Seattle. *Transportation Research Record: Journal of the Transportation Research Board,* 1485, 160-167.

Brumfield, R. & Pulugurtha, S. S., 2011. *When Distracted Road Users Cross Paths,* Washington DC: Public Roads.

Bungum, T. J., Day, C. & Henry, L. J., 2005. The association of Distraction and Caution Displayed by Pedestrians at A Lighted Crosswalk. *Journal of Community Health,* August, 30(4), 269-279.

Burritt, B. E., Buchanan, R. C. & Kalivoda, E. I., 1990. School Zone Flashers - Do They Really Slow Traffic?. *ITE Journal,* 29-31.

Cafiso, S., García, A. G., Cavarra, R. & Romero Rojas, M. A., 2011. *Crosswalk Safety Evaluation using a Pedestrian Risk Index as Traffic Conflict Measure.* Italy.

Cai, Q., Abdel-Aty, M., Lee, J. & Huang, H., 2018. Integrating Macro and Micro Level Safety Analyses: A Bayesian Approach Incorporating Spatial Interaction. *Transportmetrica A: Transport Science,* in press.

Cambridge, N. M., 2012. *Effects of Symbol Prompts and 3D Pavement Illusions on Motorist Yielding at Crosswalks.*

Campbell, B. J., 1997. *Marked Crosswalks and Safety,* Chapel Hill, North Carolina.

Campbell, B. J., Zegeer, C. V., Huang, H. H. & Cynecki, M. J., 2004. *A Review of Pedestrian Safety Research in the United States and Abroad,* McLean, VA.

CDMV, 2015. Compulsory Financial Responsibility - Accident Reports. In: C. D. o. M. Vehicles, ed. *California Vehicle Code - Veh Division 7 - Financial Responsibility Laws.* California: Government of California.

Chai, J. & Zhao, G., 2016. Effect of Exposure to Aggressive Stimuli on Aggressive Driving Behavior at Pedestrian Crossings at Unmarked Roadways. *Accident Analysis & Prevention,* 88, 159-168.

Chen, B., Zhao, D. & Peng, H., 2017. Evaluation of Automated Vehicles Encountering Pedestrians at Unsignalized Crossings. *arXiv preprint,* March.

Chen, F., 2010. *Exploring the Method to Assess the Effectiveness of Countermeasures for Proactive Traffic Safety Improvement,* Helena, Montana.

Chi, D., 2007. *Safety Effectiveness from a Behavioral Perspective of Marked vs. Unmarked Crosswalks at Unsignalized Intersections.*

Chin, H., Quek, S. & Cheu, R. L., 1992. Quantitative Examination of Traffic Conflicts. *Transportation Research Record: Journal of the Transportation Research Board,* (1376), 86-91.

Chu, X., 2006. *Pedestrian Safety at Midblock Locations,* Tallanassee, FL, US.

Chu, X., Lin, P.-S. & Kourtellis, A., 2008. *Safety Effects and Guideline Development for Uncontrolled Midblock Crosswalks.* Miami, FL, USA.

Cinnamon, J., Schuurman, N. & Hameed, M., 2011. Pedestrian Injury and Human Behaviour: Observing Road-Rule Violations at High-Incident Intersections. *PLoS One*, 6(6), 1-10.

City of Fort Collins, 2017. *Question/Request: Why don't They Put in More Stop.* [Online] Available at: http://www.fcgov.com/traffic/pdf/ntsp-stop.pdf

Clark, K., Hummer, J. & Dutt, N., 1996. Field Evaluation of Fluorescent Strong Yellow-Green Pedestrian Warning Signs. *Transportation Research Record: Journal of the Transportation Research Board,* (1538), 39-46.

Cottrell, W. & Mu, S., 2005. *Utah Intersection Safety - Recurrent Crash Sites: Identification, Issues and Factors,* Salt Lake City, Utah: University of Utah.

Coughenour, C. et al., 2017. Examining Racial Bias as a Potential Factor in Pedestrian Crashes. *Accident Analysis & Prevention,* 98, 96-100.

Crowley-Koch, B. J. & Van Houten, R., 2011. Effects of Pedestrian Prompts on Motorist Yielding at Crosswalks. *Journal of Applied Behavior Analysis,* 44(1), 121-126.

Davies, D. G., 1999. *Research, Development, and Implementation of Pedestrian Safety Facilities in the United Kingdom,* McLean, VA: Federal Highway Administration.

Delphi MRC, 2010. *Pedestrian Intersection Safety Countermeasure Handbook,* Halifax, NS.

DeVeauuse, N. et al., 1999. Driver Compliance With Stop Signs at Pedestrian Crosswalks on a University Campus. *Journal of American College Health,* 47(6), 269-274.

Dhar, S. & Woodin, D. C., 1995. *Fluorescent Strong Yellow-green Signs for Pedestrian/School/Bicycle Crossings: Results of a New York State Study,* Albany, NY, US.

Diogenes, M. C. & Lindau, L. A., 2010. Evaluation of Pedestrian Safety at Midblock Crossings, Porto Alegre, Brazil. *Transportation Research Record: Journal of the Transportation Research Board,* (2193), 37-43.

Dixon, M. A., Aivarez, J. A., Rodriguez, J. & Jacko, J. A., 1997. The Effect of Speed Reducing Peripherals on Motorists' Behavior at Pedestrian Crossings. *Computers & Industrial Engineering,* 33, 205-208.

Dobbs, G. L., 2009. *Pedestrian and Bicycle Safety on a College Campus: Crash and Conflict Analyses with Recommended Design Alternatives for Clemson University*.

Domarad, J., Grisak, P. & Bolger, J., 2013. *Improving Crosswalk Safety: Rectangular Rapid-Flashing Beacon (RRFB) Trial in Calgary.* Calgary, Canada.

Dougald, L., Dittberner, R. A. & Sripathi, H. K., 2012. *Creating Safer Midblock Pedestrian and Bicycle Crossing Environments: Zigzag Pavement Marking Experiment.* Washington DC.

Draskóczy, M. & Hydén, C., 1994. *Pedestrian Safety Measures - Past and Future.* Prague., pp. 86-96.

Dulaski, D. M. & Liu, Y., 2013. *Stepping off the Curb to Increase Drivers' Yielding Behavior at Mid-block Crosswalks.* Washington DC.

Dutt, N., Hummer, J. E. & Clark, K. L., 1997. User Preference for Fluorescent Strong Yellow-Green Pedestrian Crossing Signs. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1605, pp. 17-21.

Elefteriadou, L., 2014. Unsignalized Intersections. In: D. Du, ed. *An Introduction to Traffic Flow Theory.* Gainesville, FL: Springer, pp. 219-232.

Ellis, R. & Van Houten, R., 2009. Reduction of Pedestrian Fatalities, Injuries, Conflicts, and Other Surrogate Measures in Miami–Dade, Florida: Results of Large-Scale FHWA Project. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2140, pp. 55-62.

European Commission, 2017. *Speed and Accident Risk.* [Online] Available at: https://ec.europa.eu/transport/road_safety/specialist/knowledge/speed/speed_is_a_central_issue_in_road_safety/speed_and_accident_risk_en

Ewing, R., 1999. *Traffic Calming: State of the Practice,* Washington DC.

FHWA, 2001. *Manual on Uniform Traffic Control Devices for Streets and Highways,* Washington DC.

FHWA, 2009. *Manual on Uniform Traffic Control Devices for Streets and Highways.* Washington DC: Federal Highway Administration.

Fisher, D. & Garay-Vega, L., 2012. Advance Yield Markings and Drivers' Performance in Response to Multiple-threat Scenarios at Mid-block Crosswalks. *Accident Analysis & Prevention,* Volume 44, pp. 35-41.

Fitzpatrick, K., Avelar, P., Lindheimer, T. & Brewer, M. A., 2016a. Comparison of Above-Sign and Below-Sign Placement of Rectangular Rapid-Flashing Beacons. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2562, pp. 45-52.

Fitzpatrick, K., Brewer, M. A., Avelar, R. & Lindheimer, T., 2016b. *Will You Stop for Me? Roadway Design and Traffic Control Device Influences on Drivers Yielding to Pedestrians in a Crosswalk with a Rectangular Rapid-Flashing Beacon,* College Station, TX, US.

Fitzpatrick, K. et al., 2011. *Evaluation of Pedestrian and Bicycle Engineering Countermeasures: Rectangular Rapid-Flashing Beacons, HAWKs, Sharrows, Crosswalk Markings, and the Development of an Evaluation Methods Report,* Texas.

Fitzpatrick, K. et al., 2006. *Improving Pedestrian Safety at Unsignalized Crossings,* Washington DC.

Fitzpatrick, K., Ullman, B. & Trout, N., 2004. *On-Street Pedestrian Surveys of Pedestrian Crossing Treatments.* Washington DC.

Fizpatrick, K., Turner, S. & Brewer, M. A., 2007. Improving Pedestrian Safety at Unsignalized Intersections. *ITS Journal,* May, 77(5), pp. 34-41.

Foomani, M., Alecsandru, C. & Awasthi, A., 2015. *Safety Performance Assessment of Stop-Operated Intersection Equipped with Active Road Sign.* Montreal.

Fu, T., Miranda-Moreno, L. F. & Saunier, N., 2016. Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime: Use of Thermal Video Data and Surrogate Safety Measures. *Transportation Research Record: Journal of the Transportation Research Board,* Volume 2586, pp. 90-99.

Fu, T., Miranda-Moreno, L. & Saunier, N., 2018. A Novel Framework to Evaluate Pedestrian Safety at Non-signalized Locations. *Accident Analysis & Prevention,* Volume 111, pp. 23-33.

Gårder, P., 2004. The Impact of Speed and other Variables on Pedestrian Safety in Maine. *Accident Analysis & Prevention,* September, 36(4), pp. 533-542.

Gibby, A. R., Stiles, J. L., Thurgood, G. S. & Ferrara, T. C., 1994. *Evaluation of Marked and Unmarked Crosswalks at Intersections in California,* Chico, CA.

Gitelman, V. et al., 2012. Characterization of Pedestrian Accidents and an Examination of Infrastructure Measures to Improve Pedestrian Safety in Israel. *Accident Analysis & Prevention,* November, Volume 44, pp. 63-73.

Gitelman, V., Carmel, R., Pesahov, F. & Chen, S., 2016a. Changes in Road-user Behaviors Following the Installation of Raised Pedestrian Crosswalks Combined with Preceding Speed Humps, on Urban Arterials. *Transportation Research Part F: Traffic Psychology and Behaviour.*

Gitelman, V., Carmel, R., Pesahov, F. & Hakkert, S., 2016b. An Examination of the Influence of Crosswalk Marking Removal on Pedestrian Safety as Reflected in Road User Behaviours. *Transportation Research Part F: Traffic Psychology and Behaviour.*

Goddard, T., Arlie, A. & Kahn, K. B., 2014. *Racial Bias in Driver Yielding Behavior at Crosswalks,* Portland, OR: PDXScholar.

Goh, B. H., Subramaniam, K., Wai, Y. T. & Mohamed, A. A., 2012. Pedestrian Crossing Speed: The Case of Malaysia. *International Journal of Traffic and Transportation Engineering,* 2(4), pp. 323-332.

Gómez, R. A. et al., 2011. Do Advance Yield Markings Increase Safe Driver Behaviors at Unsignalized, Marked Midblock Crosswalks? Driving Simulator Study. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2264, pp. 27-33.

Gómez, R. A. et al., 2014. Mitigation of Pedestrian–Vehicle Conflicts at Stop-Controlled T-Intersections. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2464, pp. 20-28.

Google, 2018. *Google Scholar.* [Online]
Available at: https://scholar.google.ca/

Granié, M.-A.et al., 2014. Influence of built environment on pedestrian's crossing decision. *Accident Analysis & Prevention,* Feburary, Issue 67, pp. 75-85.

Greenbaum, H. & Rubinstein, D., 2011. *The New York Times.* [Online]
Available at: http://www.nytimes.com/2011/12/11/magazine/stop-sign.html

Hakkert, A. S., Gitelman, V. & Ben-Shabat, E., 2002. An Evaluation of Crosswalk Warning Systems: Effects on Pedestrian and Vehicle Behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, pp. 275-292.

Harrison, D., 2017. *Study of Distracted Pedestrians' Behavior when Using Crosswalks,* Mississippi State, US.

Hauer, E., Harwood, D. W., Council, F. M. & Griffith, M. S., 2002. Estimating Safety by the Empirical Bayes Method: A Tutorial. *Transportation Research Record: Journal of the Transportation Research Board,* Volume 1784, pp. 126-131.

Herms, B. F., 1972. Pedestrian Crosswalk Study: Accidents in Painted and Unpainted Crosswalks. *Highway Research Record,* Issue 406, pp. 1-13.

Highway Safety Branch, Ministry of Transportation and Highways, 1994. *Pedestrian Crossing Control Manual for British Columbia.* Victoria, B.C.: Ministry of Transportation and Highways.

Huang, H., 2000. *An Evaluation of Flashing Crosswalks in Gainesville and Lakeland,* Tallahassee, FL.

Huang, H. & Cynecki, M., 2001. *The Effects of Traffic Calming Measures on Pedestrian and Motorist Behavior,* McLean, VA: U.S. Department of Transportation.

Huang, H., Hughes, R., Zegeer, C. & Nitzburg, M., 1999. *An Evaluation of the LightGuard (Trade Mark) Pedestrian Crosswalk Warning System.*

Huang, H., Zegeer, C. & Nassi, R., 2000. Effects of Innovative Pedestrian Signs at Unsignalized Locations: Three Treatments. *Transportation Research Record: Journal of the Transportation Research Board,* pp. 43-52.

Hughes, R., Huang, H., Zegeer, C. & Cynecki, M., 2001. *Evaluation of Automated Pedestrian Detection at Signalized Intersections,* McLean.

Hummer, J., Stephenson, R. & Carter, D., 2000. *Highway Safety Program Evaluation and Statistical Crash Table Development*, Raleigh, NC: North Carolina Department of Transportation.

Hydén, C., 1976. *A Traffic-conflicts Technique and its Practical Use in Pedestrian Safety Research,* Lund, Sweden.

Hydén, C., 1987. *The Development of A Method For Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique,* Lund, Sweden.

Hydén, C. & Linderholm, L., 1991. *The Swedish Traffic Conflict Technique,* Lund, Sweden.

Ibrahim, N. I., Kidwai, F. A. & Karim, M. R., 2005. Motorists and Pedestrian Interaction at Unsignalized Pedestrian Crossing. *Journal of the Eastern Asia Society for Transportation Studies,* Volume 5, pp. 120-125.

Iowa DOT, 2002. Chapter 3 Traffic Volume Counts. In: *Handbook of Simplified Practice for Traffic Studies.* Iowa State: Center for Transportation Research and Education.

Ishaque, M. M. & Noland, R. B., 2012. Making Roads Safe for Pedestrians or Keeping Them Out of the Way?. *The Journal of Transport History,* 27(1), pp. 115-137.

Islam, M. S. et al., 2014. Explaining Pedestrian Safety Experience at Urban and Suburban Street Crossings Considering Observed Conflicts and Pedestrian Counts. *Journal of Transportation Safety & Security,* 6(4), pp. 335-355.

Ivan, J. M., Gårder, E. P. & Zajac, S. S., 2001. *Finding Strategies to Improve Pedestrian Safety in Rural Areas,* Cambridge, MA, US.

Ivan, J. N., Ravishanker, N., Islam, M. S. & Serhiyenko, V., 2012. *Evaluation of Surrogate Measures for Pedestrian Safety in Various Road and Roadside Environments,* Storrs, CT, US.

Jiang, X., 2012. *Intercultural Comparison of Road User Behavior Centred Vehicle-Pedestrian Conflict in Urban Traffic.*

Jiang, X., Wang, W., Bengler, K. & Guo, W., 2015. Analyses of Pedestrian Behavior on Mid-block Unsignalized Crosswalk comparing Chinese and German Cases. *Advances in Mechanical Engineering,* 7(11), pp. 1-7.

Johansson, C. & Leden, L., 2007. Short-term Effects of Countermeasures for Improved Safety and Mobility at Marked pedestrian Crosswalks in Borås, Sweden. *Accident Analysis & Prevention,* May, 39(3), pp. 500-509.

Jones, T. & Tomcheck, P., 2000. Pedestrian Accidents in Marked and Unmarked Crosswalks: A Quantitative Study. *ITE Journal,* September, 70(9), pp. 42-46.

Kadali, B. R. & Perumal, V., 2016. Analysis of Critical Gap based on Pedestrian Behaviour during Peak Traffic Hours at Unprotected Mid-block Crosswalks. *Asian Transport Studies,* 4(1), pp. 261-277.

Kadali, B. R., Rathi, N. & Perumal, V., 2014. Evaluation of Pedestrian Mid-block Road Crossing Behaviour using Artificial Neural Network. *Journal of Traffic and Transportation Engineering,* 1(2), pp. 111-119.

Karkee, G. J., Nambisan, S. S. & Pulugurtha, S. S., 2010. Motorist Actions at a Crosswalk with An In-pavement Flashing Light System. *Traffic Injury Prevention,* 11(6), pp. 642-649.

Karsch, H. M., Hedlund, J., Tison, J. & Leaf, W. A., 2012. *Review of Studies on Pedestrian and Bicyclist Safety, 1991-2007,* Trumbull.

Keall, M., 1995. Pedestrian Exposure to Risk of Road Accident in New Zealand. *Accident Analysis & Prevention,* 27(5), pp. 729-740.

Khatoon, M., Tiwari, G. & Chatterjee, N., 2013. *Modeling of Pedestrian Unsafe Road Crossing Behavior: Comparison at Signalized and Nonsignalized Crosswalks.* Washington DC.

Kloeden, C. N., McLean, A. J., Moore, V. M. & Ponte, G., 1997. *Travelling Speed and the Risk of Crash Involvement,* South Australia: NHMRC Road Accident Research Unit.

Knoblauch, R., Nitzburg, M. & Seifert, R., 2001. *Pedestrian Crosswalk Case Studies: Richmond, Virginia; Buffalo, New York; Stillwater, Minnesota,* McLean, VA, US.

Knoblauch, R. & Raymond, P., 2000. *The Effect of Crosswalk Markings on Vehicle Speeds in Maryland, Virginia, and Arizona,* McLean, VA.

Koepsell, T. et al., 2002. Crosswalk Markings and the Risk of Pedestrian-Motor Vehicle Collisions in Older Pedestrians. *J.A.M.A,* 288(17), pp. 2136-2143.

Kudryavtsev, A. V. et al., 2012. Explaining Reduction of Pedestrian Motor Vehicle Crashes in Arkhangelsk, Russia, in 2005-2010. *International Journal of Circumpolar Health,* September, 71(19107), pp. 1-8.

Laureshyn, A. et al., 2016. *Review of Current Study Methods for VRU Safety. Appendix 6 - Scoping Review: Surrogate Measures of Safety in Site-based Road Traffic Observations*, s.l.: InDeV, Horizon 2020 Project.

Laureshyn, A. et al., 2017. In Search of the Severity Dimension of Traffic Events: Extended Delta-V as a Traffic Conflict Indicator. *Accident Analysis & Prevention*, Volume 98, pp. 46-56.

Leduc, G., 2008. *Road Traffic Data: Collection Methods and Applications,* Seville, Spain: European Commission.

Li, M. & Ming, X., 2016. *Study on the Effect of Distraction for Pedestrian Crossing.*

Liu, P., Huang, J., Wang, W. & Xu, C., 2011. Effects of Transverse Rumble Strips on Safety of Pedestrian Crosswalks on Rural Roads in China. *Accident Analysis & Prevention,* November, 43(6), pp. 1947-1954.

Liu, Y.-C. & Tung, Y.-C., 2014. Risk analysis of pedestrians' road-crossing decisions: effects of age, time gap, time of day, and vehicle speed. *Safety Science,* November, Issue 63, pp. 77-82.

Lu, L. et al., 2016. A Cellular Automaton Simulation Model for Pedestrian and Vehicle Interaction Behaviors at Unsignalized Mid-block Crosswalks. *Accident Analysis & Prevention,* Volume 95, pp. 425-437.

Malenfant, L. & Van Houten, R., 1990. Increasing the Percentage of Drivers Yielding to Pedestrians in three Canadian Cities with a Multifaceted Safety Program. *Health Education Research,* 5(2), pp. 275-279.

Martin, A., 2006. *Factors Influencing Pedestrian Safety: a Literature Review,* London, UK.

McGee, H. W. et al., 2015. *Unsignalized Intersection Guide.*

Mead, J., Zegeer, C. & Bushell, M., 2014. *Evaluation of Pedestrian-Related Roadway Measures: A Summary of Available Research.*

Millard-Ball, A., 2016. Pedestrians, Autonomous Vehicles, and Cities. *Journal of Planning Education and Research,* pp. 1-7.

Mitman, M. F., Cooper, D. & DuBose, B., 2010. Driver and Pedestrian Behavior at Uncontrolled Crosswalks in Tahoe Basin Recreation Area of California. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2198, pp. 23-31.

Mitman, M. F. & Ragland, D. R., 2007. Crosswalk Confusion More Evidence Why Pedestrian and Driver Knowledge of the Vehicle Code Should Not Be Assumed. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2002, pp. 55-63.

Mitman, M. F. & Ragland, D. R., 2008. *Driver/Pedestrian Understanding and Behavior at Marked and Unmarked Crosswalks.*

Mitman, M. F., Ragland, D. R. & Zegeer, C. V., 2008. Marked-Crosswalk Dilemma: Uncovering Some Missing Links in a 35-Year Debate. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2073, pp. 86-93.

Mohamed, G. M. & Saunier, N., 2013. Motion Prediction Methods for Surrogate Safety Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 2386, pp. 168-178.

Molen, H., 1981. Child Pedestrian's Exposure, Accidents and Behavior. *Accident Analysis & Prevention,* 13(3), pp. 193-224.

MTO, 2016. *Ontario Traffic Manual: Pedestrian Crossing Treatments,* St. Catharines, Ontario.

Najm, W. G., Smith, J. & Smith, D., 2001. *Analysis of Crossing Path Crashes,* Washington DC.

Nemeth, B., Tillman, R., Melquist, J. & Hudson, A., 2014. *Uncontrolled Pedestrian Crossing Evaluation Incorporating Highway Capacity Manual Unsignalized Pedestrian Crossing Analysis Methodology,* St. Paul, MN, US.

Nteziyaremye, P., 2013. *Understanding Pedestrian Crossing Behaviour: A Case Study in the Western Cape, South Africa.*

Olszewski, P. et al., 2016. *Review of Current Study Methods for VRU Safety,* Poland: Euopean Commission.

Ovid Technologies, 2018. Ovid. [Online]
Available at: https://ovidsp.tx.ovid.com/sp-3.31.1b/ovidweb.cgi

Oxley, J. et al., 2005. Crossing Roads Safely: an Experimental Study of Age Differences in Gap Selection by Pedestrians. *Accident Analysis & Prevention,* September, 37(5), pp. 962-971.

Plainis, S., Murray, I. J. & Pallikaris, I. G., 2006. Road Traffic Casualties: Understanding the Night-time Death Toll. *Injury Prevention*, 12(2), pp. 125-128.

Papadimitriou, E., Yannis, G. & Golias, J., 2009. A Critical Assessment of Pedestrian Behaviour Models. *Transportation Research Part F: Traffic Psychology and Behaviour,* Issue 12, pp. 242-255.

Pawar, D. S. & Patil, G. R., 2015. Pedestrian Temporal and Spatial Gap Acceptance at Mid-block Street Crossing in Developing World. *Journal of Safety Research,* Issue 52, pp. 39-46.

Pécheux, K., Bauer, J. & McLeod, P., 2009. *Pedestrian Safety Engineering and ITS-Based Countermeasures Program for Reducing Pedestrian Fatalities, Injury Conflicts, and Other Surrogate Measures Final System Impact Report,* McLean, VA: United States Department of Transportation.

Percer, J., 2009. *Child Pedestrian Safety Education: Applying Learning and Developmental Theories to Develop Safe Street-Crossing Behaviors,* Washington DC.

Perkins, S. R. & Harris, J. I., 1968. Traffic Conflict Characteristics: Accident Potential at Intersections. *Highway Research Record,* Volume 225, pp. 35-43.

Pfortmueller, C. A. et al., 2014. Injury Severity and Mortality of Adult Zebra Crosswalk and Non-Zebra Crosswalk Road Crossing Accidents: A Cross-Sectional Analysis. *Plos One,* 9(3), pp. 1-6.

Postorino, M. N., 2003. *Indexes and Models to Analyse Road Safety Within the Aggregate Approach.*

Pulugurtha, S. S., 2015. Pedestrian and Motorists' Actions at Pedestrian Hybrid Beacon Sites: Findings from a Pilot Study. *International Journal of Injury Control and Safety Promotion,* 22(2), pp. 143-152.

Pulugurtha, S. S., Maradapudi, M. R. J. & Miatudila Sr., A. S., 2011. *Effect of Road User Distractions on Pedestrian Safety at Mid-block Crosswalks on a College Campus.* Washington DC, Transportation Research Board.

Road Research Laboratory, 1963. *Research on Road Safety,* London.

Rosenbloom, T., Nemrodov, D. & Eliyahu, A. B., 2006. Yielding Behavior of Israeli Drivers: Interaction of Age and Sex. *Perceptual and Motor Skills,* Issue 103, pp. 387-390.

Saunier, N. & Sayed, T., 2006. *A Feature-based Tracking Algorithm for Vehicles in Intersections.*, p. 59.

Sayed, T., Zaki, M. & Autey, J., 2013. Automated Safety Diagnosis of Vehicle–Bicycle Interactions using Computer Vision Analysis. *Safety Science,* November, Volume 59, pp. 163-172.

Schroeder, B. J., 2008. *A Behavior-Based Methodology for Evaluating Pedestrian-Vehicle Interaction at Crosswalks.*

Schroeder, B. J. & Rouphail, N. M., 2011. Event-Based Modeling of Driver Yielding Behavior at Unsignalized Crosswalks. *Journal of Transportation Engineering,* July, 137(7), pp. 455-465.

Schroeder, B. J., Rouphail, N. M. & Hughes, R. G., 2010. Working Concept of Accessibility: Performance Measures for Usability of Crosswalks by Pedestrians with Vision Impairments. *Transportation Research Record: Journal of the Transportation Research Board,* January, Issue 2140, pp. 103-110.

Schroeder, B. et al., 2014. *Empirically-Based Performance Assessment and Simulation of Pedestrian Behavior at Unsignalized Crossings,* Gainesville, FL, US.

Serag, M. S., 2014. Modelling Pedestrian Road Crossing at Uncontrolled Mid-block Locations in Developing Countries. *International Journal of Civil and Structural Engineering,* 4(3), pp. 274-285.

Shi, J., Chen, Y., Ren, F. & Rong, J., 2007a. Research on Pedestrian Behavior and Traffic Characteristics at Unsignalized Midblock Crosswalk: Case Study in Beijing. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2038, pp. 23-33.

Shi, J., Wang, Z. & Chen, Y., 2007b. *Analysis on Behaviours and Safety of VRUs at Unsignalized Roadway Crosswalk.* Beijing, China.

Shoarian-Sattari, K. & Powell, D., 1987. Measured Vehicle Flow Parameters as Predictors in Road Traffic Accident Studies. *Traffic Engineering,* 28(6), pp. 328-335.

Shurbutt, J. & Van Houten, R., 2010. *Effects of Yellow Rectangular Rapid-Flashing Beacons on Yielding at Multilane Uncontrolled Crosswalks,* McLean.

Sisiopiku, V. & Akin, D., 2003. Pedestrian Behaviors at and Perceptions towards Various Pedestrian Facilities: An Examination based on Observation and Survey Data. *Transportation Research Part F: Traffic Psychology and Behaviour,* December, 6(4), pp. 249-274.

Smith, T. J., Hammond, C., Somasundaram, G. & Papanikolopoulos, N., 2009. *Warning Efficacy of Active Versus Passive Warnings for Unsignalized Intersection and Mid-Block Pedestrian Crosswalks,* Minneapolis, MN.

Solah, M. S. et al., 2016. The Effects of Mobile Electronic Device Use in Influencing Pedestrian Crossing Behaviour. *Malaysian Journal of Public Health Medicine,* Volume 1, pp. 61-66.

Strauss, J., Miranda-Moreno, L. & Morency, P., 2014. Multimodal Injury Risk Analysis of Road Users at Signalized and Non-signalized Intersections. *Accident Analysis & Prevention*, Volume 71, pp. 201-209.

St-Aubin, P., 2016. *Driver Behavior and Road Safety Analysis using Computer Vision and Applications in Roundabout Safety*, Montreal: École Polytechnique de Montreal.

St-Aubin, P. et al., 2018. *Speed at Partially and Fully Stop-Controlled Intersections.* Washington DC.

St-Aubin, P., Miranda-Moreno, L. F. & Saunier, N., 2013. An Automated Surrogate Safety Analysis at Protected Highway Ramps using Cross-sectional and Before-after Video Data. *Transportation Research Part C: Emerging Technologies,* Volume 36, pp. 284-295.

Stipancic, J., Miranda-Moreno, L., Saunier, N. & Labbe, A., 2018. Surrogate Safety and Network Screening: Modelling Crash Frequency using GPS Travel Data and Latent Gaussian Spatial Models. *Accident Analysis & Prevention*, pp. 174-187.

Sun, D., Ukkusuri, S. V., Benekohal, R. F. & Waller, S. T., 2003. *Modeling of Motorist-Pedestrian Interaction at Uncontrolled Mid-block Crosswalks.* Washington DC.

Sun, X. & Lu, J., 2011. *Study on the Pedestrian-Vehicle Safety based on Traffic Conflict at Uncontrolled Intersection.* Lushan, China., pp. 1614-1616.

Svensson, Å., 1998. *A Method for Analyzing theTraffic Process in a Safety Perspective*: Lund University.

Svensson, Å. & Hydén, C., 2006. Estimating the Severity of Safety Related Behavior. *Accident Analysis & Prevention,* Issue 38, pp. 379-385.

Tan, C. H. & Zegeer, C. V., 1995. European Practices and Innovations for Pedestrian Crossings. *ITE Journal,* 65(11), pp. 24-31.

Tarko, A., Davis, G., Saunier, N., Sayed, T., & Washington, S., 2009. *White Paper: surrogate safety measures of safety.* ANB20 (3) Subcommittee on Safety Data Evaluation and Analysis Contributors.

The Times, 1868. Street Traffic Signaling. *The Times (London),* p. 5f.

Transport Canada, 2015. *National Collision Database (NCDB)*, s.l.: s.n.

Transportation Research Board, 2018. TRID - the TRIS and ITRD databse. [Online] Available at: https://trid.trb.org/

Turner, S., Fitzpatrick, K., Brewer, M. & Park, E. S., 2006. Motorist Yielding to Pedestrians at Unsignalized Intersections. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1982, pp. 1-12.

Van Derlofske, J., Boyce, P. & Gilson, C., 2003. Evaluation of In-Pavement, Flashing Warning Lights on Pedestrian Crosswalk Safety. *International Municipal Signal Association (IMSA) Journal,* May, 41(3), pp. 54-61.

Van Houten, R., 1988. The Effects of Advance Stop Lines and Sign Prompts on Pedestrian Safety in a Crosswalk on a Multilane Highway. *Journal of Applied Behavior Analysis,* 21(3), pp. 245-251.

Van Houten, R., Healey, K., Malenfant, L. & Retting, R., 1998. Use of Signs and Symbols To Increase the Efficacy of Pedestrian-Activated Flashing Beacons at Crosswalks. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1636, pp. 92-95.

Van Houten, R. & Malenfant, L., 1992. The Influence of Signs Prompting Motorists to Yield Before Marked Crosswalks on Motor Vehicle-Pedestrian Conflicts at Crosswalks with Flashing Amber. *Accident Analysis & Prevention,* 24(3), pp. 217-225.

Van Houten, R. & Malenfant, L., 1999. *Canadian Research on Pedestrian Safety,* McLean, VA.

Van Houten, R., Malenfant, L. & McCusker, D., 2001. Advance Yield Markings: Reducing Motor Vehicle–Pedestrian Conflicts at Multilane Crosswalks with Uncontrolled Approach. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1773, pp. 69-74.

Van Houten, R. et al., 2002. Advance Yield Markings and Fluorescent Yellow-Green RA 4 Signs at Crosswalks with Uncontrolled Approaches. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1818, pp. 119-124.

Van Houten, R. & Retting, R., 2001. Increasing Motorist Compliance and Caution at Stop Sign. *Journal of Applied BehaviorAnalysis,* 34(2), pp. 185-193.

Várhelyi, A., 1998. Drivers' Speed Behaviour at a Zebra crossing: a Case Study. *Accident Analysis & Prevention,* 30(6), pp. 731-743.

Wa, H., 1993. Older Motorist Yielding to Pedestrians: Are Older Drivers Inattentive and Unwilling to Stop? *International Journal of Aging and Human Development,* 36(2), pp. 115-127.

Waizman, G., Shoval, S. & Benenson, I., 2014. Micro-Simulation Model for Assessing the Risk of Vehicle–Pedestrian Road Accidents. *Journal of Intelligent Transportation Systems,* Issue 19, pp. 63-77.

Wallberg, S. & Wisenbord, P., 2000. *Pedestrian Safety at Zebra Crossings in Amman: Minor Field Study,* Sweden.

Wang, C., Ye, Z., Wang, X. & Li, W., 2017. Effects of Speed-control Measures on the Safety of Unsignalized Midblock Street. *Traffic Injury Prevention,* pp. 1-6.

Wang, J. & Fang, S., 2008. Pedestrian-Vehicle Conflict Observation and Characteristics of Road Section. *Journal of Tongji University (Nature Science),* 36(4), pp. 503-507.

WHO, 2004. Road safety - Speed. In: *World Report on Road Traffic Injury Prevention.* World Health Organization.

WHO, 2018. Safety Lit. [Online]
Available at: https://www.safetylit.org/

Xiang, H.-Y., Zhang, Q.-q. & Fan, W.-B., 2016. A Safety Degree Model of Pedestrian No-signal Crossing Walk Based on Monte Carlo Simulation. *Journal of Transportation Systems Engineering and Information Technology,* August, 16(4), pp. 171-177.

Yan, X. et al., 2008. Validating a Driving Simulator using Surrogate Safety Measures. *Accident Analysis & Prevention*, Volume 40, pp. 274-288.

Yannis, G., Papadimitriou, E. & Theofilatos, A., 2013. Pedestrian Gap Acceptance for Mid-block Street. *Transportation Planning and Technology,* 36(5), pp. 450-462.

Ye, Z., Zhang, Y. & Lord, D., 2012. Goodness-of-fit Testing for Accident Models with Low Means. *Accident Analysis & Prevention*, Volume 61, pp. 78-86.

Yu, R., 2012. *Real-time Traffic Safety Evaluation Models and Their Application for Variable Speed Limits,* Orlando, FL: University of Central Florida.

Zegeer, C. V., Stewart, R., Huang, H. & Lagerwey, P., 2001. Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations: Analysis of Pedestrian Crashes in 30 Cities. *Transportation Research Record: Journal of Transportation Research Board,* Volume 1773, pp. 56-68.

Zegeer, C. V. et al., 2005. *Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations: Final Report and Recommended Guidelines,* McLean, VA.

Zhuang, X. & Wu, C., 2014. Pedestrian Gestures Increase Driver Yielding at Uncontrolled Mid-block Road Crossings. *Accident Analysis & Prevention,* Volume 70, pp. 235-244.

Link between chapter 2 and chapter 3

The previous chapter summarizes data collection methods used in previous studies in investigating pedestrian safety at non-signalized intersection. The advantages of using vision-based techniques have been recognized; however, limitations have also been outlined in using regular cameras for traffic data collection. The regular camera detects objects in visible light spectrum. This makes it sensitive to different environmental factors such as lighting, shadow and weather conditions. The thermal camera detects the thermal signal, instead of visible light spectrum. Therefore, it provides a potential solution to collect video data as an alternative to regular cameras, especially for situations when the regular camera is not able to function well.

Work regarding to the performance validation of using the thermal camera for traffic data collection under different environment and understanding its advantages over the visible spectrum camera could provide a useful reference for researchers who are interested to develop this technology and practitioners who wish to use this technology in the field of transportation. This motivates the study in the following chapter. In Chapter 4, the performance of thermal and visible spectrum videos for the automated collection and traffic data extraction is evaluated in terms of road user detection, classification, and vehicle speed estimation.

Chapter 3

Automatic Traffic Data Collection under Varying Lighting and Temperature Conditions in Multimodal Environments: Thermal versus Visible Spectrum Video-Based Systems

Chapter 3 Automatic Traffic Data Collection under Varying Lighting and Temperature Conditions in Multimodal Environments: Thermal versus Visible Spectrum Video-Based Systems

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3.1 ABSTRACT

Vision-based monitoring systems using visible spectrum (regular) video cameras can complement or substitute conventional sensors and provide rich positional and classification data. Although new camera technologies, including thermal video sensors, may improve the performance of digital video-based sensors, their performance under various conditions has rarely been evaluated at multimodal facilities. The purpose of this research is to integrate existing computer vision methods for automated data collection and evaluate the detection, classification, and speed measurement performance of thermal video sensors under varying lighting and temperature conditions. Thermal and regular video data was collected simultaneously under different conditions across multiple sites. Although the regular video sensor narrowly outperformed the thermal sensor during daytime, the performance of the thermal sensor is significantly better for low visibility and shadow conditions, particularly for pedestrians

and cyclists. Retraining the algorithm on thermal data yielded an improvement in the global accuracy of 48 %. Thermal speed measurements were consistently more accurate than for the regular video at daytime and nighttime. Thermal video is insensitive to lighting interference and pavement temperature, solves issues associated with visible light cameras for traffic data collection, and offers other benefits such as privacy, insensitivity to glare, storage space, and lower processing requirements.

3.2 INTRODUCTION

In transportation management, planning, and road safety, collecting data for both motorized and non-motorized traffic is necessary (Robert, 2009). Collecting vehicle data was traditionally limited to manual data collection or inductive loops at fixed locations (Bahler, et al., 1998), to the point that loops became standard in many jurisdictions and are still widely used today (Coifman, 2005). However, traditional loops do not provide any spatial coverage and do not capture all road user types (loop detectors exist for bicycles but do not count vehicles or pedestrians). Trajectory data for all users (pedestrians, bicycles, and vehicles) is essential to understand microscopic behavior and surrogate safety analysis in critical road facilities such intersections with high non-motorized traffic volumes (Zangenehpour, et al., 2016). These factors have spurred the development of non-intrusive traffic sensors of which video-based devices are among the most promising (Robert, 2009). Vision-based monitoring systems are widely used in ITS applications (Yoneyama, et al., 2005), can complement or substitute conventional sensors (Cho & Rice, 2006), enable multiple lane detection (Bahler, et al., 1998), and provide rich positional and classification data (Zangenehpour, et al., 2015) beyond the capabilities of traditional devices (Iwasaki, et al., 2013).

These benefits notwithstanding, there are several critical limitations associated with using regular video cameras, also referred to as visible spectrum video cameras, for traffic data collection. As these cameras rely on the visible light spectrum, the accuracy of detection, tracking, and classification is “sensitive to environmental factors such as lighting, shadow, and weather conditions” (Fu, et al., 2015; Yoneyama, et al., 2005). Perhaps the greatest limitation of regular cameras is varied performance in low light conditions and darkness (Sangnoree &

Chamnongthai, 2009). Considering detection and classification at nighttime, “the light sensitivity and contrast of the camera...are generally too weak” (Robert, 2009) to compensate for “the interference of illumination and blurriness” (Thi, et al., 2008). This is particularly problematic because the increased injury risk associated with nighttime conditions leads to more, and more severe, road traffic crashes (Huang, et al., 2000). During daytime, shadows and glare degrade the accuracy of extracted data (Yoneyama, et al., 2005; Iwasaki, et al., 2013). This is why typical computer vision approaches developed for daytime surveillance may not work under all conditions (Robert, 2009), and the advancement of vision-based traffic sensors is a pressing matter (Iwasaki, et al., 2013).

Recently, new camera (sensor) technologies, including thermal or infrared sensors for traffic surveillance, have become available. Although the present cost of these cameras has prevented their widespread use in traffic analysis, cost will continue to decrease as the technology advances. Recognizing that it “is difficult to cope with all kinds of situations with a single approach” (Yoneyama, et al., 2005), the performance of thermal cameras must be compared to regular cameras across varied lighting and visibility conditions to satisfy the desire for an “around-the-clock” video-based traffic sensor (Iwasaki, et al., 2013). In recent years, various computer vision techniques for tracking, classification, and surrogate safety analysis have been developed (Zangenehpour, et al., 2015; Saunier, n.d.), though nearly all these methods were developed and tested using regular video cameras. It is unclear if these methods can be directly applied to thermal video and whether thermal cameras offer a performance advantage compared to regular cameras across lighting and temperature conditions.

The purpose of this study is i) to integrate existing tracking and classification computer-vision methods for automated thermal-video data collection under low visibility conditions, nighttime and shadows and ii) to evaluate the performance of thermal video sensors under varying lighting and temperature conditions compared to visible light cameras. Performance is evaluated with respect to road user detection, classification, and vehicle speed measurements. Lighting and temperature conditions where each camera outperformed the other are identified to provide practical recommendations for the implementation of video-based sensors. An early version of this paper has been presented previously (Fu, et al., 2016; Fu, et al., 2016).

3.3 LITERATURE REVIEW

The difficulties associated with collecting traffic data using regular cameras, and attempts to rectify these issues, have been well documented in the existing literature, though many existing studies do not appropriately report performance, be it for detection, classification, or tracking. Yoneyama, Yeh, and Kuo (2005) demonstrated that nighttime detection misses are up to 50 % and false alarms are 3.4 % of the ground truth total, much higher than for daytime detection. Robert (Robert, 2009) showed that vehicle counts were accurate in various lighting, weather, and traffic conditions when using a headlight detection method, although sample sizes were generally 100 vehicles or less. Methods that detect headlights or taillights are typically only applicable at night, and the headlight detection method may increase the difficulty of vehicle classification (Iwasaki, et al., 2013). Thi et al. (2008) proposed a methodology using eigenspaces and machine learning for classification from regular video at nighttime. The authors found a successful classification rate of 94 % compared to 70 % or lower for other classification schemes. Coifman et al. (1998) suggested that “to be an effective traffic surveillance tool … a video image processing system … should … function under a wide variety of lighting conditions”. The authors proposed feature-based tracking as an improvement over those methods dependent on identifying an entire vehicle, because even under different lighting or visibility conditions, “the most salient features at the given moment are tracked” (Coifman, et al., 1998). The proposed algorithm was evaluated on highways where it was generally successful at tracking vehicles in situations including congestion, shadows, and varying lighting conditions.

With the limited success of regular cameras in adverse conditions, many researchers have considered alternative technologies for traffic data collection. Balsys, Valinevicius, and Eidukas (2009) identified that weather interference could be avoided using infrared (thermal) cameras, demonstrating that the cameras eliminated issues associated with headlight glare at night and cast shadows during the day. Thermal video demonstrated a 15 % improvement in detection rate over visible light cameras. Sangnoree and Chamnongthai (2009) presented a method for detecting, classifying, and measuring speeds of vehicles at night using thermal videos. Although classification and speed estimation were successful, detection worked best when only a single vehicle was present in the video frame (84 % success) but suffered when two or more vehicles were present (41-76 % success). Iwasaki (2008) developed a vision-based monitoring system that works robustly around-the-clock using infrared thermography. Iwasaki, Kawata, and Nakamiya (2013) achieved 96 % successful detection of vehicles using thermal video in poor visibility conditions. MacCarley, Hemme, and Klein (2000) compared several infrared and visible light cameras, and found that many infrared cameras were “virtually immune to headlight or streetlight backscatter” and therefore performed best in darkness, fog, or the combination of darkness and fog. However, without fog or with light fog, the visible light camera outperformed infrared cameras, and “there appears to be a limited number of situations for which non-visible spectrum imaging appears to be justified”, including dense fog or scenes with glare or shadows (MacCarley, et al., 2000).

Thermal video has been used successfully for nighttime pedestrian detection, an area of particular importance because pedestrians may be less visible to drivers at night, and are therefore at a greater risk of collision (Huang, et al., 2000). Xu, Liu, and Fujimura (2005) used a support vector machine (SVM) to detect and classify pedestrians using a thermal camera mounted to a moving vehicle. Although detection was successful in many cases, occlusion of pedestrians in heavy traffic was a significant limitation. Krotosky and Trivedi (2007) analyzed multiple camera technologies. Recognizing that regular and thermal cameras provide “disparate, yet complementary information about a scene”, the authors recommend combining visible light and infrared technologies (Krotosky & Trivedi, 2007).

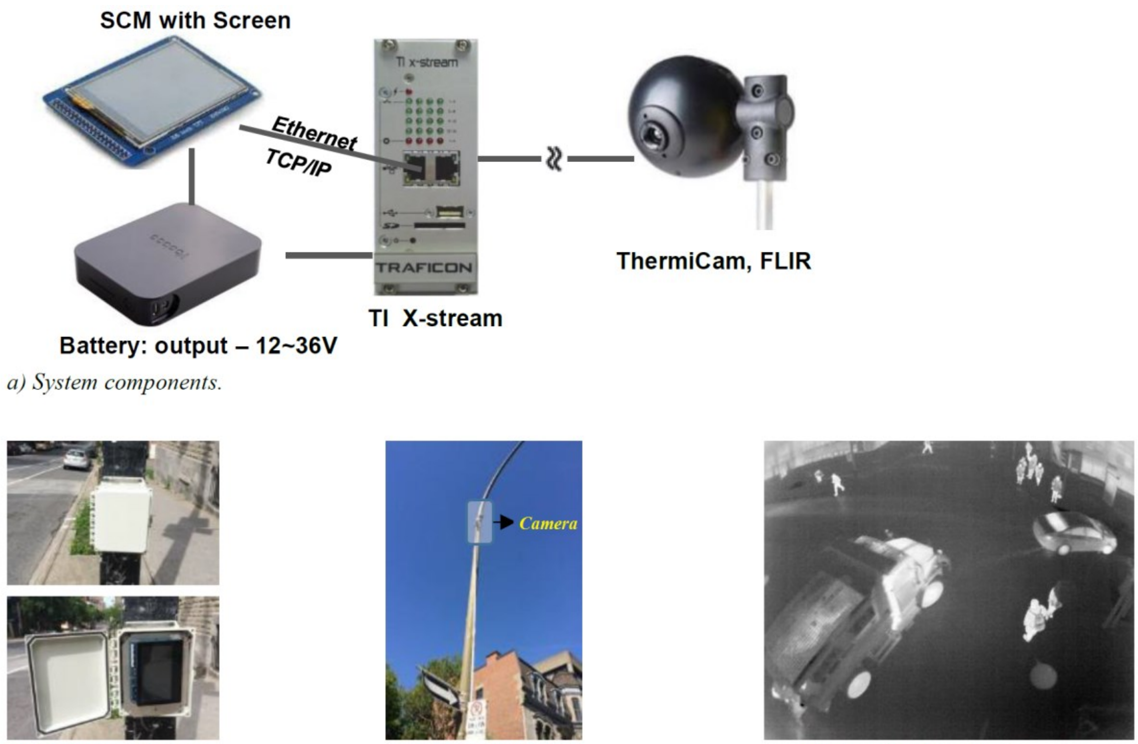
Despite this existing work, several shortcomings exist. Although several studies have addressed detecting vehicles or pedestrians, there has been limited work on detecting and classifying multiple road user types (including bicycles) from thermal video in mixed-traffic environments such as urban intersections. No studies have attempted to identify the effect of pavement temperature on the quality of thermal video. Although thermal video sensors are promising, their performance must be comprehensively evaluated and the adaptation of existing computer vision software must be studied. Most studies do not appropriately report performance and cannot be reproduced since the software code and/or datasets are not available. Detection rate alone is too limited to represent performance. The whole confusion matrix should be presented and receiver operating characteristic (ROC) curves should be used to evaluate detectors or classifiers as parameters are adjusted. Separate data sets for calibration and performance measurements should be required. When available, researchers should use standard metrics such as the Measure of Tracking Accuracy (MOT) (Bernardin & Stiefelhagen, 2008). This research aims to address these gaps and integrate thermal sensors into existing data collection and safety tools, in particular under conditions where regular video presents limitations.

3.4 METHODOLOGY

The methodology considers three steps: i) technology integration and data collection, ii) implementation of detection and classification algorithms, and iii) vehicle speed validation. The three steps are detailed below.

3.4.1 Technology Integration and Data Collection

The two technologies involved in this study are thermal-video sensors with a resolution of 368x296 pixels and visible-light cameras with a resolution of 1920x1080 pixels. The thermal camera system consists of a thermal sensor, a signal converter, and a power supply unit. Thermal video data is stored on a simple chip microcomputer (SCM). The thermal sensor, the ThermiCam by FLIR, is connected to an X-stream edge card that reads the thermal signal and converts and outputs the signal to a video file. The video file from the X-stream edge card is transferred to the SCM using an Ethernet connection where it is saved using the VLC Software (VideoLAN Organization, n.d.). The camera and X-stream edge card are powered using a battery with an output of 12-24 V. The SCM, the battery and the X-stream edge card are placed in a small enclosure which can be easily installed for data collection. FIGURE 3-1 presents the components of the thermal camera system and a sample frame from the thermal camera recorded at night in FIGURE 3-1d.



a) System components.

b) System enclosure *c) Installation* *d) Sample video frame*

FIGURE 3-1 Thermal camera system*[4]

Three primary sources of data are required: thermal video data, visible spectrum video data, and environmental and pavement temperature data. The regular visible-spectrum camera and thermal camera systems are installed simultaneously using a telescoping-fibreglass mast to ensure nearly identical fields of view. The regular camera system, introduced previously (Zangenehpour, et al., 2015), uses an inexpensive and commercially available video camera which stores video and is powered internally.

Since the road pavement is the primary background in the video scenes, pavement temperature is regarded as the main temperature variable affecting thermal video performance. Pavement temperature data were collected using the FLIR ONE thermal camera (FLIR Systems, Inc., 2015), which attaches to an iPhone to capture thermal video and temperatures using the FLIR ONE iPhone application. The camera was held close to the road surface to get an accurate temperature as suggested in the user manual (FLIR Systems Inc., 2014). Based on field-testing,

[4] Note that in the field, the battery, SCM and the TI X-stream are enclosed in a small waterproof case.

the temperature measured by the FLIR ONE camera was within 2°C of the actual pavement temperature. FIGURE 3-2 shows the camera system, its user interface, and field measurement of the pavement temperature data.

a) FLIR ONE camera (FLIR Systems, Inc., 2015) b) App user interface c) Field measurement

FIGURE 3-2 Pavement temperature measuring sensor – FLIR ONE thermal camera

3.4.2 Implementation of Detection and Classification Algorithms

As thermal videos detect thermal energy, they are expected to solve the issues associated with visible light cameras under different lighting conditions. Though, existing detection and classification algorithms are used for automated data collection, they must be re-trained and evaluated under different lighting and temperature conditions. Additional details of the methods for detection, tracking and classification are presented in the next sub-sections.

