A VIDEO-BASED METHODOLOGY FOR EXTRACTING MICROSCOPIC DATA AND EVALUATING SAFETY COUNTERMEASURES AT INTERSECTIONS USING SURROGATE SAFETY INDICATORS

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Pedestrians and cyclists are amongst the most vulnerable road users as their accidents involving motor vehicles result in high injury and fatality rates for these two modes. Data collection for non-motorized road users remains a challenge and automated data collection methods are far more advanced for motorized traffic. To improve cyclist safety and promote urban cycling, cities have been building bicycle infrastructure, such as cycle tracks and bicycle boxes. These facilities have been built and expanded but due to the lack of appropriate data and problems with automated cyclist data collection, very little in-depth research has been carried out to investigate the safety impacts of these infrastructures. The majority of non-motorized safety studies are based on traditional methods which use observed accident and injury data. An important shortcoming of this approach is the need to wait for accidents to occur over several years. An alternative to traditional safety analysis is surrogate safety methods which can provide statistically sufficient data in a shorter time period. However, to perform surrogate safety studies, microscopic data from road users is needed. To address the shortcomings of the current literature and to improve the microscopic data collection tools for non-motorized road users, this thesis presents an automated methodology to classify road users in traffic videos – this methodology is complementary to existing object-tracking tools. The methodology is tested and validated using a large dataset from signalized intersections with high mixed traffic in Montreal, Canada. Road users are classified into three main categories: pedestrian, cyclist, and motor vehicle, with an overall accuracy of over 95 %. The proposed methodology is capable not only of counting the movements of the different road users (generating exposure measures), but also provides microscopic data separately for each road user type for safety analysis. As a result, performing automated surrogate safety studies becomes possible for facilities with mixed motorized and non-motorized traffic. As part of this thesis, the relationship between the surrogate safety measure used in this research, post encroachment time, and the historical accident data has been investigated and shows promising correlation. Using several hours of video recorded from a sample of signalized intersections in Montreal, and analyzed using the proposed techniques, the safety effects of two types of bicycle infrastructure, cycle tracks and bicycle boxes, have been investigated. The results show that based on the interactions between cyclists and turning vehicles, having a cycle track on the right side of the road is safer than not having a cycle track or

than having a cycle track on the left side of the road. Also the study on the safety of bicycle boxes at intersections reveals that this type of bicycle facility is associated with a significant reduction in the severity of interactions (increase in post encroachment time) between cyclists and vehicles.

RÉSUMÉ

Les piétons et les cyclistes sont parmi les usagers les plus vulnérables de la route puisque leurs accidents avec des véhicules motorisés entraînent des taux élevés de blessures et de décès pour ces usagers. La collecte de données pour les usagers de la route non-motorisés demeure un défi et les méthodes de collecte de données automatiques sont beaucoup plus avancés pour les usagers motorisés. Pour améliorer la sécurité des cyclistes et promouvoir le cyclisme urbain, les villes construisent des infrastructures pour les cyclistes comme des pistes cyclables et des sas vélo (« bicycle box »). Ces aménagements se sont répandus, mais en raison du manque de données et des problèmes avec la collecte de données automatique pour les cyclistes, peu d'études approfondies ont été réalisées pour mesurer les impacts sur la sécurité de ces infrastructures. La majorité des études de la sécurité des usagers non-motorisés repose sur des analyses traditionnelles des données d'accidents et de blessures. Une lacune importante de cette approche traditionnelle est la nécessité d'attendre que des accidents se produisent pendant plusieurs années pour effectuer les évaluations des traitements de sécurité. Parmi les alternatives aux méthodes d'analyse de la sécurité traditionnelles, se développent les méthodes substituts de sécurité qui peuvent fournir des données statistiquement suffisantes pendant une période de temps plus courte. Cependant, pour réaliser des études substituts de sécurité, des données microscopiques sur les usagers de la route sont nécessaires. Pour combler les lacunes de la littérature et améliorer la collecte de données microscopiques pour les usagers de la route non motorisés, cette thèse présente une méthode automatique (qui complète un système de suivi vidéo développé précédemment) pour classifier les usagers de la route dans des vidéos de circulation. Les usagers de la route sont classifiés en trois catégories principales: les piétons, les cyclistes et les véhicules motorisés, avec une précision globale de plus de 95 %. En plus de la capacité de cette méthode à compter les différents mouvements des usagers de la route (constituant des mesures d'exposition), cette méthode fournit des données microscopiques de trajectoire pour chaque type d'usager. En conséquence, la réalisation d'études substituts de sécurité automatiques, y compris des études impliquant des usagers non-motorisés, devient possible. Dans le cadre de cette thèse, la relation entre la mesure substitut de sécurité utilisée dans cette recherche, soit le temps post-empiètement, et des données historiques d'accidents a été étudiée et montre une forte corrélation. À l'aide de plusieurs heures de vidéo enregistrées dans un ensemble d'intersections à Montréal, analysées avec les techniques proposées, les effets de deux types d'infrastructures cyclables, à savoir les pistes cyclables et les sas vélo, ont été étudiés. Les résultats montrent que pour les interactions entre les cyclistes et les véhicules qui tournent, une piste cyclable sur le côté droit de la route est plus sûre que l'absence de piste cyclable ou qu'une piste cyclable sur le côté gauche de la route. De plus, l'étude de la sécurité des sas vélo aux intersections révèle que ce type d'installation est associé à une réduction significative de la sévérité des interactions (augmentation du temps post empiétement) entre les cyclistes et les véhicules.