3.4.2.1 Detection and Tracking Algorithm

The videos were processed using the tracker available in Traffic Intelligence, an open-source computer-vision software project (Saunier & Sayed, 2006). Individual pixels are first detected and tracked from frame to frame, and recorded as feature trajectories using the Kanade-Lucas-Tomasi feature tracking algorithm (Shi & Tomasi, 1994). Feature trajectories are then grouped based on consistent common motion to identify unique road users. The techniques used in the tracker are further explained by Shi & Tomasi (1994) and Saunier & Sayed (2006). Algorithm parameters were calibrated through trial and error, in order to minimize both false alarms and misses. False alarms and misses respectively result mostly from over-segmentation (one user being tracked as multiple users) and over-grouping (multiple users being tracked as one user).

3.4.2.2 Classification Algorithm

Road user classification was performed using the method developed by Zangenehpour, Miranda-Moreno, and Saunier (2015). Classifier V classifies detected road users as vehicles, pedestrians, or cyclists based on the combination of appearance, aggregate speed, speed frequency distribution, and location in the scene. An SVM is used to learn the appearance of each road user type as described by the well-known Histogram Oriented Gradients (HOG). The SVM was trained based on a database containing 1500 regular images of each road user type. The overall accuracy of this classification method at intersections with high volumes and mixed road user traffic is approximately 93 %, an improvement over simpler algorithms using only one or two classification cues (Zangenehpour, et al., 2015). The classifiers are available in Traffic Intelligence (Saunier, n.d.). For more details regarding the original classification method, readers are referred to (Zangenehpour, et al., 2015).

3.4.2.3 Algorithm Retraining

Considering that the classifier uses the appearance of the road user as a parameter, and the fact that road users in thermal videos appear quite differently than they do in visible light videos, the SVM classifier for appearance classification, as part of the Classifier V (Zangenehpour, et al., 2015) that is used in this study, needs to be retrained on a dataset of thermal images for all road user types. Although the shape and proportions of the road users should be roughly equivalent, it is unclear how their appearance described by HOG varies between the visible and thermal images. Furthermore, the reduced resolution of the thermal video may impact the classification performance as less information and fewer details are available. The accuracy of the classification algorithm must therefore be explored further.

The retraining work mainly consists of three steps: 1) extracting the square sub-images of all moving objects as tracked by the algorithm in the sample videos; 2) manually labeling images of the different road user types and preparing the database for training; 3) using the database to train the SVM classifier. The steps of the retraining work for the SVM classifier are presented in FIGURE 3-3. For retraining purpose, this study used a database containing 1500 thermal images from several videos (separate from the ones used for performance evaluation) for each type of road user to train the SVM. FIGURE 3-4 shows the samples of the images of the road users in the database which covers different lighting and temperature conditions. Results using the Classifier V with the SVM trained respectively on the regular and the thermal datasets are compared in the experimental results.

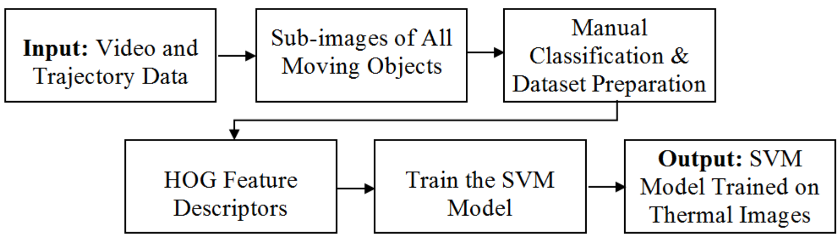
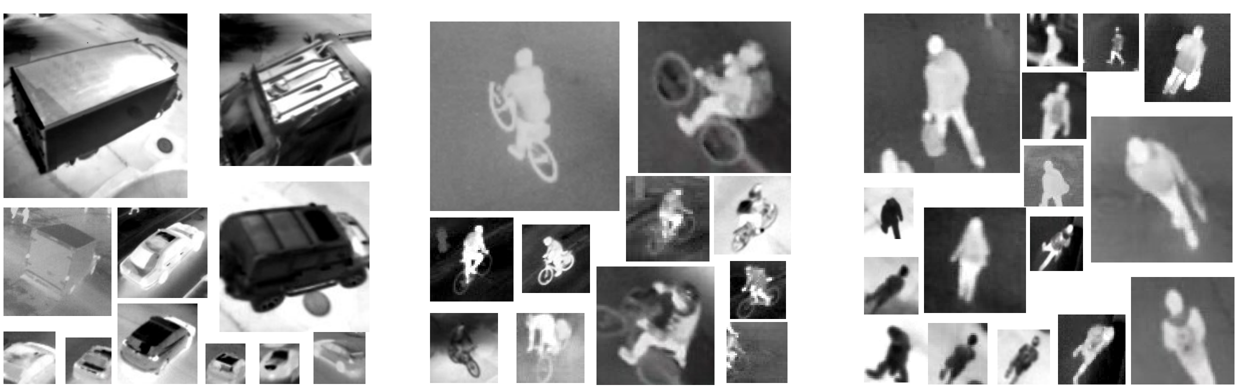


FIGURE 3-3 Steps involved in retraining the classifier (Zangenehpour, et al., 2015)

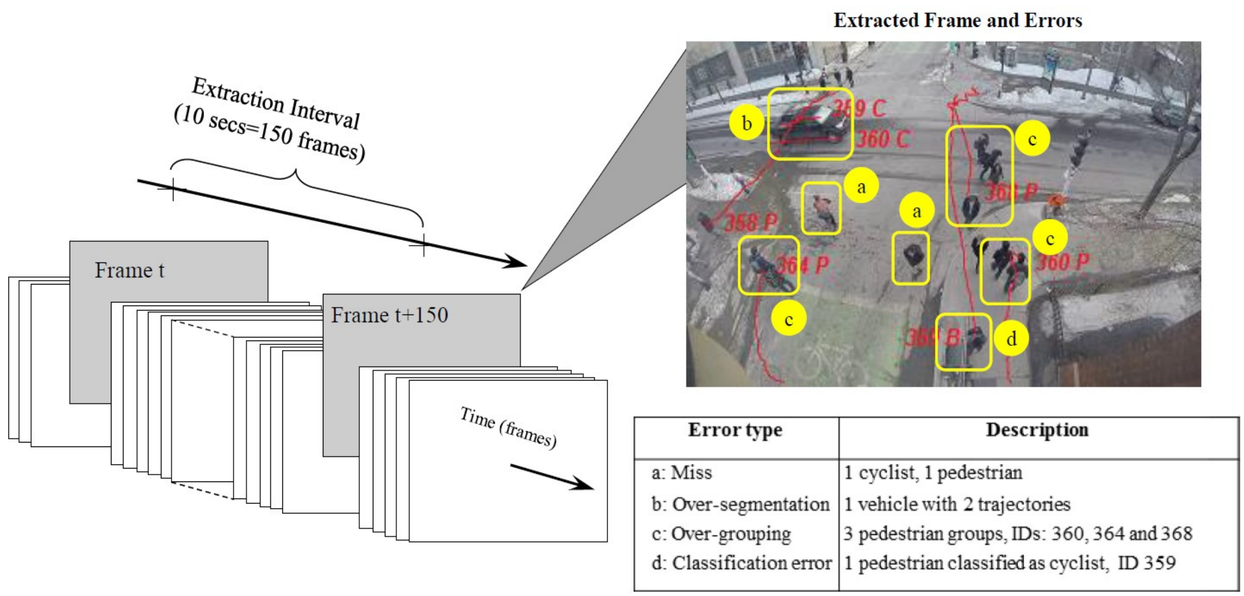


a) Sample of vehicles *b) Sample of cyclists* *c) Sample of pedestrians*

FIGURE 3-4 Sample of extracted road user images used for retraining

3.4.2.4 Detection and Classification Performance Metrics

The detection and classification performance are measured using different metrics and by extracting video data from frames every 10 seconds. This corresponds to 150 frames considering a frame rate of 15 frames per second (fps). Data (detection, user class, and speed) is then extracted by observing the results of the tracking and classification algorithms and compared visually with the ground truth. The interval of 10 s was chosen to be large enough in order to avoid evaluating the same road user twice. Most road users are tracked for less than 10 s continuously as the tracking algorithm tracks only moving road users (if stopped, a road user is not tracked anymore: tracking resumes when the road user starts moving again): trajectories are typically less than 5 s long for vehicles, and less than 10 s for pedestrians and cyclists. Also, 10 s is short enough to provide enough observations to evaluate the detection and classification performance. For the extracted frames, detection and classification errors are counted as shown in FIGURE 3-5.



Error type	Description
a: Miss	1 cyclist, 1 pedestrian
b: Over-segmentation	1 vehicle with 2 trajectories
c: Over-grouping	3 pedestrian groups, IDs: 360, 364 and 368
d: Classification error	1 pedestrian classified as cyclist, ID 359

FIGURE 3-5 Video sampling and data extraction for detection & classification Performance

Different metrics are computed to evaluate the performance of thermal vs regular video. For the classification problem, the confusion matrix is used to investigate the technology performance and derive metrics. In the general case with N classes, the confusion matrix is an NxN matrix that contains in each cell c_{ij}, the number of objects of true class i predicted as class j. The detection and tracking step can be also evaluated as a binary classification problem (a matrix with N=2 classes, miss and detected), where the class of objects to be detected is the positive class. The matrix in this binary case is presented in TABLE 3-1 with the particular names taken by the instances depending on their true and predicted class. Misses are the false negatives and false alarms are the false positives.

TABLE 3-1 Corresponding Table of Confusion & Basic Terms from Confusion Matrix

		Predicted class		
		Positive	**Negative**	
True class	**Positive**	True Positives (TP)	False Negatives (FN)	$Recall = \frac{TP}{TP + FN}$
	Negative	False Positives (FP)	True Negatives (TN)	
		$Precision = \frac{TP}{TP + FP}$		

The most common metric is the global accuracy defined as the proportion of correct predictions and is computed as:

$$Accuracy = \frac{\sum c_{kk}}{\sum_i \sum_j c_{ij}} \tag{1}$$

The majority of existing studies have used global accuracy to measure classification performance, both for road user detection and classification methods. This is however insufficient to properly report the performance, both for two-class classification, i.e. detection (since false alarms are not accounted for by a single detection rate) and for classification with three and more classes such as in multimodal environments, e.g. with pedestrians, cyclists, and vehicles. As used widely in the field of machine learning, this study relied on the confusion matrix to derive the following disaggregate metrics per class:

$$Precision_k = \frac{c_{kk}}{\sum_i c_{ik}} \tag{2}$$

$$Recall_k = \frac{c_{kk}}{\sum_j c_{kj}} \tag{3}$$

In the case of a binary classification problem, precision and recall are typically reported only for the positive class, and can be written in terms of true/false positives/negatives as follows:

$$Precision = \frac{TP}{TP+FP} = \frac{c_{11}}{c_{11}+c_{21}} \tag{4}$$

$$Recall = \frac{TP}{TP+FN} = \frac{c_{11}}{c_{11}+c_{12}} \tag{5}$$

From which, the miss rate can be derived as, $miss\ rate\ =\ 1 - Recall = \frac{FN}{TP+FN}$.

The above metrics are computed by populating the confusion matrix through the visual assessment of each frame extracted every 10 s or 150 frames as shown in FIGURE 3-5**.** Since pedestrians often move in groups, and detecting and tracking individual pedestrians within groups is difficult (and actually an open problem in all conditions in computer vision), the unit of analysis is individual pedestrians or groups of pedestrians. In FIGURE 3-5**,** the groups of pedestrians labeled c (over-grouping) are then considered correctly detected. Miss rate is the main metric reported for detection performance used for all test cases in the experimental results, while precision and recall at the individual level, overall and per known (true) type of road user, are also reported for two test cases for a more complete assessment.

The road user classification problem has three classes: pedestrians, cyclists and vehicles. Precision and recall are reported for each class, as well as global accuracy, from the confusion matrix accumulated over all extracted frames.

3.4.3 Vehicle Speed Validation

Once road users have been detected and classified, parameters such as vehicle speed are of interest for traffic studies. Many existing studies have used mean relative error (MRE) to quantify the error of video speeds extracted automatically from video. However, a previous study by Anderson-Trocmé et al. (Anderson-Trocme, et al., 2015) showed that it “is insufficient at capturing the true behaviour of detectors and other measures are necessary to define device precision and accuracy separately”, where accuracy is the systematic error or bias, and precision is the residual error. However, because video-based sensors tend to overestimate speed, and because this overestimation is roughly constant with respect to speed, simple methods for calculating relative precision error and relative accuracy error were developed.

The vehicle speed validation process begins by plotting automatically extracted speeds against manually measured speeds (speeds calculated based on known distances and video frame rate) in order to observe trends across visibility and temperature conditions. The line *y=x* represents ideal detector performance, and data points above the line indicate overestimation of speed, while points below the line indicate underestimation. As the overestimation bias is typically constant, a line with slope equal to one is fitted to the data. The y-intercept and R-squared values of this fitted line represent accuracy and precision respectively. However, converting these results to relative error values “matches the approach utilized in existing literature, and provides an intuitive and communicable comparison” between multiple environments (Anderson-Trocme, et al., 2015). Relative precision error (RPE) is quantified similarly to mean relative error, with the subtraction of a correction factor equal to the y-intercept of the fitted line. To normalize the intercept value consistently with the relative mean error, the y-intercept is evaluated at every data point (divided by the harmonic mean of observed speed) for the relative accuracy error (RAE). The RAE represents the over- or under-estimation bias present in the video data. The RPE can be seen as the best possible performance that could be expected from calibrated video data (Anderson-Trocme, et al., 2015). Values for relative error, relative precision and accuracy error are calculated as

$$Mean\ Relative\ Error\ (MRE) = \frac{1}{100}\sum\frac{|V_e - V_o|}{V_o} \tag{6}$$

$$Relative\ Precision\ Error\ (RPE)\ =\ \frac{1}{100}\sum\frac{|(V_e - y\ intercept) - V_o|}{V_o} \tag{7}$$

$$Relative\ Accuracy\ Error\ (RAE) = \frac{1}{100}\sum\frac{|y\ intercept|}{V_o} \tag{8}$$

Where V_e and V_o stands for the automatically extracted and manually measured speeds respectively.

3.5 DATA DESCRIPTION

To evaluate the performance of the thermal and regular cameras, 14 test cases (camera installations), with approximately one to four hours of video data for each case, were used. The lighting test cases, presented in TABLE 3-2, include videos during the day and at night. Daytime test cases focussed on various sun exposures and shadow conditions, while nighttime test cases focussed on the level of visibility, with one case in near complete darkness, one nearly completely illuminated, and one in between. Speed performance was evaluated on a sample size of 100 vehicles for each test case, while classification and detection performance was evaluated on 30 minutes of sample videos.

A similar approach was adopted for the temperature test cases, shown in TABLE 3-3. To evaluate detection and classification performance under different temperature conditions, thermal video data were collected from the same site with the same camera angle throughout a sunny summer day when the pavement temperature rose from 20°C in the morning to 50°C in the afternoon. Data collected from the same site in winter when the pavement temperature was close to 0°C was included. As with the lighting test cases, speed performance was evaluated on a 100-vehicle sample, and classification and detection performance was evaluated on 20-minute video samples. In TABLE 3-3, the thermal images change drastically from cold to hot pavement temperature. Road users are light on a dark background when the pavement temperature is low, and dark on a light background when pavement temperature is high.

TABLE 3-2 Summary of Lighting Test Cases

Lighting Condition		VEHICLE SPEED			CLASSIFICATION		
		Sample Size	Season	Road Type	Video Length	Season	Road type
Daytime	Overcast	100 vehicles	Winter	Segment	Every 10 s for 30 minutes	Summer	Intersection
	Sun, little shadow		Spring			Summer	Intersection
	Sun, slight shadows		Spring			N/A	N/A
	Sun, strong shadows		Summer			Summer	Intersection
Nighttime	High visibility	100 vehicles	Spring	Segment	Every 10 s for 30 minutes	Winter	Intersection
	Medium visibility			Intersection			
	Low visibility			Intersection			

SAMPLE CAMERA VIEWS UNDER DIFFERENT LIGHTING CONDITIONS

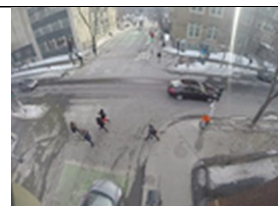
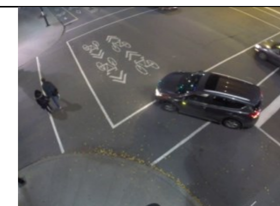
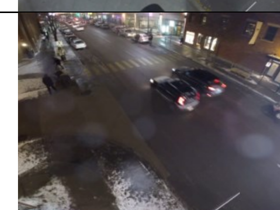
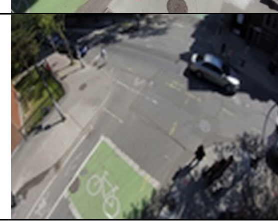
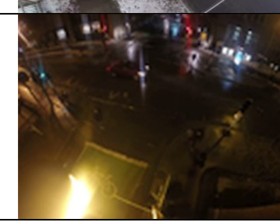
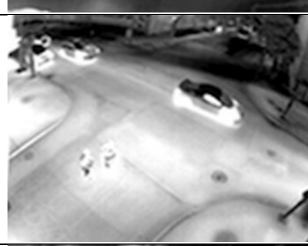
Daytime Conditions	Thermal Camera	Regular Camera	Nighttime Conditions	Thermal Camera	Regular Camera
Overcast			High visibility		
Sun, little shadow			Medium visibility		
Sun, strong shadows			Low visibility		

TABLE 3-3 Summary of Temperature Test Cases

Pavement Temp.	Ambient Temp.	Sample Size	Season	Road Type
VEHICLE SPEED				
0 °C- 5°C	~ 0 °C		Winter	Segment
20 °C-25°C	~ 20 °C		Summer	Segment
25 °C-30°C	~ 20 °C	100 vehicles	Summer	Segment
30 °C-35°C	~ 20 °C		Summer	Segment
35 °C-40°C	~ 20 °C		Summer	Segment
40 °C-45°C	~ 20 °C		Summer	Intersection
CLASSIFICATION				
0 °C- 5°C	~ 0 °C		Winter	
20 °C-25°C	~ 20 °C		Summer	
25 °C-30°C	~ 20 °C		Summer	
30 °C-35°C	~ 20 °C	Every 10 s (150 frames) for 20 minutes	Summer	Intersection
35 °C-40°C	~ 20 °C		Summer	
40 °C-45°C	~ 20 °C		Summer	
45 °C-50°C	~ 20 °C		Summer	

SAMPLE CAMERA VIEWS UNDER DIFFERENT TEMPERATURE

Pavement Temp.	Camera View	Pavement Temp.	Camera View
0°C- 5°C		35°C-40°C	
20°C-25°C		40°C-45°C	
25°C-30°C		45°C-50°C	
30°C-35°C			

3.6 RESULTS

3.6.1 Detection and Classification

3.6.1.1 Lighting

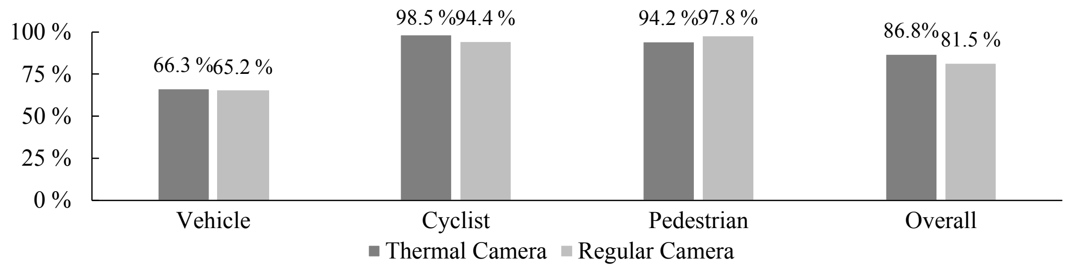
Results of detection and classification for the thermal and regular video are presented in TABLE 3-4 for the lighting test cases. The thermal camera reported a miss rate of 5 % or less for all road user types in nearly all test cases. While the vehicle miss rate of the regular camera was also lower than 5 % in all test cases, the rate increased significantly for pedestrians and cyclists in all nighttime test cases, where very few pedestrians and cyclists were detected with the regular camera (more than 75 %). Vehicles were well detected by both technologies under all conditions, possibly because their lit headlights and larger size provide more features for tracking compared to pedestrians and cyclists. In conditions without interference of darkness or shadows (test cases of "overcast" and "sun, little shadow"), excellent performance was obtained for the regular videos. However, daytime cases with shadows showed a decrease in performance, as shadows inhibit the tracking and detection of pedestrians, cyclists, and some vehicles. The miss rates of pedestrians and cyclists both increased to around 15 %, 10 % points higher than those in the thermal videos.

TABLE 3-4 Detection and Classification Performance for Different Lighting Conditions – Thermal and Regular Video

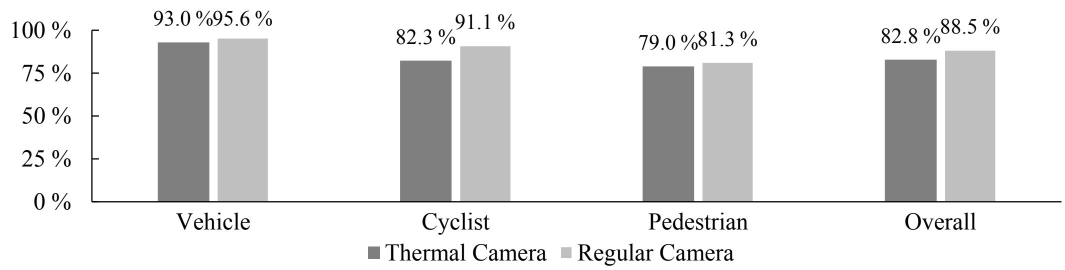
Lighting Condition		THERMAL VIDEO				REGULAR VIDEO			
		No. of Presence	No. of Missed/ Miss Rate	Classification Precision	Classification Recall	No. of Presence	No. of Missed/ Miss Rate	Classification Precision	Classification Recall
Vehicle Detection and Classification									
Daytime	Overcast	121	0 / 0.0 %	53.3 %	97.0 %	192	0 / 0.0 %	78.9 %	99.3 %
	Sun, little shadow	52	2 / 3.8 %	46.3 %	100.0 %	74	0 / 0.0 %	67.9 %	100.0 %
	Sun, strong shadows	77	0 / 0.0 %	44.2 %	100.0 %	83	3 / 3.6 %	55.0 %	100.0 %
Nighttime	High visibility	102	1 / 1.0 %	66.7 %	91.2 %	102	4 / 3.9 %	74.5 %	97.6 %
	Medium visibility	249	4 / 1.6 %	99.0 %	96.2 %	241	11 / 4.6 %	97.2 %	99.5 %
	Low visibility	42	1 / 2.4 %	56.3 %	96.4 %	42	2 / 4.8 %	91.4 %	100.0 %
Cyclist Detection and Classification									
Daytime	Overcast	26	1 / 3.8 %	36.1 %	81.3 %	38	1 / 2.6 %	30.9 %	96.7 %
	Sun, little shadow	46	1 / 2.2 %	95.8 %	54.8 %	57	4 / 7.0 %	87.8 %	78.3 %
	Sun, strong shadows	68	4 / 5.9 %	90.3 %	50.0 %	67	11 / 16.4 %	63.0 %	68.0 %
Nighttime	High visibility	44	1 / 2.3 %	70.2 %	93.0 %	44	36 / 81.8 %	42.9 %	37.5 %
	Medium visibility	12	0 / 0.0 %	64.7 %	100.0 %	12	12 / 100.0 %	0.0 %	Invalid
	Low visibility	10	0 / 0.0 %	69.2 %	90.0 %	10	10 / 100.0 %	Invalid	Invalid
Pedestrian Detection and Classification									
Daytime	Overcast	314	9 / 2.9 %	98.3 %	68.5 %	356	14 / 3.9 %	99.1 %	68.3 %
	Sun, little shadow	78	2 / 2.6 %	82.1 %	56.1 %	63	0 / 0.0 %	93.8 %	66.2 %
	Sun, strong shadows	118	9 / 7.6 %	100.0 %	46.8 %	130	19/ 14.6 %	86.6 %	59.2 %
Nighttime	High visibility	149	5 / 3.4 %	97.8 %	68.9 %	149	109 / 73.1 %	90.0 %	25.7 %
	Medium visibility	85	3 / 3.5 %	94.5 %	94.5 %	77	68 / 88.3 %	100.0 %	14.3 %
	Low visibility	286	4 / 1.4 %	99.5 %	89.5 %	286	278 / 97.2 %	Invalid	0.0 %
Total Detection and Classification									
				Accuracy				**Accuracy**	
Daytime	Overcast	461	10 / 2.2 %	74.9 %		586	15 / 2.6 %	79.1 %	
	Sun, little shadow	176	5 / 1.8 %	66.2 %		194	4 / 2.1 %	80.2 %	
	Sun, strong shadows	263	13 / 4.9 %	62.8 %		280	33 / 11.8 %	69.1 %	
Nighttime	High visibility	295	7 / 2.4 %	79.4 %		295	159 / 50.5 %	74.0 %	
	Medium visibility	346	7 / 2.0 %	96.1 %		330	91 / 27.6 %	96.8 %	
	Low visibility	338	5/ 1.5 %	90.3 %		338	290 / 85.8 %	91.4 %	

For classification performance, the measures of recall and precision are also presented in TABLE 3-4. Higher values of recall and precision in classifying vehicles using regular videos indicate that, in general, the performance of classifying vehicles was improved when using the regular camera over the thermal camera. However, from medium to low visibility conditions, regular cameras perform poorly in the classification of cyclists and pedestrians. For cases with medium and low visibility specifically, the algorithm failed to recognize pedestrians and cyclists in regular videos. In such cases, since classification is performed only for tracked road users, computing the precision may not be possible when no road user of the class was detected or representative if too few were detected. Thermal videos perform reliably in nighttime cases, even when using the classification algorithm trained on the regular, or visible spectrum, images of road users. In daytime conditions, the classification of pedestrians and cyclists is only slightly better by regular camera, as the global accuracy values are slightly higher in regular videos than those in thermal videos in most cases. The classification performance per class indicates the need for improving the classification algorithm for thermal videos by training the algorithm on images from thermal cameras. Nevertheless, even with the algorithm trained only on regular video data, the thermal camera correctly classifies road users more often in low visibility conditions, especially at nighttime.

A more complete detection performance evaluation, in particular for individual pedestrians, is reported for two extreme test cases: i) the sunny daytime case without the interference of shadow, which has the best lighting environment, presented in FIGURE 3-6, and, ii) the worst lighting condition case shown in FIGURE 3-7, which is nighttime condition with low visibility. From the results, the thermal camera and the regular camera perform similarly well in detecting different road users in the good lighting environment. For low visibility condition at night, the two camera systems have similar capability in detecting vehicles; however, the regular camera failed to detect the cyclists and pedestrians under such a low visibility condition (low recall) where the thermal camera can still work efficiently – this is in accordance with the previous analysis. With similar performance for good lighting conditions and much better performance for low visibility conditions, compared to the visible spectrum camera system, thermal cameras can be used for all weather and lighting conditions.

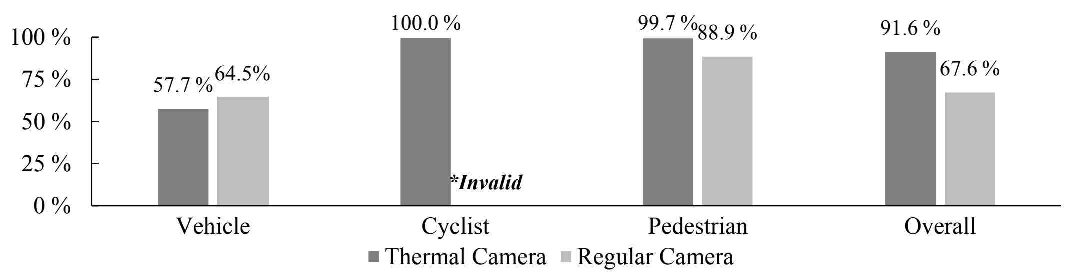


a) Precision

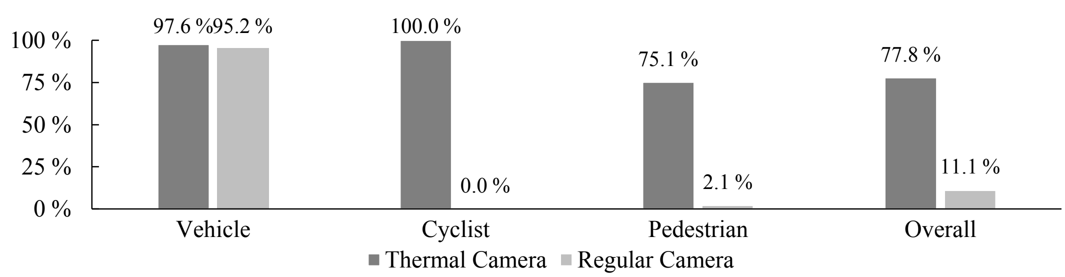


b) Recall

FIGURE 3-6 Detection performance results – Test Case: daytime, sun, little shadow



a) Precision - * Invalid because no cyclist is detected (TP and FP are both 0).



b) Recall

FIGURE 3-7 Detection performance results – Test Case: nighttime, low visibility

3.6.1.2 Temperature

The classifier trained on the thermal dataset was applied in the different temperature test cases where the outputs of the thermal videos changed greatly with the change of temperature. TABLE 3-5 presents the results of detection and classification performance for the classifier trained on the regular or thermal dataset for each test case. Again, the thermal video provided detection rates exceeding 95 % for nearly all test cases, and temperature had little impact on detecting different road users. Even when the pavement temperature approaches that of the road users, miss rate remained low. Observing the videos, temperature variation within each road user likely explains this good performance: features are still detected for the areas of high and low temperature within road users.

Although miss rate was low, classification results were generally poor before retraining the algorithm, and classification accuracy reduced systematically as temperature increased from 90.3 % in the lowest temperature case to 30.8 % in the highest. This result indicates that, for the thermal video, the object appearance described by HOG (Zangenehpour, et al., 2015) varies with pavement temperature, and therefore the SVM should be trained on thermal images to account for the different appearance of road users. The classification accuracy after the new training showed improvements, particularly at higher pavement temperatures. At 45-50 °C, overall classification accuracy improved by 48.6 % points, from an accuracy of 30.8 to 79.4 %. The excellent performance of detection and the higher classification accuracy rates for the algorithm trained on thermal data indicate the possibility of using this algorithm to correctly detect and classify different types of road users under different temperature conditions.

TABLE 3-5 Detection and Classification Performance for Different Pavement Temperatures – Thermal Camera

Pavement Temp.	No. of Presence	No. of Missed /Miss Rate	Classifier Trained on Regular data		Classifier Trained on Thermal data		Improvement (% points)	
			Precision	Recall	Precision	Recall	Precision	Recall
	Vehicle Detection and Classification							
0 °C- 5°C	42	1 / 2.4 %	56.3 %	96.4 %	67.4 %	96.7 %	11.2 %	0.2 %
20 °C-25°C	58	0 / 0.0 %	89.1 %	100.0 %	96.1 %	100.0 %	7.0 %	0.0 %
25 °C-30°C	37	2 / 5.4 %	67.6 %	100.0 %	83.9 %	100.0 %	16.2 %	0.0 %
30 °C-35°C	20	0 / 0.0 %	27.9 %	100.0 %	68.4 %	100.0 %	40.5 %	0.0 %
35 °C-40°C	45	1 / 2.2 %	35.6 %	100.0 %	67.5 %	100.0 %	31.9 %	0.0 %
40 °C-45°C	31	1 / 3.2 %	23.6 %	100.0 %	65.4 %	100.0 %	41.7 %	0.0 %
45 °C-50°C	19	0 / 0.0 %	12.1 %	100.0 %	47.6 %	100.0 %	35.5 %	0.0 %
Average			44.6 %	99.5 %	70.9 %	99.5 %	26.3 %	0.0 %
	Cyclist Detection and Classification							
0 °C- 5°C	10	0 / 0.0 %	69.2 %	90.0 %	64.3 %	100.0 %	-4.9 %	10.0 %
20 °C-25°C	33	0 / 0.0 %	72.1 %	96.9 %	64.6 %	96.9 %	-7.5 %	0.0 %
25 °C-30°C	22	0 / 0.0 %	70.0 %	46.7 %	70.8 %	94.4 %	0.8 %	47.8 %
30 °C-35°C	36	0 / 0.0 %	93.8 %	51.7 %	75.8 %	86.2 %	-18.0 %	34.5 %
35 °C-40°C	27	2 / 7.4 %	88.9 %	33.3 %	67.9 %	76.0 %	-21.0 %	42.7 %
40 °C-45°C	40	0 / 0.0 %	88.9 %	22.9 %	83.8 %	86.1 %	-5.1 %	63.3 %
45 °C-50°C	26	0 / 0.0 %	100.0 %	6.7 %	85.0 %	85.0 %	-15.0 %	78.3 %
Average			83.3 %	49.7 %	73.2 %	89.2 %	-10.1 %	39.5 %
	Pedestrian Detection and Classification							
0 °C- 5°C	286	4 / 1.4 %	99.5 %	89.5 %	100.0 %	92.0 %	0.5 %	2.5 %
20 °C-25°C	71	0 / 0.0 %	100.0 %	66.0 %	100.0 %	66.7 %	0.0 %	0.7 %
25 °C-30°C	39	0 / 0.0 %	86.4 %	67.9 %	100.0 %	66.7 %	13.6 %	-1.2 %
30 °C-35°C	53	3 / 5.7 %	75.0 %	42.9 %	97.0 %	74.4 %	22.0 %	31.6 %
35 °C-40°C	51	2 / 3.9 %	62.5 %	12.5 %	96.7 %	63.0 %	34.2 %	50.5 %
40 °C-45°C	44	2 / 4.5 %	50.0 %	23.3 %	96.3 %	70.3 %	46.3 %	46.9 %
45 °C-50°C	44	2 / 4.5 %	61.1 %	33.3 %	100.0 %	71.1 %	38.9 %	37.7 %
Average			76.4 %	47.9 %	98.6 %	72.0 %	22.2 %	24.1 %
	Total Detection and Classification							
			Accuracy		**Accuracy**		**Accuracy**	
0 °C- 5°C	338	5 / 1.5 %	90.3 %		92.8 %		2.6 %	
20 °C-25°C	162	0 / 0.0 %	86.3 %		85.9 %		-0.3 %	
25 °C-30°C	98	3 / 3.1 %	74.2 %		84.4 %		10.2 %	
30 °C-35°C	109	3 / 2.7 %	54.2 %		82.4 %		28.1 %	
35 °C-40°C	123	5 / 4.1 %	43.3 %		76.5 %		33.2 %	
40 °C-45°C	115	3 / 2.6 %	35.9 %		82.2 %		46.3 %	
45 °C-50°C	89	2 / 2.2 %	30.8 %		79.4 %		48.6 %	
Average			59.3 %		83.4 %		24.1 %	

Looking at the per-class performance measures, better recall and precision were found in almost all temperature cases for vehicles and pedestrians when using the algorithm trained with thermal data (with an average increase of 26.3 % points in precision for vehicles, and an average increase of 24.1 % points in recall and 22.2 % points in precision for pedestrians). The recall for cyclists increases in all cases by 39.5 % points on average; however, precision decreases in most of the cases by 10.1 % points on average. This is explained by considering that, before training the algorithm on thermal data, a smaller portion of the detected cyclists are successfully classified which leads to a deceptively high precision. In other words, fewer cyclists were classified as such by the algorithm trained with regular videos, but the algorithm made few mistakes, and the other cyclists were classified as pedestrians or vehicles resulting in lower precision for these road user types. With a the newly trained algorithm, more road users, including actual cyclists are classified as cyclists, which increases cyclist recall; but in doing so, more vehicles and pedestrians are also misclassified as cyclists, causing a decrease in cyclist precision. A general issue for both types of cameras is confusing pedestrians and cyclists since they have similar appearances. Global accuracy improved by as much as 50 % points in the multimodal environments. Moreover, the % point improvement was larger for high temperature cases, indicating that training the algorithm for data collection using thermal videos is both necessary and effective.

3.6.2 Vehicle Speed Validation

To compare the performance of the camera systems in vehicle speed extraction accuracy, a data visualization exercise was completed for all test cases. One example, shown in FIGURE 3-8, demonstrates the performance of the two camera systems under sun with strong shadows.

3.6.2.1 Speed and Lighting

TABLE 3-6 provides the equation of the fitted line, its R-squared value, MRE, RAE, and RPE for each lighting conditions test case. For comparison purpose, a t-test was conducted to test the significance of the difference in the intercepts of models for using the two camera systems. The level of significance was set at 10 %. As given in TABLE 3-6, the intercept was found to be significantly different between the thermal camera and the regular camera for all lighting conditions, except for the low visibility condition.

From the results, the first important observation was that the intercept value in nearly all test cases was positive for both technologies. This result is consistent with previous research and shows that video sensors tend to overestimate speeds (Anderson-Trocme, et al., 2015). The R-square values for thermal video are significantly higher for daytime with shadows as well as median and low visibility conditions. RPE is perhaps the most critical value in TABLE 3-6. The thermal camera had a lower RPE in all test cases other than overcast sky, in which the regular camera was expected to perform well without lighting interference. In the other test cases, the thermal video consistently provided a 2-3 % points improvement in RPE over the regular camera. Despite this good performance, the RAE was highly variable both across conditions and across cameras. This again supports previous research, and indicates that the overestimation bias is less a function of camera or conditions as it as a function of user calibration error (Anderson-Trocme, et al., 2015). In general, the RPE was within 5-10 % of ground truth, which is consistent with previously measured performance of video sensors (Anderson-Trocme, et al., 2015).

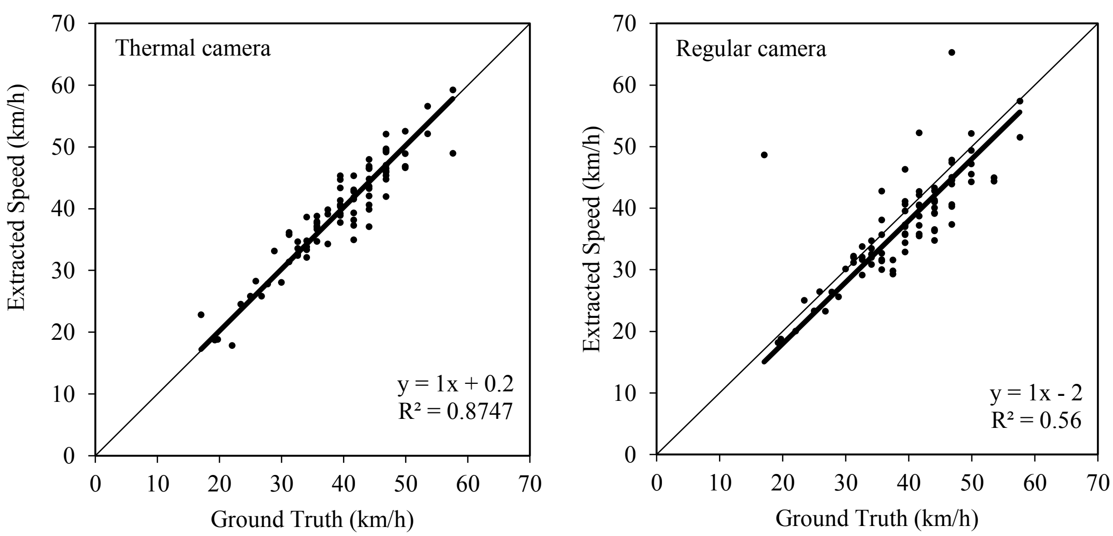


FIGURE 3-8 Example of vehicle speed estimation performance for thermal and regular cameras under sun with strong shadows

TABLE 3-6 Vehicle Speed Performance for Different Lighting Conditions – Thermal and Regular Video

		DIFFERENCE IN INTERCEPTS		THERMAL VIDEO		REGULAR VIDEO	
Lighting Condition		**p-value**	**Level of Significance**	**Calibration Model**	**R^2**	**Calibration Model**	**R^2**
Daytime	Overcast	<0.01	*	y = x - 1.97	0.91	y = x - 0.04	0.95
	Sun, little shadow	<0.01	*	y = x + 2.91	0.96	y = x + 1.77	0.92
	Sun, slight shadows	<0.01	*	y = x + 2.50	0.93	y = x + 5.75	0.90
	Sun, strong shadows	<0.01	*	y = x + 0.20	0.88	y = x - 2.00	0.56
Nighttime	High visibility	<0.01	*	y = x + 4.49	0.93	y = x + 0.01	0.92
	Medium visibility	0.09	+	y = x + 2.45	0.86	y = x + 4.14	0.46
	Low visibility	0.52	ns	y = x + 0.17	0.97	y = x + 0.83	0.93

		THERMAL VIDEO			REGULAR VIDEO		
Lighting Condition		**MRE**	**RAE**	**RPE**	**MRE**	**RAE**	**RPE**
Daytime	Overcast	0.067	0.058	0.067	0.059	0.001	0.059
	Sun, little shadow	0.106	0.116	0.045	0.069	0.071	0.062
	Sun, slight shadows	0.103	0.105	0.047	0.226	0.242	0.063
	Sun, strong shadows	0.061	0.005	0.061	0.108	0.053	0.097
Nighttime	High visibility	0.150	0.151	0.047	0.051	0.000	0.051
	Medium visibility	0.104	0.082	0.072	0.150	0.138	0.104
	Low visibility	0.036	0.026	0.033	0.060	0.005	0.059

Note: for significance test of each pair of groups, ns means that the difference between the pair of the group was not statistically significant (p-value > 0.1), + means that the difference was statistically significant at the significance level of 10% (0.05 < p-value < 0.1), * means that the difference was significant with p-value < 0.05.

3.6.2.2 Speed and Temperature

Similarly for the temperature test cases, parameters of the fitted line and the segregated relative errors values are presented in TABLE 3-7. The RPE for all but one test case was 0.06 or less, and was not observed to vary greatly with temperature. For one test case (35-40°C), several outliers greatly increased the reported error. A slight increase in RPE was noted between 20 and 30°C. These pavement temperatures most closely match the surface temperature of vehicles, and so a slight performance decrease may be explained by tracking issues associated with the low contrast with the pavement temperature. Despite the slight effect of temperature, the thermal videos performed reliably and consistently across all temperature test cases, with errors equal to what is expected from existing research. Thermal videos can be an effective substitute for regular videos with regards to speed data extraction under various lighting and temperature conditions.

TABLE 3-7 Vehicle Speed Performance for Different Pavement Temperature – Thermal Video

Pavement Temp.	Calibration Model	R^2	MRE	RAE	RPE
0°C- 5°C	y = x + 2.50	0.930	0.103	0.105	0.047
20°C-25°C	y = x + 0.20	0.870	0.061	0.005	0.061
25°C-30°C	y = x + 1.52	0.770	0.066	0.039	0.056
30°C-35°C	y = x + 2.88	0.830	0.106	0.087	0.046
35°C-40°C	y = x + 2.63	0.930	0.103	0.126	0.114
40°C-45°C	y = x + 2.48	0.900	0.087	0.081	0.058

3.7 CONCLUSIONS

This paper presents an approach to integrate and evaluate the performance of thermal and visible light videos for the automated collection and traffic data extraction under various lighting and temperature conditions in urban intersections with high pedestrian and bicycle traffic. The two technologies were evaluated in terms of road user detection, classification, and vehicle speed estimation. Considering the above results, several key conclusions are drawn.

- The regular camera only narrowly outperformed the thermal camera in terms of detection and classification of all road users during daytime conditions. Also, the regular camera detects and classifies vehicles adequately under nighttime conditions. However, the performance of the regular camera deteriorates for pedestrians and cyclists in all nighttime test cases, while miss rate by the thermal camera remained around 5 %, showing stability across the tested conditions.
- Based on the results at the individual level from the two test cases, the two cameras performed similarly in the favorable case; while for the night, low visibility case, the

advantage of using thermal camera was more significant compared to the results at the group level.

- Training of the classifier to account for variation in the appearance of road users in the thermal video was observed to increase classification performance (recall, precision, and global accuracy) for the thermal camera, particularly at higher temperatures. Training the algorithm using more thermal videos is expected to improve the classification performance by thermal video also during the day, where the thermal camera was slightly inferior to regular video.

- Speed measurements by the thermal camera were consistently more accurate than measurements by the regular video. Additionally, speed measurement accuracy was observed to be generally insensitive to lighting and temperature conditions.

Summarizing these points, regular video works well for "overcast" and "sun, little shadow" conditions without lighting interference such as shadow, glare, low visibility, or reflection. The thermal camera performs similarly in these conditions (although classification must be improved by training the algorithm on thermal data). However, with shadows or at night, the performance of the regular camera was greatly reduced, and the thermal camera was superior in terms of detection, classification, and vehicle speed measurement. The thermal videos are insensitive to lighting interference, and solve the issues associated with visible light cameras for traffic data collection, especially for active road users such as pedestrians and cyclists. The thermal camera is also generally insensitive to the effects of pavement temperature. Thermal videos are more reliable and stable compared to regular videos in an around-the-clock collection campaign. Furthermore, greyscale thermal videos with lower resolution provide comparable results during the day, yet require less storage space and processing power, which are key concerns. Finally, thermal videos cause no privacy issues, which are a major hurdle for the application of video-based sensors, especially in the U.S. and European countries.

As part of its contributions, this paper provides an approach for integrating existing tracking and classification algorithms for automated thermal video collection and analysis under varied lighting and weather conditions. The proposed approach can be used for automated counting, speed studies and surrogate safety analyses in particular during low visibility conditions and in environments with high pedestrian and bicycle traffic activity.

Though general improvement of the classification performance was achieved by training the classifier on thermal data, the results (average 83.4 % global accuracy over all cases, in TABLE 3-5) are lower than what has been reported previously for regular videos (93.3 %) (Zangenehpour, et al., 2015). Reasons for this reduced performance must be considered in future work, including lower resolution of thermal videos, and the need for more training image samples of road users under different temperature conditions. Validation of the classification algorithms on thermal videos will be better characterized using the ROC curve to compare different methods over several parameter settings. Although past literature shows visual improvements when using thermal cameras in foggy conditions, no work has been done to quantify the improvement of thermal videos during adverse weather conditions. The evaluation of thermal video in adverse weather conditions, such as heavy precipitation and fog, is a key focus of future work. Finally, a hybrid system that combines the advantages of both technologies can be designed to automatically calibrate and process video data from both thermal and visible spectrum sensors.

3.8 ACKNOWLEDGEMENT

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3.9 REFERENCES

Anderson-Trocme, P., Stipancic, J., Miranda-Moreno, L. & Saunier, N., 2015. Performance Evaluation and Error Segregation of Video-collected Traffic Speed Data. Washington DC, s.n.

Bahler, S. J., Kranig, J. M. & Minge, E. D., 1998. Field Test of Nonintrusive Traffic Detection Technologies. *Transportation Research Record*, Volume 1643, pp. 161-170.

Balsys, K., Valenvicius, A. & Eidukas, D., 2009. Urban Traffic Control Using IR Video Detection Technology. *Electronics and Electrical Engineering,* Volume 8, pp. 43-46.

Bernardin, K. & Stiefelhagen, R., 2008. Evaluating Multiple Object Tracking Performance: The CLEAR MOT Metrics. *EURASIP Journal on Image and Video Processing,* Volume 2008, pp. 1-10.

Cho, Y. & Rice, J., 2006. Estimating Velecoty Fields on a Freeway from Low-resolution Videos. *IEEE Transactions of Intelligent Transportation Systems,* 7(4), pp. 463-469.

Coifman, B., 2005. Freeway Detector Assessment: Aggregate Data from Remote Traffic Microwave Sensor. *Transportation Research Record,* Volume 1917, pp. 150-163.

Coifman, B., Beymer, D., McLauchlan, P. & Malik, J., 1998. A Real-time Computer Vision System for Vehicle Tracking and Traffic Surveillance. *Transportation Research Part C,* Volume 6, pp. 271-288.

FLIR Systems, Inc., 2015. *FLIR ONE is Lightweight, Easy to Connect and Easy to Use..* [Online] Available at: http://www.flir.com/flirone/content/?id=62910

FLIR Systems. Inc., 2014. *FLIR ONE User Manual,* s.l.: s.n.

Fu, T. et al., 2016. *Comparison of Regular and Thermal Cameras for Traffic Data Collection under Varying Lighting and Temperature Conditions.* Washington D.C., s.n.

Fu, T. et al., 2015. Using Microscopic Video Data Measures for Driver Behavior Analysis during Adverse Winter Weather: Opportunities and Challenges. *Journal of Modern Transportation,* May, 23(2), pp. 81-92.

Huang, H., Zegeer, C. & Nassi, R., 2000. Effects of Innovative Pedestrian Signs at Unsignalized Locations - Three Treatments. *Transportation Research Record,* Volume 1705, pp. 43-52.

Iwasaki, Y., 2008. *A Method of Robust Moving Vehicle Detection for Bad Weather Using an Infrared Thermography Camera.* Hong Kong, s.n., pp. 86-90.

Iwasaki, Y., Kawata, S. & Nakamiya, T., 2013. Vehicle Detection Even in Poor Visibility Conditions Using Infrared Thermal Images and Its Application to Road Traffic Flow Monitoring. In: T. Sobh & K. Elleithy, eds. *Emerging Trends in Computing, Informatics, Systems Sciences, and Engineering.* New York: Springer Science+Business Media, pp. 997-1009.

Krotosky, S. J. & Trivedi, M. M., 2007. On Color-, Infrared-, and Multimodal-Stereo Approaches to Pedestrian Detection. *IEEE Transactions on Intelligent Transportation Systems,* 8(4), pp. 619-629.

MacCarley, C. A., Hemme, B. M. & Klein, L., 2000. *Evaluation of Infrared and Millimeter-wave Imaging Technologies Applied to Traffic Management,* s.l.: s.n.

Robert, K., 2009. *Night-Time Traffic Surveillance A Robust Framework for Multi-Vehicle Detection, Classification and Tracking.* s.l., s.n., pp. 1-6.

Sangnoree, A. & Chamnongthai, K., 2009. *Robust Method for Analyzing the Various Speeds of Multitudinous Vehicles in Nighttime Traffic Based on Thermal Images.* s.l., s.n., pp. 467-472.

Saunier, N., n.d. *Traffic Intelligence.* [Online]
Available at: https://bitbucket.org/Nicolas/trafficintelligence/

Saunier, N. & Sayed, T., 2006. *A Feature-based Tracking Algorithm for Vehicles in Intersections.* s.l., IEEE Xplore.

Shi, J. & Tomasi, C., 1994. *Good Features to Track.* s.l., s.n., pp. 593-600.

Thi, T. H., Robert, K., Lu, S. & Zhang, J., 2008. *Vehicle Classification at Nighttime Using Eigenspaces and Support Vector Machine.* s.l., IEEE Xplore.

VideoLAN Organization, n.d. *VideoLAN.* [Online]
Available at: http://www.videolan.org/vlc/index.html

Xu, F., Liu, X. & Fulimura, K., 2005. Pedestrian Detection and Tracking With Night Vision. *IEEE Transactions on Intelligent Transportation Systems,* 6(1), pp. 63-71.