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CONTRIBUTIONS OF AUTHORS

Please note that this is a manuscript-based thesis consisting of four journal papers. These papers were written in collaboration with other authors. The title of the articles, name of the authors, and the related journals are listed below. It is worth mentioning that two of the journal papers the author of this thesis is the sole student, among the co-authors, and in the other two journal papers the author of this thesis is the first author who was responsible for conducting the research, developing the methodologies, analyzing the data and preparing the manuscripts. The author's supervisor, Prof. L. Miranda-Moreno, and co-supervisor, Prof. N. Saunier, provided guidance and editorial revisions throughout the entire process. Also, minor changes (edits) have been made to the original published papers.

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. "Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application." *Transportation Research Part C: Emerging Technologies 56:161–76*. The *preliminary version of this paper was presented at Transportation Research Board 93rd annual meeting and the 24th Canadian Multidisciplinary Road Safety Conference.*

Zangenehpour, Sohail, Taras Romancyshyn, Luis Miranda-Moreno,and Nicolas Saunier. 2015. "Video-Based Automatic Counting For Short-Term Bicycle Data Collection in a Variety of Environments." *Journal of Intelligent Transportation Systems; Technology, Planning, and Operations, under review for publication. A preliminary version of this paper was presented at Transportation Research Board 94th annual meeting. In this paper Taras Romancyshyn was in charge of most of the video recordings and manually counting cyclists, as well as a part of literature review.*

Zangenehpour, Sohail, Jillian Strauss, Luis Miranda-Moreno,and Nicolas Saunier. 2015. "Are Signalized Intersections With Cycle Tracks Safer? A Control-Case Study Based On Automated Surrogate Safety Analysis Using Video Data." *Accident Analysis & Prevention 86:161-172. Preliminary versions of this paper were presented at Transportation Research Board 94th annual meeting and 25th Canadian Association of Road Safety Professionals. In this paper Jillian Strauss was in charge of gathering historical accident data, as well as a part of literature review.*

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. "Impact of Bicycle Boxes on Cyclist Behaviour and Safety: A Surrogate Study Using Manual and Automatic Video-Data Measures." *Transportation Research Part F: Traffic Psychology, under second review for publication. A preliminary version of this paper was presented at Transportation Research Board 92nd annual meeting.*

GLOSSARY OF TERMS

Bicycle Box: a designated area for cyclists to stop ahead of stopped cars at signalized intersections during the red phase while waiting for the light to turn green.

Collision: impact event between two or more road users.

Collision Point: location of the first physical contact when two road users hit each other.

Cycle Track: a physically separated lane dedicated only for cyclists. There are two main types of cycle tracks: unidirectional and bidirectional.

Evasive Maneuver: action that is taken by a road user to resolve a conflict situation and involves braking, accelerating, and/or swerving (Archer 2005).