Yoneyama, A., Yeh, C.-H. & Kuo, C.-C. J., 2005. Robust Vehicle and Traffic Information Extraction for Highway Surveillance. *EURASIP Journal on Applied Signal Processing,* Volume 14, pp. 2305-2321.

Zangenehpour, S., Miranda-Moreno, L. F. & Saunier, N., 2015. Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application. *Transportation Research Part C: Emerging Technologies,* July, Volume 56, p. 161–176.

Zangenehpour, S., Miranda-Moreno, L. F. & Saunier, N., 2015. *Video-based Automatic Counting for Short-term Bicycle Data Collection in a Variety of Environments.* Washington D.C., s.n.

Zangenehpour, S., Strauss, J., Miranda-Moreno, L. F. & Saunier, N., 2016. Are Intersections with Cycle Tracks Safer? A Control-case Study based on Automated Surrogate Safety Analysis using Video Data. *Accident Analysis & Prevention*, Volume 86, pp. 161-172.

Link between chapter 3 and chapter 4

The previous chapter introduced the thermal camera and validated its performance in automated traffic data collection. Being insensitive to lighting interference and resistant to the effects of pavement temperature, thermal videos are more reliable and stable compared to visible spectrum cameras for the round-the-clock traffic data collection purpose. Results also showed the data collection approach using existing tracking and classification algorithms and the thermal camera can be used for automated counting, speed studies and safety analyses in particular during low visibility conditions and in environments with high pedestrian and bicycle traffic activity. With the help of thermal camera, the next chapter will use existing surrogate measures of safety to investigate pedestrian-vehicle interactions at non-signalized crosswalks during nighttime situations.

Chapter 4

Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime: Use of Thermal Video Data and Surrogate Safety Measures

Chapter 4 Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime: Use of Thermal Video Data and Surrogate Safety Measures

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4.1 ABSTRACT

This paper proposes a methodology to evaluate crosswalk pedestrian safety at nighttime by using surrogate safety measures derived from thermal video data. The methodology is illustrated for two non-signalized crosswalk locations in downtown Montreal, Quebec, Canada. Video recordings from a thermal camera were used to compare nighttime and daytime safety conditions with surrogate safety measures that included vehicle approaching speed, post-encroachment time (PET), yielding compliances, and conflict rates. A disaggregate measure of pedestrian exposure that excludes non-interacting road users is also proposed. A thermal camera was used to alleviate issues pertaining to low visibility at night for video analysis when road users, especially pedestrians, are difficult to track. The results showed that the thermal-video–based methodology could effectively collect interaction data at night regardless of lighting conditions. Through the use of thermal video data and the methodology proposed in this paper, the interactions between crossing pedestrians and motor vehicles, with related measures such as PET and speed, could be

analyzed to evaluate the effect of different crosswalk treatments on pedestrian safety in low-visibility conditions.

4.2 INTRODUCTION

Pedestrian safety has become a priority for many cities because of the increased awareness of pedestrians' vulnerability compared with that of other road users. In 2013, the United States counted 14 % of its total road crash fatalities as pedestrians (NHTSA, 2015), while Canada experienced 15.6 % of its road crash fatalities as pedestrians (Transport Canada, 2015). Studies indicate that nearly half (46 %) of pedestrian fatalities in the United States (2013) and 57 % of pedestrian fatalities in Ontario, Canada (2015), occur at nighttime. Most crashes happen as pedestrians cross the streets while exposed to motorized traffic. A study in Europe showed that roughly 31 % of all pedestrian victims of road crashes were injured on marked crosswalks (Czajewski, et al., 2013). Pedestrians are also vulnerable at locations with non-signalized crossings. For instance, Hunter et al. found that 40 % of intersection crashes and 93 % of midblock crashes occurred at non-signalized locations (Hunter, et al., 1996). Compared with daytime, there is less motorized and pedestrian traffic at nighttime, generally leading to higher vehicle speeds as well as lower levels of driver awareness and attention. This difference in traffic and driving behavior leads to an increase in crash frequency and severity, especially when pedestrians are involved (Plainis, et al., 2006). In addition, Huang et al. point out that nighttime crosswalks and pedestrians can be less visible for drivers to see in time for a stop (Huang, et al., 2007). Crosswalk safety and related treatments have been looked into by numerous studies; however, evaluating the treatment is challenging, particularly at nighttime, because of the sparse nature of crash data and the lack of exposure measures (e.g., nighttime count data). Most often, short-term counts for safety analysis are taken only during daytime (Ryus, et al., 2014).

Moreover, the pedestrian safety literature has been built mainly through the use of historical crash data, focusing on crash frequency and severity as direct measures for road safety (Nabavi Niaki, et al., 2014; Zahabi, et al., 2011). However, vehicle-pedestrian crash data is not always available in sufficiently large quantity and suffers from known problems such as low-mean small sample, underreporting, mislocation and misclassification. Tarko et al. list the limitations of using crash data for road safety analysis (Tarko, et al., 2009). In addition, the low-mean problem causes statistical issues when one works with pedestrian nighttime crash data, in which, given the low level of exposure, the mean number of crashes is typically very low. Using historical data for pedestrian safety analysis requires long periods of observation (many years), meaning that recent treatments cannot be quickly evaluated from crash data because of the lack of after-treatment crash data (St-Aubin, et al., 2013a). To overcome this problem, proactive methods have been proposed that do not require waiting for crashes to happen but rely on surrogate measures of safety.

Surrogate safety measures obtained from automated video analytics are gaining increasing popularity in road safety analysis for their various benefits (St-Aubin, et al., 2013a; Tarko, et al., 2009). Some studies have used such measures for identifying risk factors or evaluating treatment effectiveness by using a before–after or control–case study approach (Brosseau, et al., 2013; St-Aubin, et al., 2013a; St-Aubin, et al., 2013b; Zangenehpour, et al., 2013; Zangenehpour, et al., 2016). Despite the important developments on surrogate safety analysis, there has been no nighttime safety evaluation using surrogate safety measures. Among the reasons can be mentioned the technological limitations of regular video cameras (in the visible spectrum) and other technologies that are unable to provide high-quality nighttime data.

The objective of this work is to propose a surrogate safety methodology to quantify pedestrian safety on crosswalks during nighttime by using thermal video sensors. To get effective video data under nighttime conditions, this paper used a thermal-camera–based system; the details of this system are reported by Fu et al. (2017). The trajectories were then extracted from video data and analyzed by calculating speeds of crossing vehicles, postencroachment time (PET), exposure based on PET, cumulative distribution PET, conflict ratios, and yielding compliance rates.

4.3 LITERATURE REVIEW

Using traffic trajectory data obtained from video recordings is the most widely adopted method for automatically calculating surrogate safety measures. Different trackers have been developed and used to obtain trajectory data (Jodoin & Saunier, 2014; Saunier, n.d.; Saunier & Sayed, 2006;

Shi & Tomasi, 1994). Saunier (Saunier, n.d.) and Saunier and Sayed (Saunier & Sayed, 2006) adapted feature-based tracking to intersections by continuously detecting new features and adding them to current feature groups. An improved multiple object tracking system, named Urban Tracker, was developed for tracking different types of road users in urban mixed traffic (Jodoin & Saunier, 2014). To count different road users in mixed traffic conditions and to identify interactions based on their trajectories and those between different types of road users, Zangenehpour et al. developed a classification algorithm to distinguish between three types of road users: pedestrians, vehicles, and cyclists (Zangenehpour, et al., 2015). The proposed classifier uses the occurrence area, speed distribution, and presence, or appearance, of the road users. The data can then be used for surrogate safety analysis of the interactions between different road users. The overall accuracy of the classification algorithm at intersections with high traffic volumes and mixed road user traffic was approximately 93 %. This algorithm was trained for thermal video by Fu et al. (2017) and results for mixed traffic conditions demonstrated an overall accuracy of 70 %.

Other studies have also used trajectory data for obtaining traffic information such as volume, speed, and conflict measures, which are fundamental for surrogate safety measures (Alhajyaseen, et al., 2012; Brosseau, et al., 2013; Peesapati, et al., 2011; St-Aubin, et al., 2013a; St-Aubin, et al., 2013b; Zangenehpour, et al., 2015). Laureshyn (2010) looked at various indicators in behavioral and road safety research in terms of validity and reliability. The indicators included time to collision, PET, GT, encroachment time, time headway or gap, and compliance with yielding rules and stop sign requirements. Other studies used different measures for different conditions. St-Aubin et al. (2013a; 2013b) computed time to collision using the equations presented by Laureshyn for highway safety (Laureshyn, 2010). Tang and Nakamura relied on PET for evaluating conflict severity at signalized intersections (Tang & Nakamura, 2009).

For pedestrian safety at crosswalks, PET has been used widely (Alhajyaseen, et al., 2012; Brosseau, et al., 2013). For instance, Alhajyaseen et al. (2012) used PET and vehicle speed at a crosswalk as the surrogate measures of safety to assess pedestrian safety at intersections. Other indicators, such as speed and yielding compliance to evaluate crosswalk safety, have been used extensively (Huybers, et al., 2004; Smith, et al., 2009). Another important safety concept is exposure to the risk of collision (Qin & Ivan, 2001). Exposure is traditionally measured through the pedestrian and vehicle volumes passing the area of interest (i.e., crosswalks for this study). But exposure is a general concept that represents the opportunities or necessary conditions for a collision to occur: it can be measured in various ways, depending on the purpose of the study. Pedestrians' exposure was included in a 1989 study of pedestrian safety at traffic signals by use of a manual traffic conflict technique (Garder, 1989). In 1998, Silcock et al. proposed a method that used video recording to automatically extract the number of crossing movements and pedestrian–vehicle interactions (Silcock, et al., 1998). However, the definition of the conflicts (e.g., the threshold used on the surrogate measure of safety to distinguish from other events) was not clarified (Papadimitriou, et al., 2012). Exposure is generally used to calculate a pedestrian's risk of collision with vehicles through crash or conflict ratios. The ratio is calculated on the basis of the number of crashes or conflicts over the exposure, which reflects the probability dimension of risk; i.e., the probability of a crash or conflict per unit of the chosen exposure. The most recent work using surrogate safety analysis with rate calculations can be found in Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application (Zangenehpour, et al., 2015). In that paper, the authors use the ratio of the total number of conflicts and severe conflicts divided by the product of the pedestrian and vehicle volumes.

Different measures of pedestrian exposure have been proposed (Papadimitriou, et al., 2012). In the literature, the number of pedestrian crossings per hour, vehicle volume, or their product has been used as the key indicators; however, these measures do not correspond to events where a pedestrian and a vehicle may actually interact (i.e., where they are close enough to each other at the site of interest that they are at least aware of each other). There is a huge gap between the product of traffic volumes and an actual interaction between a pedestrian and a vehicle. This gap is even larger during nighttime, when pedestrian and vehicle flows are much lower and can present more temporal variability. Vehicle–pedestrian interactions change from site to site and from time to time. Besides, upstream signalization has a large impact on the arrival time of pedestrians and vehicles, which also influences pedestrian exposure. All these uncertainties may explain the low or unreported fitness of the crash-based models in past studies.

Consequently, existing exposure measures must be validated and new ones proposed where necessary.

4.4 METHODOLOGY

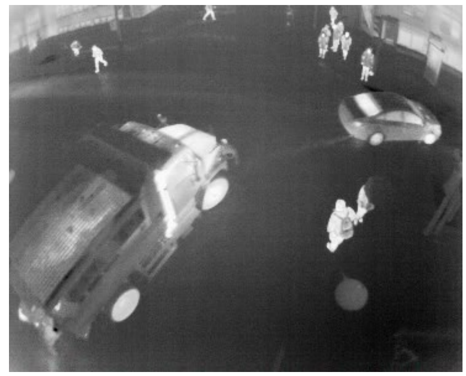
The proposed methodology consists of three steps: video data collection at nighttime using thermal video sensors, extraction of road user trajectories, and computation of surrogate safety measures. Some additional details are given below.

4.4.1 Thermal Video System, Object Tracking and Validation of Detection Performance

A thermal camera system was used for data collection. For details about the system and its performance in nighttime conditions, one can refer to Fu et al. (2017). The system components are presented in FIGURE 4-1a. For field measuring purposes, the camera was mounted on an adjustable mast against existing poles (i.e., lamppost or telephone pole) with an ideal coverage area and camera angle. FIGURE 4-1b shows a sample snapshot from the thermal video, which was taken at nighttime where regular cameras in the visible spectrum fail to provide enough details about road users because of the darkness, reflection, shadow, and glare from different light sources. FIGURE 4-1c presents the issues of using regular videos for video data collection at night, and how thermal video is not affected by these lighting issues.

Once video was collected, video data processing was carried out using the tracker in the open source Traffic Intelligence project (Saunier, n.d.); as an outcome, road user trajectories were obtained. The techniques used in the tracker are explained by Shi and Tomasi (1994) and Saunier and Sayed (2006). Fu et al. has validated the performance of video analysis using thermal video for traffic data collection in multimodal environments in various lighting and temperature conditions, and has shown the reliability of this technique (Fu, et al., 2017). Compared with mixed traffic conditions at intersections, non-signalized crosswalks are much simpler because road users travel in fixed directions along fixed segregated paths. Therefore, the performance of the tracker for detecting road users at crosswalks is expected to be higher. This study uses the performance measures introduced by Fu et al., where miss rate was defined as "the proportion of road users whose movement is not captured by any trajectories; for pedestrians, the detection performance was evaluated at the group level, i.e., a group of pedestrians not tracked is counted as one miss" (Fu, et al., 2017). Precision and recall for detection are also reported.

(a) Camera system and installation



(b) Sample of thermal video

(c) Issues for using regular videos at night paired with the corresponding thermal videos

FIGURE 4-1 Thermal camera system and a comparison with regular videos at nighttime.

4.4.2 Validation of the Classification Tool for Pedestrian-Vehicle Interactions at Crosswalks

To calculate the PETs, a classification method is required to identify the vehicle–pedestrian interactions. A previously developed method for object classification in video (Zangenehpour, et al., 2015) was adapted by changing the image database for detecting road user presence in thermal videos. Details are available at Zangenehpour et al. (2015) and Fu et al. (2017).

Fu et al. (2017) shows the overall accuracy of the classification algorithm in terms of classification performance measures to be more than 80 % for mixed traffic, with the average precision of 70.9 % and the average recall of 99.5 % for vehicles, the average precision of 73.2 % and the average recall of 89.2 % for cyclists, and the average precision of 98.6 % and the average recall of 72.0 % for pedestrians. While the rates are relatively high, they are not high enough to conduct a safety analysis. However, with the simpler traffic conditions at non-signalized crosswalks, the classification performance is expected to be better. Similar to work of Fu et al. (2017), the classification performance was validated in terms of precision, recall, and overall accuracy.

4.4.3 Safety Measures

For evaluating the safety status of a crosswalk during nighttime, the following three measures were defined.

4.4.3.1 Pedestrian-Vehicle Interaction

FIGURE 4-2 describes a pedestrian–vehicle interaction at a crosswalk. PET is defined as the time gap between two road users arriving at and leaving the crossing area; PET is used in this study as the surrogate safety measure for interactions between pedestrians crossing the street and the vehicles, because their trajectories will always intersect allowing PET to thus always be computed. The fact that PET may not be computed for some interactions is otherwise a known shortcoming of that measure. Based on the road user classification and the trajectory data of each road user, the PETs of pedestrian–vehicle interactions are calculated by the following equation:

$$PET = \begin{cases} T_{CA} - T_{PL}, if\ T_{PL} < T_{CA} \\ T_{PA} - T_{CL}, if\ \ T_{CL} < T_{PA} \end{cases} \tag{1}$$

Where definitions are presented in FIGURE 4-2: $T_{PL} < T_{CA}$ indicates the case where a pedestrian arrives at the crossing area before the vehicle, and $T_{CL} < T_{PA}$ means the opposite, with the vehicle arriving before the pedestrian. This study used a computer vision safety analysis tool to automatically calculate the PET values for each pair of interacting vehicles and pedestrians; because detecting the tracking method does not provide a contour of the vehicle, the front and rear of the vehicle were considered to be 2 m before and after the centroid (along the trajectory). Interactions with PETs less than 5 s were considered as conflicts, and those with PETs less than 1.5 s were defined as dangerous conflicts (Zangenehpour, et al., 2016). In the cases where several pedestrians are tracked as a group, only one interaction with the whole group is counted.

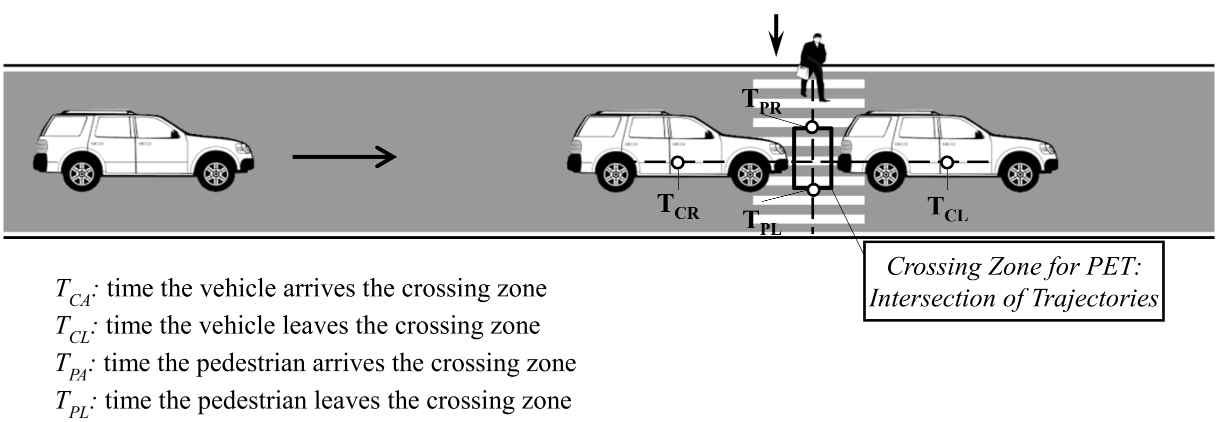


FIGURE 4-2 Description of pedestrian-vehicle interactions at a crosswalk

4.4.3.2 Pedestrian Exposure Measure

Different exposure measures can be used, depending on the purpose, and can be considered in the traditional safety hierarchy framework of surrogate safety analysis based on earlier work by

Hydén, among others (Hyden, 1987), illustrated in FIGURE 4-3, with collisions as the most severe events at the top and undisturbed passages at the bottom. Using microscopic trajectory data, this work can measure exposure at the level of road user interactions when two road users are close enough in time and space. This paper sets an arbitrary threshold of 20 s on PET for interactions considered as exposure to the risk of pedestrian–vehicle collisions. The threshold of 20 s is chosen because little possibility exists for the vehicle passage to affect the safety of pedestrian who crosses 20 s before or after.

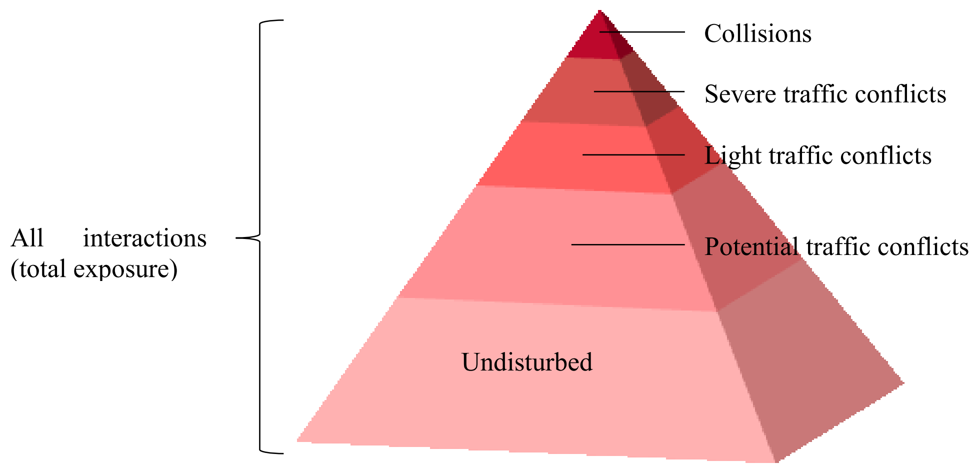


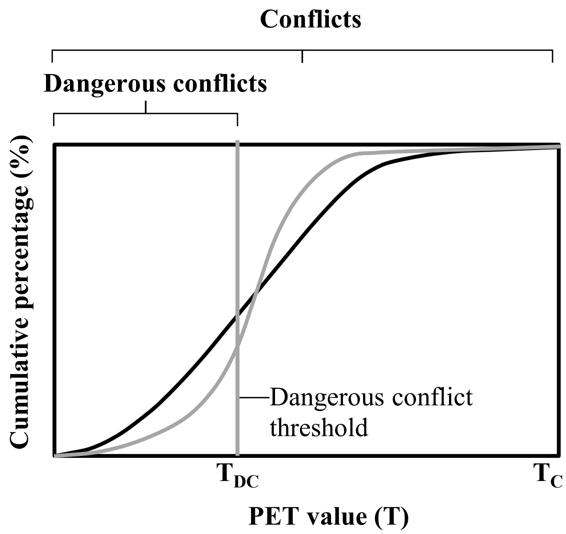
FIGURE 4-3 Pedestrian-vehicle interactions in the safety hierarchy (Hyden, 1987)

4.4.3.3 Safety Measures

To evaluate and compare the safety status across sites, safety measures are computed and compared on the basis of cumulative distribution functions (CDFs) and the interaction rates, in seconds, which are computed as the number of conflicts over the number of interactions (exposure). The definitions of the safety measures are provided as follows:

(5) **Cumulative Distribution Functions (CDFs)**

FIGURE 4-4 illustrates how two CDFs (from two different sites) can be compared for safety analysis. The elevated line indicates a higher proportion of dangerous conflicts. The gray line in the figure represents the dangerous conflict threshold, and the right border of the figure is the conflict threshold. This method of showing safety is intuitive; however, as illustrated by St-Aubin et al., using cumulative distribution is not always conclusive (St-Aubin, et al., 2015).



T_{DC}: PET threshold for dangerous conflicts (T = 1.5 s)
T_C: PET threshold for conflicts (T = 5 s)

FIGURE 4-4 Illustration of different cumulative distribution functions

(6) **Conflict Ratio**

Two conflict rates are used. For a given site i, the conflict rate (R_{Ci}) is defined as the number of pedestrian–vehicle conflicts, which are the interactions of less than 5 s with PETs, divided by the number of interactions with PET of less than 20 s. denoted N_{Ei} (exposure). The dangerous conflict rate (R_{DCi}) is defined as the number of dangerous conflicts, which are the interactions with PET less than 1.5 s, divided by the same exposure measure N_{Ei} .

(7) **Crossing Speed**

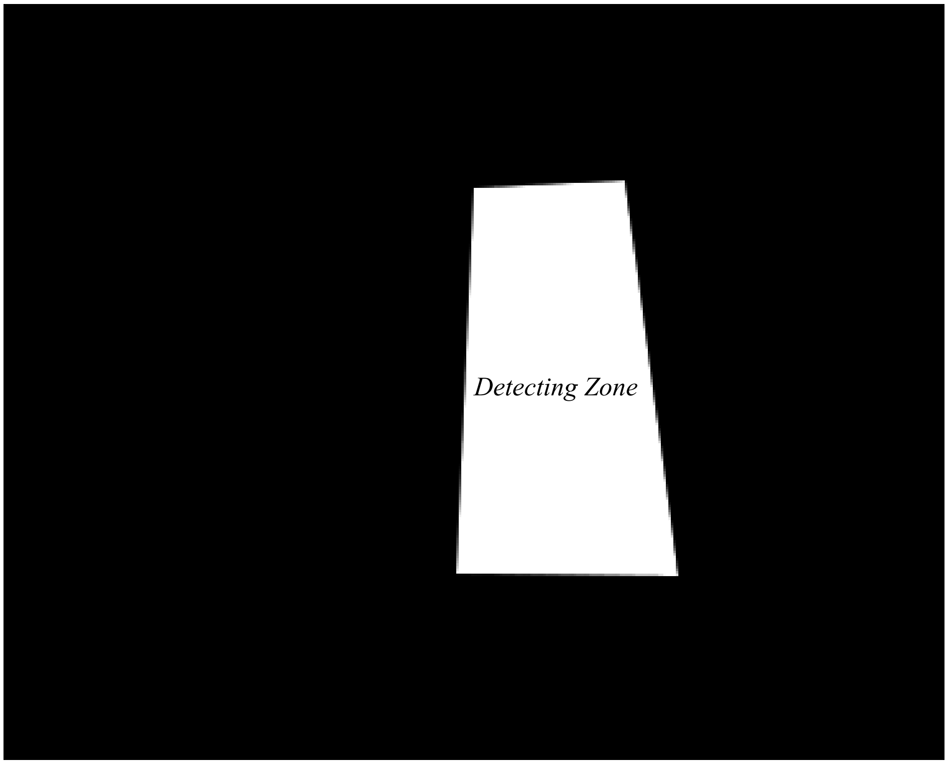
The crossing speed of vehicles passing the crosswalk is also used as a safety measure in this paper. Crossing speeds are automatically extracted from the videos through the computer vision software and have been shown to be reliable in (Fu, et al., 2016). A script was used for extracting velocities and calculating the speeds for vehicles passing the crosswalk. FIGURE 4-5 presents how the crossing speeds were extracted. A mask was prepared for the detection zone – the crosswalk in this case, shown in FIGURE 4-5 a). In video collected from site i, for a certain vehicle j, $j = (1, \ldots, N)$, where N is the total number of vehicles, if its trajectory falls in the detecting zone in video frame m, $m \epsilon (p, p+1, \ldots, q)$, its velocity $\overrightarrow{v_{ijm}}$ is extracted and the instantaneous speed s_{ijm} is calculated. The crossing speed is calculated by averaging the instantaneous speeds in these frames, as presented in the following equation:

$$s_{ij} = \frac{1}{q-p+1} \sum_{m=p}^{q} (s_{ijm}) \tag{2}$$

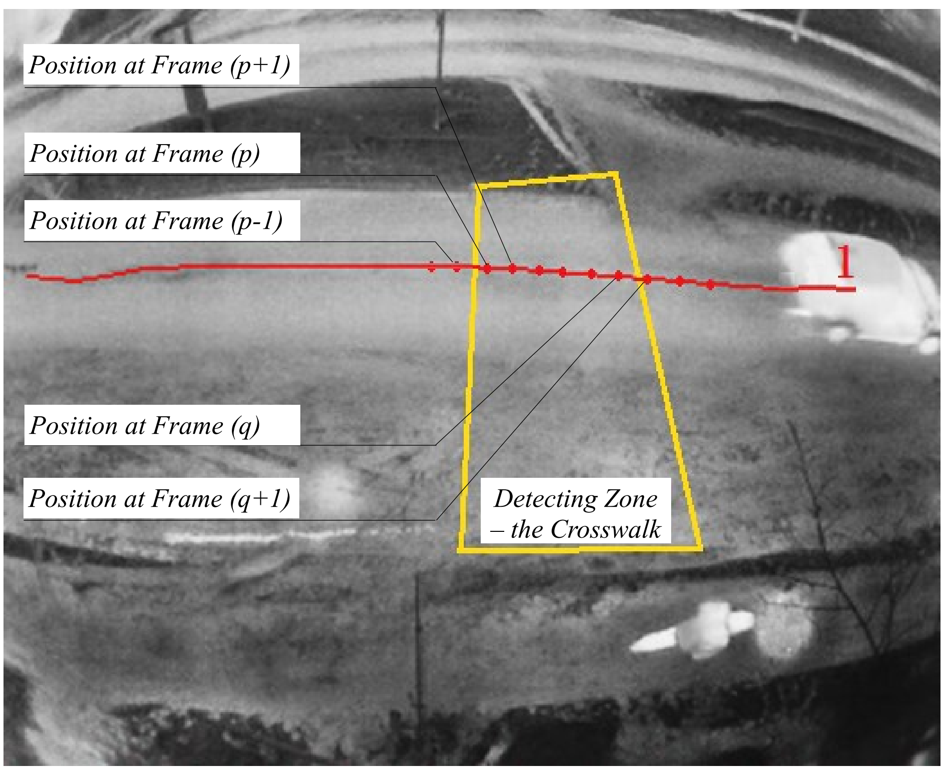
The average crossing speed for site i would be:

$$s_i = \frac{1}{N} \sum_{j=1}^{N} (s_{ij}) \tag{3}$$

The speed distributions and average crossing speeds of all the passing vehicles are compared.



(a) Mask for detecting zone



(b) Sample of a trajectory

FIGURE 4-5 Sample of speed extraction through the computer vision software

(8) **Yielding Compliance**

The law requires vehicles to yield to a pedestrian starting or indicating the intention to cross the road. In this case, yielding compliance refers to the rate of drivers' yielding behavior among the pedestrian–vehicle interactions, which require the drivers to slow down or stop to give pedestrians the right-of-way. Yielding compliance rate (YCR) was calculated by manually counting the vehicle yielding maneuvers. For site i, if a pedestrian arrives at the crosswalk before a certain vehicle j, the yielding behavior of this vehicle involved in an interaction with a pedestrian can be quantified by the following measures

$$Y_i = \sum_1^M X_{ij} \quad (5)$$

$$YCR_i = \frac{Y_i}{M_i} \quad (6)$$

Where X_{ij} is 1 if the vehicle yields to pedestrians and 0 otherwise at site i for interaction j. M_i is the total number of pedestrian-vehicle interactions involving pedestrians who have already started or indicated their intention to cross, and where, to avoid a collision, at least one involved road user must yield. Y_i is the total number of yielding drivers and YCR_i is the yielding compliance rate.

4.5 CASE STUDY

For this study, two crosswalk locations with different traffic and environmental conditions were selected in downtown Montreal.

4.5.1 Site Selection and Data Description

For testing the thermal camera system and investigating the crosswalk safety, two crosswalk locations with different traffic and environmental conditions were selected in downtown Montreal:

- **Site du Fort** This crosswalk is located on Rue du Fort at the intersection of Rue du Fort and Rue Baile. It is a painted crosswalk crossing two one-way lanes separated by a median. Because the left lane was observed to have very little traffic, only the right lane was analyzed. Located on a secondary road, this site has a relatively low traffic volume.

- **Site St-Laurent** The crosswalk is located on one of the main arteries in downtown Montreal, Boulevard Saint-Laurent, at the intersection of Boulevard Saint-Laurent and Rue Bagg. It is a painted crosswalk crossing two one-way lanes. This location is busier than the du Fort site in terms of vehicular and pedestrian traffic.

For each site, thermal video data were collected in both daytime and nighttime conditions. For comparison purposes, all video data were collected in the same season with similar traffic, weather, and road surface conditions (i.e., in good weather conditions with bare pavement in winter). All the videos were recorded during the afternoon peak period and at nighttime on weekdays when higher crash rates were observed. Details of the video data are presented in TABLE 4-1.

TABLE 4-1 Description of the Video Recorded from Each Site

Site Name	Date	Period of a Day	Time	Duration (hour)
du Fort	11-Nov-2014	Day	03:00-04:40pm	1.6
		Night	07:00-08:15pm	1.2
	14-Jan-2015	Night	06:30-08:20pm	1.8
	15-Jan-2015	Day	03:30-04:30pm	1.0
		Night	07:00-08:40pm	1.6
Saint-Laurent	31-Dec-2014	Day	03:00-04:10pm	1.2
		Night	06:30-09:15pm	2.8
	01-Jan-2015	Day	02:00-04:30pm	2.4
		Night	06:00-09:15pm	3.3

4.5.2 Detection and Classification Validation

The tracker and the classification algorithm were validated using 30 minute video samples from each site. Results of the detection and classification performance are provided in TABLE 4-2. Based on the results, the tracker and the classification algorithm worked almost perfectly in detecting and classifying the pedestrians and vehicles at each crosswalk—very few misses and around 95 % of precision, recall, and global accuracy rates in most cases, except for the lower recall values in detecting pedestrians (around 80 %), mainly resulting from the overgrouping of pedestrians moving together (Fu, et al., 2017). These values are much higher than those for mixed traffic tested by Fu et al., indicating the reliable performance of using the tracker and the classification algorithm at crosswalks (Fu, et al., 2017). The small portion of the misclassified road users could be easily manually corrected if needed.

TABLE 4-2 Classification Accuracy Validation Results

Road User Type	No. of Presence	No. of Missed /Miss Rate	Detection Performance		Classification Performance	
			Precision	Recall	Precision	Recall
du Fort *(Video length of 30 minutes, from night, 14-Jan-2015)*						
Vehicle	68	1 / 1.7 %	97.1 %	97.1 %	98.5 %	98.5 %
Pedestrian	60	1 / 1.6 %	100 %	81.1 %	100 %	98.3 %
Overall	128	2 / 1.6 %	91.4 %	98.4 %	*Global Accuracy = 97.7 %*	
Saint-Laurent *(Video length of 30 minutes, from night, 31-Dec-2014)*						
Vehicle	205	0 / 0 %	97.6 %	98.6 %	94.8 %	97.6 %
Pedestrian	104	1 / 1.0 %	100 %	80.0 %	100 %	93.0 %
Overall	309	1 / 0.3 %	93.1 %	98.4 %	*Global Accuracy = 91.7 %*	

4.5.3 Results and Analysis

The proposed methodology was applied to the selected sites. For the du Fort site, an average of 319 vehicles and 161 pedestrians per hour were detected during the 2.6 h of video data collected in daytime conditions, while a volume of 414 vehicles and 127 pedestrians per hour were detected from the 4.6 h of video taken at night. The Saint-Laurent site had a volume of 848 vehicles and 994 pedestrians per hour during 3.6 h of daytime video recordings, and a vehicle flow of 833 vehicles and 407 pedestrians per hour during 6.1 h of nighttime video recordings. TABLE 4-3, TABLE 4-4 and TABLE 4-5 present a summary of the results of different safety measures, which includes the average vehicle crossing speed, vehicle yielding compliance rate, exposure measured in the traditional way, using the product of pedestrian and vehicle volume, number of the conflicts, conflict rate, and number and rate of dangerous conflicts, for both sites. FIGURE 4-6 presents the distributions of speeds and the CDFs of PET for conflicts for both day and night.

TABLE 4-3 Results: Volume, Speed, and Yielding Compliance

		Vehicle Volume (vph)		**Pedestrian Volume (pph)**		**Average Cro. Speed (km/h)/SD**		**Yielding Compliance (%)**	
Site Name	Date	Day	Night	Day	Night	Day	Night	Day	Night
du Fort	November 13, 2014	359.4	439.2	53.8	23.3	28.0 / 5.9	30.6 / 8.9	20.83	50.00
	January 14, 2015	--	469.4	--	167.8	--	31.2 / 9.1	--	38.52
	January 15, 2015	331.9	255.0	160.6	127.0	26.6 / 6.5	30.8 / 7.3	11.76	18.18
	All	319.2	413.7	81.9	127.6	26.7 / 6.1	31.2 / 8.3	15.52	37.66
Saint-Laurent	December 31, 2014	1333.3	629.3	1087.5	423.2	24.4 / 10.0	32.0 / 10.9	32.69	18.18
	January 1, 2015	605.0	1005.8	946.7	392.7	25.0 / 7.9	33.7 / 14.0	30.11	25.40
	All	847.8	833.0	993.6	406.7	24.7 / 9.1	33.8 / 13.3	31.47	22.92

Note: vph = vehicles per hour; pph = pedestrians per hour; -- = data not collected.

TABLE 4-4 Results: Exposure Measures

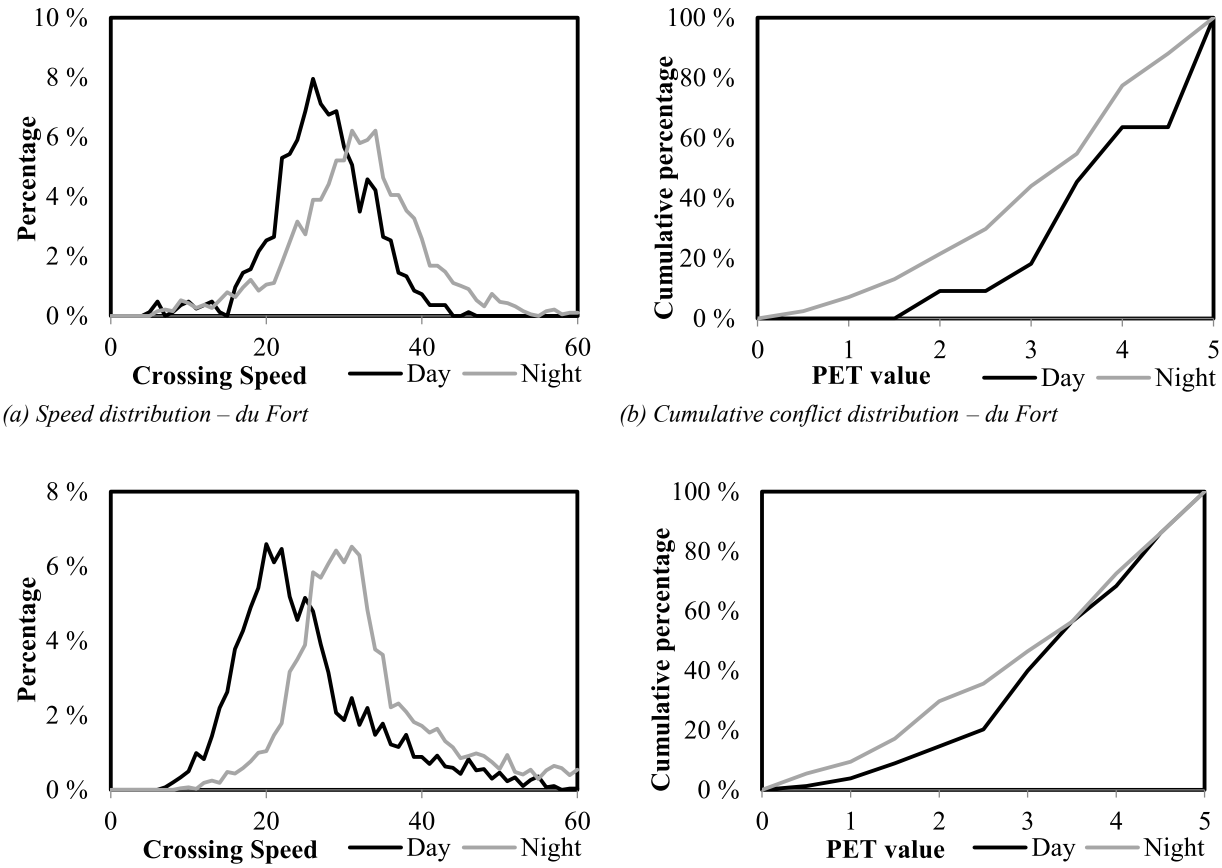
		Traditional Exposure (per hour)		**Number of Interactions with PET Less Than 20 s per Exposure (per hour)**		**Number of Interactions per Traditional Exposure (per thousand)**	
Site Name	Date	Day	Night	Day	Night	Day	Night
du Fort	November 13, 2014	19316	10247	126.9	114.2	6.6	11.1
	January 14, 2015	--	78762	--	517.2	--	6.6
	January 15, 2015	53307	32385	213.1	208.0	4.0	6.4
	All	26152	52791	158.1	306.3	6.0	5.8
Saint-Laurent	December 31, 2014	1450000	266323	6129.2	1758.9	4.2	6.6
	January 01, 2015	572733	394988	3659.2	5280.9	6.4	13.4
	All	842361	338779	4531.9	3664.3	5.4	10.8

Note: -- = data not collected.

TABLE 4-5 Results: Conflict Measures and Conflict Rates

Site Name	Date	Number of Conflicts (per hour) Day	Number of Conflicts (per hour) Night	Conflict Rate (%) Day	Conflict Rate (%) Night	Number of Dangerous Conflicts Day	Number of Dangerous Conflicts Night	Dangerous Conflicts Rate (%) Day	Dangerous Conflicts Rate (%) Night
du Fort	November 13, 2014	2.5	5.0	1.97 %	4.38 %	0.0	0.0	0.00 %	0.00 %
	January 14, 2015	--	36.1	--	6.98 %	--	3.9	--	0.75 %
	January 15, 2015	9.0	8.1	4.22 %	3.89 %	0.0	2.5	0.00 %	1.20 %
	All	5.0	18.3	3.16 %	5.97 %	0.0	2.4	0.00 %	0.78 %
Saint-Laurent	December 31, 2014	55.8	27.1	0.91 %	1.54 %	5.0	2.9	0.08 %	0.16 %
	January 1, 2015	37.9	44.2	1.04 %	0.84 %	3.3	9.1	0.09 %	0.17 %
	All	43.9	36.4	0.97 %	0.99 %	3.9	6.2	0.09 %	0.17 %

Note: -- = data not collected.



(a) Speed distribution – du Fort

(b) Cumulative conflict distribution – du Fort

(c) Speed distribution – Saint-Laurent

(d) Cumulative conflict distribution – Saint-Laurent

FIGURE 4-6 Visualization results of the two sites – speed distributions and PET CDFs

Looking at FIGURE 4-6a and 6c, it can be observed that increases in the crossing speed were detected at night for both sites. Also, from TABLE 4-3, for the crosswalk safety situation, the average crossing speeds were found to be higher (by 9.3 % to 16.8 %) at the crosswalk of the du Fort site at nighttime compared with daytime; for the Saint-Laurent site, the average crossing speeds increased by around 30 % at night compared with daytime speeds. Possible reasons for this observation could be 1) although the traffic flow is similar between afternoon peak hours and early nighttime hours for both sites, the volumes at the second site are higher during the afternoon peak hours, which leads to the congestion of the adjacent road segments; 2) during the afternoon peak hour, a large number of vehicles are searching for parking spots, and their parking maneuvers block the traffic. This phenomenon is especially evident for the site of St-Laurent, where a pharmacy and many restaurants are located. Many parking maneuvers were observed in the daytime, while fewer occurred at night; 3) Because of lower traffic volumes and less pedestrian activity at night, drivers drive faster. This increase in the average crossing speeds of the passing vehicles at the crosswalks at nighttime indicates that pedestrians are exposed to higher probabilities of severe crashes at night.

Exposure was measured in both the traditional way using the pedestrian-vehicle volume product and the exposure using PET and compared by computing their ratio. From TABLE 4-4, most of the values were in the order of 4 to 13 events with PET less than 20 s per 1000 potential interactions computed from the traditional exposure. The number of interactions with PET less than 20 s is used in the study. From the results, a higher exposure can be observed in daytime compared with nighttime in most cases except for data collected at the du Fort site on Wednesday, January 14, when a hockey game brought about a large number of people at nighttime, and data collected from the Saint-Laurent site on Thursday, January 15, when people go out clubbing

From FIGURE 4-6b and 6d, among all interactions, a higher percentage of dangerous conflicts (with PET less than 1.5 s) were observed at nighttime compared with daytime, which indicates that pedestrians were involved in more dangerous interactions with vehicles at the crosswalks at night. Looking at the rates, R_C values do not necessarily change from daytime to nighttime, while the R_{DC} values indicate that pedestrians experience higher risks of being involved in a dangerous conflict at night.

These results concerning the speeds and conflict rates indicate that at these two locations, pedestrians were at higher risks of being involved in a dangerous interaction at night, when crossing speeds were on average higher.

However, regarding the yielding behavior of the drivers, it was found that yielding compliance varies from site to site. Site du Fort had a higher yielding rate at nighttime; however the yielding rate was reduced at night at the Saint-Laurent site. Upon a field inspection of Rue du Fort in daytime, vehicles were parked near the crosswalk along the sidewalk; however, that site was free of parked vehicles at night. This observation might explain the increase in yielding rate at night at this site as it was easier to detect pedestrians in advance by drivers. Drivers did not yield to pedestrians at nighttime as much as they did in daytime at the Saint-Laurent site. This might be due to the reduced visibility of the pedestrians and less willingness for drivers to yield with increased speed at nighttime. In any case, the overall yielding compliances of the drivers at these two locations were both low (on an average of 15 % to 38 % for the two sites).

4.6 CONCLUSIONS

This paper presented an automated video-based methodology for safety analysis of pedestrian crossings at nighttime by using thermal video data. Different surrogate safety measures were used for this purpose. The proposed automated methodology can be implemented for assessing different crosswalk treatments, such as LED pedestrian warning signs, an automated pedestrian detection–warning system, and geometric–marking treatments for improving crosswalk safety at nighttime. The preliminary results showed that pedestrians were exposed to higher risk levels at the study sites during nighttime as opposed to daytime conditions. That is, average vehicle crossing speeds and percentage of dangerous conflicts were higher during nighttime when compared with daytime, indicating that pedestrians were at higher risks during nighttime. Not much difference was found concerning the two other indicators, yielding compliance and the conflict rates; however, at both sites, the yielding compliance rate was quite low.

Thermal camera sensors provide a reliable solution to the limitation of common video sensors in the visible spectrum when used for nighttime analysis. The main advantages of using thermal cameras rather than regular ones are higher accuracy and the ability to collect reliable video data under different environmental conditions, such as in instances of low visibility, glare, or shadows caused by different light sources. Although the economic cost of thermal camera sensors is relatively high, future developments are expected to make them more accessible to researchers, governments, and personal users.

The validation work and the potential future work involving the thermal camera have been discussed extensively by Fu et al. (2017). The use of the thermal camera system for safety analysis at different locations and for different types of road users in nighttime conditions will be explored. The exposure used in this paper potentially provides a more precise measure to describe the pedestrian–vehicle interactions, which, compared with exposure measures based on traffic volumes, are more closely related to pedestrian safety. A PET threshold of 20 s was set empirically and arbitrarily to cover all potential conflicts. However, this value needs to be calibrated, and its use needs to be further explored and validated. Sensitivity analysis should be performed to examine the use of the threshold in describing pedestrian exposure. The methodology and the safety measures used in this paper could be adapted for the analysis of signalized intersections.

4.7 ACKNOWLEDGEMENT

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4.8 REFERENCES

Alhajyaseen, W. K., Asano, M. & Nakamura, H., 2012. Estimation of Left-turning Vehicle Maneuvers for the Assessment of Pedestrian Safety at Intersections. *IATSS Research,* Volume 36, p. 66–74.

Brosseau, M., Zangenehpour, S., Saunier, N. & Miranda-Moreno, L. F., 2013. The Impact of Waiting Time and other Factors on Dangerous Pedestrian Crossings and Violations at Signalized Intersections: A Case Study in Montreal. *Transportation Research Part F: Traffic Psychology and Behaviour,* Volume 21, pp. 159-172.

Czajewski, W., Dabkowskib, P. & Olszewski, P., 2013. Innovative Solutions for Improving Safety at Pedestrian Crossings. *Archives of Transport System Telematics,* May, 6(2), pp. 16-22.

Fu, T. et al., 2016. *Comparison of Regular and Thermal Cameras for Traffic Data Collection under Varying Lighting and Temperature Conditions.* Washington D.C., s.n.

Garder, P., 1989. Pedestrian Safety at Traffic Signals: A Study Carried Out with the Help of a Traffic Conflicts Technique. *Accident Analysis & Prevention,* 21(5), pp. 435-444.

Huang, H., Zegeer, C. & Nassi, R., 2007. Effects of Innovative Pedestrian Signs at Unsignalized Locations - Three Treatments. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 1705, pp. 43-52.

Hunter, W. W., Stutts, J. C., Pein, W. E. & Cox, C. L., 1996. *Pedestrian and Bicycle Crash Types of Early 1990's,* s.l.: s.n.

Huybers, S., Van Houten, R. & Malenfant, J. E. L., 2004. Reducing Conflicts between Motor Vehicles and Pedestrians: the Separate and Combined Effects of Pavement Markings and a Sign Prompt. *Journal of Applied Behavior Analysis,* 37(4), pp. 445-456.

Hyden, C., 1987. *The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique,* Lund: s.n.

Jodoin, J. P. & Saunier, N., 2014. *Urban Tracker: Multiple Object Tracking in Urban Mixed Traffic.* s.l., s.n.

Laureshyn, A., 2010. *Application of Automated Video Analysis to Road User,* s.l.: Lund University.

Nabavi Niaki, M. et al., 2014. Method for Road Lighting Audit and Safety Screening at Urban Intersections. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2458, pp. 27-36.

NHTSA, 2013. *Traffic Safety Facts 2011 Data,* s.l.: s.n.

NHTSA, 2015. *Traffic Safety Facts 2013 Data,* s.l.: s.n.

Office of the Chief Coroner for Ontario, 2015. *Pedestrian Death Review,* Ontario: s.n.

Papadimitriou, E., Yannis, G. & Golias, J., 2012. Analysis of Pedestrian Risk Exposure in Relation to Crossing Behavior. *Transportation Research Record: Journal of the Transportation Research Board,* 10(3141), pp. 79-90.

Peesapati, L. N., Hunter, M., Rodgers, M. & Guin, A., 2011. *A Profiling Based Approach to Safety Surrogate Data Collection.* Indianapolis, USA,, s.n.

Plainis, S., Murray, I. J. & Pallikaris, I. G., 2006. Road Traffic Casualties: Understanding the Night-time Death Toll. *Injury Prevention : Journal of the International Society for Child and Adolescent Injury Prevention,* 12(2), pp. 125-128.

Qin, X. & Ivan, J., 2001. Estimating Pedestrian Exposure Prediction Model in Rural Areas. *Transportation Research Record: Journal of the Transportation Research Board,* Volume 1773, pp. 89-96.

Ryus, P. et al., 2014. *Methods and Technologies for Pedestrian and Bicycle Volume Data Collection,* s.l.: s.n.

Saunier, N., n.d. *Traffic Intelligence.* [Online]
Available at: https://bitbucket.org/Nicolas/trafficintelligence/wiki/Home

Saunier, N. & Sayed, T., 2006. *A Feature-based Tracking Algorithm for Vehicles in Intersections.* s.l., s.n., p. 59.

Shi, J. & Tomasi, C., 1994. Good Features to Track. *In CVPR,* June, Issue 1063-6919, pp. 593-600.

Silcock, D. T., Walker, R. & Selby, T., 1998. *Pedestrians at Risk.* s.l., s.n., pp. 209-220.

Smith, T. J., Hammond, C., Somasundaram, G. & Papanikolopoulos, N., 2009. *Warning Efficacy of Active Versus Passive Warnings for Unsignalized Intersection and Mid-Block Pedestrian Crosswalks,* Minneapolis, Minnesota: s.n.

St-Aubin, P., Miranda-Moreno, L. F. & Saunier, N., 2013. An Automated Surrogate Safety Analysis at Protected Highway Ramps using Cross-sectional and Before-after Video Data. *Transportation Research Part C: Emerging Technologies,* Volume 36, pp. 284-295.

St-Aubin, P., Saunier, N. & Miranda-Moreno, L. F., 2015. *Comparison of Various Objectively Defined Surrogate Safety Analysis Methods.* Washington, D.C., s.n., pp. 11-15.

St-Aubin, P., Saunier, N., Miranda-Moreno, L. F. & Ismail, K., 2013. Use of Computer Vision Data for Detailed Driver Behavior Analysis and Trajectory Interpretation at Roundabouts. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2399, pp. 65-77.

Tang, K. & Nakamura, H., 2009. Safety Evaluation for Intergreen Intervals at Signalized Intersections based on Probabilistic Methodology. *Transportation Research Record: Journal of Transportation Research Board,* Issue 2128, p. 226–235.

Tarko, A., Davis, G., Saunier, N., Sayed, T., & Washington, S., 2009. *White Paper: surrogate safety measures of safety.* ANB20 (3) Subcommittee on Safety Data Evaluation and Analysis Contributors.

Transport Canada, 2015. *Canadian Motor Vehicle Traffic Collision Statistics 2013,* s.l.: s.n.

Zahabi, S. A. H., Strauss, J., Miranda-Moreno, L. F. & Manaugh, K., 2011. Estimating Potential Effect of Speed Limits, Built Environment, and other Factors on Severity of Pedestrian and Cyclist Injuries in Crashes. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2247, pp. 81-90.

Zangenehpour, S., Miranda-Moreno, L. F. & Saunier, N., 2013. *Impact of Bicycle Boxes on Safety of Cyclists: a Case Study in Montreal.* Washington DC, s.n.

Zangenehpour, S., Miranda-Moreno, L. F. & Saunier, N., 2015. Automated Classification based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application. *Transportation Research Part C,* April, Volume 56, pp. 161-176.

Zangenehpour, S., Strauss, J., Miranda-Moreno, L. F. & Saunier, N., 2016. Are Intersections with Cycle Tracks Safer? A Control-case Study Based on Automated Surrogate Safety Analysis using Video Data. *Accident Analysis & Prevention,* 1, Volume 86, pp. 161-172.

Link between chapter 4 and chapter 5

The previous chapter presents the work investigating pedestrian safety at non-signalized crosswalk locations at nighttime, with a methodology based on available SMoS. Interesting findings have been obtained. However, the shortcoming of the methodology in describing how interactions unfold over time is further recognized. A new framework, represented in the distance-velocity (DV) diagram and referred as the DV model, will be presented in the following chapter to describe pedestrian-vehicle interactions, considering the position and speed changes of road users over time during the interaction. The framework is demonstrated through a case study in evaluating pedestrian safety at three non-signalized crossings in different types: a marked crosswalk, an uncontrolled crosswalk, and a crosswalk controlled by stop signs.

Note that: the contents in Chapter 5 were published earlier in Accident Analysis & Prevention. To keep it consistent with the original version of publication, the terms for the different crosswalk types were kept the same as the publication version. In other parts of the dissertation including this page, however, "***painted***" and "***unprotected***" were revised into "***marked***" and "***uncontrolled***" respectively.

Chapter 5

A Novel Framework to Evaluate Pedestrian Safety at Non-signalized Locations

Chapter 5 A Novel Framework to Evaluate Pedestrian Safety at Non-signalized Locations

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5.1 ABSTRACT

This paper proposes a new framework to evaluate pedestrian safety at non-signalized crosswalk locations. In the proposed framework, the yielding maneuver of a driver in response to a pedestrian is split into the reaction and braking time. Hence, the relationship of the distance required for a yielding maneuver and the approaching vehicle speed depends on the reaction time of the driver and deceleration rate that the vehicle can achieve. The proposed framework is represented in the distance-velocity (DV) diagram and referred as the DV model. The interactions between approaching vehicles and pedestrians showing the intention to cross are divided in three categories: i) situations where the vehicle cannot make a complete stop, ii) situations where the vehicle's ability to stop depends on the driver reaction time, and iii) situations where the vehicle can make a complete stop. Based on these classifications, non-yielding maneuvers are classified as "non-infraction non-yielding" maneuvers, "uncertain non-yielding" maneuvers and "non-yielding" violations, respectively. From the pedestrian perspective, crossing decisions are classified as dangerous crossings, risky crossings and safe crossings accordingly. The yielding compliance and yielding rate, as measures of the yielding behavior, are redefined based on these categories. Time to crossing and deceleration rate required for the vehicle to stop are used to measure the probability of collision. Finally, the framework is demonstrated through a case study in evaluating pedestrian safety at three different

types of non-signalized crossings: a painted crosswalk, an unprotected crosswalk, and a crosswalk controlled by stop signs. Results from the case study suggest that the proposed framework works well in describing pedestrian-vehicle interactions which helps in evaluating pedestrian safety at non-signalized crosswalk locations.

5.2 INTRODUCTION

Pedestrians, referred often as vulnerable road users, are highly susceptible to severe road injuries and fatalities when involved in vehicle crashes. For example, in 2013, 14 % of total road crash fatalities reported in the US (NHTSA, 2015), and 15.6 % of road crash fatalities in Canada were pedestrians (Transport Canada, 2015). A large proportion of crashes occur either at uncontrolled crossings (without stop signs or traffic signals) or at non-signalized crossings (without traffic signals), for instance, more than 70 % of the intersection-related fatal crashes in the US in the years from 2010 to 2012 occurred at non-signalized intersections (McGee et al., 2015).

Road safety studies are traditionally limited to analysis based on historical crash data (Nabavi Niaki et al., 2015) (Abdel-Aty & Haleem, 2010), which suffers from problems such as low-mean small sample, underreporting, mislocation and misclassification (Fu et al., 2016). Moreover, recent treatments cannot be rapidly evaluated due to the lack of after-treatment crash data which requires long periods (multiple years) of observation (St-Aubin et al., 2013). To overcome such issues related to crash data analysis, proactive methods based on surrogate safety measures, that do not require crashes to occur, have been gained some momentum in the literature.

Several studies have used surrogate safety measures for identifying risk factors or evaluating treatment effectiveness (St-Aubin et al, 2013) (Zangenehpour et al., 2013) (Zangenehpour et al., 2016). Despite important developments in surrogate safety analysis, the issue of the relationship between surrogate measures and crash-based measures remains (Tarko et al., 2009). Compared to the vehicle safety literature, pedestrian safety has attracted much less attention, in particular surrogate safety measures for pedestrian-vehicle interactions at crosswalks. The vulnerability of pedestrians explains why vehicles should yield right-of-way to pedestrians at crosswalks. Yielding behavior is therefore a critical part of interactions at non-signalized intersections. Yielding should therefore be considered among other surrogate safety measures used in previous studies (e.g. time-to-collision or post-encroachment time). Past research has considered yielding compliance (Lacoste et al., 2014) (Shurbutt & Van Houten, 2010), but their definition of yielding compliance is ambiguous. Furthermore, there are situations where it is impossible for the vehicle to yield considering its proximity and speed to the crosswalk at the occurrence of the pedestrian. Such situations are likely considered as violations in most previous studies.

This research aims to address the above-mentioned research gaps in the pedestrian safety literature. The main purpose is two-fold: i) to propose a new surrogate safety framework to investigate pedestrian-vehicle interactions at non-signalized crosswalks, and ii) using a case study, to apply the proposed approach to explore pedestrian safety issues and the efficiency of countermeasures at crosswalks.

5.3 LITERATURE REVIEW

5.3.1 Pedestrian-vehicle Interactions and Surrogate Safety Measures for Crosswalk Safety

Due to the limitations of using crash data, many studies have attempted to use different surrogate safety measures to investigate pedestrian-vehicle interactions. Hydén depicted the general safety hierarchy framework of surrogate safety analysis, suggesting a relationship between crashes and conflicts, their position is the hierarchy representing their chance of resulting in a crash (Hydén, 1987). Laureshyn considered the validity and reliability of different surrogate safety measures in behavioral and road safety research (Laureshyn, 2010), and the indicators include time to collision (TTC), post-encroachment time (PET), gap time (GT), compliance with the yielding rules and stop sign requirements. Some researchers have used TTC and PET for pedestrian safety (Almodfer et al., 2015) (Tang & Nakamura, 2009), with (Almodfer et al., 2015) finding these measures as the most used. Some have indicated their preference for using PET in situations where road user trajectories are crossing (e.g. pedestrian safety at crosswalks) (Almodfer et al., 2015) (Tang & Nakamura, 2009). Conflicts between pedestrians and vehicles may be divided into discrete severity levels based on different PET and TTC thresholds (Malkhamah et al., 2005) (Ismail et al., 2011). Pedestrian-vehicle interactions are difficult to describe because of the unpredictable behavior of the road users (Almodfer et al., 2015), especially pedestrians whose direction, speed, and acceleration/deceleration can change rapidly. This paper will use the more general term of interactions instead of conflicts, as conflicts have specific definitions in existing traffic conflict techniques such as the Swedish traffic conflict technique (Hydén, 1987). Interactions are defined as situations where the road users of interest are close enough in time and space, such that they may interact with each other (Nicolas et al., 2010).

Different data generation techniques and sensors (e.g., loops, radar, GPS devices and video cameras), have been used to extract information for surrogate safety analysis (Stipancic et al., 2016) (Golob et al., 2004) (Lee et al., 2002). Among these sensors, video-based devices, which provide rich positional data and other information beyond the capabilities of most other devices, are the most promising (Robert, 2009). The development of video-based techniques (computer vision) has brought about the possibility of investigating yielding compliance and crossing decision in a more precise and microscopic way.

5.3.2 Yielding Compliance and Crossing Decision Studies

Many studies that are not explicitly in the literature on surrogate measures of safety have investigated vehicle-yielding behavior at non-signalized crosswalks (Lacoste et al., 2014) (Shurbutt & Van Houten, 2010) (Fitzpatrick, et al., 2006). For example, Fitzpatrick used the driver yielding rate to check effectiveness of different crosswalk treatments through meta-analysis (Fitzpatrick, et al., 2006). A study conducted in Winnipeg found crosswalks with overhead flashing devices had higher average yielding rates than those with the side-mounted passive signs (Lacoste et al., 2014). Shurbutt and Van Houten used yielding rate to validate the performance of the rectangular rapid-flashing beacon (RRFB) at non-signalized crosswalks (Shurbutt & Van Houten, 2010). Many studies have used “yielding compliance” to describe vehicle yielding behavior (Lacoste et al., 2014) (Shurbutt & Van Houten, 2010) (Fitzpatrick et al., 2006). The yielding compliance of a driver at non-signalized crosswalks refers to situations where the driver yields to pedestrians following the traffic rules. The majority of past studies consider non-yielding maneuvers as violations and use the rate of non-yielding maneuvers to measure the yielding compliance. However, in some situations, vehicles are too close in time to the crosswalk to stop at the moment the pedestrian shows the intention to cross. In such situations, drivers cannot yield even if they want to, and such situations cannot be treated as violations. Only the study presented in (Shurbutt & Van Houten, 2010) has identified these situations and excluded them from violations in a simple way by using a fixed distance from the crosswalk. Furthermore, the definition of non-yielding maneuvers is often unclear and relatively subjective, in particular regarding the pedestrian's intent to cross.

Many researchers have looked into pedestrian crossing decisions. For example, Granié et al. investigated pedestrian crossing decisions under various urban environments through a survey using sets of photographs presenting five different environments (Granié et al., 2014). Participants' decision to cross or not, perception of comfort and safety, and elements influencing decision-making were collected and analyzed (Granié et al., 2014). Liu and Tung looked at the effects of age, time gap, time of day, and vehicle approaching speed on the decision of pedestrians to cross the road based on pre-recorded videos of different road scenes (Liu & Tung, 2014). Using the simulated road environment from a mid-range driving simulator, Oxley et al. conducted a study to analyze pedestrians' gap selection and their crossing decisions (Oxley et al., 2005). Due to the limited available techniques for data collection, most of these past studies have been based on off-road, laboratory experiments, such as tests in simulators, and picture- or video-based surveys, which may not properly reflect real situations.

5.3.3 Driver Reaction on Road Safety

Driver response time, also called perception-response time or reaction time, has a great impact on road safety, creating significant interest in this area of research (Hick, 1952) (Hyman, 1953) (Koppa, 2000) (Green, 2009). The distribution of driver response time is often called the Hick-Hyman "Law" (Hick, 1952) (Hyman, 1953) .Vehicle yielding maneuvers at pedestrian crossings include two critical times (and corresponding distances): 1) a perception-response time, which allows the driver to observe the pedestrian's intention to cross and make a decision to yield, and 2) a time to brake or perform another evasive action if necessary. Driver response time at crosswalks refers to the time lag between detection of the pedestrian and the initiation of braking. Response time greatly affects driver's yielding behavior at crosswalks and the risk that pedestrians face when they are crossing the street. Therefore, response time needs to be considered in crosswalk safety studies, which is uncommon in the literature.

Response time varies between individuals and depends on various factors such as age, gender and driving experience, the appearance of the pedestrians, distraction, and the built environment (Kosinski, 2005). Different studies have looked into driver response time and different distributions have been recommended (Koppa, 2000) (Green, 2009). Many of these studies considered response time to expected and unexpected events. At crosswalks, drivers are aware of the presence of pedestrians, thus pedestrian crossing events should be considered as expected, which is associated with shorter reaction times compared to unexpected events (Fitch et al., 2010). Among the past studies, Koppa and Rodger decompose the driver braking response prior to the actual braking into perception-reaction time and movement time (the amount of time required to move the foot to the brake pedal). Results from this work were consistent with past literature but followed a stronger investigation (Koppa, 2000). The report briefly discussed non-signalized intersections and used 1.57 sec of driver response time as a realistic worst-case scenario (99^{th} percentile) (Koppa, 2000). Based on this report, movement time ranges from 0.2 sec to 0.26 sec based on the vertical separation between the brake pedal and the driver's foot (Koppa, 2000). Based on this report and other literature, the driver response during a pedestrian-vehicle interaction (the entire reaction period prior to the actual braking) at crosswalks takes between 0.5 s and 2 s.

5.4 THE NEW SAFETY FRAMEWORK

The proposed pedestrian-vehicle interaction model, referred to also as the DV model, is represented in a two-dimensional distance-velocity space and helps investigate pedestrian safety based on vehicle reaction and braking behavior.

5.4.1 Basic Distance-Velocity Model

The evolution of a yielding maneuver unfolds over time and space is presented in FIGURE 5-1. Several basic assumptions are made in analyzing road user behavior for crosswalk safety: 1) during a yielding maneuver, a driver has a response time after the occurrence of the pedestrian, and the vehicle keeps constant speed over this time; 2) a braking period, when the driver brakes at a constant deceleration rate, occurs after the reaction time; 3) drivers have knowledge of whether they are able to stop before reaching the crosswalk, i.e., they know the maximum deceleration rate required to stop and yield; 4) the maximum deceleration rate of the vehicle is defined by the pavement friction rate.

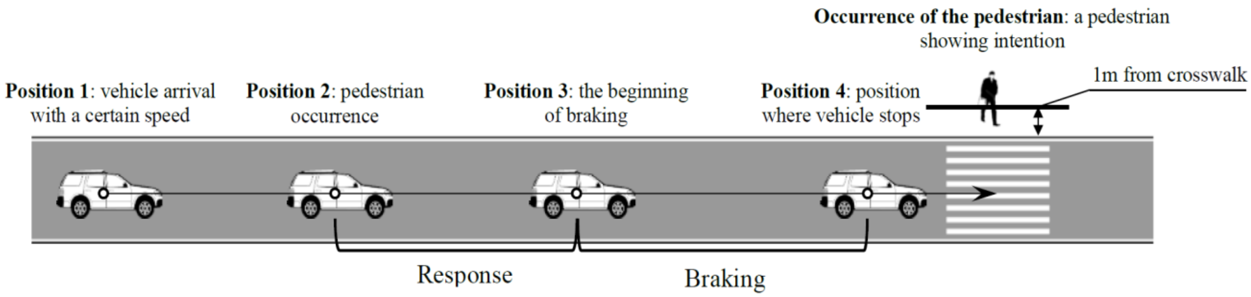


FIGURE 5-1 Vehicle yielding maneuver at a crosswalk

5.4.1.1 Practical Definitions of Pedestrian Occurrence and Crossing Decision

As yielding behavior of the vehicle greatly depends on whether drivers noticed the crossing intention of the pedestrian, the occurrence and crossing decision of the pedestrian are closely associated to vehicle yielding compliance and pedestrian safety. The definitions of pedestrian occurrence and crossing decision are as follows:

Pedestrian Occurrence: This may be the most important event to define in the pedestrian-vehicle interactions at crosswalks. The occurrence of the pedestrian is the time when the pedestrian arrives close to the beginning crosswalk, defined in this paper as arriving within a cross-section distance of 1 m from the beginning of the crosswalk (see FIGURE 5-1), and shows the intention to cross the street by either facing the road or turning their head toward the road, unless his/her behavior obviously implies they do not intend to cross the street (e.g. standing and talking, squatting, or staying in this area for specific purposes such as equipment installation and etc.).

Pedestrian Crossing Decision: The pedestrian crossing decision is defined as the time when the pedestrian starts to cross the street, regardless if he/she is later forced to retreat by non-yielding vehicles. Actual crossing attempts may happen when a pedestrian keeps a constant walking speed to cross after arrival without waiting, or starts to cross after waiting or hesitates after arrival.

Pedestrian Occurrence and Crossing Decision for Pedestrian Groups: Several pedestrians can arrive at a similar time and cross in the same gap. The occurrence of the group is defined as the first occurrence of a pedestrian from the group. However, each pedestrian is considered to be individually exposed to the risk of collision.

Interactions of interest are the situations in which a vehicle approaches a crosswalk and a pedestrian is either already moving to cross or present in a position showing willingness to cross. Situations in which the pedestrian is already crossing and would have left the roadway well in advance of the expected arrival of the vehicle at the crosswalk, i.e. where the approaching vehicle is not required to decelerate or yield to avoid a collision, are excluded.

5.4.1.2 Model Description

Driving maneuver during a yielding behavior consists of two periods, as shown in FIGURE 5-1: 1) the response period, when the driver observes the pedestrian and decides to yield, and; 2) the braking period, from the moment the driver applies pressure to the brake pedal until the vehicle completely stops. As usually adopted in transportation engineering (Jammer, 1957), the minimum distance required for a vehicle to make a full stop to yield to a pedestrian (D_{min}) at constant deceleration is:

$$D_{min} = vt_r + \frac{v^2}{2g(\mu_{max} - \theta)} \tag{3}$$

where v is the initial speed (velocity) of the vehicle at the occurrence of the pedestrian, t_r is the perception-reaction time of the driver, μ_{max} is the maximum friction coefficient of the road surface, and θ is the angle of roadway slope. Based on these assumptions and formula derivations, the ability for the driver to stop is a function of the distance (D) and the vehicle approaching speed (v). Assuming the reaction time range as $[t_{r\_min}, t_{r\_max}]$, then D_{min} is in a range of $[D_0, D_1]$ = $[vt_{r\_min} + \frac{v^2}{2g(\mu_{max} - \theta)}, vt_{r\_max} + \frac{v^2}{2g(\mu_{max} - \theta)}]$. An early version of this paper with additional details of the model can be seen at Fu et al. (2017). Müller et al. (2004) found that the maximum friction coefficient ranges from 0.85 to 1.15 on dry road, while on soapy road it the coefficient ranges from 0.45 to 0.75. In this paper, a fixed value of 0.75 is used for the model illustration and test purposes.

FIGURE 5-2 shows the basic elements in the model with plausible values. The Distance-Velocity (DV) diagram is divided into three areas by the D_0 and D_1 curves: i) the first area, defined as phase I, where vehicles cannot make a full stop, ii) the second area, phase II, where whether vehicles can stop and yield depends on the driver's reaction time, and iii) the third area, phase III, where vehicles can stop. Line A in the figure represents the distance and speed over time during an example interaction where a vehicle approaches at constant speed, then brakes at constant deceleration after the pedestrian starts to cross. The DV coordinates at the time when the pedestrian shows crossing intention and when the pedestrian decides to cross (starts crossing maneuver) are marked in the diagram.

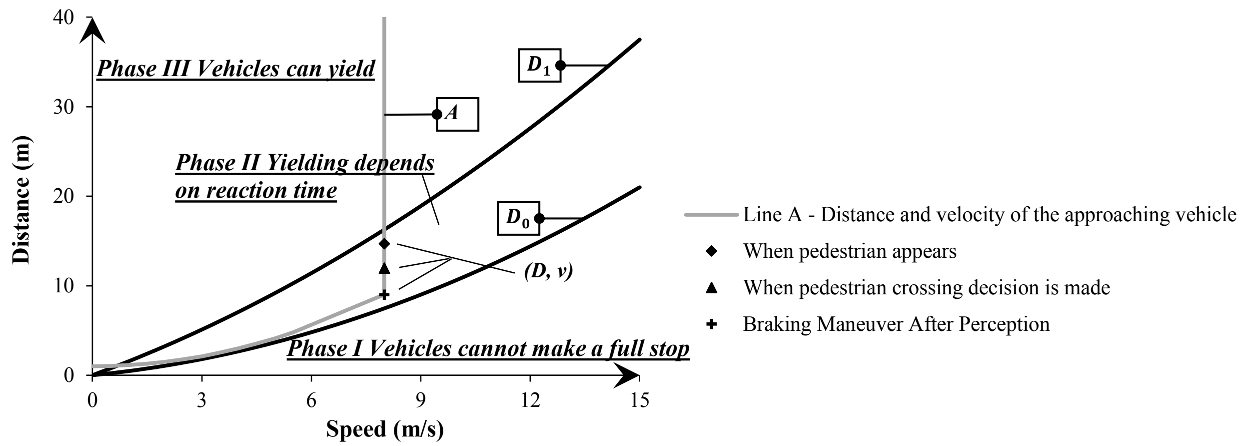


FIGURE 5-2 Explanation of D-V diagram with example values

5.4.2 Behavior Measures

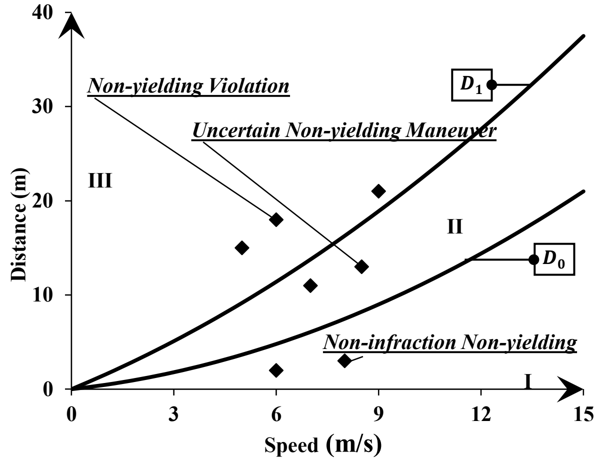
Based on the D-V diagram and the situations represented by the three phases, drivers' non-yielding maneuvers and pedestrians' crossing decisions can be classified; then, yielding compliance and crossing decision ratios can be used to evaluate the safety status of a given crosswalk.

5.4.2.1 Vehicle Yielding

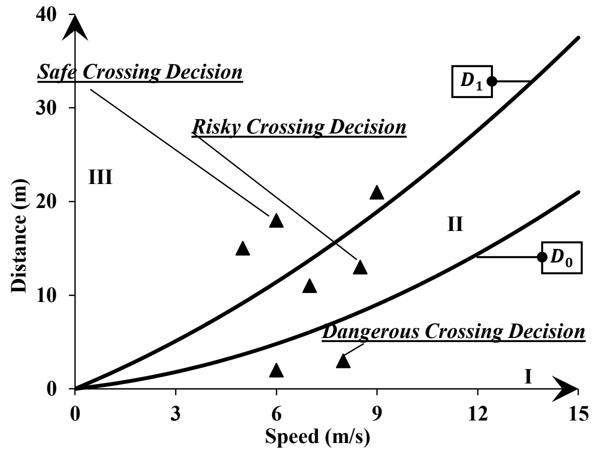
5.4.2.1.1 Non–Yielding Maneuver

Vehicle yielding behavior can be analyzed with knowledge of the pedestrian occurrence, i.e. the time when the pedestrian starts or intends to cross the street. Non-yielding maneuvers are defined as the events in which drivers do not provide right-of-way to pedestrians, regardless as to whether drivers do not intend or are not able to yield (Lacoste et al., 2014) (Fitzpatrick et al., 2006) (Campbell, 2012). By plotting in the DV diagram the speed V_{occ} of vehicles conducting non-yielding maneuvers and their distance D_{occ} to the crossing at the occurrence of the pedestrian, a vehicle's ability to stop in front of the crosswalk can be classified. According to the DV diagram, non-yielding maneuvers can be placed into three categories, as presented in FIGURE 5-3a:

- **Non-infraction Non-yielding:** If $D_{occ} < D_0$ (corresponding to Phase I in the two diagrams in FIGURE 5-3), the vehicle will not have enough time to make a full stop to yield. Non-yielding maneuvers in such situations should not be considered as a non-yielding behavior.
- **Uncertain Non-yielding Maneuver:** If $D_0 < D_{occ} < D_1$(corresponding to Phase II), the driver may or may not be able to react to the crossing pedestrian in time to yield. Although drivers are required be attentive to crossing pedestrians, reaction time can vary. In this category, it is hard to determine whether the driver is not able to or not willing to yield. These situations are therefore called uncertain non-yielding maneuvers. Vehicles in Phase II are still required to yield to pedestrians, as they are required to pay attention and react as quickly as possible.
- **Non-yielding Violation:** If $D_1 < D_{occ}$ (corresponding to Phase III), the vehicle has enough time to react and yield to the pedestrian. All non-yielding maneuvers in this situation are voluntary and therefore violations.



a) Classification of the non-yielding maneuvers



b) Classification of the pedestrian crossing decisions

FIGURE 5-3 Classification of non-yielding maneuvers and crossing decisions in the DV diagram

5.4.2.1.2 Yielding Rate and Yielding Compliance

Past studies used yielding rate and yielding compliance as interchangeable terms, while in fact they are different. In most past studies, all non-yielding maneuvers have been considered as non-compliance, including those where vehicles are too close to the crosswalk to have the option to yield (phase I in the DV model). This paper presents clearly the definitions of yielding rate and yielding compliance by taking into account situations where vehicles are not able to yield:

- **Yielding Rate:** Yielding rate is defined as the proportion of vehicles that yield to pedestrians over all the pedestrian-vehicle interactions.
- **Yielding Compliance:** Yielding compliance is the proportion of vehicles that yield to pedestrians over the vehicles that are physically able to yield to crossing pedestrians.

According to this, yielding rate for phase i ($i = I, II, III$: $I - Phase\ I$, $II - Phase\ II$, $III - Phase\ III$) refers to the ratio of yielding maneuvers among all interactions reaching phase i. The overall yielding rate, which is improperly used for yielding compliance, is the proportion of total number of yielding maneuvers over the number of all pedestrian-vehicle interactions. The yielding compliance rate considers interactions where the vehicle D_{occ}, V_{occ} coordinates fall in Phase II and III at the occurrence of the pedestrian. Yielding rate and yielding compliance can be expressed using the following equations:

$$YR_i = \frac{N_{yielding_i}}{N_{interaction_i}} \tag{4}$$

$$YR = \frac{\sum N_{yielding_i}}{\sum N_{interaction_i}} \tag{5}$$

$$YC = \frac{N_{yielding_{II}} + N_{yielding_{III}}}{N_{interaction_{II}} + N_{interaction_{III}}} \tag{6}$$

Where, YR_i is the yielding rate for Phase i, $N_{yielding_i}$ is the number of yielding maneuvers in Phase i, $N_{interaction_i}$ is the number of pedestrian-vehicle interactions of interest (defined in 3.1.1) in Phase i, YR is the overall yielding rate, and YC is the yielding compliance.

5.4.2.1.3 Uncertainty Zone for Yielding

Based on the DV diagram, if an interaction falls in Phase II ($D_0 < D_{occ} < D_1$), either the driver, or the outside observer cannot know whether the driver is able to stop or not. Such a situation is defined as the uncertainty zone for yielding. A better understanding of this uncertainty zone should shed light on driver behavior during the pedestrian-vehicle interactions, and may help improve models, specifically in simulating pedestrian-vehicle interactions. This paper provides a brief exploration of the uncertainty zone for yielding by looking at the yielding rate for Phase II (YR_{II}), and the proportion of interactions in Phase II among all the interactions ($\frac{N_{interaction_{II}}}{\sum N_{interaction_i}}$).

5.4.2.2 Crossing Decision

In order to describe the pedestrian crossing decisions in an interaction, the speed and distance (D_{cross}, V_{cross}) coordinates of the vehicle when the pedestrian starts to cross the street are extracted. As illustrated in the DV diagram in FIGURE 5-3b, the pedestrian crossing decisions can be classified in three types:

- **Dangerous Crossings:** When the crossing decision occurs in the situation where $D_{cross} < D_0$ (Phase I), pedestrians expose themselves to dangerous interactions with vehicles that cannot brake to yield.
- **Risky Crossings:** When the crossing decision occurs in the situation where $D_0 < D_{cross} < D_1$ (Phase II), it is still unsafe for pedestrians to cross the street as drivers may not have enough time to react and yield. Drivers with longer reaction times will either brake sharply or may collide with pedestrians.
- **Safe Crossings**: When the crossing decision occurs in the situation where $D_1 < D_{cross}$ (Phase III), pedestrians are relatively safe. Drivers have enough time to react and yield to pedestrians.

Ratios of different types of crossing decisions over the total number of interactions where pedestrians start to cross can be used to evaluate pedestrian crossing behavior.

5.4.3 Surrogate Measures of Safety

The proposed framework also attempts to measure the probability dimension of the risk of collision, which is not represented by the yielding compliance and crossing decision indicators presented previously. In the DV model, vehicles have less space and time to react and brake with the situations moving clockwise, i.e. moving from phase III, to phase II, then phase I; therefore, the probability of collision increases clockwise. In this study, it is quantified by two indicators: time to crossing and deceleration rate required to stop and yield.

5.4.3.1 Time to Crossing

Time to crossing (TC) refers to the time required for the vehicle to reach the pedestrian crossing path if continuing at constant speed. Assuming the *(D,V)* coordinate of the vehicle at a certain instant to be, TC is calculated as D/V, which is the slope of the line going through the origin and the point *(D,V)* in the DV diagram. TC represents the available time for the drivers to attempt evasive actions before reaching the crosswalk.

5.4.3.2 Deceleration Rate required to Stop

Deceleration rate required to stop (DRS) is the constant deceleration rate required for the vehicle to stop and give the right-of-way to pedestrians. Assuming the driver is aware of the pedestrian at the pedestrian occurrence and reacts immediately then $t_r = t_{r\_min}$.

Assuming the deceleration rate as a, the distance for the entire reaction-braking maneuver is $D = vt_r + \frac{v^2}{2a}$; then, the deceleration rate can be calculated as:

$$a = \frac{v^2}{2(D - vt_r)} \quad (7)$$

For determining the DRS, as $t_r = t_{r\_min}$, we get:

$$DRS = \frac{v^2}{2(D - vt_{r\_min})}\ ,\ if\ D > vt_{r\_min} \quad (8)$$

TC and DRS of the vehicle at the time of the pedestrian occurrence and of the time of the pedestrian crossing decision (or attempt) will be collected and analyzed.

The relationship between pedestrian safety and yielding compliance of the drivers can be better understood using the DV model. The level of safety in an interaction between a driver and a pedestrian evolves throughout the interaction. For instance: an interaction involving a driver that fails to yield in Phase III, considered a relatively safe situation, will result in a more dangerous situation (Phase I); a timely stop/slow-to-yielding maneuver in Phase II may result in a safe crossing in Phase III. The probability of collision can be analyzed based on TC and DRS. Moreover, TC, DRS and other surrogate measures of safety may help explain the fine details of interactions, such as the detailed process of yielding maneuvers and its impact on pedestrian crossing decisions.

5.5 CASE STUDY

A study was conducted to illustrate the use of the DV model to evaluate pedestrian safety at three different types of non-signalized crossings: a painted crosswalk, an unprotected crosswalk (a crossing location with neither sign nor pavement treatment to protect the pedestrians), and a crosswalk controlled by stop signs. Road user trajectories were extracted using automated video-based techniques. Multiple cameras were used to cover large road sections for the sites where a single camera installation failed to cover the entire road section being analyzed. Using the trajectory data, the framework was applied. Results were analyzed using the DV model. Details of data collection and processing methods, and the comparative analysis of pedestrian safety are provided in this section.

5.5.1 Data Collection and Processing

5.5.1.1 Data Collection

For temporary trajectory data collection, mobile cameras are the easiest, most feasible, means of data collection. GoPro's Hero and Hero 3 Edition cameras were used in HD resolution (1920 by 1080 pixels). The cameras were mounted on mobile masts and fixed to existing facilities such as lampposts and traffic light poles.

One of the limitations of using mobile video data collection is the limited field of view and trajectory length due to the restricted installation height and location, which means that a single camera is not sufficient to cover a sufficiently large observation area for most sites. Therefore, multiple cameras may be required to observe the approaching road user trajectories. In this study, cameras were installed in sequence along the approach studied with a portion of their views overlapping for synchronization purposes.

5.5.1.2 Data Processing

As presented in FIGURE 5-4, the data processing work mainly consists of four steps:

STEP 1: Trajectory Data Extraction from Video After data collection, video data processing was carried out using the tracker in the open source Traffic Intelligence project (Saunier & Sayed, 2006), which provides accurate positioning and velocity outputs of the road users, as done in (Fu et al., 2016; Anderson-Trocme et al., 2015). Moreover, the most up-to-date version of the project was used which addresses errors caused by the lens distortion ("fish-eye" effect) (Forsyth & Ponce, 2012). The output is the trajectory data (positions and velocity vectors) of the road users in each frame saved in a SQLite database.

STEP 2: Preparation of the Trajectory Database For sites requiring multiple cameras, merged trajectory outputs through consecutive cameras is ideal, but not completely implemented and validated in the Traffic Intelligence project. In this study, the videos from different locations in the same site were processed separately. In order to learn how driver react to different pedestrian occurrences and crossing decisions at different distances, the position and time of the vehicle through different camera views should be extracted, thereby requiring video synchronization based on the time offsets of the video recordings for the different camera views.

STEP 3: Filter and Mark the Interactions As currently available computer techniques are either unable to detect, or detect accurately, the fine details of pedestrian occurrence, in particular the detection of the pedestrian's intention to cross, pedestrian occurrences and their crossing decisions were determined manually. In the study, videos were scanned manually for interactions of interest. Timestamps (in the format of frame number) of pedestrian occurrences and relative crossing decisions during these interactions were manually recorded.

STEP 4: Extraction of the Distance and Velocity Data Based on the frame numbers from Step 3, the distance and velocity of the vehicle at the time of pedestrian occurrences and crossing decisions are calculated using a simple script. In the DV framework, distance to the pedestrian crossing path is required. Reference lines to measure the distance are set at the middle of the crosswalk painting for the painted crosswalk and stop sign controlled crosswalk locations. For the unprotected location, the position of the pedestrian crossing is the geometrical separation of the approach and the center of the intersection or crossing zone (see example in FIGURE 5-4). As most people crossed within the crosswalk limits at the painted crosswalk and stop sign crosswalk locations, the distance to the reference line is used. For those who crossed outside of the crosswalk, and those at the unprotected crosswalk location, the distance is adjusted by adding or subtracting the displacement of the pedestrian to the reference line. In addition, since the tracker only tracks moving objects, the distances of the vehicles already stopped at the times of measurement are extracted manually.

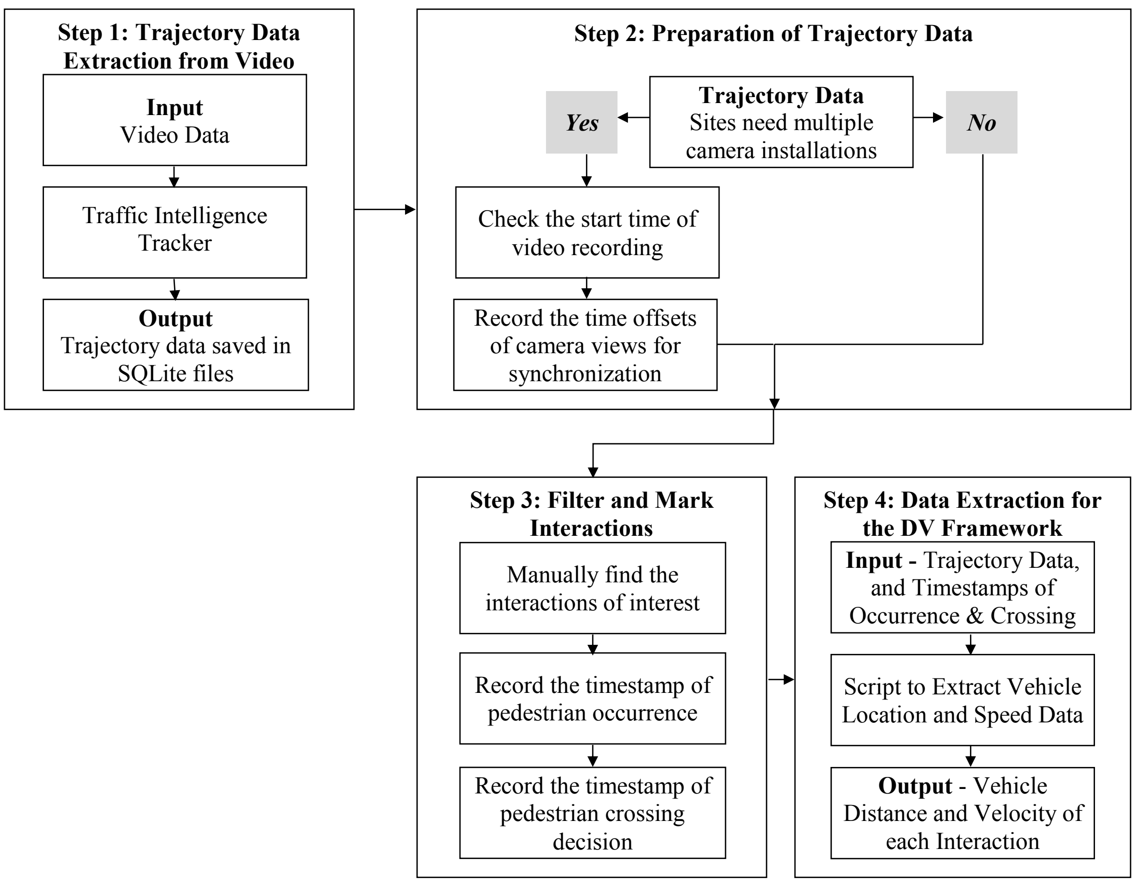
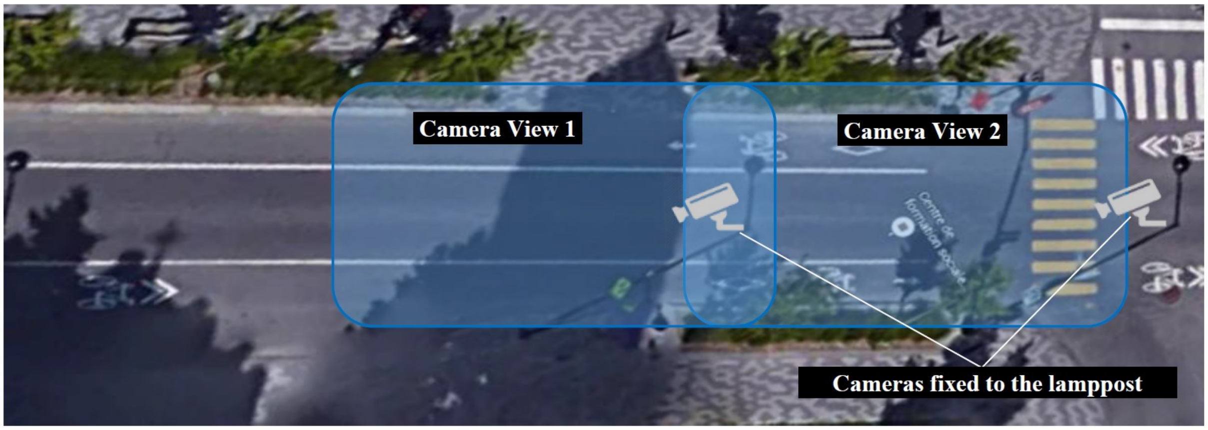


FIGURE 5-4 Steps involved in data processing

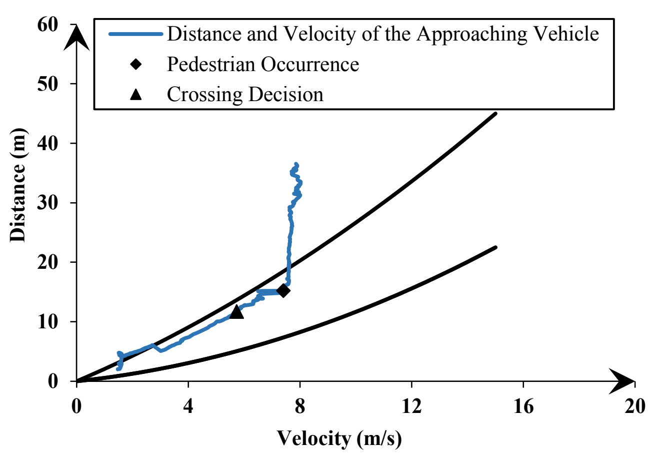
5.5.1.3 Illustration of the Results

For illustration purpose, this paper provides an example with the outputs of one interaction, as shown in FIGURE 5-5. Two cameras were installed in sequence to cover approximately 35 meters. FIGURE 5-5a provides an illustration of the camera installation. FIGURE 5-5b provides snapshots from the two camera views showing the trajectory of the same vehicle at the same time. Cameras are synchronized by knowing the time offset between the starts of the recordings for the two camera views. For illustration purposes, FIGURE 5-5c gives the DV diagram with the DV coordinates of the vehicle during the entire process of interaction. Markers in the DV diagram shows the DV coordinates at the times of the occurrence and of the crossing decision of the pedestrian. The outputs in the DV figure align well with the assumption illustrated in FIGURE 5-2. At the occurrence of the pedestrian, the vehicle, possibly driven by a vigilant driver, began decelerating to yield to the potential crossing by the pedestrian. Based on the framework, the occurrence and crossing decision fall in Phase II where a timely reaction and a relative high deceleration rate are required of the driver. The TC and the DRS for the pedestrian occurrence and crossing decision can be computed. In this interaction, TC and DRS at the time of the pedestrian occurrence were found to be 2.06 s and 2.38 m/s^2. TC and DRS at the time of the pedestrian crossing decision were 2.05 s and 1.85 m/s^2.



a) Camera locations and installations on the aerial map

b) Trajectories of the same vehicle through multiple cameras (displayed on the video frames after the correction for lens distortion)



c) DV relationship of the entire interaction

FIGURE 5-5 Illustration of the results for one pedestrian-vehicle interaction

5.5.2 Data Description

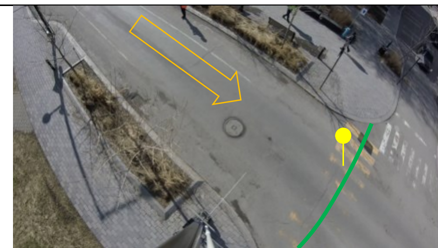
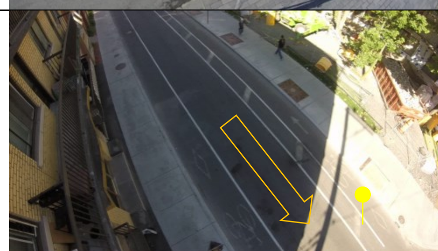
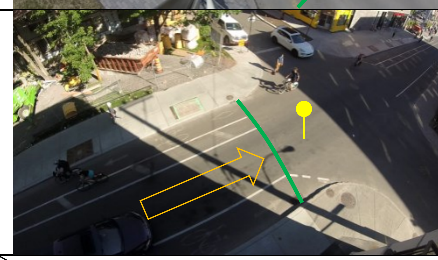
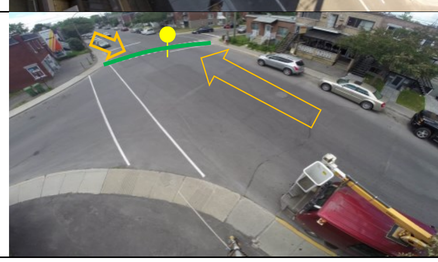
For the case study, three pedestrian crossing locations with different crosswalk designs were selected in central Montreal:

- Site Laurier_Berri: crosswalk located on Avenue Laurier at the intersection of Avenue Laurier and Rue Berri – it is a painted crosswalk crossing on Avenue Laurier, a one-way, one-lane street.
- Site Laurier_Drolet also located on Avenue Laurier at the intersection of Avenue Laurier and Rue Drolet – it is a pedestrian crossing location with no crosswalk paintings or signs to mark the crossing.
- Site 13e_Belair: crosswalk located on Rue Belair at the intersection of Rue Belair and 13e Avenue – it is a pedestrian crosswalk with both the crosswalk painting and stop signs where vehicles must stop and yield to pedestrians. All three crosswalks are located at level roads, which means the road slope is 0.

Video data were collected for each site. Details of the video data are presented in TABLE 5-1.

TABLE 5-1 Descriptions of the Video Recorded at Each Site

Type of Crosswalk	Site name	Date	Time	Duration (hour)
Painted	**Laurier_Berri**	March 17th 2016	14:00-18:40	4.7
Unprotected	**Laurier_Drolet**	June 17th 2016	10:00-14:30	4.5
Stop sign controlled	**13e_Belair**	June 21st 2016	09:00-13:30	4.5

Site name	# of Cameras	Camera View 1	Camera View 2
Laurier_Berri	2		
Laurier_Drolet	2		
13e_Bélair	1		

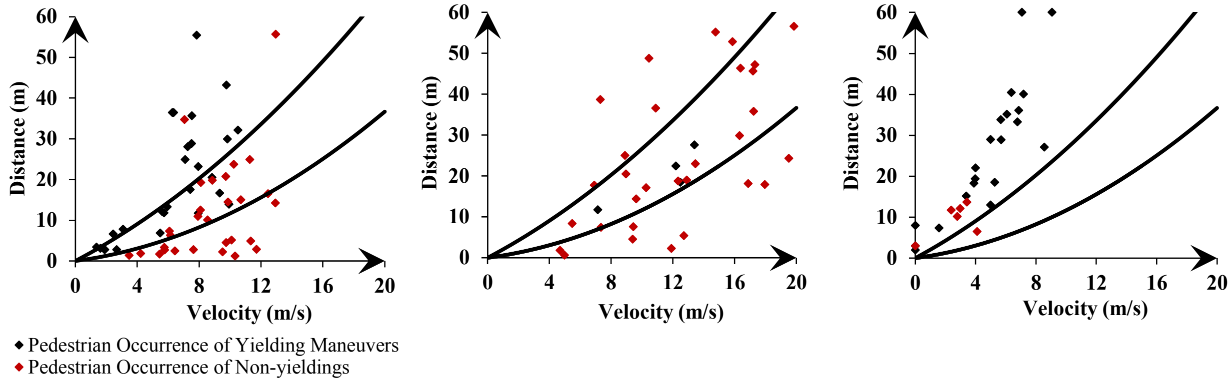
Note: in the pictures of the camera views, orange arrows indicate the direction of the approach studied, yellow pins indicate the crosswalk locations, and green lines are the reference lines as described in 4.1.2

5.5.3 Results and Discussion

5.5.3.1 Vehicle Yielding Behavior

Results of measures for vehicle yielding behavior are presented in FIGURE 5-6 and TABLE 5-2. From FIGURE 5-6, the DV framework, with its parameters of reaction time, is useful to describe and analyze the interactions. No yielding maneuver was observed for interactions in Phase I, where vehicles are very close to the crosswalk and cannot yield. Vehicle maneuvers in interactions in Phase II vary greatly among drivers. This suggests the existence of the uncertainty zone of yielding associated with Phase II. Considering the interactions in Phase III, for the painted crosswalk and the stop sign controlled crosswalk locations where drivers know that they must yield the right-of-way to crossing pedestrians, most drivers did yield. This provides evidence that vehicles in the situations of Phase III have enough time to react and yield to the pedestrians, and non-yielding maneuvers happening in such situations are (voluntary) violations. Considering yielding rates and driver compliances, as shown in TABLE 5-2, the large difference (a maximum difference of 16.9 % points) between the overall yielding rate (YR) and the yielding compliance (YC) shows that the yielding compliance used in many past studies (which is, in fact, the overall yielding rate) may not properly describe the yielding compliance of the drivers.

From the results, most interactions that occurred at the stop sign controlled crosswalk fall in Phase III as from the DV plots, and the overall yielding rate and yielding compliance was 77.8 %, which is the highest among all the sites. For the painted crosswalk location, the yielding compliance was 64.3 %. The yielding rate of Phase III was 82.3 % suggesting a high compliance of the drivers at this site. However, due to the non-yielding maneuvers for the interactions falling in Phase II and Phase I, the overall yielding rate was only 52.0 %, which suggests a less safe environment for pedestrians compared to the stop sign controlled crosswalk. The unprotected crosswalk performs poorly in terms of pedestrian safety. No vehicle yielded in Phase III, where the driver has sufficient time to react and yield. The yielding compliance for this site was only 10.8 % and the overall yielding rate was only 8.7 %. The reason for these low rates may be that most drivers think they have right to cross without yielding. Moreover, from the comparison of the DV plots, the stop sign is found to move the interactions toward reduced speeds, since most drivers slow down as they approach the stop sign. Based on the indicators of the DV model, the stop sign controlled crosswalk provides the safest accommodation for pedestrians to cross by offering the best yielding compliance of the drivers, while the unprotected crosswalk is the least safe.



a) Painted crosswalk *b) Unprotected crosswalk* *c) Stop sign controlled crosswalk*

FIGURE 5-6 DV plot for pedestrian occurrence and yielding behavior

TABLE 5-2 Results of Yielding Rates

Phase	No. Obs.	Type of Non-yielding	No. of Non-yielding	Yielding Rate for Phase *i*
		Painted Crosswalk (Site Laurier_Berri, 57 interaction observations)		
I	15	Non-infraction Non-yielding	15	0.0 %
II	25	Uncertain Non-yielding	12	52.0 %
III	17	Non-yielding Violation	3	82.4 %
Overall yielding rate (YR) - yielding compliance rate used in past studies				47.4 %
Rate for redefined yielding compliance (YCR)				64.3 %
		Unprotected Crosswalk (Site Laurier_Drolet, 46 interaction observations)		
I	9	Non-infraction Non-yielding	9	0.0 %
II	18	Uncertain Non-yielding	14	22.2 %
III	19	Non-yielding Violation	19	0.0 %
Overall yielding rate (YR) - yielding compliance rate used in past studies				8.7 %
Redefined yielding compliance rate (YC)				10.8 %
		Stop Sign Controlled Crosswalk (Site 13e_Bélair, 27 interaction observations)		
I	0	Non-infraction Non-yielding	0	undefined
II	1	Uncertain Non-yielding	1	0.0 %
III	26	Non-yielding Violation	5	80.8 %
Overall yielding rate (YR) - yielding compliance rate used in past studies				77.8 %
Redefined yielding compliance rate (YC)				77.8 %

Note: Phase I refers to where vehicles cannot make full stop, Phase II is where yielding depends on reaction time, and Phase III is where vehicles can stop and yield.