Interaction: situations where road users readjust their speeds and movements due to their proximity to other road users

Post Encroachment Time (PET): the time between the departure of the encroaching road user from a potential collision point (at the intersection of the two trajectories) and the arrival of the next road user at the potential collision point.

Surrogate Safety Measure: is a measure based on an observable non-collision event that is related to accidents.

Time to Collision (TTC): the time until two objects would collide if their movements remain unchanged (it can be computed at any instant).

Traffic Accident: a collision that happens unexpectedly and unintentionally, involving a road user crashing with another road user, and typically resulting in property damage or injury.

Traffic Conflict: an observable situation in which two or more road users approach each other in time and space to such an extent that there is a possibility of collision if their movements remain unchanged (Hydén 1987).

Traffic Conflict Technique: a non-accident-based method for traffic safety estimation based on observation of traffic conflicts. The basic hypothesis of traffic conflict techniques is that accidents and conflicts originate from the same type of processes in traffic and a relation between them can be found (Laureshyn 2010).

Trajectory: series of x-y coordinates of road users at each instant.

Trajectory Heat-map: density of the road user trajectories in the camera view.

Chapter 1

Introduction

Chapter 1: Introduction

This chapter presents a brief introduction to the issue of road traffic safety as well as to the methods used for safety diagnosis and countermeasure evaluation using traditional and surrogate techniques. Particular emphasis is given to the traffic safety of vulnerable road users, which is the main focus of this research. This chapter also provides a literature review on automated data collection techniques as well as a few methods for evaluating engineering safety treatments. The contributions and objectives of this work are also presented in this chapter. Finally, the general methodology proposed to address the gaps in the literature is discussed.

1.1. CONTEXT

According to World Health Organization (WHO) (Toroyan et al. 2013), road traffic injuries are the 8th leading cause of death in the world. It is expected that if the current trends do not change, in 15 years, road traffic injuries will become the 5th leading cause of death worldwide. On average, more than 1.2 million people die every year as a result of road traffic injuries. Although the value of human life cannot be given a monetary value, dealing with the consequences of road traffic deaths and injuries costs more than US$500 billion worldwide (estimated based on the value of US$ in 1998) (Jacobs et al. 1999).

In 2010, the United Nations General Assembly adopted a resolution calling for a "Decade of Action for Road Safety 2011–2020" (WHO). Although in recent years the number of vehicles has increased by around 15 %, the total number of deaths on the world's roads remains almost the same, more than 3,200 every day. By improving different aspects of road safety, 88 countries were able to reduce the number of deaths on their roads between 2007 and 2010, showing that safety improvements are possible and there is potential to save many more lives if governments take further action. However, in 87 countries the number of road traffic deaths over the same time period has increased (WHO). Worldwide, 27 % of all road traffic deaths are pedestrians and cyclists, giving strong incentive to governments to address the safety needs of non-motorized road users.

In the current context where cities are striving to achieve sustainable mobility, non-motorized transportation modes are gaining popularity. Many cities in North America are experiencing an increase in pedestrian and cyclist activity, as well as infrastructure investments and programs to promote non-motorized transportation modes. However, among barriers for non-motorized transportation modes, their safety is one of the biggest. Even in Canadian cities, whose roads are safer compared to cities in developing countries, pedestrian and cyclist safety is still a fundamental issue. According to the statistics (Canadian Motor Vehicle Traffic Collision Statistics, 2012), Canada witnesses over 2,000 road traffic fatalities every year. 15 % and 3 % of these fatalities are related to pedestrians and cyclists, respectively (Figure 1-1, taken from Canadian Motor Vehicle Traffic Collision Statistics, 2012). In order to encourage people to use non-motorized transportation modes, walking and cycling need to be made safer, in particular in urban areas. Considering the ratio of accidents and casualties involving pedestrians and cyclists, addressing their safety is critical to successfully encourage more people to walk or bike, as well as to reduce the total number of road traffic deaths.