The TC and DRS of the interactions can be generated to quantify the probability of collisions. The median TC and DRS at the times of pedestrian occurrences and their standard deviations can be calculated. Results are provided in FIGURE 5-7. From the results, the stop sign controlled crosswalk has a median TC that is doubled, and a median DRS of pedestrian occurrences that is much lower, compared to the other two crosswalk locations. This indicates that stop signs generally provide better conditions for vehicles to respond and decelerate in order to yield to pedestrians. On the other hand, the unprotected crosswalk has the highest median DRS, suggesting that it will be more difficult for vehicles to yield to pedestrians. The unprotected crosswalk has a similar median TC value to that of the painted crosswalk, which shows similar conditions provided by the two crosswalks for vehicles to respond. These findings suggested that the stop sign controlled crosswalk performs best for pedestrian safety, while the unprotected crosswalk is the worst. The painted crosswalk provides a safer accommodation for pedestrians compared to the unprotected crosswalk, but not as good as the stop sign controlled crosswalk.

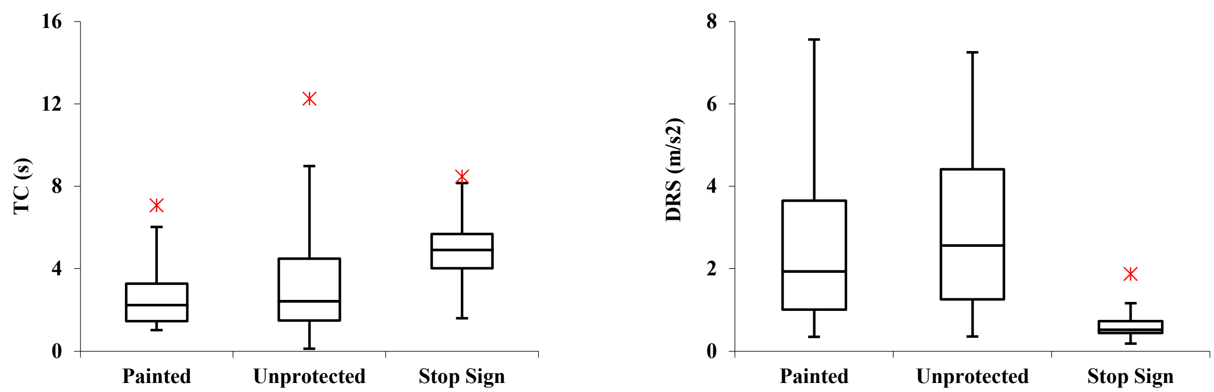
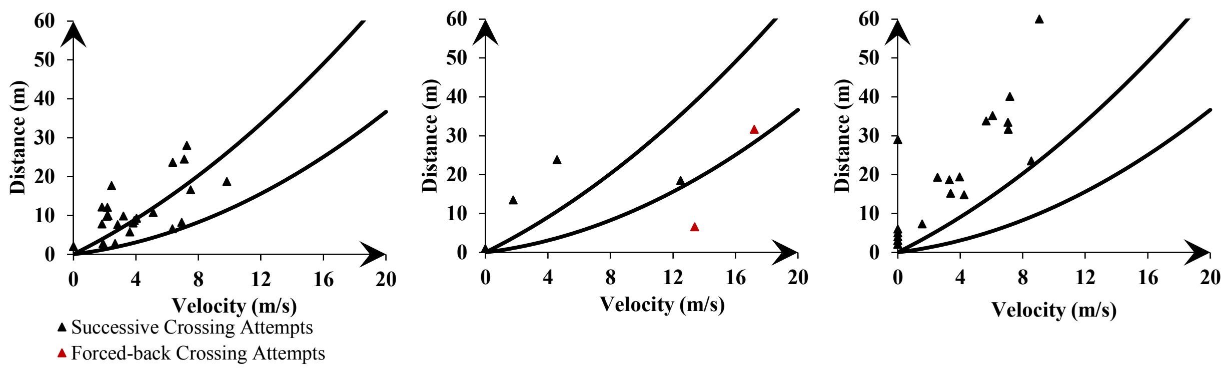


FIGURE 5-7 Result comparisons for yielding behavior at three types of crosswalks

5.5.3.2 Pedestrian Crossing Decisions

Results for crossing decisions are provided in FIGURE 5-8 and FIGURE 5-9. Crossing decisions at the painted crosswalk fall in Phase II and Phase III, with the median TC of 2.29 s and the median DRS of 1.71 m/s^2 when pedestrian decisions were made. For crossing decisions at the stop sign controlled crosswalk, most of the crossing decisions are made in Phase III, where vehicles have enough time to react and yield. The median TC is 4.89 s and the median DRS is 0.32 m/s^2. The TC and DRS for the times at which the pedestrian crossing decisions were made are presented in FIGURE 5-9. The higher TC and lower DRS for interactions at the stop sign location can be attributed to their location in the DV diagram (Phase III) and the high yielding compliance, illustrated in FIGURE 5-8. Based on the comparison of the median TC and DRS across the three intersection types, the stop sign controlled location is safer compared to the painted crosswalk by leading pedestrians to make safe crossing decisions. Due to the reduced yielding compliance at the unprotected crosswalk, the majority of the crossing decisions were made after the vehicle passed. Therefore, only six crossing attempts were observed, making it insufficient for comparison as can be seen in the higher variability of TC and DRS in FIGURE 5-9. However, as presented in FIGURE 5-8, two dangerous crossing attempts, where the pedestrians had to retreat as the vehicles did not give the right-of-way, were found at the unprotected crosswalk location, suggesting the reduced safety at the unprotected crosswalk location.



a) Painted crosswalk *b) Unprotected crosswalk* *c) Stop sign controlled crosswalk*

FIGURE 5-8 DV plots for pedestrian crossing decision

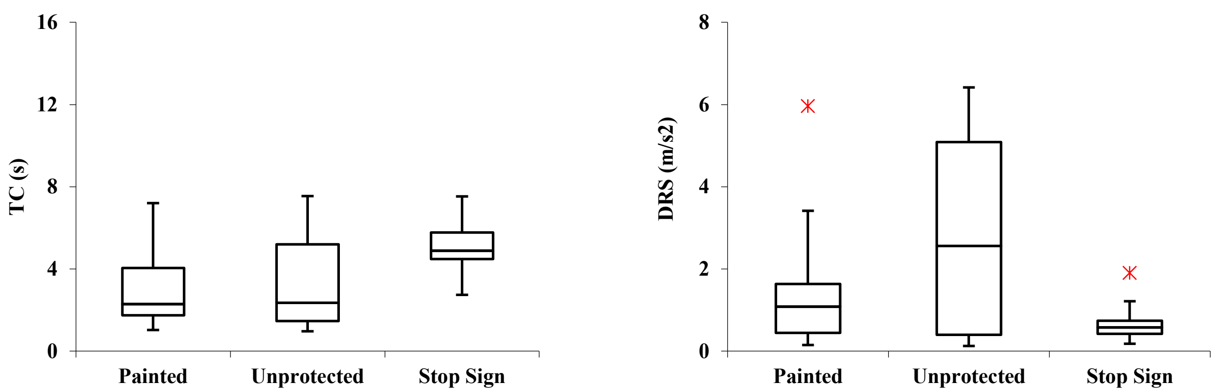


FIGURE 5-9 Result comparisons for crossing decisions at three types of crosswalks

5.6 CONCLUSION

This paper proposes an original framework to study pedestrian-vehicle interactions at non-signalized crosswalk locations based on the vehicle trajectory speed and distance to the pedestrian crossing. This model utilizes trajectories coming from video analysis. The framework, also referred to as the DV model, shows promise in studying vehicle yielding and pedestrian crossing behavior at non-signalized locations. The data generation process is semi-automated using an existing automated tracking tool, manual identification of events (pedestrian occurrences and crossing decisions), and automated data extraction. The proposed framework is tested through a case study using video data from three different types of non-signalized crossing locations in Montreal.

Based on a case study, the DV framework, along with the derived measures, is used for analyzing driver interactions with crossing pedestrians, by identifying the situations in which the driver can and cannot stop to yield to the pedestrian, and by characterizing both users' behavior and maneuvers. The framework better explains pedestrian-vehicle interactions compared to typical safety studies based on traffic conflict techniques such as (Almodfer et al., 2015) (Malkhamah et al., 2005) (Tang & Nakamura, 2009) which fall short in describing unpredictable behavior of the road users. Surrogate measures of safety selected in the paper, TC and DRS, are integrated in the framework to diagnose the safety of the interactions. The framework provides reasonable results in classifying driver yielding behaviors. The absence of yielding maneuvers in Phase I indicates the existence of situations where vehicles are so close to the crosswalk at the pedestrian occurrence that they cannot stop and give the right-of-way. The high yielding rate in Phase III indicates that in such situations drivers have enough time to react and most of them are willing to yield to pedestrians (as required by the law). The reduced yielding rate in Phase II indicates the situations where drivers either require increased reaction time or are unwilling to yield to pedestrians. The reaction time range of 0.5 to 2 s thus seems reasonable.

Results of the case study are intuitive. The stop sign controlled crosswalk can better protect the pedestrians compared to the other two crosswalks in terms of driver compliance, overall yielding rates and crossing decisions the pedestrians make. The unprotected crosswalk performs inadequately for pedestrian safety as the yielding compliance is very low and the safety level as measured by the vehicle yielding behavior is the lowest. As the key contribution, this paper provides a new approach to describe pedestrian-vehicle interactions. The proposed approach can be used for different purposes in road safety including treatment (countermeasure) evaluation, simulation of pedestrian-vehicle interaction, behavior analysis, safety monitoring (detecting vehicle violations), and improvements of yielding enforcement policies.

However, the model needs to be further validated through a sufficiently large number of observations and locations. The maximum friction rate is influenced by many factors including weather, type of the pavement, type of the tire and braking system specifications. The treatment of the maximum friction can be improved in future work. The range of reaction time also needs to be further calibrated. The existence of the uncertainty zone and its impact on pedestrian safety should be further explored. Other surrogate measures of safety than TC and DRS, such as TTC and PET will be used and compared in future studies. Data will be collected from a large number of sites for the model validation and improvement based on available historical crash data. In addition, the behavior of drivers and pedestrians is an important factor. One must assume that users are similar overall at different sites for the performance validation of different treatments.

Studies on road user behavior such as vehicle yielding compliance and pedestrian crossing decision during vehicle-pedestrian interactions will be further conducted using the DV model with video data. Also, as part of future work, the effectiveness of different crosswalk treatments will be further evaluated based on the framework. The effects of various factors (traffic volume, time-of-day, the geometric design, built environment, etc.) will be investigated. Driver glance behavior and driving distraction, which are important explanatory factors for pedestrian safety, require the installation of in-vehicle sensors like eye trackers and have thus not been much investigated yet (Bichicchi et al., 2017). The model could be applied to improve microsimulation simulation models in better describing vehicle-pedestrian interactions.

5.7 ACKNOWLEDGEMENT

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5.8 REFERENCES

Abdel-Aty, M., & Haleem, K., 2010. Analysis of the Safety Characteristics of Unsignalized Intersections. *12th World Conference on Transport Research (WCTR).* Lisbon, Portugal.

Almodfer, R., Xiong, S., Fang, Z., Kong, X., & Zheng, S., 2015. Quantitative Analysis of Lane-based Pedestrian-vehicle Conflict at a Non-signalized Marked Crosswalk. *Transportation Research Part F: Traffic Psychology and Behaviour*, in Press.

Anderson-Trocme, P., Stipancic, J., Miranda-Moreno, L., & Saunier, N., 2015. Performance Evaluation and Error Segregation of Video-collected Traffic Speed Data. *Transportation Research Board Annual Meeting.* Washington DC.

Bichicchi, F., Mazzotta, C., Lantieri, V., Vignali, A., Simone, G., Dondi, G., & Costa, M., 2017. The Influence of Pedestrian Crossings Features on Driving Behavior and Road Safety. *the Aiit International Congress on Transport Infrastructure and Systems (Tis 2017)*, (pp. 741-746). Rome, Italy.

Campbell, R. J., 2012. *An Analysis Framework for Evaluation of Traffic Compliance Measures.* PhD's Thesis Report, University of California at Berkeley.

Fitch, G. M., Blanco, M., Morgan, J. F., & Wharton, A. E., 2010. Driver braking performance to surprise and expected events. *Proceedings of the Human Factors and Ergonomics Society 54th Annual Meeting*, (pp. 2076-2080).

Fitzpatrick, K., Turner, S., Brewer, M., Carlson, P., Ulman, B., Trout, N. Lord, D., 2006. *Improving pedestrian safety at unsignalized crossings.* Transportation Research Board, Washington D.C.

Forsyth, D. A., & Ponce, J., 2012. *Computer Vision: A Modern Approach, 2nd Edition* (2nd ed.). (T. Dunkelberger, Ed.) Upper Saddle River, US: Pearson.

Fu, T., Miranda-Moreno, L. F., & Saunier, N., 2016. Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime using Thermal Video Data and Surrogate Safety Measures. *Transportation Research Record: Journal of the Transportation Research Board, 2586*, 90-99.

Fu, T., Miranda-Moreno, L., & Saunier, N., 2017. A Novel Framework to Evaluate Pedestrian Safety at Non-signalized Locations using Video-based Trajectory Data. *96th Annual Meeting of Transportation Research Board*, (p. 16p). Washington DC.

Fu, T., Stipancic, J., Zangenehpour, S., Miranda-Moreno, L., & Saunier, N., 2017. Automatic Traffic Data Collection under Varying Lighting and Temperature Conditions in Multimodal Environments: Thermal versus Visible Spectrum Video-Based Systems. *Journal of Advanced Transportation, 2017*, 1-17.

Golob, T., Recker, W. W., & Alvarez, V. M., 2004. Freeway Safety as a Function of Traffic Flow. *Accident Analysis & Prevention*, Volume 36, 933-946.

Granié, M.-A., Brenac, T., Montel, M.-C., Millot, M., & Coquelet, C., 2014. Influence of built environment on pedestrian's crossing decision. *Accident Analysis & Prevention* (67), 75-85.

Green, M., 2009. Perception-reaction Time: is All You Need to Know? *Collision, 4*, 88-95.

Hick, W. E., 1952. On the Rate of Gain of Information. *Journal of experimental psychology, 4*, 11-26.

Hydén, C., 1987. *The development of a method for traffic safety evaluation: The Swedish Traffic Conflicts Technique.* Lund Institute of Technology, Lund.

Hyman, R., 1953. Stimulus information as a determinant of reaction time. *Journal of Experimental Psychology, 45*, 188-196.

Ismail, K., Sayed, T., & Saunier, N., 2011. Methodologies for aggregating indicators of traffic conflict. *Transportation Research Record,* Vol. 2237, 10-19.

Jammer, M., 1957. *Concepts of Force: A Study in the Foundations of Dynamics.* Mineola, New York, US: Dover Publications, Inc.

Koppa, R. J., 2000. *Revised monograph on traffic flow theory: Chapter 3.* Technical Report, FHWA.

Kosinski, R. J., 2005. *A literature review of reaction time.* Literature Review, Clemson University. Retrieved from http://www.fon.hum.uva.nl/rob/Courses/InformationInSpeech/CDROM/Literature/LOTwinterschool2006/biae.clemson.edu/bpc/bp/Lab/110/reaction.htm

Lacoste, J., Campbell, A., Klassen, S., & Montufar, J., 2014. Pedestrian safety at crosswalks - examining driver yielding behavior at crosswalks with GM1 and OF systems. *the 2014 Conference of the Transportation Association of Canada.* Montreal, Quebec.

Laureshyn, A., 2010. *Application of automated video analysis to road user.* Lund University.

Lee, C., Saccomanno, F., & Hellinga, B., 2002. Analysis of Crash Precursors on Instrumented Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, (1784), 1-8.

Liu, Y.-C., & Tung, Y.-C., 2014. Risk analysis of pedestrians' road-crossing decisions: effects of age, time gap, time of day, and vehicle speed. *Safety Science*, (63), 77-82.

Malkhamah, S., Tight, M., & Montgomery, F., 2005. The development of an automatic method of safety monitoring at pelicen crossings. *Accident Analysis & Prevention, 37*(5), 938-946.

McGee, H. W., Soika, J., Fiedler, R., Albee, M., Holzem, A., Eccles, K. & Quinones, J., 2015. *Unsignalized Intersection Improvement Guide.* Final Report, Institute of Transportation Engineers (ITE), Federal Highway Administration (FHWA).

Müller, S., Uchanski, M. and Hedrick, K., 2004. Estimation of the maximum tire-road friction coefficient. *Journal of Dynamic Systems, Measurement, and Control,* 125(4), 1–11.

Nabavi Niaki, M., Fu, T., Miranda-Moreno, L., Amador-Jimenez, L., & Bruneau, J.-F., 2015. Effects of road lighting on bicycle and pedestrian accident frequency: Case study in montreal, canada. *Transportation Research Record: Journal of the Transportation Research Board, in Press*.

NHTSA, 2015. *Traffic safety facts 2013 data.* National Highway Traffic Safety Administration.

Nicolas, S., Sayed, T., & Ismail, K., 2010. Large Scale Automated Analysis of Vehicle Interactions and Collisions. *Transportation Research Record: Journal of the Transportation Research Board, 2147*, 42-50.

Oxley, J., Ihsen, E., Fildes, B. N., Charlton, J. L., & Day, R. H., 2005. Crossing roads safely: an experimental study of age differences in gap selection by pedestrians. *Accident Analysis & Prevention, 37*(5), 962-971.

Robert, K., 2009. Night-Time Traffic Surveillance A Robust Framework for Multi-Vehicle Detection, Classification and Tracking. *Advanced Video and Signal Based Surveillance*, 1-6.

Saunier, N., & Sayed, T., 2006. A Feature-based Tracking Algorithm for Vehicles in Intersections. *IEEE.*

Shurbutt, J., & Van Houten, R., 2010. *Effects of yellow rectangular rapid-flashing beacons on yielding at multilane uncontrolled crosswalks.* Technical Report, Federal Highway Administration, McLean, VA.

St-Aubin, P., Miranda-Moreno, L. F., & Saunier, N., 2013. An automated surrogate safety analysis at protected highway ramps using cross-sectional and before-after video data. *Transportation Research Part C: Emerging Technologies, 36*, 284-295.

Stipancic, J., Miranda-Moreno, L., & Saunier, N., 2016. Who & Where of Road Safety: Extracting Surrogate Indicators from Smartphone-Collected GPS Data in Urban Environments. *Transportation Research Board Annual Meeting*. Washington DC.

Tang, K., & Nakamura, H., 2009. Safety evaluation for intergreen intervals at signalized intersections based on probabilistic methodology. *Transportation Research Record: Journal of the Transportation Research Board,* 2128, 226–235.

Tarko, A., Davis, G., Saunier, N., Sayed, T., & Washington, S., 2009. *White Paper: surrogate safety measures of safety.* ANB20 (3) Subcommittee on Safety Data Evaluation and Analysis Contributors.

Transport Canada, 2015. *Canadian motor vehicle traffic collision statistics 2013.* Canadian Council of Motor Transport Administrators.

Zangenehpour, S., Miranda-Moreno, L. F., & Saunier, N., 2013. Impact of bicycle boxes on safety of cyclists: a case study in Montreal. *Transportation Research Board 92nd Annual Meeting.* Washington DC.

Zangenehpour, S., Strauss, J., Miranda-Moreno, L. F., & Saunier, N., 2016. Are intersections with cycle tracks safer? A control-case study based on automated surrogate safety analysis using video data. *Accident Analysis & Prevention, 86*, 161-172.

Link between chapter 5 and chapter 6

The previous chapter introduced the DV framework and demonstrated it through a case study involving three sites of different types. However, this is far from being sufficient for testing and valuating the framework. The city of Montreal has been recently investing in improving pedestrian safety at non-signalized crosswalk locations. Based on the project our laboratory has with the city, we are able to conduct a large-scaled data collection involving multiple sites in Montreal. As part of the project, the model is applied to evaluate the performance of the three main types of crosswalks (the marked crosswalk, the uncontrolled crosswalk, and the stop sign controlled crosswalk) on pedestrian safety through in an extended study involving 15 different crosswalk locations selected from City of Montreal. The model is further tested. The performance of the three types of crosswalk on pedestrian safety is investigated and compared. Though thermal camera has been proved to perform well for traffic data collection, the study still used video data collected from regular cameras. This was due to 1) the use of the thermal camera was not included in the design of the project; 2) the accessibility of limited number of thermal cameras (only one available) did not allow efficient data collection given a data collection permission with limited dates; 3) there are safety concerns for data collection at night. Detailed work is presented in the following chapter.

Chapter 6

Model Application for Multiple Sites

Chapter 6 Model Application for Multiple Sites

6.1 INTRODUCTION

Chapter 5 has given the definition of interaction of interest. An interaction of interest between the pedestrian and the vehicle covers the entire procedure starting from when the vehicle and the pedestrian approach to each other, ending by successful passages, evasive maneuvers, or in worst case, a crash. **In terms of behavior analysis, pedestrian safety is mainly decided by four elements**:

1) The occurrence of the interaction – Based on the definition of interaction of interest, an interaction happens when a pedestrian presents at the crosswalk with his intention to cross, and a vehicle is approaching the crosswalk location. For an interaction of interest, the trigger of the interaction is the occurrence of a pedestrian intending to cross; therefore, the pedestrian occurrence, defined in ***Chapter 5***, also represents the occurrence of the interaction. The initial status of the vehicle at the occurrence of the interaction is important as it determines the capability (the time and distance from the crossing pedestrian) of the drivers to respond.

2) The vehicle yielding behavior – In response to pedestrian occurrence, drivers decide to yield or not. Driver yielding behaviors are strongly associated with pedestrian safety. Driver compliance to the yielding law helps reduce the risk of pedestrians. Yielding behavior can be analyzed using the DV framework.

3) The crossing decision of the pedestrian – During a pedestrian-vehicle interaction, pedestrians cross the street when they feel confident to. The pedestrian can be endangered if the crossing decision is made when the vehicle is still at a high speed, with his yielding intention unknown. The pedestrian decision can be analyzed based on the status of the vehicle when the decision is made.

4) The outcome of the interaction – an interaction of interest ends up three types of outcomes. *i)* The pedestrian crosses before the vehicle passage, being given right-of-way. *ii)* The pedestrian have to cross after the vehicle passage not being yielded. *iii)* An evasive maneuver or a crash happens if the pedestrian decides to cross the street in front of the vehicle, but he is not given right-of-way by the driver. Due to the limitation of crash data analysis (Fu, et al., 2016; Tarko, et al., 2009), evasive maneuvers have been an important measure of safety (Dhar & Woodin, 1995; Fitzpatrick, et al., 2006; Gitelman, et al., 2016). Evasive maneuvers include reactions such as rushing to complete or aborting a crossing (for pedestrians) and swerving, lane changing, or braking.

As the main purpose, this part is to test and validate the DV framework through multiple sites. An extended study involving 15 different crosswalk locations selected from City of Montreal was conducted. Detailed analysis was made based on the information extracted from the video data collected from these sites. The occurrences of interactions, vehicle yielding behavior, pedestrian crossing decisions, and the observation of evasive maneuvers are investigated.

6.2 SITE DESCRIPTION

For model validation, pedestrian safety at the three main types of non-signalized crosswalks, which include uncontrolled crosswalks (Type A), marked crosswalks (Type B in the chapter), and stop sign controlled crosswalks (Type C), were further analyzed. For the three types of crosswalk, each involved video data collected from five site locations. FIGURE 6-1 presents locations of the sites. Detailed descriptions for each site are included in APPENDIX II.

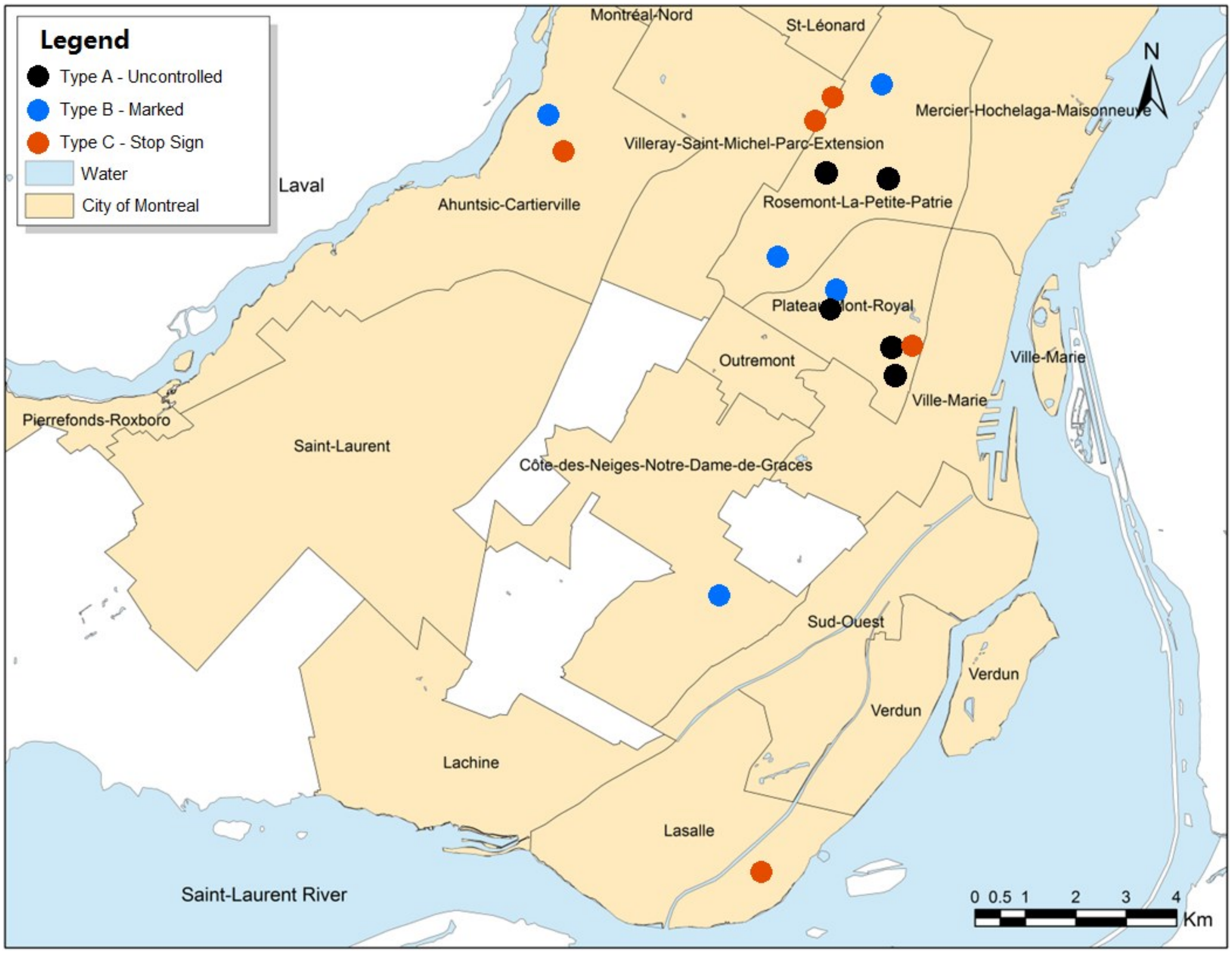


FIGURE 6-1 Map of Site Locations

6.3 DATA COLLECTION

Video data were collected using the same method described in ***Chapter 5***. Details of the video data are presented in TABLE 6-1. Data were collected from the fifteen sites, totaling to 80.8 hours (21.9 hours from uncontrolled crosswalk locations, 30.3 hours from marked crosswalk locations, and 28.6 hours from crosswalk locations controlled by the stop sign).

TABLE 6-1 Descriptions of the Video Recorded at Each Site

Type of Crosswalk	Site ID	Site Name	Date	Time	Duration (hr)
Uncontrolled	**A-1**	NotreDamedeGrace-D'Oxford	July 20th 2016	08:10-13:50	5.7
- Type A -	**A-2**	Clark-PrinceArthur	July 23rd 2016	09:10-12:00	2.9
	A-3	Masson-6e	July 4th 2016	08:30-12:55	4.4
	A-4	Beaubien-Molson	June 28th 2016	08:10-12:35	4.4
	A-5	Laurier_Drolet	June 17th 2016	10:00-14:30	4.5
	Total duration for Type A				21.9
Marked	**B-1**	Prieur-DeLaRoche	September 23rd 2016	09:30-18:50	9.3
- Type B -	**B-2**	NotreDamedeGrace-OldOrchard	July 20th 2016	08:50-13:40	4.8
	B-3	Beaubien-SaintVallier	June 30th 2016	08:30-14:20	5.9
	B-4	Beaubien-27e	July 7th 2016	10:15-15:50	5.6
	B-5	Laurier_Berri	March 17th 2016	14:00-18:40	4.7
	Total duration for Type B				30.3
Stop sign	**C-1**	Roy-HenriJulien	June 16th 2016	09:40-17:50	8.2
- Type C -	**C-2**	George-Gagne	June 9th 2017	09:15-15:20	6.1
	C-3	Sauriol-Millen	September 20th 2016	09:00-11:00	2.2
	C-4	19e-Belair	June 21st 2016	09:10-15:50	7.6
	C-5	13e_Belair	June 21st 2016	09:00-13:30	4.5
	Total duration for Type C				28.6
	Total duration for all sites				80.8

6.4 RESULTS AND DISCUSSION

After data collection, video data were processed and trajectory information of the road users was extracted and analyzed using the same approach given in ***Chapter 5***. Interactions of interest were analyzed for each site included in each crosswalk type. 682 interactions were observed from the 15 sites with 292 from uncontrolled crosswalks, 222 from marked crosswalks and 168 from stop sign controlled crosswalks. This chapter mainly focuses on results summarized for different types of crosswalks. For one who wants to check more details, results for each specific site are included in APPENDIX III.

As the main purpose of this chapter, the performances of the three main types of non-signalized crosswalks on pedestrian safety are analyzed and compared. The intensity of observed interactions at their occurrences, and vehicle yielding behaviors and pedestrian crossing decisions in response to these interactions are analyzed using the DV framework. Results for each type of crosswalk are given in TABLE 6-2. Results are discussed in three parts: 1) interactions of interest; 2) yielding behavior of vehicles; and 3) crossing decisions of pedestrians.

TABLE 6-2 Results from DV Model for Different Crosswalk Types

Type of Crosswalk		Type A Uncontrolled	Type B Marked	Type C Stop sign controlled	All Sites
		Results for Interactions of Interest			
Number of Interactions					
No. of Total Interactions		292	222	168	682
No. of Interactions in Phase I (*Percentage over the total)		32 (11.0 %)	33 (14.9 %)	5 (3.0 %)	70 (10.3 %)
No. of Interactions in Phase II (Percentage over the total)		43 (14.7 %)	58 (26.1 %)	35 (20.8 %)	136 (19.9 %)
No. of Interactions in Phase III (Percentage over the total)		217 (74.3 %)	131 (59.0 %)	128 (76.2 %)	476 (69.8 %)
TC and DRS at the Occurrence of Interaction					
TC (sec)	*Median*	5.60	3.73	3.92	4.31
	Std. Dev.	6.39	4.89	4.50	5.64
DRS (m/s^2)	*Median*	0.79	0.61	0.48	0.69
	Std. Dev.	3.09	2.29	0.84	2.49
		Results for Yielding Behavior			
No. of Non-infraction Non-yieldings		32	33	4	69
No. of Uncertain Non-yieldings		38	31	10	79
No. of Non-Yielding Violations		207	50	21	278
No. of Yielding Maneuvers		15	108	133	256
Yielding Rate		5.1 %	48.7 %	79.2 %	37.5 %
Yielding Compliance		5.8 %	57.1 %	81.6 %	41.8 %
		Results for Crossing Decision			
No. of Decisions to Cross after Vehicle Passage		267	112	34	412
No. of Decisions to Cross before Vehicle Passage		25	111	134	270
No. of Dangerous Crossings (Percentage over the total)**		2 (8.0 %)	12 (10.8 %)	0 (0.0 %)	14 (5.2 %)
No. of Risky Crossings (Percentage over the total)		6 (24.0 %)	23 (20.7 %)	24 (17.9 %)	53 (19.6 %)
No. of Safe Crossings (Percentage over the total)		17 (68.0 %)	76 (68.5 %)	110 (82.1 %)	203 (75.2 %)
No. of Crossings with Evasive Maneuvers		10	3	1	14
TC (sec)	*Median*	5.54	4.03	4.40	4.14
	Std. Dev.	3.65	4.22	5.01	4.55
DRS (m/s^2)	*Median*	0.75	0.63	0.30	0.50
	Std. Dev.	1.77	3.25	1.07	2.30

Note that: *Percentage over the total in results for occurrence of interactions is the percentage of each type of interactions over the total number of interactions observed. **Percentage over the total in results for crossing decisions is the percentage of each type of crossing decisions over all the crossing attempts made to cross before the vehicle passage.

6.4.1 Interactions of Interest

Intensity of interactions of interest when they occur and yielding behavior of drivers during these interactions are investigated. FIGURE 6-2 presents the outputs for the position and speed of vehicles when interactions occur, and their yielding behavior, in the format of the DV diagram. Results for surrogate measures of safety including TC and DRS at the occurrence of interactions for different types of crosswalk are virtualized using boxplots in FIGURE 6-3.

The percentages of each type of interactions over the total number of interactions of interest are compared among different types of crosswalk. From TABLE 6-2, the type of crosswalk controlled by stop signs has the highest percentage (76.17 %) of interactions that happened in Phase III, where vehicles can stop. Besides, the lowest percentage (2.98 %) of interactions that happened in Phase I where vehicles cannot make a full stop can be observed at stop sign controlled locations. These indicate that stop sign controlled crosswalks effectively reduce the chance of pedestrians to expose to interactions that occur with high risk situations. Compared to uncontrolled crosswalks, marked crosswalks have a lower percentage of interactions in Phase III, and a higher percentage of interactions that occur in Phase I, suggesting that interactions at marked crosswalks occur with averagely more intense situations over the other two crosswalk types. These findings align with what are given in the DV plots in FIGURE 6-2. As marked with the grey mask, vehicles states at interaction occurrence falls mostly in Phase II and Phase III where vehicles have time to react and yield to pedestrians with reduced speed at stop sign controlled crosswalks. From the figure, as marked with grey mask, occurrences of pedestrians are more dispersed in the DV diagram mainly because vehicles approaching the crosswalks have averagely higher speeds.

Intensity of interactions at occurrence can also be represented using TC and DRS at pedestrian occurrence. Checking from TABLE 6-2 and FIGURE 6-3, uncontrolled crosswalks have the highest median TC compared to the other two types of crosswalks which indicates that interactions are less intense at uncontrolled crosswalks in terms of the time left for drivers to observe and react to a pedestrian at his presence at the crosswalk location to cross the street compared to those happen at marked and stop sign controlled crosswalk locations. However, median DRS value for interactions at uncontrolled crosswalks is the highest among all site types, which means vehicles should decelerate at a higher rate to stop to yield during the occurrence of an interaction compared to other two types. Interactions happen at stop sign locations are the least intense as they require averagely least deceleration rate to decelerate at pedestrian occurrence.

From the results in ***Chapter 5***, more pedestrians might be stuck by non-yielding maneuvers of multiple vehicles in sequence at uncontrolled crosswalks. In these cases, the pedestrian tends to wait for an extended period of time to cross. Because of the extended waiting time, more interactions of interest generated, occurring with large TC values and small DRS values. This may explain why the median TC at uncontrolled crosswalk is the highest. Comparing only among indicators for the occurrences of interactions is not sufficient. To further verify this and to investigating pedestrian safety at these three types of crosswalk, vehicle yielding behavior and pedestrian crossing decision are to be explored.

6.4.2 Vehicle Yielding Behavior

From TABLE 6-2 and FIGURE 6-2, among all the 682 interactions, no yielding maneuver was observed for interactions in Phase I, where vehicles are very close to the crosswalk and cannot yield. High proportions of vehicles not giving right-of-way to pedestrians with several yielding indicate the existence of uncertainty zone of yielding associate with Phase II. During the interactions that occur with a situation of Phase III where drivers know that they must yield, most of vehicles did yield. This further supports the conclusion in ***Chapter 5*** that "the DV framework, with its parameters of reaction time, is useful to describe and analyze the interactions".

From the results, yielding rate at stop sign controlled crosswalks was 79.17 %, which is the highest among the three types of crosswalk. The yielding compliance shows that 81.60 % of the vehicles, who could yield to pedestrians, actually yielded. Among the interactions that occur at marked crosswalks, less than half of the vehicles involving in interactions of interest yielded, while there are around 60 % of drivers who could yield gave right-of-way. Uncontrolled crosswalks however, had the lowest yielding rate of 5.14 %, and the lowest yielding compliance of 5.77 %.

The results indicate that stop sign controlled crosswalks not only reduces high-intensity interactions but also help increase vehicle yielding compliance, guaranteeing right-of-way for pedestrians and providing a safe environment for pedestrians to cross. Marked crosswalks have a reduced yielding compliance, which mean pedestrians are less safe to cross at marked crosswalks compared to stop sign controlled crosswalks. Drivers did not yield to pedestrians when passing by them at uncontrolled crosswalks showing the least safe environment for pedestrian to cross the street at such sites.

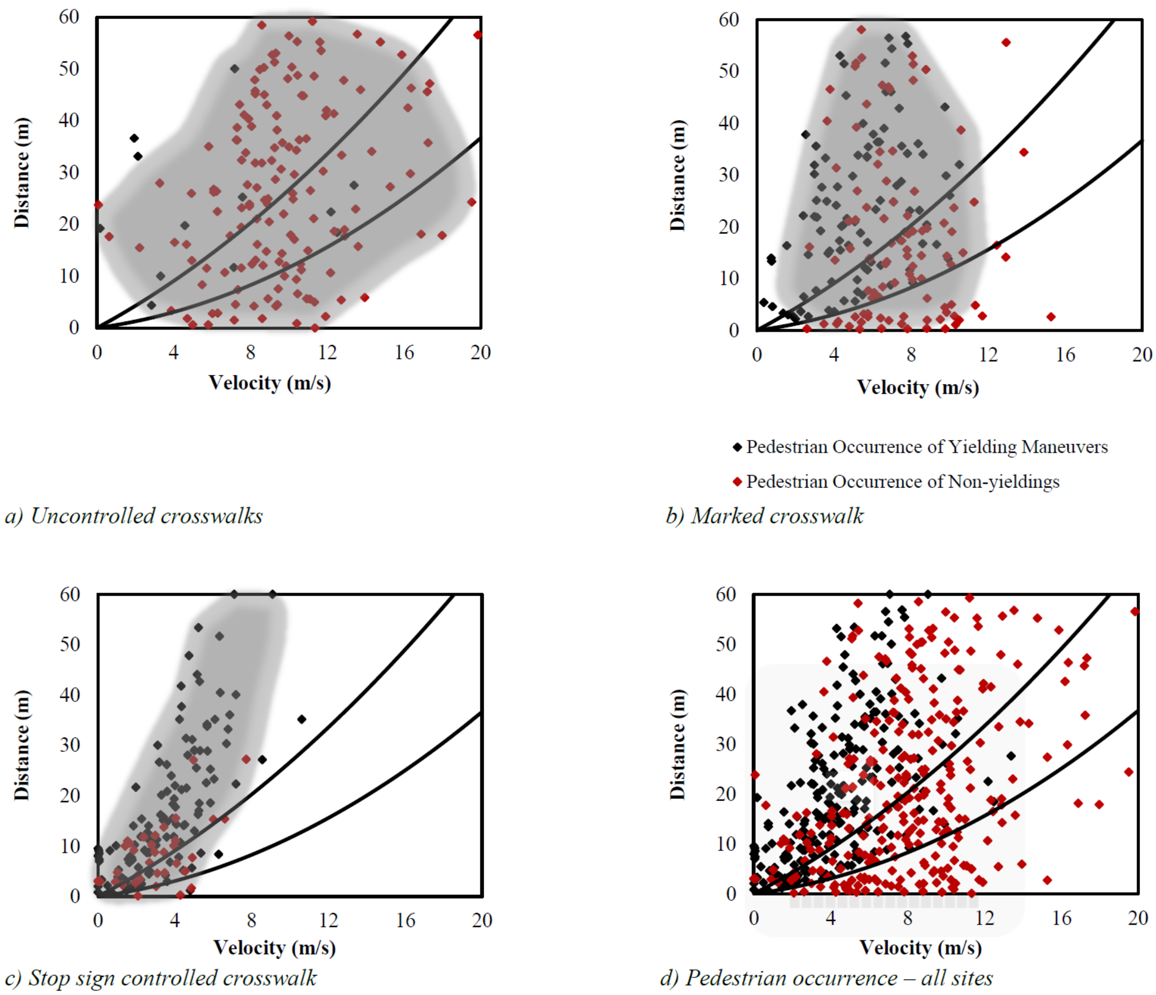


FIGURE 6-2 DV plot for pedestrian occurrence and yielding behavior

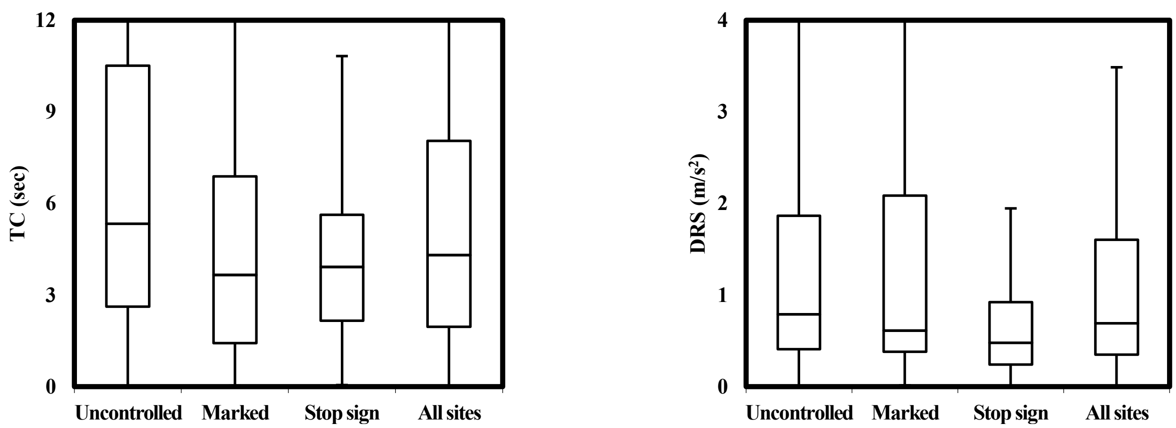


FIGURE 6-3 Result comparisons for pedestrian occurrence at three types of crosswalks

6.4.3 Pedestrian Crossing Decision

In interactions with approaching vehicles, pedestrians decide the time to cross the street by judging whether they are sufficiently safety to cross. Being a zero-sum game (if one gains, another loses) for pedestrian right-of-way at crosswalks, pedestrian decisions to cross after vehicle passages and vehicle yielding maneuvers are tightly correlated. Results for pedestrian crossing decisions are also included in TABLE 6-2. As one can see from the table, because of vehicles with non-yielding maneuvers, many pedestrians had to cross after vehicle passages without risking themselves in front of the vehicles: half of the pedestrians at marked crosswalks crossed after vehicle passages; most pedestrians at uncontrolled crosswalks gave up right-of-way to vehicles; at stop sign controlled crosswalks, however, only small amount of pedestrian (34 out of 168) crossed after the pedestrians.

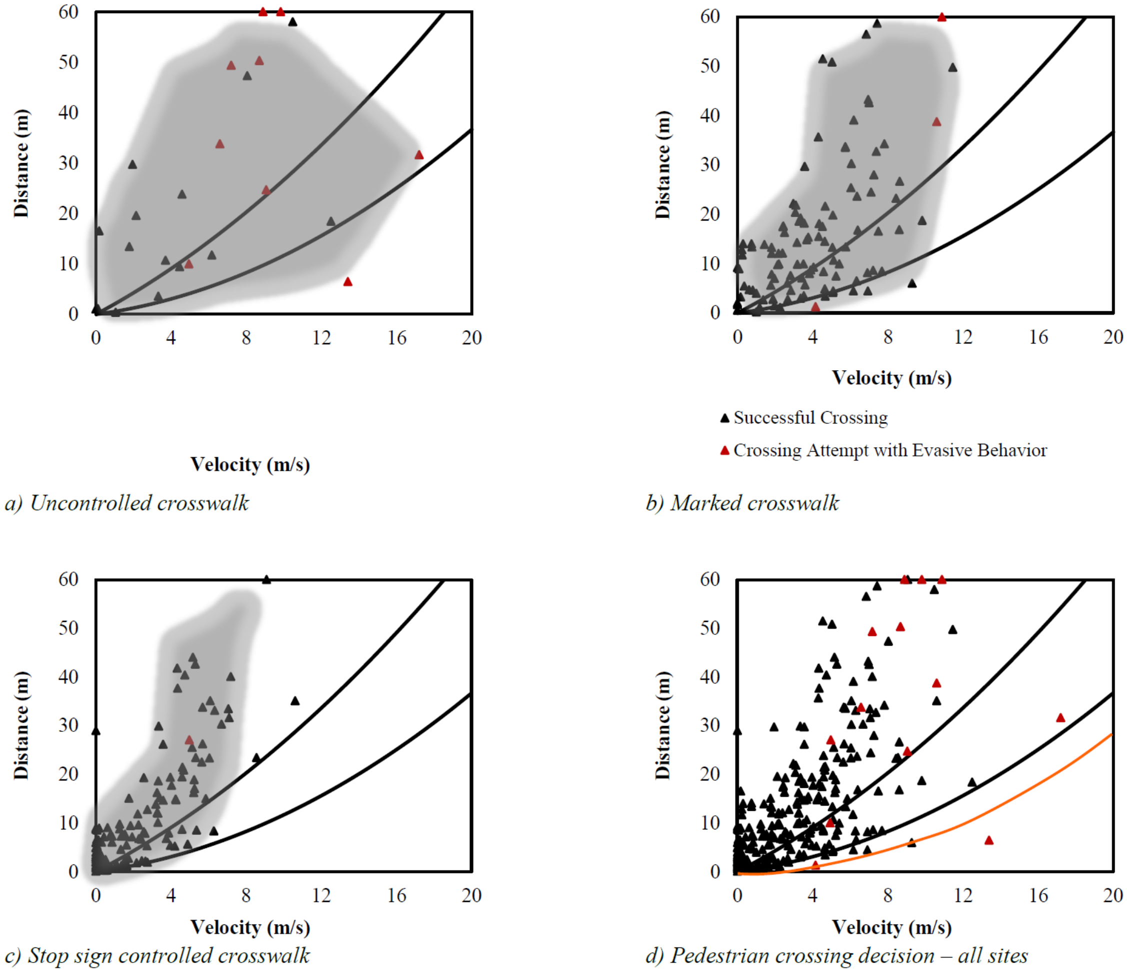
Pedestrian crossing before vehicle passages closely related to their safety as they expose themselves in front of vehicles. Therefore, pedestrian crossings before vehicle passages are essential to be investigated. DV plots for pedestrians crossing decisions to cross before vehicle passages for the three types of crosswalk are shown in FIGURE 6-4. FIGURE 6-5 gives the comparison of the TC and DRS for the times at which the pedestrian cross decisions were made.

According to TABLE 6-2, for stop sign locations, most pedestrians (around 82.09 %) decided to cross in a safe situation. Besides, zero dangerous crossings have been observed. Compared to stop sign controlled crosswalks, marked and uncontrolled crosswalk locations have reduced proportions of pedestrian safe crossings and increased proportions of dangerous crossings. This is also illustrated in FIGURE 6-4**c** where the plots represent the states of vehicles when pedestrian crossing decisions were made. All pedestrian crossing decisions at stop sign controlled crosswalks fall in Phase II and Phase III. Marked crosswalks and uncontrolled ones have similar proportions in different types of crossing decisions (roughly 68 % for safe crossings, and 21 for risky crossings while 10 % for risky crossings). From FIGURE 6-4, crossing decisions made at uncontrolled crosswalks are associated with increased vehicle speed (Miranda-Moreno, et al., 2019) compared to those at marked crosswalks.

Looking at the TC and DRS results in TABLE 6-2 and FIGURE 6-5, the median TC for pedestrian crossing decisions at uncontrolled crosswalks is the highest among the three types of crosswalk. However, this does not mean that uncontrolled crosswalks protect the pedestrian crossings better. With the lower expectation of being yielded by vehicles, larger proportion of pedestrians crossing at uncontrolled crosswalks prefer a safe situation with a high TC to cross before vehicle passages, or otherwise cross after. Such crossing decisions increase median TC at uncontrolled crosswalks. Results for DRS can better illustrate pedestrian safety at these sites. The median DRS at uncontrolled crosswalks are the highest indicating that pedestrians crossing at uncontrolled crosswalks exposed to situations where drivers need sharper brakes with less comfort to yield. Pedestrians crossing before vehicle passages at marked crosswalks face less intense situations in terms of DRS. Stop sign controlled crosswalks have a much smaller DRS illustrating a noticeably safer situation for pedestrians crossing before vehicle passages.

From TABLE 6-2 and FIGURE 6-4, 3 out of the 111 crossing decisions (and 222 total interactions) at marked crosswalks ended up with evasive maneuvers. 10 out of the 25 crossing decisions (and 292 total interactions) made at uncontrolled crosswalks resulted in evasive maneuvers. Only 1 out of 134 crossing decisions (and 168 total interactions) ended up with an evasive maneuver at stop sign controlled crosswalks. Results for evasive behaviors also show that crosswalks controlled using stop signs protect pedestrians better by reducing the pedestrians, while uncontrolled crosswalks performs worst in terms of protecting pedestrians from evasive situations. Marked crosswalks have a better performance compared to uncontrolled crosswalks.

Interestingly, from FIGURE 6-4, the pedestrians made several dangerous crossing decisions but the crossings did not result in the drivers' evasive maneuvers or crashes. Checking from the video, the reason is that during those interactions vehicles already started to yield with their intention observed by pedestrians.



a) Uncontrolled crosswalk

b) Marked crosswalk

c) Stop sign controlled crosswalk

d) Pedestrian crossing decision – all sites

FIGURE 6-4 DV plots for pedestrian crossing decision before vehicle passages

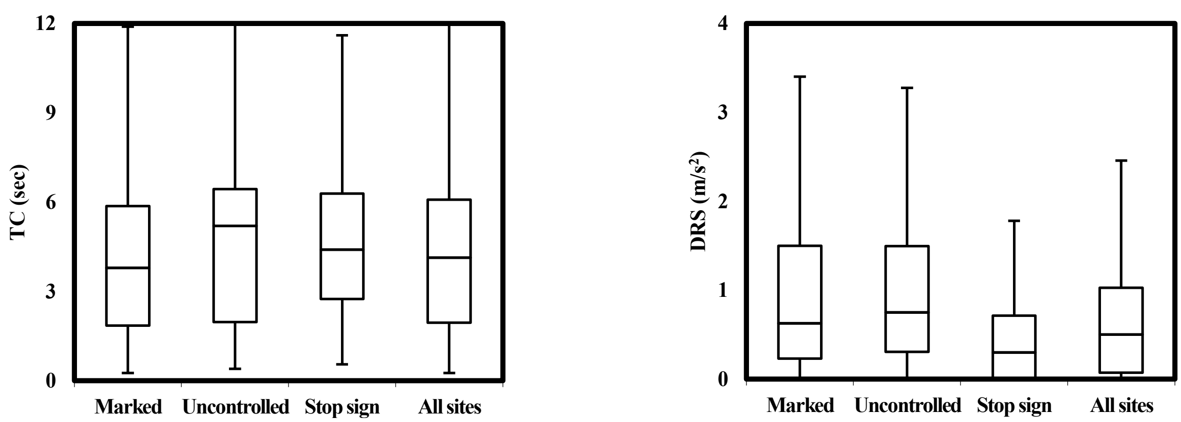


FIGURE 6-5 Result comparisons for crossing decisions before vehicle passages

6.5 CONCLUSION

This chapter validates the DV framework through data collected from multiple sites. Results suggest that the DV framework describes pedestrian-vehicle interactions in a proper way. The framework provides a novel and reliable insight at vehicle yielding behavior and pedestrian crossing decisions, as the main behavior factors related to pedestrian safety at non-signalized crosswalk locations. Assumptions made in the framework and parameters applied (the range of reaction time) have been proved to be reasonable through a large number of observations.