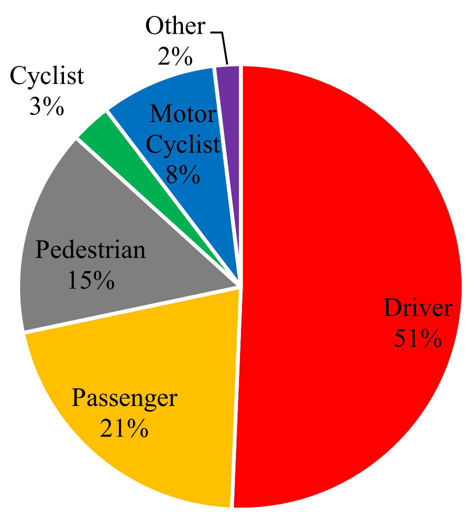


Figure 1-1. Distribution of fatalities on Canadian roads by road user class for 2012

1.2. PROBLEM STATEMENT

As the importance of non-motorized transportation modes is becoming clearer to the authorities, the safety of these modes has attracted a lot of attention among researchers and policy makers. There are two main streams of safety analysis and treatment evaluation in the current literature.

The first approach is based on historical observed accidents and injury data. The alternative approach uses surrogate measures of safety, i.e. methods that do not require waiting for accidents to happen. Both approaches have their strengths and limitations but also can provide complementary data. Traditional safety analyses based on accident data are reactive, requiring accidents to happen before the causes can be identified and treatments can be evaluated. In practical terms, traditional safety analysis requires several years of observation and data gathering before traffic safety engineers can perform a crash risk analysis or evaluate the effectiveness of countermeasures. On the other hand, surrogate safety techniques reduce the reliance on accident data by analyzing interactions (events that are physically and predictably related to traffic accidents) rather than accidents. However analyses based on surrogate safety measures in a shorter period of time may not be able to represent the general safety condition as they are biased towards the period of time involved in the data collection.

Recently, to examine different safety aspects of non-motorized transportation modes, in particular the safety of cyclists, several research papers have been published, mainly using the traditional approach. Thomas & DeRobertis (2013) reviewed 23 papers on the safety effect of cycle tracks from different countries, all using accident and injury data. However due to relatively fewer cycle tracks in North America, only one of these reviewed studies was based on data collected outside of Northern Europe. In another literature review (Reynolds et al. 2009), 23 papers on the impacts of infrastructure on cyclist safety were reviewed. From these papers, using injury data, fifteen and eight studies focused on the safety of cyclists on road segments and at intersections, respectively. Using accident and injury data, other studies also investigated different aspects of cyclist safety (Lusk et al. 2011a, Teschke et al. 2012, S. Jensen 2008, Gårder et al. 1994), such as biking in cycle tracks, bicycle lanes and other infrastructure.

Despite the popularity of traditional safety methods, in recent years studies have shifted from using accident and injury data toward using surrogate measures of safety. From this growing literature, one can mention studies looking at different aspects of vehicle and pedestrian safety (Sayed et al. 2012; St-Aubin et al. 2013; Shahdah et al. 2014; El-Basyouny & Sayed 2013; Autey et al. 2012; Ismail et al. 2010a; Ismail et al. 2010b; Ismail, Sayed, Saunier, et al. 2009; Saunier et al. 2010). There are however very few studies looking at cyclist safety based on surrogate measures of safety. Two recent examples of studies on cyclists safety based on surrogate measures are the studies done by Kassim et al. and Sayed et al. (2014a; 2013a).

One of the most critical and unsafe elements of the road network in urban areas is signalized intersections, where a high concentration of interactions and accidents occur. This is not surprising, since intersections are not only the locations where pedestrians and cyclists are more exposed to motorized traffic but also where a variety of motorized movements at intersections generate several points of conflict between different movements. In cities such as Montreal, 60 % of non-motorized injuries occur at intersections (signalized and non-signalized) (Strauss, Miranda-Moreno, et al. 2013). Given the importance of this topic, several studies have looked at safety at intersections using traditional approaches based on historical accident data (Miranda-Moreno et al. 2011) and surrogate safety approaches such as conflict analysis (Ismail, Sayed & Saunier 2009b).