The performance of three main types of non-signalized crosswalks, including uncontrolled crosswalks, marked crosswalks and stop sign controlled crosswalks, on pedestrian safety have been further investigated. Results are in consistence with the previous study described in ***Chapter 5***. Stop sign controlled crosswalks have the best performance in protecting pedestrians by reducing intensity of interactions at occurrence, increasing vehicle yielding rates and compliances, and reducing dangerous crossing decisions and the chance of evasive maneuvers. Uncontrolled crosswalks do not perform effectively in protecting pedestrians as yielding compliances are very low at all the sites studied and the chance of evasive maneuvers are the highest. Marked crosswalks perform similarly in terms of the occurrence of interactions and pedestrian crossing decisions made. However, marked crosswalks have much higher yielding rates and driver yielding compliances, and reduced chance of the occurrence of evasive maneuvers indicating a better performance compared to uncontrolled crosswalks.

Despite the better performance in pedestrian safety by stop sign controlled crosswalks, stop signs reduce greatly the efficiency of vehicles which is also one of the main concerns in the field of transportation. Besides, drivers are less likely to comply stop signs if they are installed everywhere. This increases the risk for pedestrians who might pay less attention when expecting vehicles to yield. The overall performance of stop sign installations is still an open question which requires more efforts in both research and engineering. Cities should be hesitant to install stop signs at non-signalized crosswalks without further engineering analysis.

6.6 ACKNOWLEDGEMENT

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6.7 REFERENCES

Dhar, S. & Woodin, D. C., 1995. *Fluorescent Strong Yellow-green Signs for Pedestrian/School/Bicycle Crossings: Results of a New York State Study*, Albany, NY, US.

Fitzpatrick, K. et al., 2006. *Improving Pedestrian Safety at Unsignalized Crossings*, Washington DC.

Fu, T., Miranda-Moreno, L. F. & Saunier, N., 2016. Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime: Use of Thermal Video Data and Surrogate Safety Measures. *Transportation Research Record: Journal of the Transportation Research Board*, 2586, 90-99.

Gitelman, V., Carmel, R., Pesahov, F. & Chen, S., 2016. Changes in Road-user Behaviors Following the Installation of Raised Pedestrian Crosswalks Combined with Preceding Speed Humps, on Urban Arterials. *Transportation Research Part F: Traffic Psychology and Behaviour*.

Miranda-Moreno, L., Saunier, N., Ledezma-Navarro, B., St-Aubin, P., & Fu, T., 2019. *Pilot Project on the Road Safety of All-way Stops Intersections using Surrogate Safety Methods*. Direction des Transports, Ville de Montréal.

Tarko, A., Davis, G., Saunier, N., Sayed, T., & Washington, S., 2009. *White Paper: surrogate safety measures of safety.* ANB20 (3) Subcommittee on Safety Data Evaluation and Analysis Contributors.

Link between chapter 6 and chapter 7

In the previous chapter, the DV framework was validated further through a study investigating the performance of three main types of non-signalized crosswalks on pedestrian safety. Results suggest that the framework describes pedestrian-vehicle interactions in a proper way. Through the analysis on the 682 pedestrian-vehicle interaction observations, assumptions and parameters used in the framework have been proved to be reasonable.

The framework is promising for investigating other safety topics, such as pedestrian-vehicle interactions at signalized locations (e.g. interactions between pedestrians and turning vehicles), interactions between different types of road users such as pedestrians and cyclists, or cyclists and vehicles. The following chapter is about using the framework to investigate cyclist-pedestrian interactions in urban areas, which has been a topic with grooving interest recently in both traffic safety and sustainability but underestimated in previous research.

Chapter 7

Investigating Cyclist-Pedestrian Interactions at Bus Stops and Non-signalized Intersections using a Distance-Velocity Model and Speed Measures derived from Video Data

Chapter 7 Investigating Cyclist-Pedestrian Interactions at Bus Stops and Non-signalized Intersections using a Distance-Velocity Model and Speed Measures derived from Video Data

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7.1 ABSTRACT

As walking and cycling flows increase in urban areas, cyclist-pedestrian interactions also increase at road facilities. Cyclist yielding compliance rates at these locations can be low which could deteriorate pedestrian safety and comfort. To investigate pedestrian safety at these locations, this study introduces a framework using cyclists' distance, speed and yielding maneuver information at the time of pedestrian occurrence and crossing derived from video data. The distance-to-crosswalk and speed of the cyclist are used to classify the cyclist's situation at pedestrian occurrences into three categories: i) where the cyclist cannot make a full stop; ii) where the ability to yield depends on the reaction time; and iii) where the cyclist can stop to yield. Yielding behavior and crossing decision are classified. Pedestrian safety is validated using direct measures such as yielding compliance rates, and indirect measures such as time-to-crossing and deceleration rate required to stop. Cyclist crossing speeds at the crosswalk are also analyzed.

A case study involving several crosswalk locations on cycle tracks from Montreal, Canada, was conducted. Video data was collected and video-based tracking techniques were used to extract cyclist speed and distance information. Results allow for microscopic analysis and provide insight into cyclist-pedestrian interactions. Results generally show that cyclists endanger pedestrians. The factors that contribute to the low yielding compliance of cyclists and the impact of marking, and road grade on cyclist behavior are explored. This safety analysis could inform policy on bicycle yielding enforcement and bicycle braking system standards.

Keywords: pedestrian safety; cyclist-pedestrian interaction; yielding behavior; crossing decision; distance-velocity model; cyclist facility

7.2 INTRODUCTION

Active transportation, typically in the form of walking and cycling, has gained popularity as a transportation mode in recent years for many reasons. Cycling and walking provide individual benefits such as improved health, increased likelihood of social interactions, and can save commuters both money and time (Public Heath Agency of Canada, 2014). Additionally, there are societal benefits associated with cycling and walking including reduced Greenhouse Gas (GHG) emissions, and improved public health. Therefore, shifting daily travel patterns from the use of private motorized vehicles to walking and cycling could have meaningful impacts on cities meeting their sustainability goals. Cities and regions across the globe have been promoting walking and cycling by updating policy, investing in infrastructure, developing bike share programs, improving public transit networks and integrating pedestrian, cycling and public transit networks. However, as vulnerable road users, pedestrians and cyclists face a greater risk of injury and are involved in a disproportionate number of collisions on roadways (NHTSA, 2017). To achieve a major shift towards active transportation, pedestrian and cyclist safety must be better addressed in research, policy and street design.

The safety of pedestrians and cyclists is a heavily researched topic (Nabavi Niaki, et al., 2016) (Abdel-Aty & Haleem, 2010) (Zahabi, et al., 2011) (Miranda-Moreno, et al., 2011) (Abdel-Aty & Nawathe, 2006) (Cai, et al., 2017). Research in pedestrian and cyclist safety typically focuses on pedestrian and cyclist risk when exposed to motorized traffic. Although crashes involving motorized vehicles occur with a greater severity, cyclist-pedestrian crashes are also a relevant topic of study. Statistical evidence suggests that cyclist-pedestrian crashes are not rare. One report indicated that in Germany in 2016, 4050 cyclist-pedestrian crashes occurred, resulting in 11 fatalities (StBA, 2017). Tuckel, Milczarski and Maisel (2014) analyzed hospital records, from 2005 to 2011, and reported 7904 pedestrians injuries from collisions with cyclists in New York State and 6177 in California. Approximately 9 % of these injuries were treated as inpatients. Additionally, evidence from news suggests that pedestrian injuries and fatalities from cyclist-pedestrian crashes are fairly common (Evans, 2017) (Kavanagh, 2012) (Scott, 2017). Furthermore, encouragement of cycling and walking through changes in policy and improved infrastructure is likely to increase the number of cyclist-pedestrian interactions occurring in cities, making cyclist-pedestrian interactions an area of greater concern. The City of Montreal has received numerous complaints from its residents concerning poor safety perception at pedestrian crosswalks along cycle paths, especially in proximity to schools. However, work regarding the safety issues related to the interactions between pedestrians and cyclists has remained surprisingly untapped (Beitel, et al., 2017) (Tuckel, et al., 2014).

Many pedestrian safety studies have been conducted through the use of crash data (Nabavi Niaki, et al., 2016) (Zahabi, et al., 2011). This approach can be problematic as crash data is not always available and suffers from issues including low-mean, small sample, underreporting, location errors and misclassification (Fu, et al., 2016). It is essentially impossible to measure pedestrian safety with respect to bicycles using crash data as crashes are often neglected or not well reported in many cities. Therefore, studying road user behavior and investigating non-crash related measures, i.e. surrogate measures of safety, in such conditions is the most promising option and will provide a better understanding of the collision processes.

This paper proposes a methodology for investigating and estimating the safety of cyclist-pedestrian interactions at pedestrian crossings located at non-signalized intersections and bus stops. This is intended to address an important research gap in the field of pedestrian safety (Afghari, et al., 2014). Based on a recently-proposed safety model framework, known as the Distance-Velocity (DV) model, presented and implemented in (Fu, et al., 2018) for vehicle-pedestrian interactions, cyclist yielding maneuvers and pedestrian crossing decisions in cyclist-pedestrian interactions are explored using video data. Speed measures were also investigated in supplement to the DV framework. The impact of crosswalk marking and road grade on the behavior and deceleration rate of upstream and downstream cyclists is investigated as well. For this purpose, video data is collected and analysed from multiple bus stops and non-signalized intersections.

7.3 LITERATURE REVIEW

The literature on cyclist-pedestrian interactions, behavior and yielding is limited. This research gap may exist because cyclist-pedestrian interactions are less likely to result in a severe collision than vehicle-pedestrian interactions. Therefore, despite the prevalence of these active transportation modes, the vast body of literature in road safety is limited to the study of interactions with vehicles. Recent practices for assessing active transportation safety rely on collision records and collision models (Zahabi, et al., 2011), (Miranda-Moreno, et al., 2011) & (Mohamed, et al., 2013). However, the use of collision-based analysis for cyclist-pedestrian safety diagnosis is impossible in most situations. Therefore, the only feasible strategy for estimating safety in cyclist-pedestrian interactions is through road user behavior analysis and surrogate safety measures (SSM).

Automated video-based techniques that use SSMs are becoming more common in road safety analysis (Fu, et al., 2016). Different techniques and sensors, including loops, radars and GPS devices have been used to extract information for surrogate safety analysis (Stipancic, et al., 2016) (Golob, 2004) (Lee, 2002). Among the several SSMs proposed in the literature, the most commonly used are time-to-collision (TTC) and post-encroachment time (PET). PET is the time difference for two road users passing at the same location. One study investigated safety in cyclist-pedestrian interactions using PET, cyclist speed and the type of interaction, based on the angle of approach and the first user to arrive at the collision point, but did not consider yielding behavior (Beitel, et al., 2017).

The importance of yielding right-of-way to pedestrians in interactions involving cyclists or vehicles is underscored by the vulnerability of pedestrians, compared to other road users. Yielding is therefore a critical component of safety in interactions at non-signalized intersections. Research considering yielding compliance of cyclists is limited. One study explained low cyclist yielding compliance based on the large effort required to make a complete stop and then accelerate back to cruising speed (Fajans & Curry, 2001). However, compared to situations where no pedestrian is present, a greater proportion of cyclists decrease their speed if they perceive a potential traffic conflict with a pedestrian (Ayres, et al., 2015). Research in vehicle-pedestrian interactions, which have been more thoroughly studied, is nonetheless limited in the area of driver yielding behavior. There are situations where it is impossible for vehicles and cyclists to yield when considering their proximity to the crosswalk at the pedestrian crossing decision. Such situations are likely considered as violations in most previous studies. The ability for a vehicle or cyclists to yield must be considered when studying vehicle and cyclist yielding behavior.

Several studies have investigated vehicle-pedestrian interactions through the analysis of yielding behavior and pedestrian crossing decision (Li, et al., 2015) (Afghari, et al., 2014). This methodology remains untested for cyclist-pedestrian interactions. Applying this methodology to cyclist-pedestrian interactions is non-trivial as bicycles and vehicles behave in different ways. This paper will address this research gap by proposing a methodology to investigate cyclist yielding behavior and pedestrian crossing decision for cyclist-pedestrian interactions. The methodology is then applied to a case study on crosswalk performance at non-signalized urban intersections with painted cycle tracks, and bus stop locations along segregated bicycle facilities in Montreal.

7.4 METHODOLOGY

The methodology section outlines the mechanism of cyclist braking systems, followed by the description of the DV framework. Data collection and processing methods are detailed as well.

7.4.1 Bicycle Braking System and Deceleration Rate

Ideally, the bicycle deceleration rate reaches a maximum when the pavement friction coefficient is at a maximum. However, this is rarely achieved for cyclists since they tend to avoid sharp deceleration and complete stops and many braking systems cannot provide the friction coefficient that matches the maximum value that the pavement can provide. The analysis in this paper makes use of past work by the USDOT that validated cyclist yielding behavior and pedestrian crossing decisions (Landis, et al., 2004): the authors investigated the deceleration rate and the corresponding friction coefficient for cyclists and found the 85th percentile deceleration rate for bicycles to be 3.3 m/s^2, and the corresponding reference friction coefficient to be 0.32 for level road situations (Landis, et al., 2004). In this paper, the reference friction coefficient is considered as the greatest friction coefficient a cyclist can achieve (μ_{max}) and is applied in the model.

For roads with a non-zero grade, the effect of the road grade is considered in calculating the deceleration rate of the bicycle. Then, the deceleration rate is a function of the grade degree and the pavement friction coefficient and can be presented as:

$$a = g(\mu - \theta) \tag{1}$$

where, a is the deceleration rate, g is the gravitational acceleration, μ is the friction coefficient and θ is the road grade in radians. The deceleration rate reaches its maximum when the friction coefficient reaches maximum, e.g. 0.32. With a change of road grade of 1° (1.75 %), the maximum deceleration rate that the cyclist can achieve changes by 5 %. Thus, road grade significantly affects cyclist deceleration. Meanwhile, due to the gravitational potential energy, bicycles traveling downhill easily reach a higher speed compared to those traveling uphill. Bicycles traveling downhill travel at higher speed and are less able to brake, leading to an increased crash probability and severity, thus an increased crash risk. The novel safety framework used to investigate vehicle-pedestrian interactions presented in (Fu, et al., 2018) can also be applied to study cyclist-pedestrian interactions.

7.4.2 DV Model for Cyclist-pedestrian Interactions

This section provides a brief introduction of the DV framework. Details for the basic assumptions, model derivation and definitions are provided in (Fu, et al., 2018). Parameters such as maximum deceleration rate are adjusted for cyclists.

7.4.2.1 Practical definitions

According to the DV framework proposed in (Fu, et al., 2018), several key definitions are given below:

- The pedestrian occurrence is the time when the pedestrian arrives at the area within a cross-section distance of 1 m from the crosswalk marking, and shows the intention to cross the street (e.g. facing the road or turning their head toward the road).
- The pedestrian crossing decision is defined as the time when the pedestrian starts to cross the street, regardless if he/she has to retreat because of non-yielding cyclists. Actual crossing attempts include keeping a constant walking speed to cross after arrival without waiting, and starting to cross after waiting or hesitating after arrival.
- For pedestrian groups, the occurrence of the group is defined as the first occurrence of a pedestrian from the group. However, each pedestrian is considered to be individually exposed to the risk of collision.
- The investigated cyclist-pedestrian interactions are the situations in which a cyclist approaches a crosswalk and a pedestrian is either already moving to cross, already present in a position showing willingness to cross, or arriving with an intent to cross.

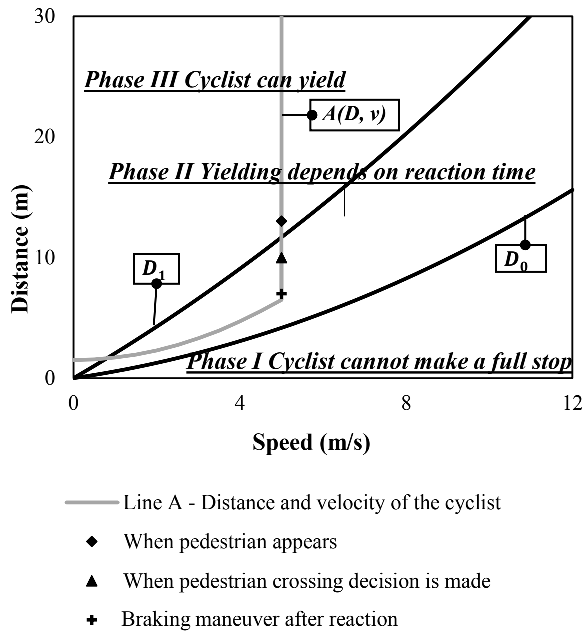
7.4.2.2 Introduction of the Model

According to (Fu, et al., 2018), the minimum distance D_{min} required for a cyclist to make a full stop to yield to a pedestrian present at the crosswalk can be computed as:

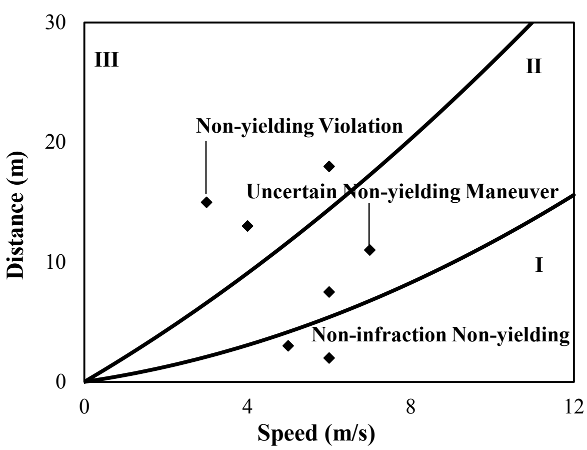
$$D_{min} = vt_r + v^2/(2g \cdot (\mu_{max} - \theta)) \tag{2}$$

where, v is the initial speed of the cyclist at the occurrence of the pedestrian, t_r is the perception-reaction time of the cyclist, μ_{max} is the maximum friction coefficient of the road and θ is the road grade.

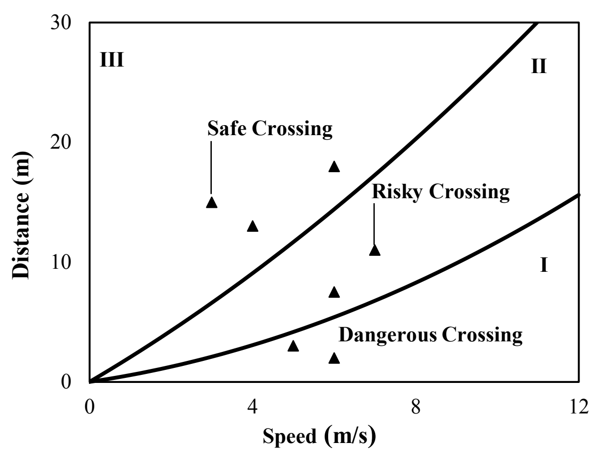
Assuming the reaction time range as $[t_{r\_min}, t_{r\_max}]$, then D_{min} is in a range of $[D_0, D_1] = [vt_{r\_min} + v^2/(2g \cdot (\mu_{max} - \theta)), vt_{r\_max} + v^2/(2g \cdot (\mu_{max} - \theta))]$. The curves of D_0 and D_1 in a DV diagram are presented in FIGURE 7-1a. The diagram is then divided into three phases: i) phase I, where cyclists cannot make a full stop, ii) phase II, where the cyclist's ability to stop and yield depends on the cyclist's reaction time, and iii) phase III, where cyclists can stop. Reaction time of the cyclist varies. According to (AASHTO, 1999), the reaction time in response to expected events varies between 0.5 and 2.5 sec.



a. Explanation of D-V diagram with example values



b. Classification of non-yielding maneuvers



c. Classification of pedestrian crossing decisions

FIGURE 7-1 DV diagram for cyclist-pedestrian interaction

7.4.2.3 Model Applications and Related Measures

According to the DV framework proposed in (Fu, et al., 2018), several classifications and safety measures can be derived from the (D,V) coordinates when the pedestrian starts to cross:

- Cyclist yielding behavior is classified as: 1) yielding maneuvers; 2) non-infraction non-yielding maneuvers (Phase I), where cyclists are not able to stop; 3) uncertain non-yielding maneuvers (Phase II), where cyclists may or may not be able to react in time to stop; and 4) non-yielding violations (Phase III) where cyclists have enough time to react and brake but choose not to yield. The classification of non-yielding maneuvers is illustrated in FIGURE 7-1b.
- The yielding rate is the proportion of cyclists that yield right-of-way to pedestrians out of the total number of cyclists studied. The yielding compliance is the proportion of cyclists yielding right-of-way out of the cyclists that are physically able to yield (interactions that fall into Phase II and Phase III).
- The classification of crossing decisions is illustrated in the DV diagram in Fig. 1c. There are four cases: 1) dangerous crossings, occurring in Phase I, where pedestrians expose themselves to dangerous interactions with cyclists that cannot yield; 2) risky crossings, occurring in Phase II, where pedestrians are at risk as cyclists may not have enough time to react and yield; 3) safe crossings, occurring in Phase III where pedestrians are relatively safe given that cyclists are either not on a collision course or have enough time to react and yield; and 4) crossings after the cyclist passage where pedestrians give up to cross with cyclists approaching.
- Collision risk measures, as proposed in (Fu, et al., 2017), comprise two measures used for quantifying the risk of collision: 1) the time to crossing (TC); and 2) the deceleration required to stop (DRS). TC refers to the time required for the cyclist to reach the pedestrian crossing path if continuing at constant speed. DRS is the constant deceleration rate required for the cyclist to stop and give the right-of-way to pedestrians.

7.5 CASE STUDY

Two types of crosswalk locations from Montreal are included: 1) crosswalks at non-signalized intersections; 2) crosswalks at bus stops along segregated cycle tracks.

7.5.1 Site and Data Description

The selected sites and their characteristics are presented in TABLE 7-1.

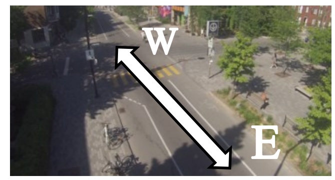
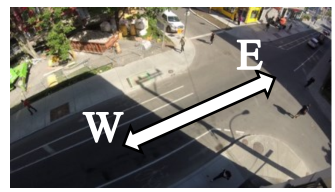
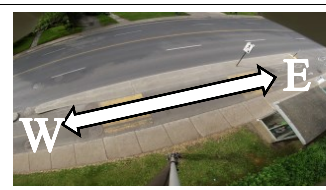
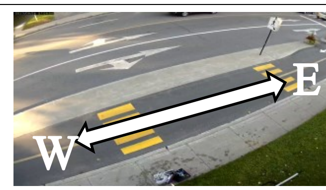
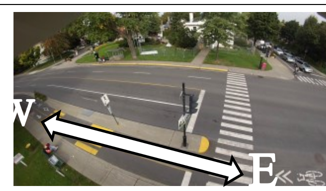
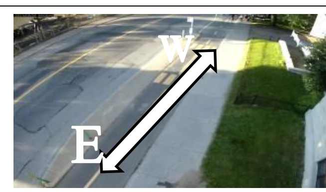
- *Crossings at non-signalized intersections:* two sites were picked from intersections without traffic lights or stop signs. Painted cycle tracks are located along the side of the road and carry a high volume of cyclists. The selected intersections have zero grade and high pedestrian volumes crossing the street. Site I-1 has a marked crosswalk, while the crosswalk at Site I-2 is unmarked. Comparisons are made to investigate the effectiveness of crosswalk markings on cyclist-pedestrian interactions.
- *Crossings at bus stops:* for investigating cyclist-pedestrian interactions at bus stops along segregated cycle tracks, five sites (with crosswalk markings) were selected from two high-traffic streets. Different grades on the study cycle tracks exist.

For data collection, mobile camera systems provide the entire view of the crosswalk area including the cycle track approaches where cyclists are coming from. GoPro's Hero 3 Edition cameras were used. The cameras were temporally mounted on portable poles, fixed to lampposts. Video data were collected on weekdays during daytime hours. For comparison, all video data for sites belonging to the same crosswalk type were collected with similar weather and traffic conditions. Additional details of the sites, including the location, road grade, built environment and the amount of video data recorded are presented in TABLE 7-1.

After data collection, automated video-based tracking techniques were applied to extract trajectory data. Video data processing was conducted using the tracker in the open source Traffic Intelligence project (Saunier & Sayed, 2006), which has been proved to provide highly accurate outputs of road users (Anderson-Trocme, et al., 2015) (Fu, et al., 2017). Details of video data processing for the DV framework have been included in (Fu, et al., 2018).

TABLE 7-1 Descriptions of Sites and Video Data Recorded

Site ID	Site Name	Type of the Road	Grade (rad.)	Date/Time	Duration (hour)
		Sites at Non-signalized Intersections			
I-1	**Laurier_Rivard**	Level	0	17-Jun-2016 / 10:00-16:30	6.5
I-2	**Laurier_Drolet**	Level	0	17-Jun-2016 / 10:00-14:30	4.5
		Sites at Bus Stop Locations			
II-1	**CSC_Dunlop**	Non-Zero Grade	0.026	02-Oct-2013 / 10:30-16:40	6.3
II-2	**CSC_Pagnuelo**	Non-Zero Grade	0.033	25-Sep-2013 / 09:00-17:15	8.3
II-3	**CSC_Courcelette**	Non-Zero Grade	0.028	25-Sep-2013 / 09:00-17:00	8.0
II-4	**Rachel_Chapleau**	Level	0	30-Sep-2013 / 09:00-17:30	8.5
II-5	**Rachel_Messier**	Level	0	30-Sep-2013 / 09:00-17:10	8.2

Site ID	Site Name	Site Description	Camera View
I-1	**Laurier_Rivard**	· **Street Located:** Rue Laurier · **The Closest Intersection:** Rue Rivard · **Cycle Track:** painted cycle track on both sides of the road · **Type of crosswalk:** marked crosswalk with pedestrian sign	
I-2	**Laurier_Drolet**	· **Street Located:** Rue Laurier · **The Closest Intersection:** Rue Drolet · **Cycle Track:** painted cycle track on both sides of the road · **Type of crosswalk:** unmarked crosswalk	
II-1	**CSC_Dunlop**	· **Street Located:** Chemin de la Côte-Sainte-Catherine · **The Closest Intersection:** Rue Dunlop · **Bus Lines:** 51, 119, and 129 · **Bus Volume:** average 10 buses per hour · **Built Environment:** a music college is near the bus stop which brings dense pedestrian traffic during peak hours when students leave school.	
II-2	**CSC_Pagnuelo**	· **Street Located:** Chemin de la Côte-Sainte-Catherine · **The Closest Intersection:** Rue Pagnuelo · **Bus Lines:** 51, and 129 · **Bus Volume:** average 10 buses per hour · **Built Environment:** the site is on the approach of the intersection, therefore cyclist traffic is affected by the traffic light.	
II-3	**CSC_Courcelette**	· **Street Located:** Chemin de la Côte-Sainte-Catherine · **The Closest Intersection:** Rue Courcelette · **Bus Lines:** 51, 119, 129, and 368 · **Bus Volume:** average 11 buses per hour · **Built Environment:** the site is on the approach of the intersection, therefore cyclist traffic is affected by the traffic light.	
II-4	**Rachel_Fullum**	· **Street Located:** Rue Rachel · **The Closest Intersection:** Rue Fullum · **Bus Lines:** 29 · **Bus Volume:** average 2 buses per hour · **Built Environment:** nothing specific	
II-5	**Rachel_Messier**	· **Street Located:** Rue Rachel · **The Closest Intersection:** Rue Messier · **Bus Lines:** 29 · **Bus Volume:** average 2 buses per hour · **Built Environment:** nothing specific	

7.5.2 Results and Discussions

The results are summarized in two parts: behavior analysis using DV framework and speed analysis.

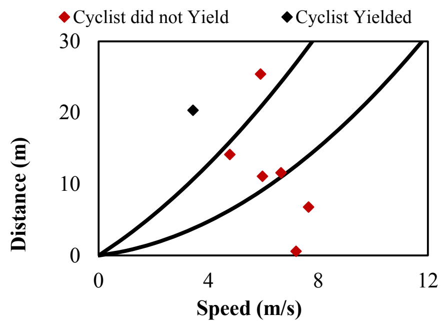
7.5.2.1 Behavioral Analysis

Based on trajectory data extracted from video recordings, cyclist-pedestrian interactions were analyzed using the DV framework, and road user behaviors were investigated. TABLE 7-2 and TABLE 7-3 provide the summary of the results.

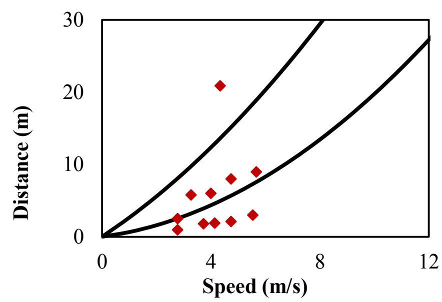
(1) **Illustration of the DV Framework Output**

The DV framework was applied to investigate cyclist-pedestrian interactions and road user behavior during these interactions. The distance to the crosswalk and the approaching speed of the cyclist at the pedestrian occurrence can be extracted to determine if the cyclist cannot, may be able to, or can stop (as represented by phases I, II, III in the DV diagram). Then, based on whether the cyclist yielded or not, their yielding behavior can be classified. Finally, the risk category in which the pedestrian decided to cross can be evaluated. Additionally, microscopic data related to road user behavior and safety can be extracted, such as TC, cyclists' DRS at the pedestrian occurrence, and cyclists' DRS at the pedestrian crossing decision.

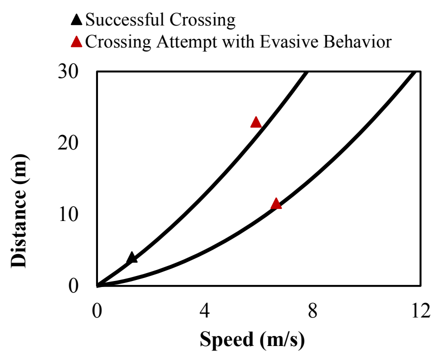
The diagram of the DV framework provides a data visualization to analyze road user behavior under different situations and for different sites. The DV output of cyclist and pedestrian behavior for Site II-1 is illustrated in FIGURE 7-2. For example, in FIGURE 7-2a, illustrating seven pedestrian interactions with downhill cyclists, there was: one yielding event, one non-yielding violation, three uncertain non-yielding interactions, and two non-infraction non-yielding interactions. Additionally, of the seven interactions, three pedestrian crossing attempts were made and are illustrated in FIGURE 7-2c. Two pedestrians made safe crossing decisions, where the cyclist could stop in time; however, one of those pedestrians was required to take evasive action due to the non-yielding violation of the cyclist. One pedestrian attempted to cross in a risky situation and was required to take evasive action. Lastly, the four interactions omitted from FIGURE 7-2c represent pedestrians who decided to cross after the cyclist passed. Results for uphill cyclists are presented in FIGURE 7-2b and 2d.



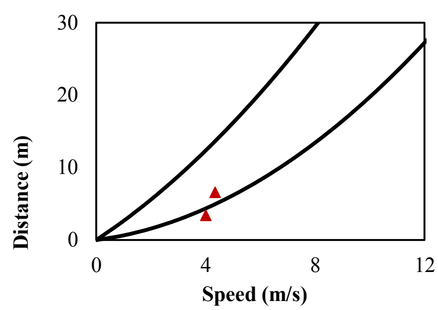
a) Yielding behavior - downhill



b) Yielding behavior uphill



c) Crossing decision - downhill cyclists



d) Crossing decisions uphill cyclists

FIGURE 7-2 Example of DV diagram for cyclist-pedestrian interaction – site I

(2) **Sites at non-signalized urban intersections**

- Yielding Behavior and Compliance

The yielding rate was found to be low for both sites, as seen in TABLE 7-2. It is important to distinguish between the two sites with respect to yielding requirements. Site 1 is a marked crossing, and therefore cyclists are required to yield to pedestrians by law. On the other hand, Site 2, the control site, is unmarked; cyclists are not required to yield to pedestrians, in fact, pedestrians are required to wait for a sufficient gap before attempting to cross. The yielding compliance of cyclists at the marked crosswalk is 14 %, higher than at the control site, with the unmarked crosswalk, where less than 3 % of cyclists yielded to pedestrians. This indicates that the crosswalk marking does prompt approximately one out of every ten cyclists to yield to pedestrians. The low proportion of cyclists that yield right-of-way to pedestrians at intersections with crosswalk markings suggests that road markings do not have a significant impact on cyclist behavior.

From TABLE 7-2, the median TC (4.72 s) was higher at the unmarked crosswalk compared to the median TC (4.21 s) at the marked crosswalk. However, this does not indicate that the unmarked crosswalk is safer. In fact, given the fact less pedestrians were yielded at the unmarked crosswalk, those pedestrians were exposed to additional and unnecessary interactions (that won't happen if the previous cyclist yields) with cyclists coming after. Although the increase in the additional and unnecessary interactions made unmarked crosswalk more dangerous, the cyclists involved in those interactions have higher TC during the pedestrian events, which will lead to an increased median TC at the unmarked crosswalk."

- Crossing Decisions

From FIGURE 7-3, most pedestrians at these two sites chose to cross after the cyclist crossed at both sites. A greater proportion of pedestrians that crossed after the cyclist passage at the unmarked crosswalk (94.1 %) is found compared to marked crosswalk (85.7 %). The reason is that, due to the increased yielding attempts at the marked crosswalk, pedestrians had more opportunity to use their right-of-way.

At the marked crosswalk, 19 interactions were found where pedestrians decided to cross before the cyclist passage, fifteen were given the right-of-way by the cyclist and the remaining four pedestrian crossings were interrupted by non-yielding cyclists. The four interactions, where the pedestrian crossing was disrupted by a non-yielding cyclist, are considered as conflicts because at least one user was required to make an evasive maneuver to avoid collisions.

(3) **Sites at bus stop locations**

- Yielding Behavior and Compliance

From TABLE 7-3, only 8.2 % of the cyclists yielded right-of-way to pedestrians. Additionally, the overall yielding compliance was 19.6 %. In other words, approximately 90 % of cyclists in the presence of a crossing pedestrian refused to yield. Although the yielding and compliance rate varied slightly across sites, they were low for all sites. Conclusions cannot be drawn by comparing different sites given the limited number of observations of yielding maneuvers.

As shown in TABLE 7-3, interactions involving downhill and uphill cyclists had similar TC values and were found in similar proportions for each phase; however, the deceleration rates required to stop (DRS) were significantly higher for downhill cyclists. As expected, this indicates that interactions involving uphill cyclists are safer as they travel more slowly, requiring a reduced DRS, and can achieve increased maximum deceleration rate due to the road grade. Larger median TC and smaller deceleration rates required to stop for cyclist-pedestrian interactions at level road crossings were found. However, half of the interactions involved non-yielding maneuvers of the multiple cyclists in sequence to one pedestrian. In these cases, the pedestrian tends to wait for an extended period of time to cross. This has the effect of generating a large TC and a small DRS.

Despite the impact that road grade may have on cyclist yielding capability, yielding compliance remained low across all road grades. In general, the cyclists that were studied appeared unwilling to yield regardless of road grade.

- Crossing Decisions

The majority (48 out of 61) of pedestrians decided to cross after the cyclist, as illustrated in TABLE 7-3. Two out of the 13 remaining crossings were dangerous, three were risky and eight were safe. The results are intuitive; a greater number of pedestrians crossed in Phase III as cyclists have more time to respond and yield by slowing down or stopping completely.

The proportion of pedestrians crossing after the cyclist passage in the interactions remained similar for all road grade types: uphill, downhill and flat. As seen in TABLE 7-3, four out of five pedestrians crossed after the cyclist for all three road grade types. This relatively high proportion may be the result of pedestrians responding to low cyclist yielding rates. Interestingly, dangerous crossing decisions were only observed among interactions occurring in uphill situations as indicated in FIGURE 7-4. This finding can be explained by the fact that pedestrians feel safer to cross in front of the cyclists going uphill given the reduced speed and increased deceleration.

TABLE 7-2 Results – Sites at Non-signalized Urban Intersections

Site ID - Name Road Type		I-1 Laurier_Rivard Level - marked	I-2 Laurier_Drolet Level - unmarked	Summary of the Two Sites
Number of Interactions				
No. of Total Interactions		133	51	184
No. of Interactions in Phase I		35	12	47
No. of Interactions in Phase II		40	11	51
No. of Interactions in Phase III		58	28	86
Results for Yielding Behavior				
No. of Non-infraction Non-Yieldings		35	12	47
No. of Uncertain Non-yieldings		34	11	45
No. of Non-Yielding Violations		50	27	77
No. of Yielding Maneuvers		14	1	15
Yielding Rate		10.5 %	2.0 %	8.2 %
Yielding Compliance		14.3 %	2.6 %	10.9 %
TC (sec)	*Median*	4.21	4.72	4.34
	Std. Dev.	4.34	4.57	4.41
DRS (m/s^2)	*Median*	0.73	0.69	0.72
	Std. Dev.	1.79	2.92	2.37
Results for Crossing Decisions				
No. of Dangerous Crossings		2	1	3
3No. of Risky Crossings		8	0	8
No. of Safe Crossings		9	2	11
No. of Decisions to Cross after Cyclist Passage		114	48	162
TC (sec)	*Median*	2.16	2.78	2.39
	Std. Dev.	2.16	1.73	2.07
DRS (m/s^2)	*Median*	0.89	0.99	0.94
	Std. Dev.	1.68	3.31	1.92

TABLE 7-3 Results – Crosswalks at Bus Stops along Segregated Cycle Tracks

Site ID - Name		II-1 CSC_Dunlop			II-2 CSC_Pagnuelo			II-3 CSC_Courcelette		
Road Type		Downhill	Uphill	Overall	Downhill	Uphill	Overall	Downhill	Uphill	Overall
Number of Interactions										
No. of Total Interactions		7	11	18	4	11	15	6	1	7
No. of Interactions in Phase I		2	6	8	2	2	4	2	0	2
No. of Interactions in Phase II		3	4	7	2	6	8	3	0	3
No. of Interactions in Phase III		2	1	3	0	3	3	1	1	2
Results for Yielding Behavior										
No. of Non-infraction Non-Yieldings		2	6	8	2	2	4	2	0	2
No. of Uncertain Non-yieldings		3	4	7	2	3	5	3	0	3
No. of Non-Yielding Violations		1	1	2	0	3	3	1	1	2
No. of Yielding Maneuvers		1	0	1	0	3	3	0	0	0
Yielding Rate		14.3 %	0.0 %	5.6 %	0.0 %	27.3 %	20.0 %	0.0 %	0.0 %	0.0 %
Yielding Compliance		20.0 %	0.0 %	10.0 %	0.0 %	33.3 %	27.3 %	0.0 %	0.0 %	0.0 %
TC (sec)	*Median*	1.86	0.90	1.54	1.98	3.77	2.26	1.93	4.55	1.94
	Std. Dev.	2.02	1.29	1.67	0.78	2.57	2.33	1.61	--	1.67
DRS (m/s^2)	*Median*	1.58	2.00	2.00	2.48	0.67	1.35	2.18	0.60	1.93
	Std. Dev.	3.53	1.01	2.51	2.12	2.04	2.11	5.51	--	5.20
Results for Crossing Decision										
No. of Dangerous Crossings		0	2	2	0	0	0	0	0	0
No. of Risky Crossings		2	0	2	0	0	0	0	0	0
No. of Safe Crossings		1	0	1	0	3	3	0	0	0
No. of Decisions to Cross after Cyclist Passage		4	9	13	4	8	12	6	1	7
TC (sec)	*Median*	3.15	1.51	1.74	--	8.33	8.33	--	--	--
	Std. Dev.	1.28	0.02	1.25	--	3.47	3.47	--	--	--
DRS (m/s^2)	*Median*	0.36	0.87	0.73	--	0.11	0.11	--	--	--
	Std. Dev.	0.00	0.20	0.32	--	0.16	0.16	--	--	--

(Continued)

TABLE 7-3 Continued

Site ID - Name		II-4 Rachel_Fullum	II-5 Rachel_Messier	Summary of the Five Sites			
Road Type		Level	Level	Downhill	Uphill	Level	Overall
		Number of Interactions					
No. of Total Interactions		3	18	17	23	21	61
No. of Interactions in Phase I		0	1	6	8	1	15
No. of Interactions in Phase II		1	1	8	10	2	20
No. of Interactions in Phase III		2	16	3	5	18	26
		Results for Yielding Behavior					
No. of Non-infraction Non-Yieldings		0	1	6	8	1	15
No. of Uncertain Non-yieldings		1	1	8	7	2	17
No. of Non-Yielding Violations		2	15	2	5	17	24
No. of Yielding Maneuvers		0	1	1	3	1	9
Yielding Rate		0.0 %	5.6 %	5.9 %	13.0 %	4.8 %	8.2 %
Yielding Compliance		0.0 %	5.9 %	9.1 %	20.0 %	5.0 %	19.6 %
TC (sec)	*Median*	7.83	6.51	1.91	1.89	6.6	2.98
	Std. Dev.	4.50	4.45	1.59	2.30	4.34	3.72
DRS (m/s^2)	*Median*	0.36	0.33	2.14	1.29	0.34	0.77
	Std. Dev.	0.69	0.34	3.94	1.67	0.39	2.61
		Results for Crossing Decision					
No. of Dangerous Crossings		0	0	0	2	0	2
No. of Risky Crossings		0	1	2	0	1	3
No. of Safe Crossings		0	4	1	3	4	8
No. of Decisions to Cross after Cyclist Passage		3	13	14	18	16	48
TC (sec)	*Median*	--	4.10	3.07	4.61	4.10	4.10
	Std. Dev.	--	1.10	1.28	4.39	1.10	2.84
DRS (m/s^2)	*Median*	--	0.83	0.81	0.37	0.83	0.73
	Std. Dev.	--	0.27	0.30	0.40	0.27	0.36

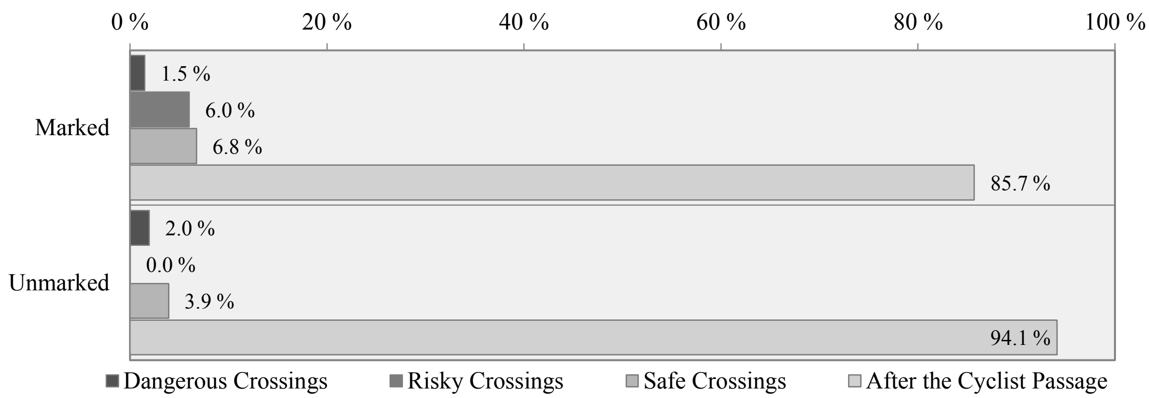


FIGURE 7-3 Crossing decisions of pedestrians at non-signalized intersections: marked vs. unmarked

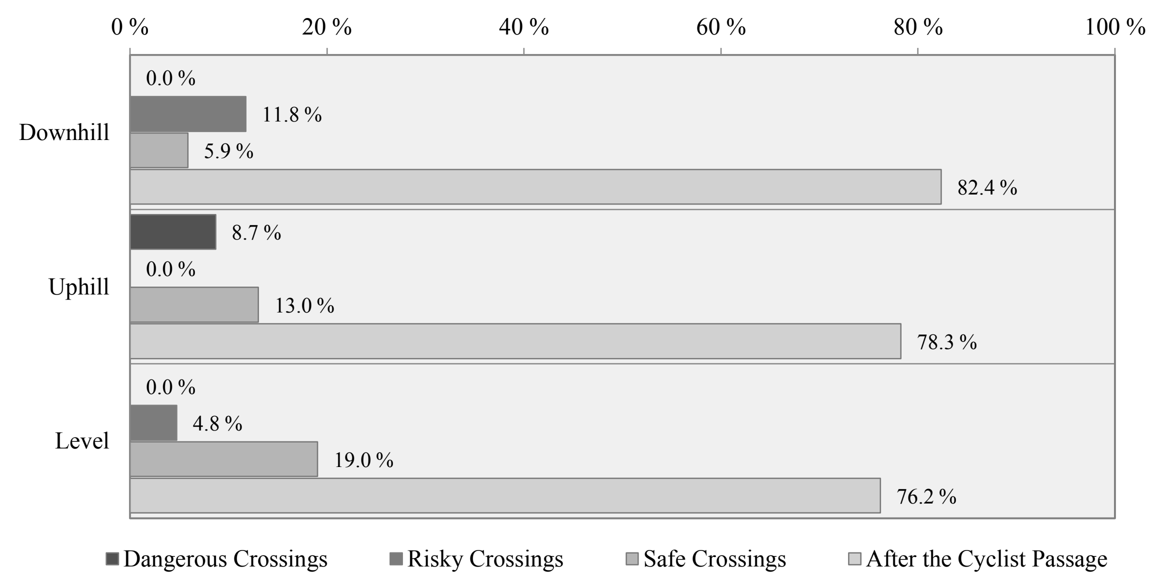


FIGURE 7-4 Crossing decisions of pedestrians at bus stop locations: different road grade situations

7.5.2.2 Speed Data

(1) **Sites at non-signalized urban intersections**

The average crossing speeds of cyclists, when passing the crossing location (Fu, et al., 2016), are investigated. The statistical summary of the crossing speed data is included in TABLE 7-4. Distributions of crossing speeds at the marked and unmarked crosswalks are presented in FIGURE 7-5a. Results suggest that the presence of crosswalk marking helps reduce cyclist crossing speed, by 3.35 km/h on average. Crossing speed data for cyclists involved in cyclist-pedestrian interactions are also presented in TABLE 7-4. The reduction in average crossing speed at the marked crosswalk is noticeable (2.89 km/h); however, cyclists do not seem to decrease their speeds when they pass by pedestrians waiting to cross. An explanation for this can be that cyclists reduce their speed when passing the marked crosswalk to avoid collisions, but do not slow down to yield right-of-way.

(2) **Sites at bus stop locations**

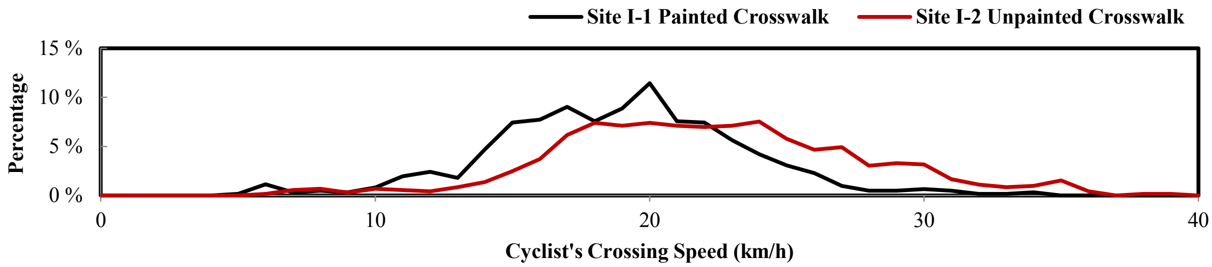
FIGURE 7-5b presents the distributions of cyclist crossing speeds extracted from each site, and lastly, a combination of all five sites separated by the three different road grade types. Due to the impact of road grade, it is not surprising to find that, on average, cyclists going downhill travel 23.2 % faster compared to those on the level road. Similarly, the mean crossing speed of cyclists going uphill is 20.6 % lower than those traveling on a level road.

No significant reduction in cyclist crossing speed was found for cyclists involved in an interaction with a pedestrian, indicating that cyclists did not slow when pedestrians were waiting along the cycle track to cross. This is different from most results in the literature for finding does not support most of the studies investigating pedestrian-vehicle interactions where vehicles were found to slow down (Boyce & Van Derlofske, 2002). In other words, pedestrian crosswalks along cycle tracks were not effective in protecting pedestrians.

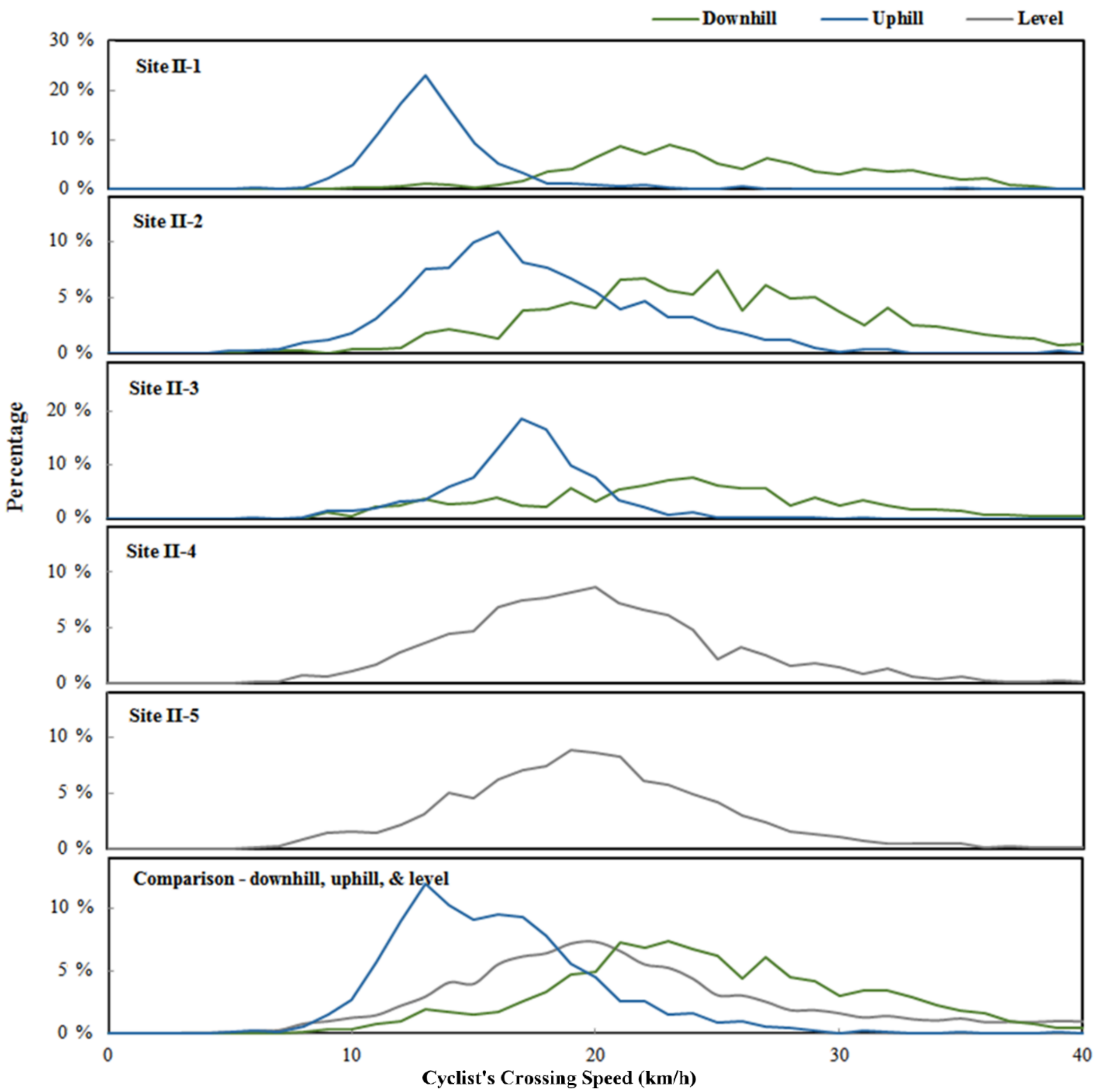
A reduction of cyclist crossing speed, associated with the pedestrian occurrence, was found to be more significant for level grade type compared to uphill and downhill grade types. This difference between grade types is intuitive. At level grade crossings, cyclists tend to stop pedaling in pedestrian interactions to avoid potential crashes, resulting in a reduction of crossing speed due to the road friction. On the other hand, cyclists traveling downhill may prepare to brake but often do not brake unless the pedestrian decides to cross first. In this situation, although the cyclist may not be pedaling, their crossing speed remains high because of the gravity potential. Lastly, cyclists traveling uphill are less likely to stop pedaling in the presence of a pedestrian due to the greater effort they need to maintain, or retrieve their crossing speed.

TABLE 7-4 Summary of the Cyclist Crossing Speed (km/h)

		Counts	Mean	Std. Dev	Max	Min
Crosswalks at Non-signalized Intersections						
		Marked vs Unmarked (all cyclist)				
Site I-1 – Marked		2717 (418 /hr)	18.36	4.49	37.61	4.71
SiteII-2 – Unmarked		2032 (451 /hr)	21.71	5.46	38.47	5.57
		Marked vs Unmarked (cyclists involved in interactions)				
Site I-1 – Marked		133	18.46	5.62	35.72	4.74
SiteII-2 – Unmarked		51	21.35	5.22	35.83	8.00
Crosswalks at Bus Stops along Segregated Cycle Tracks						
		Each Site				
	Downhill	962 (153 /hr)	24.47	5.65	43.98	7.79
Site II-1	*Uphill*	755 (120 / hr)	13.07	3.15	34.54	3.62
	Downhill	801 (97 / hr)	19.88	5.65	40.61	4.27
Site II-2	*Uphill*	797 (93 /hr)	13.59	3.84	31.48	3.34
	Downhill	545 (68 /hr)	22.38	6.59	39.90	8.03
Site II-3	*Uphill*	596 (75 /hr)	16.49	3.13	30.87	5.87
Site II-4		1795 (212 /hr)	19.49	5.54	42.49	5.67
Site II-5		1825 (223 /hr)	19.31	5.48	48.09	5.37
		Different Road Grade Types (all cyclists)				
Downhill		2308	23.90	6.25	43.98	4.27
Uphill		2148	15.41	4.19	34.54	3.34
Level		3620	19.40	5.51	42.49	5.37
		Different Road Grade Types (cyclists involved in interactions)				
Downhill		17	23.61	6.10	33.08	4.68
Uphill		23	14.56	3.93	20.40	6.48
Level		21	16.82	3.67	23.14	10.50



a) Non-signalized intersections: marked vs. unmarked



b) Bus stop locations: different road grade situations

FIGURE 7-5 Distribution of cyclist's crossing speed for site studied

7.6 CONCLUSION

This paper adapted a framework (Fu, et al., 2018), previously used to study safety in vehicle-pedestrian interactions, to study cyclist-pedestrian interactions. The framework, named the DV framework, is tested through a case study using video data from two different types of pedestrian crosswalk locations. The effectiveness of crosswalk marking, and three road grade types including uphill, downhill, and level road were studied and compared for relative safety. Results generally show that cyclists endanger pedestrians intending to cross. Some key conclusions can be drawn:

- From the case study, cyclists' yielding compliance at the marked crosswalk is surprisingly low. Most cyclists did not yield to pedestrians even when able to. Additionally, an evasive maneuver was required when a pedestrian chose to cross before the cyclist passage. Although crosswalk markings increased the yielding by approximately 10 %, with respect to the control site, overall, painted crosswalks alone fail to protect pedestrians from passing cyclists.
- The results indicate the existence of safety issues at pedestrian crossings on cycling facilities with downhill grades, which has been underestimated and seen little previous research. Currently, not much work has been taken in protecting pedestrians from cyclists. Several countermeasures, such as education, enforcement, and new road treatments should be implemented in order to protect pedestrians.
- The study, by using the DV framework and speed analysis, provides explanation and evidence that interactions between pedestrians and downhill cyclists are more risky compared to those between pedestrians and uphill cyclists, and cyclists on level roads. Cyclists are less able to yield due to the increased speed and reduced maximum deceleration rate they can achieve.

This paper introduces a new approach in studying cyclist-pedestrian interactions. This approach takes road grade, the capability of braking and the road user reaction into consideration. These are key factors contributing to the outcome of an interaction and incorporating them into the model provides a more complete picture.

From the DV framework, the cyclist's maximum deceleration rate can greatly impact his/her ability to yield right-of-way to a pedestrian. The maximum friction rate used in this study comes from (Landis, et al., 2004) which involved an empirical on-road experiment. However, cyclist braking systems vary greatly. To guarantee a successful braking maneuver in situations where cyclists should brake or in emergency situations, one avenue may be to establish requirements for cyclist braking systems. Much work remains to be done on the topic of cyclist behavior. Preferred evasive actions for cyclists can be different from drivers. More observations should be made to have a clear definition of cyclist evasive behavior to identify different types of evasive actions (such as swerving and braking, though none of them were observed in this study). Besides, the reaction time thresholds used in this paper need to be further validated.

For future work, data will be collected from a large number of sites including different environments where cyclist-pedestrian interactions happen. Different countermeasures may be proposed and implemented to improve cyclist yielding compliance. The performance of these countermeasures can be further validated using the framework. The framework can also be applied to investigate interactions between e-bike riders and pedestrians. As e-bikes have become more commonplace, this type of interaction occurs more frequently. Furthermore, because of the additional momentum that e-bikes can carry compared to regular bicycles, collisions involving pedestrians and e-bike riders are associated with greater severity.

7.7 ACKNOWLEDGEMENT

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7.8 REFERENCES

AASHTO. *Guide for the Development of Bicycle Facilities*. Washington DC: American Association of State Highway and Transportation Officials, 1999.

Abdel-Aty, M., and K. Haleem. "Analysis of the Safety Characteristics of Unsignalized Intersections." *12th World Conference on Transport Research (WCTR)*. Lisbon, Portugal, 2010.

Abdel-Aty, M., and P.A. Nawathe. "Novel Approach for Signalized Intersection Crash Classification and Prediction." *Advances in Transportation Studies, an International Journal Vol IX*, 2006: 67-80.

Afghari, Amir Pooyan, Karim Ismail, Nicolas Saunier, Abhisaar Sharma, and Luis Fernando Miranda-Moreno. "Pedestrian-cyclist Interactions at Bus Stops along Segregated Bike Paths: A Case Study of Montreal." *Transportation Research Board 93th Annual Meeting*. Washington D.C., 2014.

Anderson-Trocme, Paul, Joshua Stipancic, Luis Miranda-Moreno, and Nicolas Saunier. "Performance Evaluation and Error Segregation of Video-collected Traffic Speed Data." *Transportation Research Board Annual Meeting*. Washington DC, 2015.

Ayres, T. J., Kelkar, R., Kubose, T. & Shekhaw, V., 2015. *Bicyclist Behavior at Stop Signs.* s.l., s.n., p. 1616–1620.

Beitel, D., Stipancic, J., Manaugh, K. & Miranda-Moreno, L., 2017. *Exploring Cyclist-pedestrian Interactions in Shared Space Using.* Washington DC, s.n.

Boyce, P. & Van Derlofske, J., 2002. *Pedestrian Crosswalk Safety: Evaluating In-Pavement, Flashing Warning Lights,* New Jersey: s.n.

Cai, Q., Abdel-Aty, M. & Lee, J., 2017. Macro-level Vulnerable Road Users Crash Analysis: A Bayesian Joint Modeling Approach of Frequency and Proportion. *Accident Analysis & Prevention,* Volume 107, pp. 11-19.

Evans, M., 2017. *Cyclist Who Killed Pedestrian in High Speed Crash said People had "Zero Repect" for those on Bikes, Court Hears.* London, UK: s.n.

Fajans, J. & Curry, M., 2001. Why Bicyclist Hate Stop Signs. *ACCESS Magazine - UC CONNECT,* p. 28–31.

Fu, T., Miranda-Moreno, L. F. & Saunier, N., 2016. Pedestrian Crosswalk Safety at Non-signalized Crossings during Nighttime: Use of Thermal Video Data and Surrogate Safety Measures. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2586, pp. 90-99.

Fu, T., Miranda-Moreno, L. & Saunier, N., 2018. A Novel Framework to Evaluate Pedestrian Safety at Non-signalized Locations. *Accident Analysis & Prevention,* Volume 111, pp. 23-33.

Fu, T. et al., 2017. Automatic Traffic Data Collection under Varying Lighting and Temperature Conditions in Multimodal Environments: Thermal versus Visible Spectrum Video-Based Systems. *Journal of Advanced Transportation,* Volume 2017.

Golob, T. W. W. R. a. V. M. A., 2004. Freeway Safety as a Function of Traffic Flow. Volume 36.

Kavanagh, G., 2012. *Unraveling Ped & Bike Tension In Santa Monica.* [Online]
Available at: https://la.streetsblog.org/2012/09/10/unraveling-ped-bike-tension-in-santa-monica/

Landis, B., Petritsch, T. & Huang, H., 2004. *Characteristics of Emerging Road and Trail Users and Their Safety,* McLean, VA: s.n.

Lee, C. F. S. a. B. H., 2002. Analysis of Crash Precursors on Instrumented Freeways. Volume 1784.

Li, B. et al., 2015. The Behavior Analysis of Pedestrian-cyclist Interaction at Nonsignalized Intersection on Campus: Conflict and Interference. *Procedia Manufacturing,* Volume 3, p. 3345–3352.

Miranda-Moreno, L. F., Morency, P. & El-Geneidy, A. M., 2011. The Link between Built Environment, Pedestrian Activity and Pedestrian–Vehicle Collision Occurrence at Signalized Intersections. *Accident Analysis & Prevention,* 43(5), pp. 1624-1634.

Mohamed, . M. G., Saunier, N. & Miranda-Moreno, L. F., 2013. A Clustering Regression Approach: A Comprehensive Injury Severity Analysis of Pedestrian–vehicle Crashes in New York, US and Montreal, Canada. *Safety Science,* Volume 54, pp. 27-37.

Nabavi Niaki, M. et al., 2016. Effects of Road Lighting on Bicycle and Pedestrian Accident Frequency: Case Study in Montreal, Canada. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2555, pp. 86-94.

NHTSA, 2017. *Rearch & Data: NHTSA Studies Vehicle Safety and Driving behavior to Reduce Vehicle Crashes,* Washington DC: s.n.

Public Heath Agency of Canada, 2014. *What is Active Transportation.* [Online] Available at: http://www.phac-aspc.gc.ca/hp-ps/hl-mvs/pa-ap/at-ta-eng.php

Saunier, N. & Sayed, T., 2006. *A Feature-based Tracking Algorithm for Vehicles in Intersections.* s.l., s.n.

Scott, P., 2017. *The Number of Pedestrians Fatally or Seriously Injuried in Collisions with Cyclists has Doubled Since 2006.* London, UK: s.n.

StBA, 2017. *Verkehrsunfälle (Fachserie 8, Reihe 7),* Reutlingen, Germany: Statistisches Bundesamt.

Stipancic, J., Miranda-Moreno, L. & Saunier, N., 2016. *The Who and Where of Road Safety: Extracting Surrogate Indicators from Smartphone-Collected GPS Data in Urban Environments.* Washington DC, Transportation Research Board Annual Meeting Compendium of Papers.

Tuckel, P., Milczarski, W. & Maisel, R., 2014. Pedestrian Injuries due to Collisions with Bicycles in New York and California. *Journal of Safety Research,* pp. 7-13.

Zahabi, S. A. H., Strauss, J., Miranda-Moreno, L. F. & Manaugh, K., 2011. Estimating Potential Effect of Speed Limits, Built Environment, and other Factors on Severity of Pedestrian and Cyclist Injuries in Crashes. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2247, pp. 81-90.

Chapter 8

Conclusions and Future works

Chapter 8 Conclusions and Future Work

8.1 GENERAL CONCLUSIONS

This chapter provides a general summary of the main conclusions in this dissertation. This is followed by a discussion of the limitations, providing directions for future work.

- As a first step, an extensive literature review on pedestrian safety at non-signalized crosswalk locations was carried out. Based on the data used, methods proposed in past studies were classified into five different approaches. Based on this systematic literature review, this dissertation identified some key research gaps in the pedestrian road safety literature. One of the main gaps is the lack of efficient data collection tools under critical conditions, leading to many studies relying on small sample sizes, especially at nighttime. In addition, a comprehensive framework that describes how pedestrian-vehicle interactions unfold over time and is closely related to the outcome of crashes is missing.
- To provide an alternative to the visible-spectrum approach, the thermal camera system was validated for automated collection and traffic data extraction under varying lighting and temperature conditions, by comparing it to the use of regular visible spectrum cameras. The thermal camera proved to perform well without being sensitive to lighting interference and pavement temperatures. Results indicated that the thermal camera provides a promising alternative for traffic data collection using vision-based technologies.
- To address issues related to pedestrian safety at nighttime, this dissertation proposed a method to investigate pedestrian-vehicle interactions under low visibility conditions using thermal video sensors. Based on SMoS, which include vehicle approaching speed, PET, yielding compliances and conflict rates, the nighttime safety of pedestrians at non-signalized crosswalks was evaluated. Results from the study showed that pedestrians were exposed to higher risk levels at study sites during nighttime, compared to daytime

conditions. The thermal video sensor could effectively collect high-quality trajectory data for all road users at night regardless of lighting conditions.

- As one of the main contributions, this dissertation proposed a novel framework (the DV framework) for investigating pedestrian-vehicle interactions at non-signalized crosswalks. The framework investigates pedestrian-vehicle interactions based on the vehicle speed and distance to the pedestrian crossing. The model considers the impact of driver response and braking time. It classifies the conditions where the driver approaches a pedestrian(s) intending to cross into three types, according to the driver capability to yield. The DV framework can investigate interaction occurrences, yielding behavior and crossing decisions. More specifically, it can help investigate pedestrian safety based on safety measures including yielding rate and yielding compliance, time-to-crossing and deceleration rate required to stop. The framework was illustrated through a case study involving three non-signalized crosswalks of different types in Montreal. Results from the case study showed that the framework provides reasonable results.

- Empirical evidence for the proposed framework were obtained through the application of the proposed methodology to a case study involving data collected from multiple sites in Montreal. Pedestrian safety at three main types of non-signalized crosswalks, including uncontrolled crosswalks, marked crosswalks, and stop-controlled crosswalks, was compared. Results showed that, among the three types of non-signalized crosswalks, stop-controlled crosswalks have the best performance considering all the measures. Uncontrolled crosswalks do not protect pedestrians effectively due to the low yielding compliance rates and the highest chance of evasive maneuvers. Marked crosswalks perform better compared to uncontrolled ones. Results further suggested that the framework describes pedestrian-vehicle interactions in a proper way. While considering vehicle yielding behavior and pedestrian crossing decisions as the main behavior factors related to pedestrian safety, the framework provides a more complete picture in learning pedestrian-vehicle interactions.

- To explore the application of this model in investigating cyclist-pedestrian interactions, a case study was conducted involving two types of pedestrian crosswalk locations, non-signalized urban intersections with painted cycle tracks and bus stop locations along segregated bicycle facilities in Montreal. Results generally showed that cyclists endanger pedestrians intending to cross and that marked crosswalks alone fail to protect pedestrians from passing cyclists. Other findings include that cyclists' yielding compliance at the marked crosswalk was surprisingly low and that pedestrian safety at crossings on cycling facilities with downhill grades is an issue. The results can hopefully lead to future research and practice interest on the topic of reducing pedestrian risks during pedestrian-cyclist interactions. The study provides a good example of using the DV framework to study different safety topics.

8.2 LIMITATIONS OF THE RESEARCH

Despite the contributions and the efforts in its accomplishment, the research has its limitations. The limitations are discussed below from three aspects: methodological framework, data collection method, data processing and analysis.

8.2.1 Methodological Framework

The main limitation of the framework is that the SMoS has not yet been proved as a suitable safety predictor. Some validation is required. Although the DV framework provides precise measures of road user behavior (e.g. yielding rate and compliance), other measures (TC and DRS) used as SMoS in the model need to be further validated. Besides, this research was unable to take into account some advanced measures, such as measures using motion prediction (Mohamed & Saunier, 2013; St-Aubin, et al., 2014), that are potentially better in performance as a safety predictor. In general, a lot of work is required to build models that can predict and improve pedestrian safety to improve this framework.

8.2.2 Data Collection Method

The data collection work in the dissertation was conducted with the help of a mobile video data collection system. One of the limitations of video data collection from a mast is the limited field of view and trajectory length. Camera often fails to cover the entire road section of interest, in particular when looking at vehicle-pedestrian approaching behaviors. Wider observation areas may be required to observe the approaching road user trajectories. As part of this work, the combination of multiple cameras was applied to collect data where a single camera was not able to cover an area wide enough for the observation. Extracting vehicle trajectory information through different camera views was conducted semi-automatically (trajectory data for each camera view have been extracted automatically while matching the trajectory data of road user individuals through different camera views has been conducted manually); the challenge will however be to track, or re-identify, road users across multiple camera views.

8.2.3 Data Processing and Analysis

The limitation in data processing and analysis is mainly being lack of tools for accurately and efficiently automating the work:

- The DV framework relies highly on trajectory data with accurate position and speed information. However, the vision-based tracking tool from the Traffic Intelligence project (Jackson, et al., 2013) cannot detect and track all road users perfectly. Great effort has been spent in going through each interaction of interest and manually correcting errors in the trajectories. Such errors are mainly generated from poor lighting conditions and the trajectories of the stationary road users lost by the tracking tool. Regarding the issue with the poor lighting, the thermal camera system has already been proposed in this dissertation, though it is not continuously used in the research because of the limited availability of the thermal sensor equipment. The interrupted trajectory issue can be diminished with improvement in the field of computer vision.

- The work to match road user trajectory data through different camera views has been conducted manually, which is unduly time-consuming: videos need to be scanned to record the time offsets of camera views for synchronization, find out the same road users, and record their tracked identification number through in different camera views. The research could have benefitted greatly if tools automatically tracking road users through multiple camera views are available.

- Data analysis (preparing information in the DV framework) also highly relies on manual work. Interactions of interest, vehicle yielding maneuvers (whether vehicles yield), and pedestrian events (pedestrian occurrences and crossing decisions) are recorded by scanning videos manually. A computer tool that automatically filters interactions of interest, identifies pedestrian occurrence and crossing events (based on pedestrian facial recognition or body movement detection), and determines yielding behavior can make the work more efficient.

With the issues associated with the data collection method and the time and effort required in processing the data, this research was only able to test the DV framework through 15 sites. This is not sufficient for validation purposes. More sites need to be included to further test the DV framework and calibrate the safety indicators used in the studies.

8.3 EXTENSION FOR FUTURE WORK

Future work is discussed from two aspects: methodological development and extensive applications.

8.3.1 Methodological Development

Future work can be conducted to improve the proposed framework. A sufficiently large number of observations and locations will be included to further test and to calibrate the DV model. Analysis results from the framework will be compared to historical crash data to test for correlation – as part of the validation process. Parameters used in the model, such as deceleration rate thresholds, will also be verified and further calibrated if needed. Different SMoS will be tested in the framework to improve its performance. Advanced safety models based on motion pattern prediction will be investigated. The implementation of these models in the DV framework will be explored. Moreover, the model can be improved by considering traffic, environmental and geometric factors, and vehicular characteristics.

A full-automated analysis tool based on the framework should be developed to automate the processes, including filtering interactions of interest, identifying pedestrian occurrence and crossing events, and determining yielding behavior. Among the processes, automating the event identification work is challenging as pedestrian walking habits and patterns vary across individuals, contexts, etc. Machine learning methods will be applied in identifying the intent to cross (occurrence) and the decision made to cross (crossing decision) for the pedestrian.

As an alternative to video data collection from a mast, the use of drone data will be explored in future model-validation. Using drone for video data collection could help cover larger fields of view (Jin, et al., 2016). Alternatively, with the increasing penetration among road users, GPS data collected through GPS units or smart devices equipped on participants may also be used for model validation and parameter calibration in future work, if data sources are available.

8.3.2 Extensive Applications

More applications of the DV framework can be attempted. The model will be used to evaluate safety effects of different signs and control systems at a given intersection. In addition to interactions between pedestrians and vehicle on the approach street where vehicles enter the intersection, most studies have ignored interactions at exit streets where vehicle leave the intersection. This can potentially be more dangerous due to the driver's unclear knowledge of right-of-way, acceleration attempts to recover speed and the complex situation the driver faces at the intersection. The impact of such interactions on pedestrian safety can be investigated using the proposed interaction framework along with other safety measures.

The framework can be applied to other road environments where pedestrian-vehicle interactions always occur in the future, e.g. crosswalks at signalized locations, roundabouts, and channelized intersections. The yielding behavior of vehicles interacting with crossing pedestrians in situations where pedestrians are not allowed to cross, such as during the red phase at signalized intersections or in the middle of road segments can be explored. Moreover, the framework can be adjusted and applied in different situations in addition to pedestrian safety. It can be used to investigate interactions between different types of road users, such as pedestrian-cyclist interactions and cyclist-vehicle interactions. The model can even be used to investigate the impact of mixed traffic flows with different penetration percentage of automated vehicles (with low perception-response time) on pedestrian safety in non-signalized crosswalk environments. Meanwhile, methods and tools, derived from the DV framework, to detect the intent to cross can be implemented to define the correct response and performance of automated vehicles when facing different situations with crossing pedestrians and cyclists.

8.4 REFERENCES

Jackson, S., Miranda-Moreno, L., St-Aubin, P. & Saunier, N., 2013. Flexible, Mobile Video Camera System and Open Source Video Analysis Software for Road Safety and Behavioral Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 2365, pp. 90-98.

Jin, P., Ardestani, S., Wang, Y. & Hu, W., 2016. *Unmanned Aerial vehicle (UAV) Based Traffic Monitoring and Management*, Piscataway, NJ: Center for Advanced Infrastructure and Transportation (CAIT), the State University of New Jersey.

Mohamed, G. M. & Saunier, N., 2013. Motion Prediction Methods for Surrogate Safety Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 2386, pp. 168-178.

St-Aubin, P., Saunier, N. & Miranda-Moreno, L., 2014. Road User Collision Prediction using Motion Patterns Applied to Surrogate Safety Analysis. *The 93rd Annual Meeting of the Transportation Research Board*.

Appendix I Summary of Literature

TABLE I Results Summary of Previous Research on Pedestrian Safety at Non-Signalized Crossings

Studies	Country	Topic	Approach(s) Applied: Crash Data	Surrogate Measures of Safety: *Traffic*	*Event*	*Behavior*	*Perception*	Data Source
Almodfer, et al. (2016)	China	**Method:** *Conflict*	--	--	√	--	--	***V***ideo data, details not given
Antov, et al. (2007)	Estonia	**Behavior Analysis:** *Factors of veh. yielding*	--	√	--	√	--	[a] ***N***DS data
Arnold & Landz (2007)	US	**Performance Evaluation:** *LED stop sign & Optical speed bar*	--	√	--	--	--	[b] ***F***ield observation
Austin, et al. (2006)	US	**Performance Evaluation:** *Pedestrian prompting at stop sign*	--	--	--	√	--	***F***ield observation
Beaubien (1989)	US	**Performance Evaluation:** *Stop sign for speed controlling*	--	√	--	--	--	***D***ata from previous studies based on field observation
Bella & Silvestri (2015)	Italy	**Performance Evaluation:** *Different safety treatments*	--	--	--	√	--	***D***riving simulation
Bennett & Van Houten (2016)	US	**Performance Evaluation:** *Gateway In-street Sign*	--	--	--	√	--	***F***ield observation
Bentley (2015)	US	**Performance Evaluation:** *High-visibility crosswalks*	--	√	--	√	--	***N***DS data
Bichicchi, et al. (2017)	Italy	**Performance Evaluation:** *Geometric design on driver glancing*	--	--	--	√	--	***G***PS; Mobile eye tracking data
Boroujerdian & Nemati (2016)	Iran	**Behavior Analysis:** *Ped. gap acceptance*	--	--	--	√	--	[c] ***F***ield measurement, Laser gun; Video data, computer-based tools.
* Boyce & Van Derlofske (2002)	US	**Performance Evaluation:** *In-pavement warning light*	--	√	√	--	√	***V***ideo data, details not given; On-site survey.
* Van Derlofske, et al. (2003)	US	**Performance Evaluation:** *In-pavement warning light*	--	√	√	--	√	***V***ideo data, details not given; On-site survey.
Brewer, et al. (2006)	US	**Behavior Analysis:** *Ped. gap acceptance*	--	--	--	√	--	***F***ield observation; Video data, manually processed.
Brewer, et al. (2015)	US	**Performance Evaluation:** *RRFB sign*	--	--	--	√	--	***F***ield observation; Video data, manually processed.
Britt, et al. (1995)	US	**Performance Evaluation:** *Law enforcement*	--	--	--	√	--	***F***ield observation
Brumfield & Pulugurtha (2011)	US	**Behavior Analysis:** *Ped. distraction*	--	--	√	√	--	***F***ield observation
Bungum, et al. (2005)	US	**Behavior Analysis:** *Ped. distraction*	--	--	--	√	--	***F***ield observation
Burritt, et al. (1990)	US	**Performance Evaluation:** *School zone flashers*	--	√	--	--	--	***D***etails not given
Cafiso, et al. (2011)	Italy	**Method:** *Conflict*	--	--	√	--	--	***V***ideo data, computer-based tools
Cambridge (2012)	US	**Performance Evaluation:** *Symbol prompts & 3D pavement*	--	--	--	√	--	***F***ield observation

(Continued)

TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Campbell (1997)	US	**Performance Evaluation:** *Marked vs. unmarked*	√	--	--	--	--	***C***rash report, details not given
Chai & Zhao (2016)	China	**Behavior/Perception Analysis:** *Aggressive driving behavior*	--	--	--	√	√	***D***riving simulation; Questionnaire after simulation.
Chi (2007)	US	**Performance Evaluation:** *Marked vs. unmarked*	--	√	--	√	--	***V***ideo data, manually processed
Chen et al. (2017)	US	**Interaction Modeling/Simulation:** *Autonomous Vehicles Interaction with ped.*	--	--	--	√	--	***T***raffic simulation
* Chu (2006)	US	**Performance Evaluation:** *Lighting; marking*	√	--	--	--	--	***C***rash report, police
* Chu, et al. (2008)	US	**Performance Evaluation:** *Lighting; marking*	√	--	--	--	--	***C***rash report, police
City of Fort Collins (2017)	US	**Performance Evaluation:** *Unwarranted stop sign for speed controlling, and volume controlling*	--	√	--	--	--	***N***o data involved
Clark, et al. (1996)	US	**Performance Evaluation:** *Fluorescent strong yellow-green signs*	--	--	√	√	--	***F***ield observation
Community of Firestone (2017)	US	**Performance Evaluation:** *Unwarranted stop sign for speed controlling, and volume controlling*	--	√	--	--	--	***N***o data involved
Coughenour, et al. (2017)	US	**Behavior Analysis:** *Racial Bias in Yielding*	--	--	--	√	--	***F***ield observation
Crowley-Koch & Van Houten (2011)	US	**Performance Evaluation:** *Ped. prompts*	--	--	--	√	--	***F***ield observation; Video data, manual processed.
DeVeauuse, et al. (1999)	US	**Performance Evaluation:** *Stop sign on campus*	--	--	--	√	--	***F***ield observation
Dhar & Woodin (1995)	US	**Performance Evaluation:** *Fluorescent strong yellow-green signs*	--	√	√	√	√	***O***n-site survey; Rest details not given
Diogenes & Lindau (2010)	Brazil	**Performance Evaluation:** *Midblock crossing Crash risk modeling*	√	--	--	--	--	***C***rash report, government
Dixon, et al. (1997)	US	**Performance Evaluation:** *Speed reducing peripherals*	--	--	--	√	--	***D***etails not given
Dobbs (2009)	US	**Performance Evaluation:** *Campus pedestrian safety*	√	--	√	--	--	***C***rash report, government; Video data, manual processed
Domarad, et al. (2013)	Canada	**Performance Evaluation:** *RRFB*	--	--	--	√	--	***V***ideo data, manual processed
Dougald, et al. (2012)	US	**Performance Evaluation:** *Zig-zag pavement*	--	√	--	--	√	***F***ield measuring, ATRs & LiDAR gun; Electronically-distributed

(Continued)

TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Dulaski & Liu (2013)	US	**Performance Evaluation:** *Ped. stepping off the curb*	--	--	--	√	--	***F***ield observation
Dutt, et al. (1997)	US	**Performance Evaluation:** *Fluorescent strong yellow-green signs*	--	--	--	--	√	***E***lectronically-distributed survey
Ellis & Van Houten (2009)	US	**Performance Evaluation:** *Publicity & law enforcement*	√	--	--	--	--	***C***rash report, government
Ewing (1999)	Canada	**Performance Evaluation:** *Unwarranted stop sign for speed controlling, and volume controlling*	--	√	--	--	--	***N***ot clearly stated
Fisher & Garay-Vega (2012)	US	**Performance Evaluation:** *Advanced yielding signs*	--	--	--	√	--	***D***riving simulation
Fitzpatrick, et al. (2004)	US	**Performance Evaluation:** *Marking* *In-pavement warning light* *HAWK*	--	--	--	--	√	***V***ideo data, manually processed; On-site survey.
* Fitzpatrick, et al. (2006)	US	**Performance Evaluation & Guidelines:** *Treatment validation* *Guideline revision*	--	--	√	√	--	***V***ideo data, manually processed
* Fizpatrick, et al. (2007)	US	**Performance Evaluation & Guidelines:** *Treatment validation* *Guideline revision*	--	--	--	√	--	***V***ideo data, manually processed
* Fitzpatrick, et al. (2011)	US	**Performance Evaluation:** *Marking, RRFB, HAWK, Sharrow*	--	--	--	√	--	***V***ideo data, manually processed
* Shurbutt & Van Houten (2010)	US	**Performance Evaluation:** *Marking, RRFB, HAWK, Sharrow*	--	--	--	√	--	***V***ideo data, manually processed
Fitzpatrick, et al. (2016a)	US	**Performance Evaluation:** *Above- & below-sign RRFB*	--	--	--	√	--	***F***ield observation
Fitzpatrick, et al. (2016b)	US	**Performance Evaluation:** *RRFB with different designs*	--	--	--	√	--	***F***ield observation
Foomani, et al. (2015)	Canada	**Performance Evaluation:** *Stop-operated intersection with active road sign*	--	--	--	√	--	***V***ideo data, manually processed
Fu, et al. (2016)	Canada	**Performance Evaluation:** *Lighting - night vs. day*	--	√	√	√	--	***V***ideo data, computer-based tools
Fu, et al. (2018)	Canada	**Method:** *Interaction*	--	--	√	√	--	***V***ideo data, computer-based tools
Gårder (2004)	US	**Safety Factors:** *Crash modeling* *Speed and other factors on safety*	√	--	--	--	--	***C***rash report, government

(Continued)

TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Gibby, et al. (1994)	US	**Performance Evaluation:** *Marked vs. unmarked*	√	--	--	--	--	***C***rash report, government
Gitelman, et al. (2016a)	Israel	**Performance Evaluation:** *Raised crosswalk* *Preceding speed humps*	--	√	√	√	--	***F***ield measuring, Laser gun; Video data, manually processed
Gitelman, et al. (2016b)	Israel	**Performance Evaluation:** *Marking*	--	√	√	√	--	***F***ield measuring, laser gun; Video data, manually processed
Goddard, et al. (2014)	US	**Behavior Analysis:** *Racial Bias in Yielding*	--	--	--	√	--	***F***ield observation
Goh, et al. (2012)	Malaysia	**Behavior Analysis:** *Ped crossing speed* *Non-signalized vs. signalized*	--	--	--	√	--	***F***ield observation
Gómez, et al. (2011)	US	**Performance Evaluation:** *Advanced yielding marking*	√	--	√	√	--	***D***riving simulation
Gómez, et al. (2014)	US	**Performance Evaluation:** *Geometric Design – stop sign & T-intersections*	√	--	--	√	--	***D***riving simulation
Hakkert, et al. (2002)	Israel	**Performance Evaluation:** *Ped. warning systems* *(ARMS & Hercules systems)*	--	√	√	√	--	***F***ield measuring, laser gun; Field observation
Harrison (2017)	US	**Behavior Analysis:** *Ped. behavior*	--	--	--	√	--	***V***ideo data, manually processed
* Huang, et al. (1999)	US	**Performance Evaluation:** *Active warning system*	--	√	√	√	√	***D***etails not given
* Huang (2000)	US	**Performance Evaluation:** *Active warning system*	--	--	--	√	--	***D***etails not given
Huang, et al. (2000)	US	**Performance Evaluation:** *Overhead crosswalk sign* *Ped. safety cone* *Ped. regulatory sign*	--	--	--	√	--	***V***ideo data, manually processed
Ibrahim, et al. (2005)	Malaysia	**Behavior/Perception Analysis:** *Rule of right-of-way*	--	--	--	√	√	***V***ideo data, manually processed
Islam, et al. (2014)	US	**Method:** *Crash modeling* *Validating SSM*	√	--	√	--	--	***C***rash report, government; Field observation
Ivan, et al. (2001)	US	**Safety Factors:** *Crash modeling* *Related factors*	√	--	--	--	--	***C***rash report, government

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TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Ivan, et al. (2012)	US	**Method:** *Crash modeling* *Validating SSM*	√	--	√	--	--	***C***rash report, government; Field observation
* Jiang (2012)	German, China	**Behavior Analysis:** *Ped. & veh. with different culture*	--	--	√	√	--	***V***ideo data, computer-based tools
* Jiang, et al. (2015)	German, China	**Behavior Analysis:** *Ped. & veh. with different culture*	--	--	√	√	--	***V***ideo data, computer-based tools
Johansson & Leden (2007)	Sweden	**Performance Evaluation:** *Swedish code, speed cushion, marking, refuge, paving stone, elevated area*	--	√	√	√	√	***F***ield measuring, radar gun; Video data, manually processed; Face-to-face interview.
Jones & Tomcheck (2000)	US	**Performance Evaluation:** *Marked vs. unmarked*	√	--	--	--	--	***C***rash report, government
Kadali & Perumal (2016)	India	**Behavior Analysis:** *Ped. gap acceptance*	--	--	--	√	--	***V***ideo data, manually processed
Kadali, et al. (2014)	India	**Behavior Analysis:** *Ped. gap acceptance*	--	--	--	√	--	***V***ideo data, manually processed
Karkee, et al. (2010)	US	**Performance Evaluation:** *In-pavement flashing light sys.*	--	√	--	√	--	***F***ield observation
Keall (1995)	New Zealand	**Performance Evaluation:** *Non-signalized vs. others* *The elderly in pedestrian crashes*	√	--	--	--	--	***C***rash report, government; Survey
Khatoon, et al. (2013)	India	**Behavior Analysis:** *Gap acceptance*	--	--	--	√	--	***P***aper not found
Knoblauch & Raymond (2000)	US	**Performance Evaluation:** *Marking*	--	--	--	√	--	***F***ield observation
Knoblauch, et al. (2001)	US	**Performance Evaluation:** *Marking*	--	--	--	√	--	***F***ield observation
Koepsell, et al. (2002)	US	**Performance Evaluation:** *Marking* *Older ped.*	√	--	--	--	--	***C***rash report, details not given
Kudryavtsev, et al. (2012)	Norway, Russia	**Performance Evaluation:** *Signalized vs. non-signalized crosswalk*	√	--	--	--	--	***C***rash report, police
Li & Ming (2016)	China	**Behavior Analysis:** *Ped. distraction*	--	--	--	√	--	***F***ield observation
Liu & Tung (2014)	China	**Behavior Analysis:** *Ped. crossing*	--	--	--	√	--	***V***ideo based survey
Liu, et al. (2011)	China	**Performance Evaluation:** *Transverse rumble strip*	√	√	--	--	--	***C***rash report, government; Field measuring, radar speed gun

(Continued)

TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Lu, et al. (2016)	China	**Interaction Modeling/Simulation:** *Ped. crossing* *Driver yielding* *Ped. safety evaluation*	--	--	√	--	--	***V***ideo data, details not given
Malenfant & Van Houten (1990)	Canada	**Performance Evaluation:** *"Countesy Promotes Safety" program*	--	--	--	√	--	***F***ield observation
Millard-Ball (2016)	US	**Interaction Modeling/Simulation:** *Autonomous vehicles* *Game theory in interaction with ped.*	--	--	--	√	--	***N***o data involved
Mitman & Ragland (2007)	US	**Perception Analysis:** *Right-of-way* *Marked vs. unmarked*	--	--	--	--	√	***O***n-site survey
* Mitman, et al. (2008)	US	**Performance Evaluation:** *Marked vs. unmarked*	--	--	√	√	--	***F***ield observation; Video data, manually processed.
* Mitman & Ragland (2008)	US	**Performance Evaluation:** *Marked vs. unmarked*	--	--	√	√	--	***F***ield observation; Video data, manually processed.
Mitman, et al. (2010)	US	**Performance Evaluation:** *Marked vs. unmarked*	--	--	√	√	--	***F***ield observation
Najm, et al. (2001)	US	**Performance Evaluation:** *Vehicle-ped./cyclist collisions at signalized & non-signalized intersections*	√	--	--	--	--	***C***rash report, police
Nteziyaremye (2013)	South Africa	**Behavior/Perception Analysis:** *Ped. crossing* *Different crossing facilities*	--	--	√	√	√	***V***ideo data, manually processed; On-site survey.
Olszewski, et al. (2015)	Poland	**Safety Factors:** *Crash modeling*	√	--	--	--	--	***C***rash report, police
Oxley, et al. (2005)	Australia	**Behavior Analysis:** *Ped. crossing*	--	--	--	√	--	***S***imulator experiment
Pawar & Patil (2015)	India	**Behavior Analysis:** *Ped. gap acceptance*	--	--	--	√	--	***V***ideo data, manually processed
Pécheux, et al. (2009)	US	**Performance Evaluation:** *Different treatments*	--	--	√	√	--	***D***etails not given
Pfortmueller, et al. (2014)	Switzerland	**Performance Evaluation:** *Marked vs. unmarked*	√	--	--	--	--	***C***rash report, police & hospital
Pulugurtha, et al. (2011)	US	**Behavior Analysis:** *Driver and ped. distraction*	--	--	--	√	--	***P***aper not found
Pulugurtha (2015)	US	**Performance Evaluation:** *Ped. hybrid beacon*	--	--	√	√	--	***F***ield observation

(Continued)

TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Rosenbloom, et al. (2006)	Israel	**Behavior Analysis:** *Driver yielding* *Age & gender*	--	--	--	√	--	***F***ield observation
* Schroeder & Rouphail (2011)	US	**Behavior Analysis:** *Modeling driver yielding*	--	--	--	√	--	***F***ield observation; Field measuring, Laser gun.
* Schroeder (2008)	US	**Behavior Analysis:** *Modeling driver yielding*	--	--	--	√	--	***F***ield observation; Field measuring, Laser gun.
Schroeder, et al. (2010)	US	**Method:** *Ped. crossing at roundabouts* *Vision impaired*	--	√	--	√	--	***F***ield observation
Schroeder, et al. (2014)	US	**Behavior Analysis:** *Modeling ped./driver behavior*	--	--	--	√	--	***F***ield observation
Serag (2014)	Egypt	**Behavior Analysis:** *Modeling ped. gap acceptance*	--	--	--	√	--	***V***ideo data., manually processed
Shi, et al. (2007a)	China	**Behavior Analysis:** *Ped. crossing behavior*	--	--	--	√	--	***D***etails not given
Shi, et al. (2007b)	China	**Performance Evaluation:** *Ped. crossing behavior* *Two different sites*	--	--	--	√	--	***D***etails not given
Sisiopiku & Akin (2003)	US	**Behavior/Perception Analysis:** *Various facility*	--	--	--	√	√	***V***ideo data, manually processed; Electronically-distributed survey.
Smith, et al. (2009)	US	**Performance Evaluation:** *Active vs. passive warning system*	--	--	--	√	--	***V***ideo data, computer-based tools
Solah, et al. (2016)	Malaysia	**Behavior Analysis:** *Distraction*	--	--	--	√	--	***F***ield observation; Video data, manually processed.
St-Aubin, et al. (2018)	Canada	**Performance Evaluation:** *Stop sign* *Speed controlling* *Stopping behavior*	--	√	--	√	--	***V***ideo data, computer-based tools
Sun & Lu (2011)	China	**Method:** *Conflict*	--	--	√	--	--	***V***ideo data, details not given
Sun, et al. (2003)	US	**Interaction Modeling/Simulation:** *Ped. gap acceptance* *Motorist yield*	--	--	--	√	--	***V***ideo data, manually processed
Turner, et al. (2006)	US	**Performance Evaluation:** *Red signal* *Beacon devices* *Active signs* *Enhanced/high-visibility treatments*	--	--	--	√	--	***V***ideo data, manually processed

(Continued)

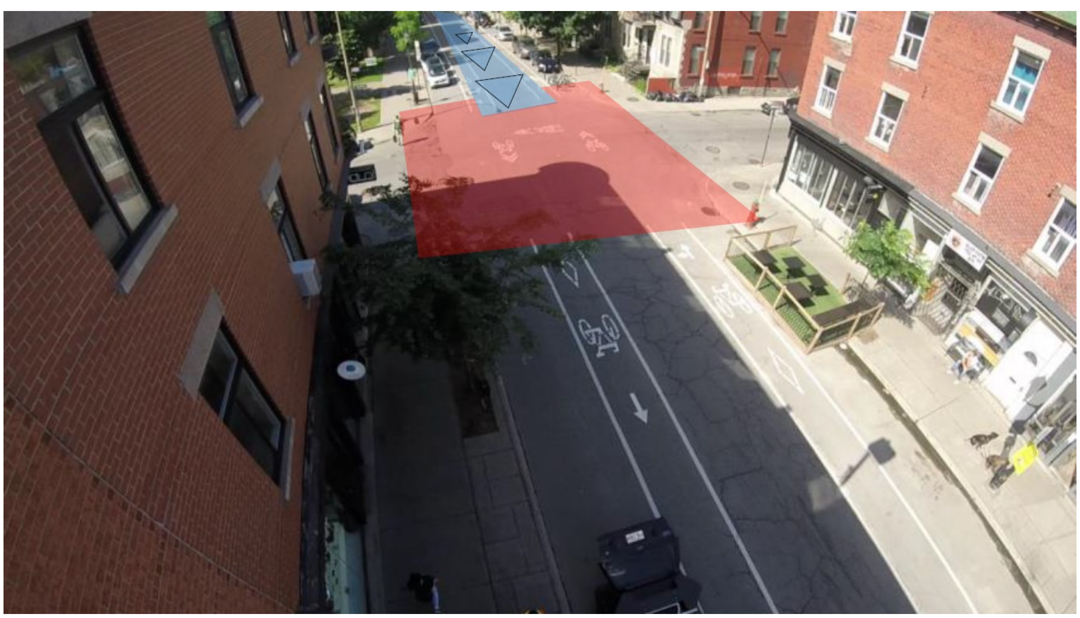
TABLE I Continued

Studies	Country	Topic	Approach(s) Applied					Data Source
			Crash Data	Surrogate Measures of Safety				
				Traffic	*Event*	*Behavior*	*Perception*	
Van Houten & Malenfant (1992)	Canada	**Performance Evaluation:** *Flashing amber*	--	--	√	√	--	***F***ield observation
Van Houten (1988)	Canada	**Performance Evaluation:** *Stop line* *Sign prompt*	--	--	√	√	--	***F***ield observation
Van Houten, et al. (1998)	Canada	**Performance Evaluation:** *Ped.-activated flashing beacons*	--	--	√	√	--	***F***ield observation
Van Houten, et al. (2001)	Canada	**Performance Evaluation:** *Advance yielding marking*	--	--	√	√	--	***F***ield observation
Van Houten & Retting (2001)	Canada	**Performance Evaluation:** *LED stop sign*	--	--	--	√	--	***F***ield observation; Video data, manually processed.
Van Houten, et al. (2002)	Canada	**Performance Evaluation:** *Advance yielding marking* *Fluorescent yellow-green RA 4 sign*	--	--	√	√	--	***F***ield observation
Várhelyi (1998)	Sweden	**Performance Evaluation:** *Non-signalized*	--	--	√	√	--	***F***ield measuring, laser gun
Wa (1993)	Canada	**Behavior Analysis:** *Old motorist*	--	--	--	√	--	***F***ield observation
Waizman, et al. (2014)	Israel	**Interaction Modeling/Simulation:** *Validation and application*	√	--	--	--	--	***T***raffic simulation
Wallberg & Wisenbord (2000)	Sweden	**Performance Evaluation:** *Marked vs. unmarked*	--	√	√	√	√	***P***aper not found
Wang, et al. (2017)	China	**Performance Evaluation:** *Speed control measures*	--	√	--	--	--	***V***ideo data, manually processed
Wang & Fang (2008)	China	**Method:** *Conflict*	--	--	√	√	--	***V***ideo data, manually processed
Xiang, et al. (2016)	China	**Method:** *Monte-Carlo simulation* *Risk prediction for ped. crossing*	--	--	--	√	--	***C***omputer simulation (Monte-Carlo)
Yannis, et al. (2013)	Greece	**Behavior Analysis:** *Ped. gap acceptance*	--	--	--	√	--	Video data, manually processed
* Zegeer, et al. (2001)	US	**Performance Evaluation:** *Marked vs. unmarked*	√	--	--	--	--	***C***rash report, police
* Zegeer, et al. (2005)	US	**Performance Evaluation:** *Marked vs. unmarked*	√	--	--	--	--	***C***rash report, police
Zhuang & Wu (2014)	China	**Performance Evaluation:** *Gesture measure*	--	--	--	√	√	***F***ield observation; Questionnaire survey.