Despite the emerging literature on surrogate methods for safety analysis, some important issues deserve more attention:

(i) The majority of non-motorized safety studies are based on traditional analyses which use accident and injury data. However, an important shortcoming of this approach is the need to wait for accidents to occur for several years to carry out a safety treatment evaluation. In addition, with the traditional approach, there is a lack of details and understanding of the cause(s) of an accident. As an alternative, or a complementary approach, surrogate safety methods provide several benefits. Interactions, and other quasi-accident events that can be related to safety, occur much more frequently than accidents and as a result, statistically sufficient data can be collected in a shorter time period.

(ii) Most of the past surrogate safety studies focused on the safety of motorized vehicles, and there are very few studies focusing on the safety of non-motorized road users. The main reason behind the lack of surrogate safety studies on non-motorized mode is the difficulty of collecting data for these modes.

(iii) For performing surrogate safety analysis in mixed environments with more than one type of road user (such as at intersections), a classification method is needed to differentiate between the different road users. The classification of road users can also help the automation of the entire process of the surrogate safety analysis. Despite the importance of road user classification in surrogate safety analysis (especially the methods based on video data), very few methods have the ability to distinguish between different road users. Due to the lack of standardized benchmarks and public implementation and since some details remain unpublished, it is difficult to replicate previous work, which puts the accuracy of these methods in question.

(iv) Short-term and long-term bicycle counts are important information for researchers and practitioners in the transportation field. This information is typically required for road safety studies to generate exposure measures or safety performance functions. In addition, during the planning and design of projects, bicycle counts are necessary to estimate bicycle activity and infrastructure needs. Counts are also required to quantify ridership growth over time after interventions and installations of bicycle facilities. Although in recent years several methods have been introduced to automatically count motorized flows, automated bicycle counting is a challenging task and very few studies have addressed this topic.

(v) One of the main shortcomings of most previous research on automatic counting is reporting the accuracy for the entire period of data collection or for a long period of time. Since over-counting and under-counting errors in shorter time periods cannot always compensate for the effect of each other, accuracy reported for longer periods of time can be subject to uncertainty and cannot be trusted.

(vi) Although cities in North America have begun to follow the lead of European cities to build cycling infrastructure, such as cycle tracks, there are still very few in-depth analyses to quantify their effects on cyclist safety. In particular, in cities such as Montreal, two types of cycle tracks exist, bidirectional cycle tracks on the right side of the road and bidirectional cycle tracks on the left side of the road. However no studies have compared the safety effect of cycle tracks on the right side against the left side of the road, and it is not clear which one of these two designs is safer.

(vii) The other cycling infrastructure that is recently becoming very popular in North America is the bicycle box. During the red signal phase at signalized intersections, bicycle boxes place cyclists in front of the stopped vehicles and it is expected to result in several positive impacts, such as the improvement of drivers' awareness of cyclists, the decrease in cyclists' exposure to the direct exhaust of vehicles, and the reduction of interactions between cyclists and vehicles. However very little research has been done to evaluate the effectiveness of this inexpensive safety treatment.

(viii) The fact that the number of accidents at a location is random and the number of accidents reported every year at the same location is usually not the same, even if the traffic conditions have not changed (Laureshyn 2010), gives some level of randomness to accident data and makes accidents hard to predict. The final goal of many safety studies is to find and reduce the causes of accidents and injuries: since the use of surrogate safety measures instead of accident and injury data has started to grow among researchers and practitioners, the relationship between surrogate safety measures and accident data has to be examined thoroughly. However almost all the past surrogate safety studies lack the validation of the surrogate safety measures used in the study.

(ix) Most past studies lack the ability to obtain disaggregate exposure measures in a short period of time, separately for each road user. It is expected that using disaggregate exposure measures, separately for each road user of interest (for example traffic flow for a few seconds before the arrival of one specific road user), helps better understand their interactions with other road users.

1.3. OBJECTIVES

The general objective of this thesis is to develop a video-based methodology for classifying road-user trajectories and evaluating safety countermeasures at intersections using surrogate safety indicators. This methodology collects traffic data separately for each road user type (pedestrian, cyclist and motor vehicle). This data includes counts, speeds and surrogate safety measurements for estimating risk (probability of accident occurrence) and evaluating the effectiveness of countermeasures. The development of this methodology is expected to shift the workload of traffic monitoring from human operators to automated systems with improved performance and the ability to perform data collection and safety analysis for non-motorized road users.