Note: **Publication marked with *** *in sequence are about the same study presented in two or more publication formats (normally a same study published in both a Journal and a report);* [a] ***NDS*** *is abbreviation for Naturalistic Driving Study which uses onboard data acquisition systems including GPS devices, video cameras, radars, accelerometer and/or other devices to get detailed information of the drivers;* [b] *Field observation means data collection manually and directly observed and recorded on site by observers;* [c] *Field measurement means data collection based on different techniques on site.*

Appendix II Sites for Model Implementation and Validation

a) Site A-1 NotreDamedeGrace-D'Oxford : *Pedestrian crossing at intersection on Avenue Notre-Dame-de-Grace and Avenue D'Oxford. The pedestrian crossing is on Avenue Notre-Dame-de-Grace, a one-way and one-lane street with a conventional bike lane.*



b) Site A-2 Clark-PrinceArthur: *Pedestrian crossing at intersection Rue Clark and Rue Prince-Arthur. The pedestrian crossing is on Rue Prince-Arthur, a one-way and one lane-street with a conventional and contraflow bike lanes.*

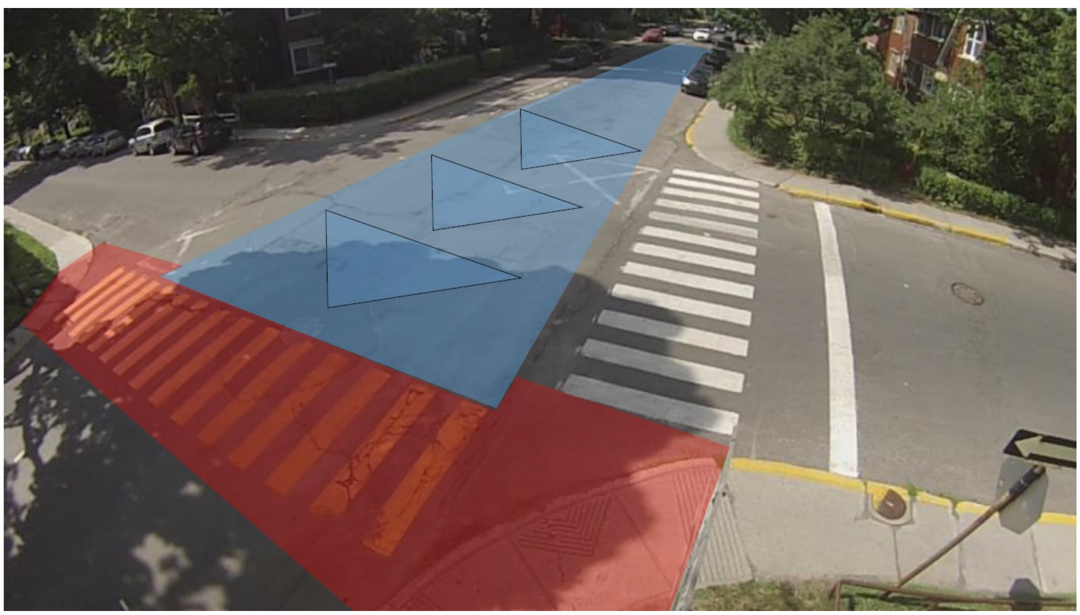
c) Site A-3 Masson-6e: *Pedestrian crossing at intersection Rue Masson and Avenue 6e. The pedestrian crossing is on Rue Masson, a two-ways and one-lane street per direction.*

d) Site A-4 Beaubien-Molson: *Pedestrian crossing at intersection Rue Molson and Rue Beaubien. The pedestrian crossing is on Rue Beaubien, a two-ways and one-lane street per direction.*

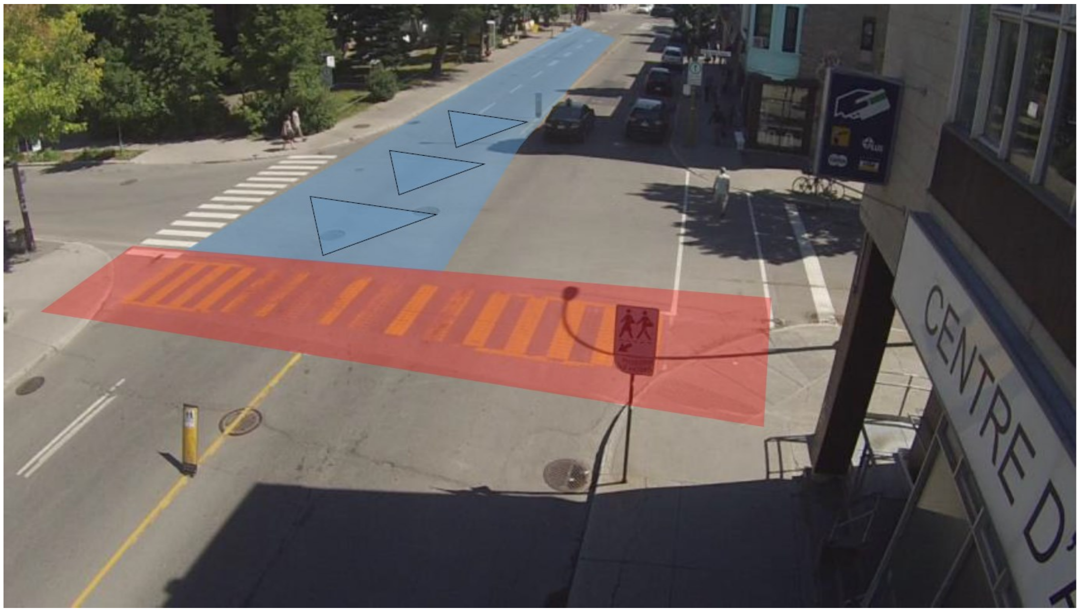
e) Site A-5 Laurier_Drolet : *Pedestrian crosswalk at intersection Avenue Laurier and Rue Drolet. The pedestrian crossing is on Avenue Lauriel, a one-way and one-lane street per direction with a conventional and buffered contraflow bike lane.*

FIGURE II-1 Site description for uncontrolled crosswalks (Type A)

a) Site B-1 Prieur-DeLaRoche: *Crosswalk located at the intersection of Rue Prieur and Rue De La Roche. The crosswalk crossing is on Rue Prieur, a one-way and one-lane bike shared street with a contraflow bike lane.*



b) Site B-2 NotreDamedeGrace-OldOrchard: *Crosswalk located at the intersection of Avenue Notre-Dame-de-Grace and Avenue Old Orchard. The crosswalk crossing is on Avenue Notre-Dame-de-Grace, a one-way and one-lane street with a conventional bike lane.*

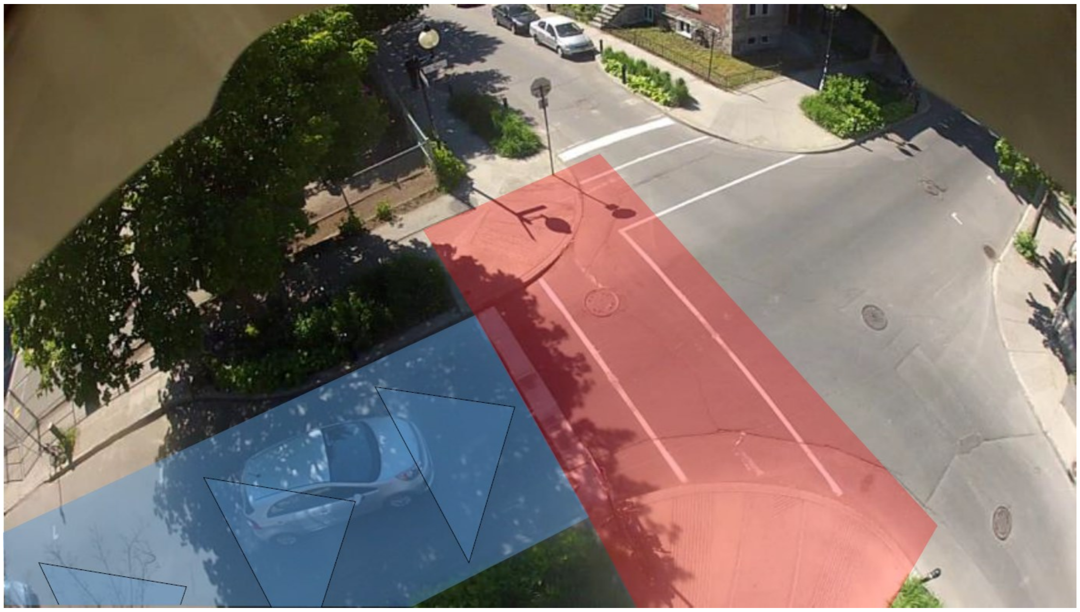


c) Site B-3 Beaubien-SaintVallier: *Crosswalk located at the intersection of Rue Beaubien and Rue De Saint-Vallier. The crosswalk crossing is on Rue Beaubien, a two-ways and one lane street per direction.*

d) Site B-4 Beaubien-27e: *Crosswalk located at the intersection of Rue Beaubien and Avenue 27e. The crosswalk crossing is on Rue Beaubien, a two-ways and one lane street per direction.*

e) Site B-5 Laurier_Berri: *Crosswalk located at the intersection of Avenue Laurier and Rue Berri. The crosswalk crossing is on Avenue Laurier, a one-way and one-lane street with a conventional and contraflow bike lane.*

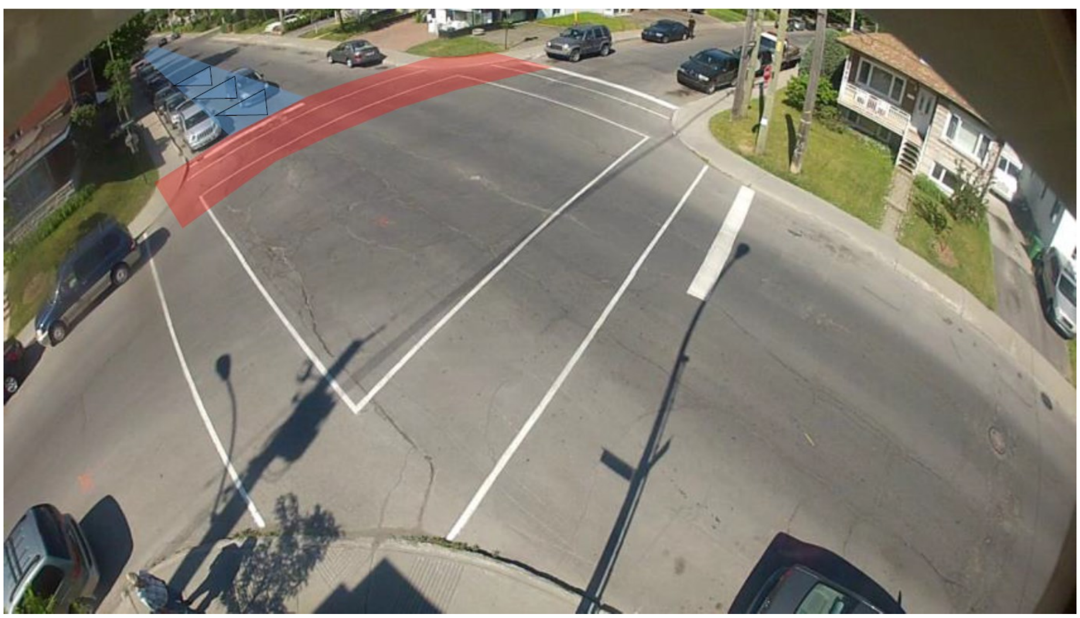
FIGURE II-2 Site description for marked crosswalks (Type B)



a) Site C-1 Roy-HenriJulien: *Intersection controlled with stop signs in all the approaches located at Avenue Henri-Julien and Rue Roy. The crosswalk crossing is on Avenue Henrie-Julien, a one-way and one-lane street.*

b) Site C-2 George-Gagne: *Intersection controlled with stop signs in all the approaches located at Rue George and Rue Gagné. The crosswalk is on Rue George, a two-ways and one-lane street.*

c) Site C-3 Sauriol-Millen: *Intersection controlled with stop signs in all the approaches at Rue Sauriol and Avenue Millen. The crosswalk is on Rue Sauriol, a two-ways and one-lane street.*

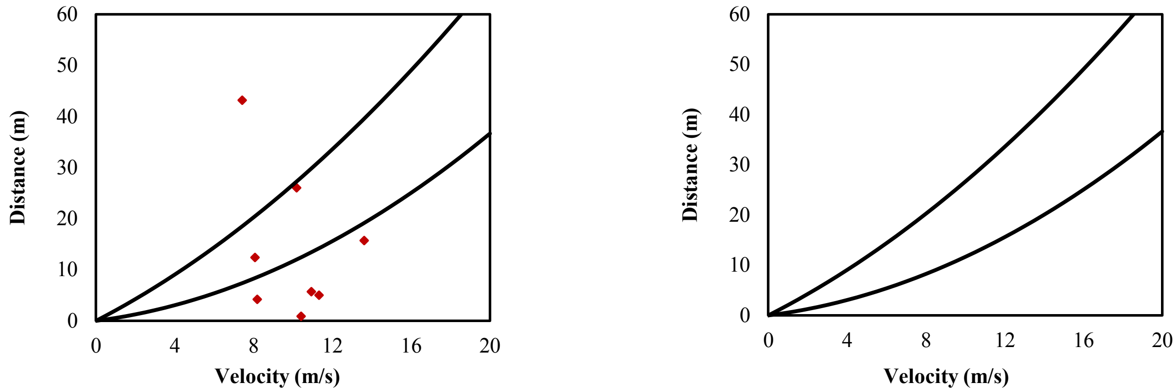


d) Site C-4 19e-Belair: *Intersection controlled with stop signs in all the approaches at Avenue 19e and Rue Bélair. The crosswalk is on Rue Bélair, a two-ways and one-lane street.*

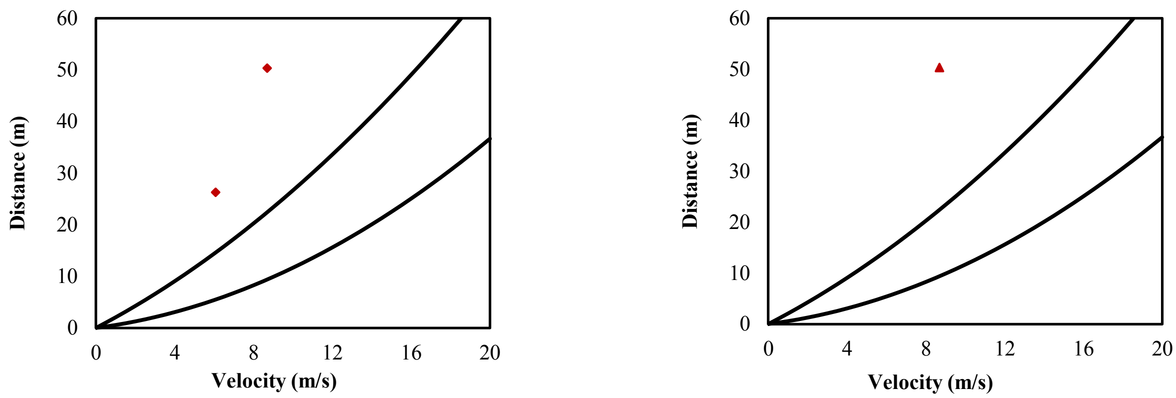
e) Site Z-5 13e_Belair: *Intersection controlled with stop signs in all the approaches at Avenue 13e and Rue Bélair. The crosswalk is on Rue Bélair, a two-ways and one-lane street.*

FIGURE II-3 Site description for stop sign controlled crosswalks (Type C)

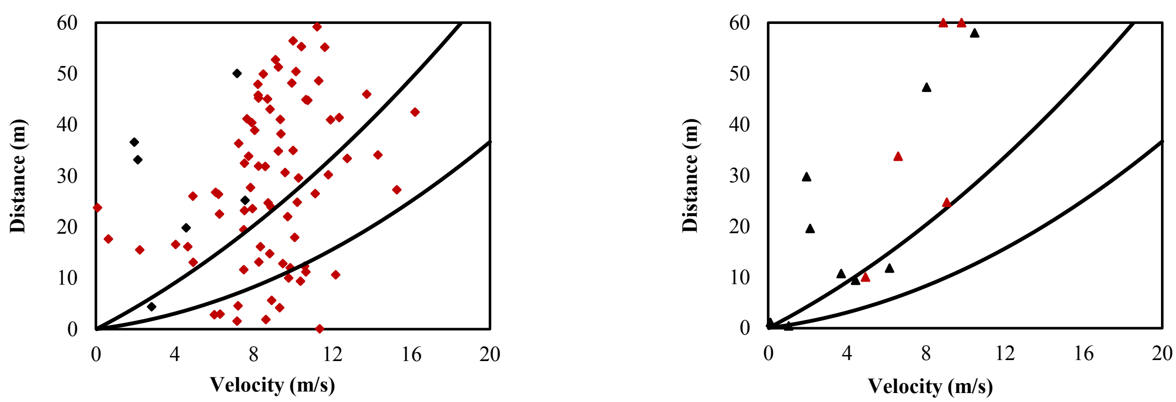
Appendix III Detailed Results and Analysis for Multiple Sites



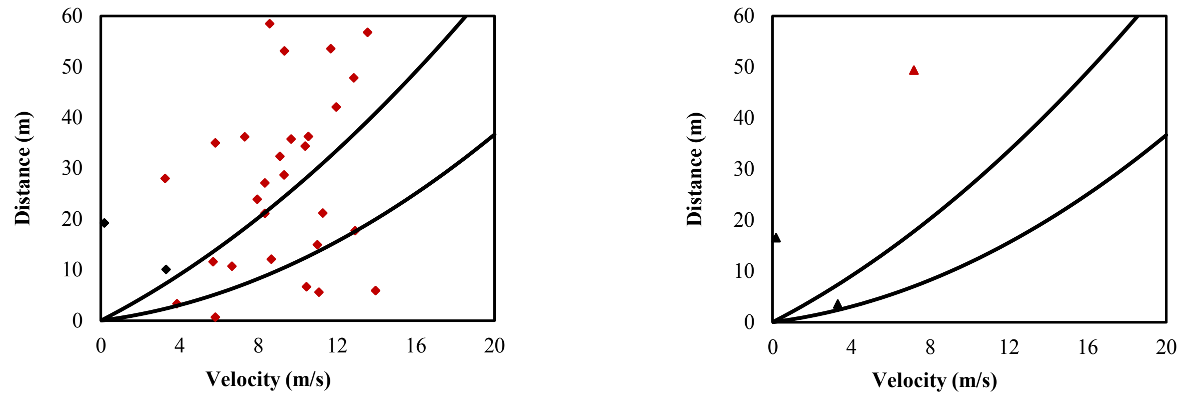
a) Site A-1



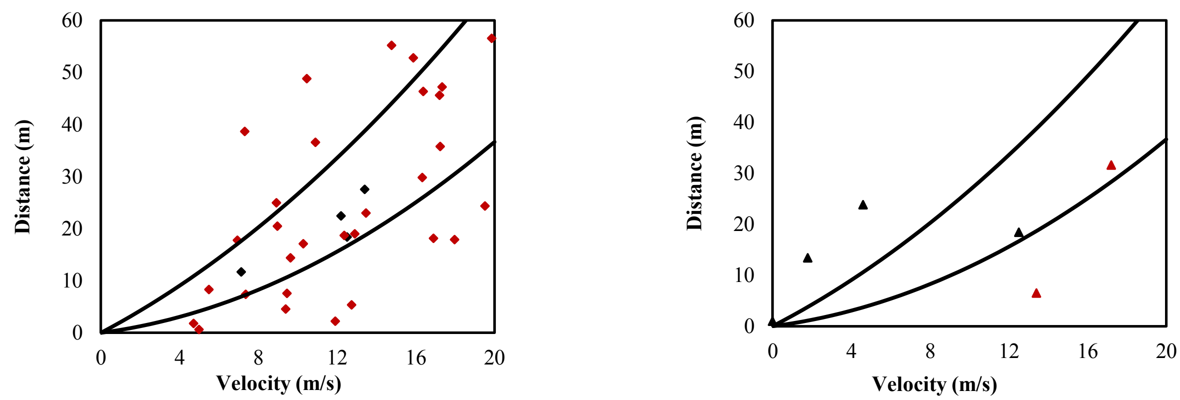
b) Site A-2



c) Site A-3

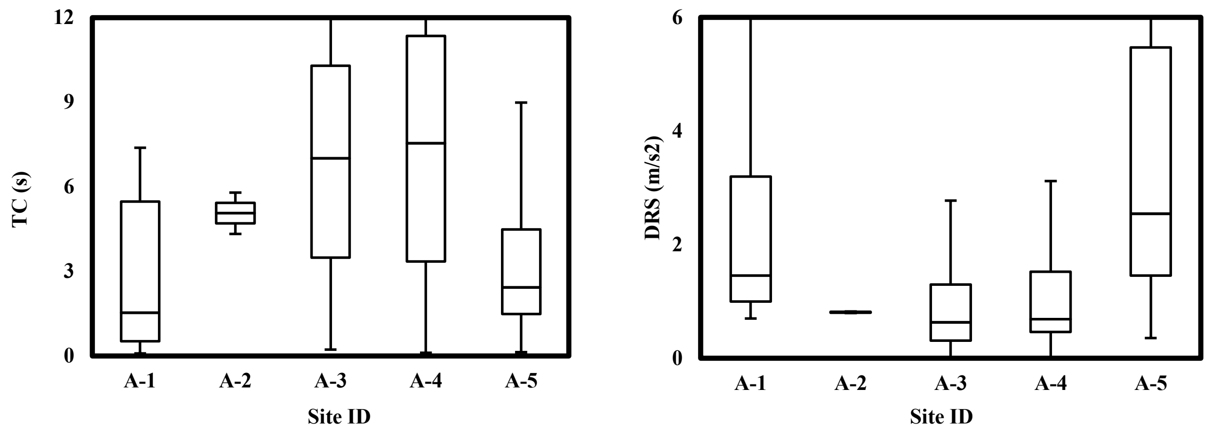


d) Site A-4

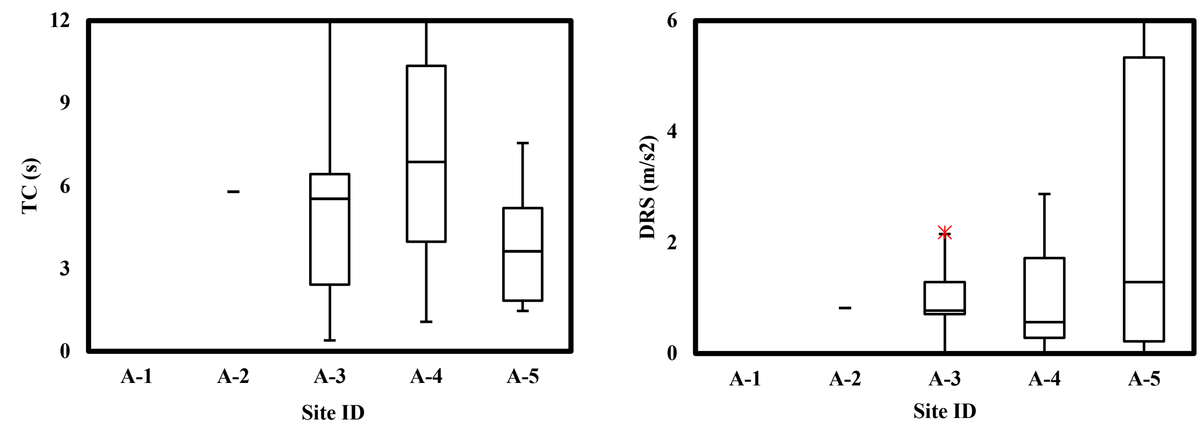


e) Site A-5

FIGURE III-1 DV plots for uncontrolled crosswalks (Type A)

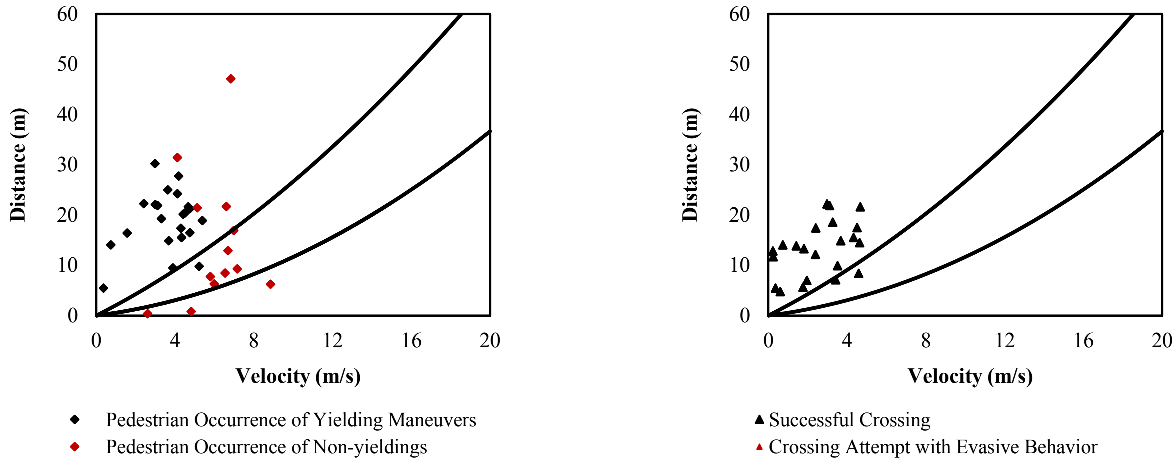


a) Pedestrian occurrence

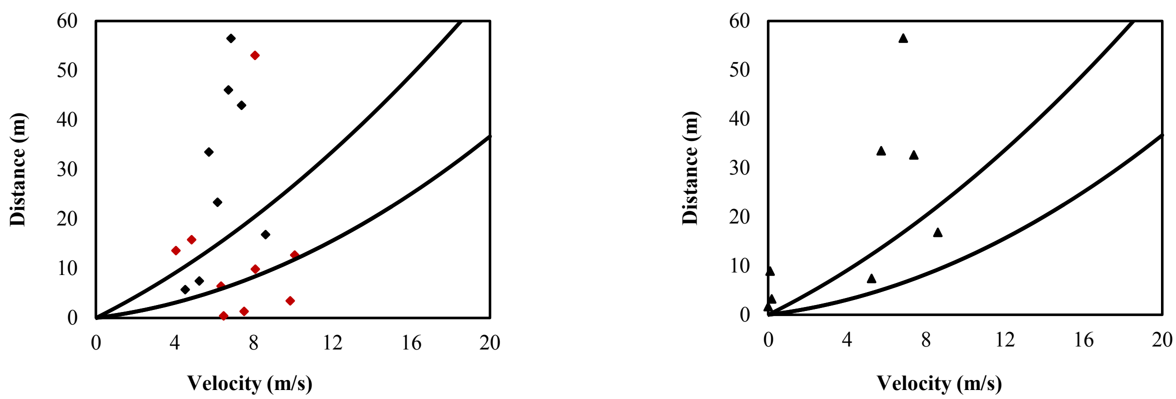


b) Crossing decision

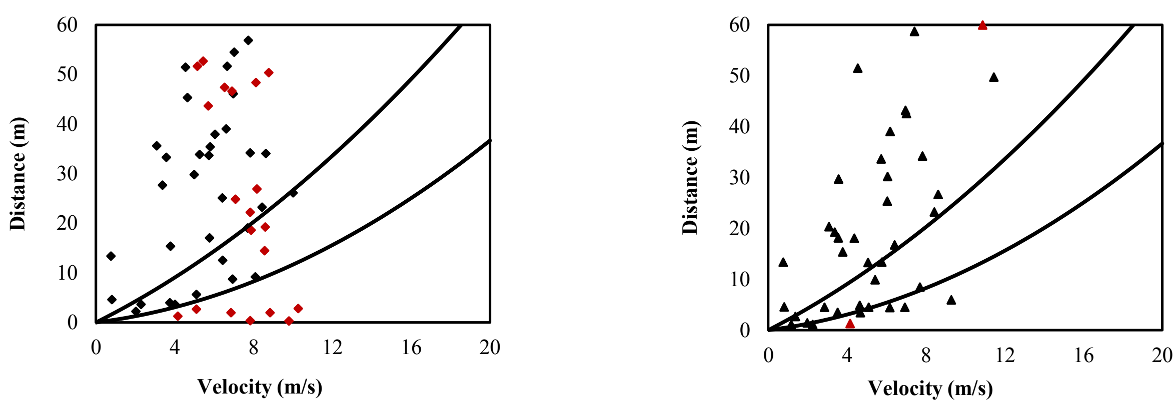
FIGURE III-2 Result comparisons pedestrian occurrence and crossing decisions at – Uncontrolled crosswalks (Type A)



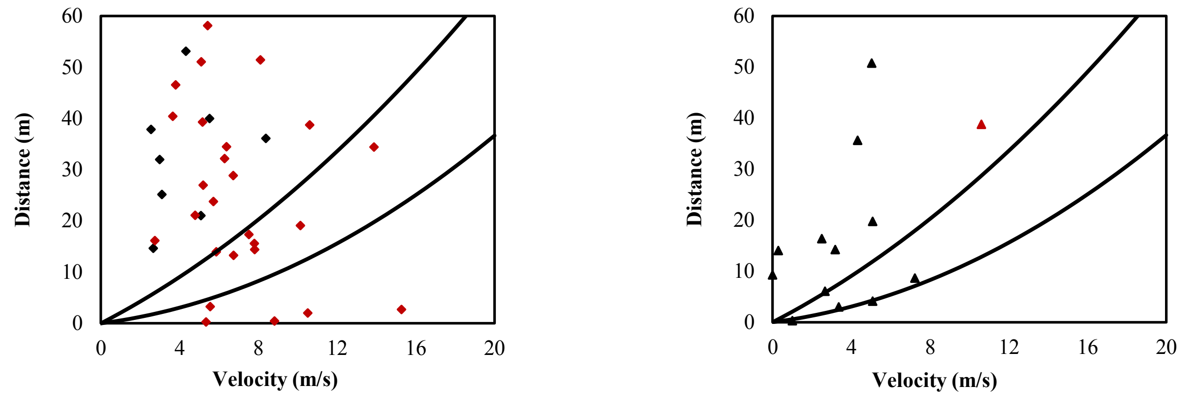
a) Site B-1



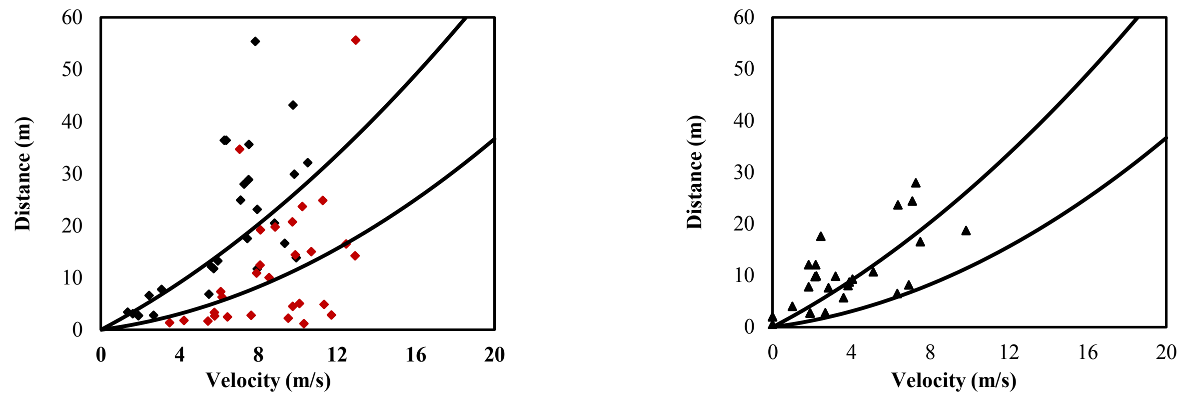
b) Site B-2



c) Site B-3

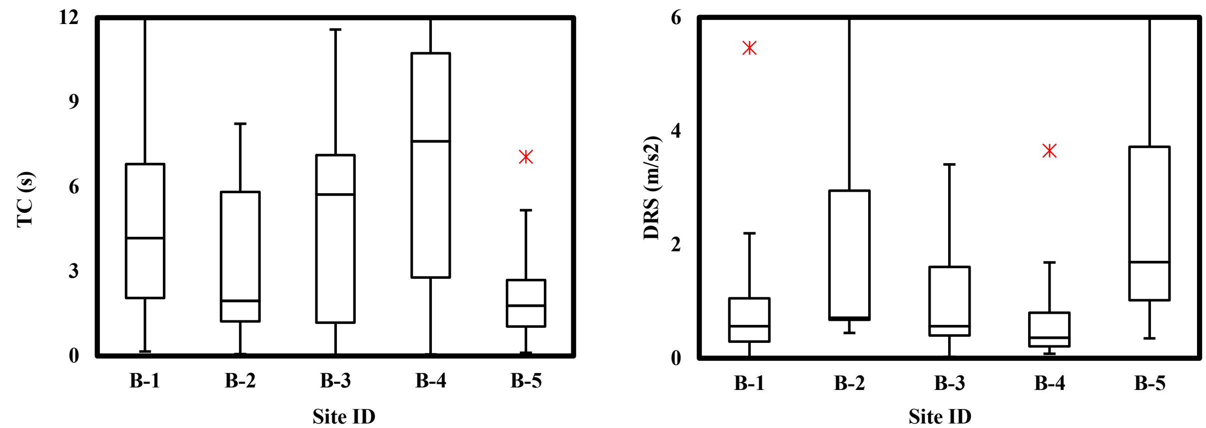


d) Site B-4

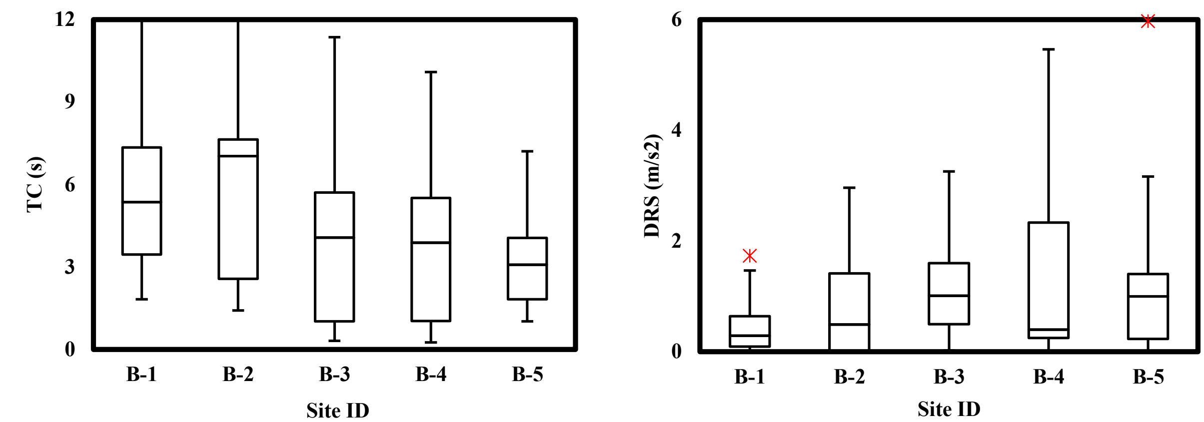


e) Site B-5

FIGURE III-3 DV plots for marked crosswalks (Type B)

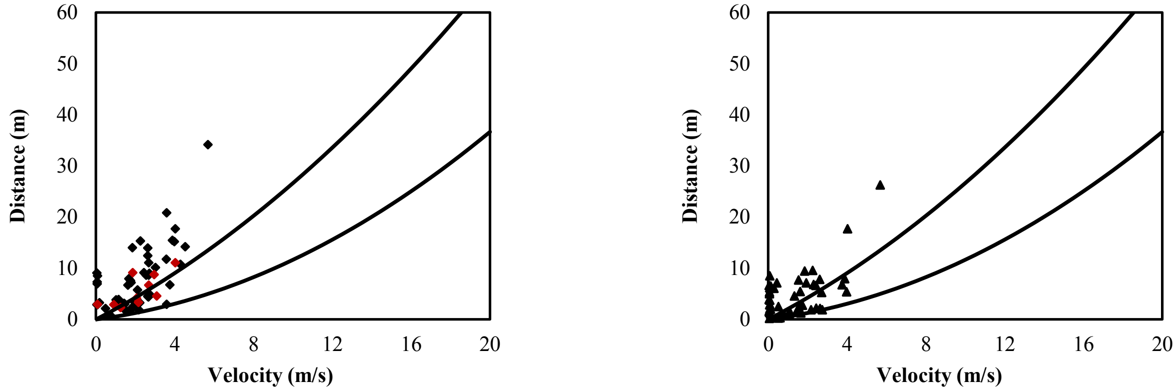


a) Pedestrian occurrence

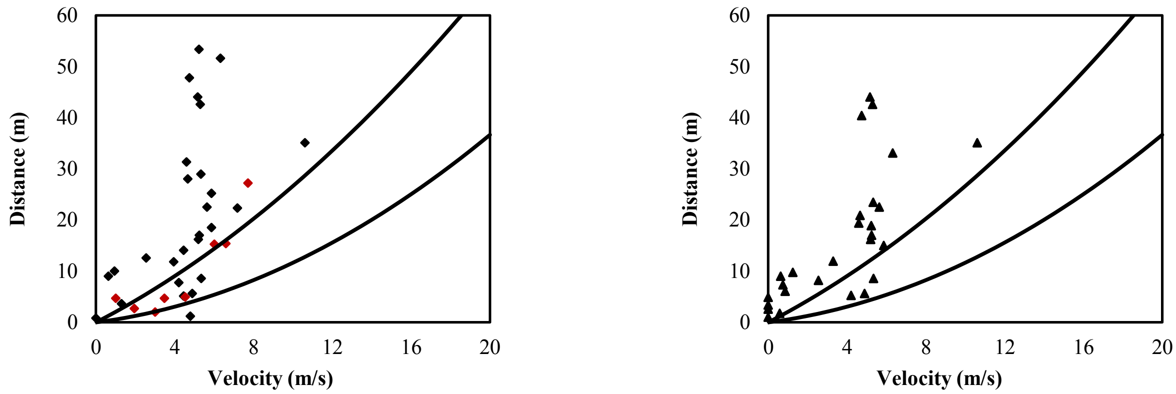


b) Crossing decision

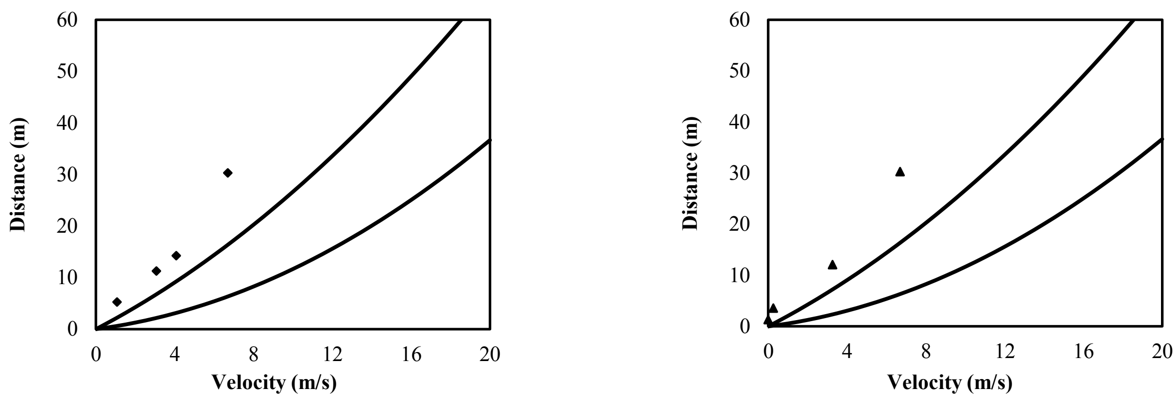
FIGURE III-4 Boxplots for pedestrian occurrence and crossing decisions at – Marked crosswalks (Type B)



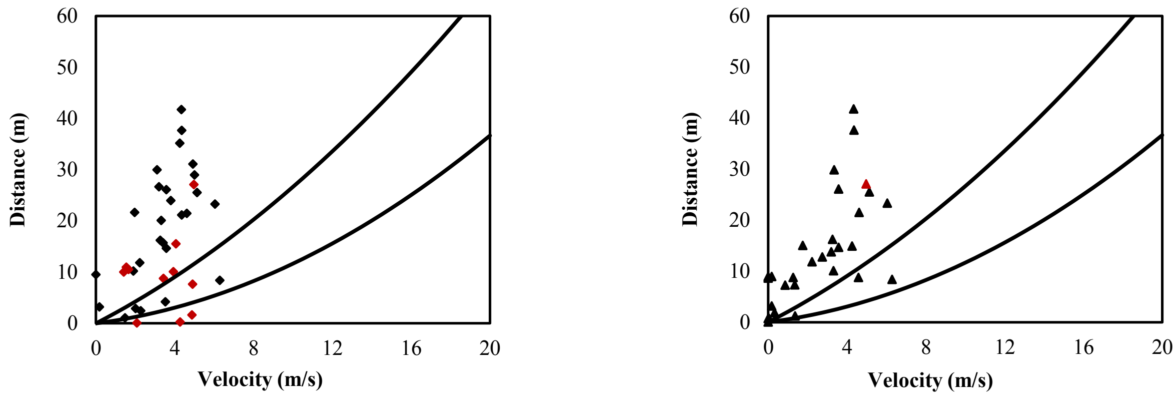
a) *Site C-1*



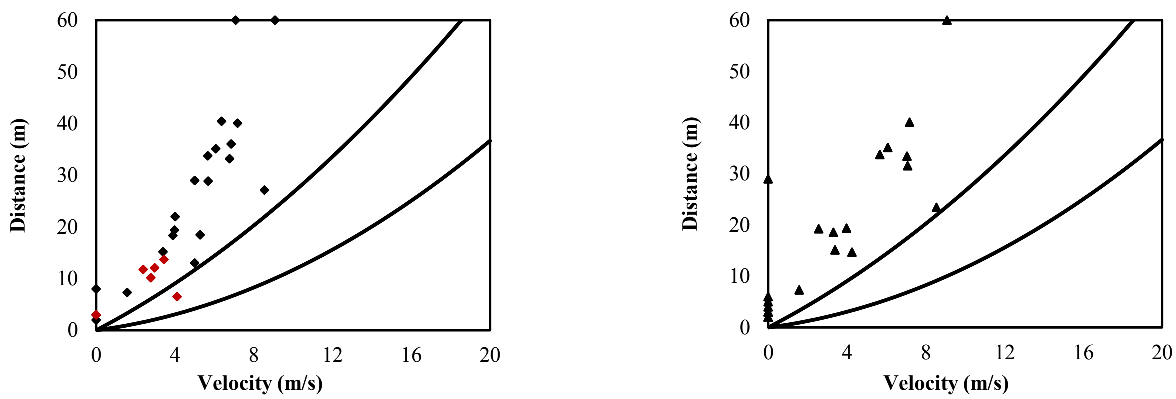
b) *Site C-2*



c) *Site C-3*

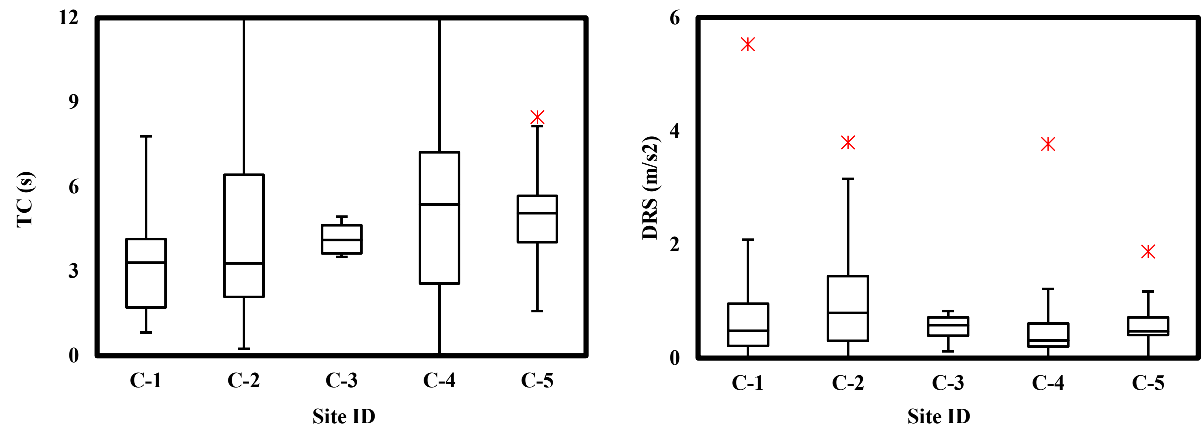


d) Site C-4

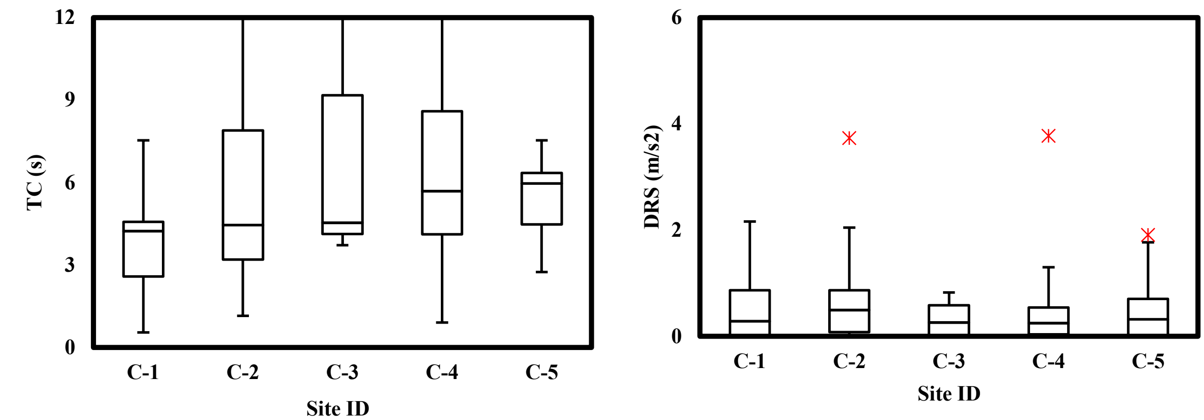


e) Site C-5

FIGURE III-5 DV plots for stop sign controlled crosswalks (Type C)



a) Pedestrian occurrence



b) Crossing decision

FIGURE III-6 Result comparisons pedestrian occurrence and crossing decisions at – Stop sign controlled crosswalks (Type C)

TABLE III-1 Results from DV Model for Marked Crosswalks

Site ID		X-1	X-2	X-3	X-4	X-5
		Results for Occurrence of Interactions				
<u>Number of Interactions</u>						
No. of Total Interactions		35	17	60	53	57
No. of Interactions in Phase I (Percentage over the total)		3 (8.57 %)	3 (17.65 %)	7 (11.67 %)	5 (9.43 %)	15 (26.32 %)
No. of Interactions in Phase II (Percentage over the total)		7 (20.00 %)	6 (35.29 %)	13 (21.67 %))	7 (13.21 %)	25 (43.86 %)
No. of Interactions in Phase III (Percentage over the total)		25 (71.43 %)	8 (47.06 %)	40 (66.66 %)	41 (77.36 %)	17 (29.82 %)
<u>TC and DRS at the Occurrence of Interaction</u>						
TC (sec)	<u>*Median*</u>	4.18	1.96	5.73	7.61	1.78
	<u>*Std. Dev.*</u>	3.29	2.65	3.57	4.90	1.68
DRS (m/s^2)	<u>*Median*</u>	0.56	0.71	0.56	0.36	1.69
	<u>*Std. Dev.*</u>	1.39	2.26	1.36	0.92	2.22
		Results for Yielding Behavior				
No. of Non-infraction Non-yieldings		3	3	7	5	15
No. of Uncertain Non-yieldings		6	3	3	7	12
No. of Non-Yielding Violations		4	3	11	29	3
No. of Yielding Maneuvers		22	8	39	12	27
Yielding Rate		62.86 %	47.06 %	65.00 %	22.64 %	47.37 %
Yielding Compliance		68.75 %	57.14 %	73.58 %	25.00 %	64.29 %
		Results for Crossing Decision				
No. of Decisions to Cross after Vehicle Passage		13	9	21	41	31
No. of Decisions to Cross before Vehicle Passage		22	8	41	13	26
No. of Dangerous Crossings (Percentage over the total)		0 (0.00 %)	0 (0.00 %)	6 (14.63 %)	2 (15.38 %)	4 (15.38 %)
No. of Risky Crossings (Percentage over the total)		2 (9.09 %)	2 (25.00 %)	10 (24.39 %)	2 (15.38 %)	7 (26.92 %)
No. of Safe Crossings (Percentage over the total)		20 (90.91 %)	6 (75.00 %)	25 (60.98 %)	9 (69.24 %)	15 (57.69 %)
No. of Crossings with Evasive Maneuvers		0	0	2	1	0
TC (sec)	<u>*Median*</u>	5.36	7.04	4.07	3.89	3.08
	<u>*Std. Dev.*</u>	4.25	6.29	2.71	3.26	1.72
DRS (m/s^2)	<u>*Median*</u>	0.29	0.49	1.01	0.40	1.00
	<u>*Std. Dev.*</u>	0.43	1.24	2.15	2.68	1.49

TABLE III-2 Results for Uncontrolled Crosswalks

Site ID		Y-1	Y-2	Y-3	Y-4	Y-5
				Results for Occurrence of Interactions		
Number of Interactions						
No. of Total Interactions		11	2	165	68	46
No. of Interactions in Phase I (Percentage over the total)		5 (45.45 %)	0 (0.00 %)	13 (7.88 %)	5 (7.35 %)	9 (19.57 %)
No. of Interactions in Phase II (Percentage over the total)		2 (18.18 %)	0 (0.00 %)	16 (9.70 %)	7 (10.29 %)	18 (39.13 %)
No. of Interactions in Phase III (Percentage over the total)		4 (36.37 %)	2 (100.00 %)	136 (82.42 %)	56 (82.36 %)	19 (41.30 %)
TC and DRS at the Occurrence of Interaction						
TC (sec)	*Median*	1.53	5.06	7.01	7.55	2.43
	Std. Dev.	2.82	1.04	5.81	6.10	3.12
DRS (m/s^2)	*Median*	1.46	0.81	0.63	0.69	2.54
	Std. Dev.	3.45	0.02	1.83	1.45	4.21
				Results for Yielding Behavior		
No. of Non-infraction Non-yieldings		5	0	13	5	9
No. of Uncertain Non-yieldings		2	0	15	7	14
No. of Non-Yielding Violations		4	2	128	54	19
No. of Yielding Maneuvers		0	0	9	2	4
Yielding Rate		0.00 %	0.00 %	5.45 %	2.94 %	8.70 %
Yielding Compliance		0.00 %	0.00 %	5.92 %	3.17 %	10.81 %
				Results for Crossing Decision		
No. of Decisions to Cross after Vehicle Passage		11	2	156	66	42
No. of Decisions to Cross before Vehicle Passage		0	1	15	3	6
No. of Dangerous Crossings (Percentage over the total)		0 (--)	0 (0.00 %)	1 (6.67 %)	0 (0.00 %)	0 (0.00 %)
No. of Risky Crossings (Percentage over the total)		0 (--)	0 (0.00 %)	3 (20.00 %)	1 (33.33 %)	3 (50.00 %)
No. of Safe Crossings (Percentage over the total)		0 (--)	1 (100.00 %)	11 (73.33 %)	2 (66.67 %)	3 (50.00 %)
No. of Crossings with Evasive Maneuvers		0	1	6	1	2
TC (sec)	*Median*	--	5.80	5.54	6.87	3.63
	Std. Dev.	--	--	3.97	56.27	2.65
DRS (m/s^2)	*Median*	--	0.82	0.77	0.56	1.29
	Std. Dev.	--	--	0.67	1.52	3.06

TABLE III-3 Results for Stop Controlled Crosswalks

Site ID		Z-1	Z-2	Z-3	Z-4	Z-5
		Results for Occurrence of Interactions				
Number of Interactions						
No. of Total Interactions		61	36	4	40	27
No. of Interactions in Phase I (Percentage over the total)		0 (0.00 %)	2 (5.56 %)	0 (0.00 %)	3 (7.50 %)	0 (0.00 %)
No. of Interactions in Phase II (Percentage over the total)		20 (32.79 %)	8 (22.22 %)	0 (0.00 %)	6 (15.00 %)	1 (3.70 %)
No. of Interactions in Phase III (Percentage over the total)		41 (67.21 %)	26 (72.22 %)	4 (100.00 %)	31 (77.50 %)	26 (96.30 %)
TC and DRS at the Occurrence of Interaction						
TC (sec)	*Median*	3.30	3.28	4.11	5.37	5.07
	Std. Dev.	5.76	3.50	0.69	4.62	1.44
DRS (m/s^2)	*Median*	0.48	0.79	0.58	0.31	0.47
	Std. Dev.	0.83	1.03	0.31	0.87	0.44
		Results for Yielding Behavior				
No. of Non-infraction Non-yieldings		0	1	0	3	0
No. of Uncertain Non-yieldings		4	4	0	1	1
No. of Non-Yielding Violations		6	3	0	7	5
No. of Yielding Maneuvers		51	28	4	29	21
Yielding Rate		83.61 %	78.00 %	100.00 %	72.50 %	77.78 %
Yielding Compliance		83.61 %	82.35 %	100.00 %	78.38 %	77.78 %
		Results for Crossing Decision				
No. of Decisions to Cross after Vehicle Passage		10	8	0	10	6
No. of Decisions to Cross before Vehicle Passage		51	28	4	31	21
No. of Dangerous Crossings (Percentage over the total)		0 (0.00 %)	0 (0.00 %)	0 (0.00 %)	0 (0.00 %)	0 (0.00 %)
No. of Risky Crossings (Percentage over the total)		18 (35.29 %)	3 (10.71 %)	0 (0.00 %)	3 (10.00 %)	0 (0.00 %)
No. of Safe Crossings (Percentage over the total)		33 (64.71 %)	25 (89.29 %)	4 (100.00 %)	27 (90.00 %)	21 (100.00 %)
No. of Crossings with Evasive Maneuvers		0	0	0	1	0
TC (sec)	*Median*	4.24	4.45	4.54	5.69	5.96
	Std. Dev.	6.98	3.34	5.60	4.00	1.27
DRS (m/s^2)	*Median*	0.28	0.49	0.26	0.25	0.32
	Std. Dev.	1.44	0.93	0.40	0.75	0.47