The specific objectives of this research are, to:

1. Develop and validate automated road user classification methods capable of classifying moving objects in a traffic video into three main categories: pedestrian, cyclist and motor vehicle.
2. Propose and evaluate the performance of an automated video-based method for counting cyclists in mixed traffic environments such as at intersections and along road segments.
3. Investigate the safety effects of cycle tracks at signalized intersections by using of a control-case study methodology and a relatively large video dataset. The other objective of this part is to investigate the relationship and correlation between historical accident data and the surrogate safety measures that are used in this research.
4. Investigate the safety effects of bicycle boxes at signalized intersections using a before-after approach and cyclist crossing behaviours in the city of Montreal.

1.4. GENERAL LITERATURE REVIEW

As mentioned previously, there are two main approaches to evaluate the safety and effectiveness of engineering treatments: 1) traditional accident based analysis, and 2) surrogate safety methods. Both approaches can be pursued using different levels of automation. An example of automation in the traditional accident analysis is the use of count data generated by preinstalled sensors at different sites (rather than manually by observers), as the exposure measure for safety analysis. Levels of automation can be even higher for surrogate safety analysis, from estimating the surrogate measures to exposure measures such as traffic flows. This automation in safety studies can be based on different sources of information and generated from a variety of sensors, such as inductive loops, magnetic sensors, microwave and laser radars, infrared and ultrasonic sensors, as well as video sensors (Klein et al. 2006). Video sensors have several advantages over other sensors, in particular the ability to capture the naturalistic movements of road users with a small risk of catching their attention, the relative ease of installation, the richness of extracted data and the relatively low cost (Saunier et al. 2011). However, to date, one of the main challenges of video sensors is the ability to extract microscopic data separately for each road user type especially at urban intersections with high and mixed traffic conditions. This issue has brought to attention the need for developing algorithms capable of classifying road users in a traffic video.

In this section, the extensive body of literature on transportation safety is divided into three parts: 1) studies looking at data collection methods, in particular the ones based on video data, 2) studies focusing on cyclist safety, and 3) studies on the validation of surrogate safety measures.

1.4.1. Video Based Data Collection

The first step for extracting microscopic data from a video is tracking road users (finding the position of each road user in time). Different methods for the detection and tracking of road users in a video data exist and can be categorized into (Forsyth et al. 2005):

- ✓ Tracking by detection: object detection is done using background subtraction with the current image (Antonini et al. 2006) or a model of image appearance using colour distribution, edge characteristics and other local descriptors (Gavrila & Munder 2006; Mikolajczyk & Schmid 2005). In many cases, especially if the objects are well separated, this approach works well.
- ✓ Tracking using flow: object detection is done by matching the object pixels in successive images. This approach is also called feature-based tracking and has been used in many traffic monitoring systems such as in Saunier & Sayed (2006).
- ✓ Tracking with probability: object detection is done with a probabilistic Bayesian tracking framework. In simple cases, independent Kalman filters can be used to predict the future state of the object and track them, but this approach will fail in situations where the objects interact and occlude each other.

Despite the significant progress in recent years, tracking performance is still difficult to report and compare, especially when the tracking systems and standard benchmarks are not publically available (Saunier et al. 2014).

Road user classification is a useful addition to traffic monitoring systems and efforts have already been made in this area. In a video, objects can be classified simply by their speed, as in Ismail, Sayed & Saunier (2009a) where the authors classified pedestrians versus motorized road users based on the maximum speed of the object, with a threshold of 3.5 m/s. However no classification accuracy was reported in this work. Arguably it is expected that classification based only on speed fails in situations with traffic congestion where vehicles move at slower speeds.

In recent years, similar to object detection and tracking in video data, significant progress has been made in object classification based on the image. Most of the research focuses on the extraction of the best features to describe the objects in the images. There are two main categories of description variables:

1. Variables describing the object's appearance, i.e. the pixels: these features are generally invariant to various image transformations such as rotation and scaling. Histogram of Oriented Gradients features (HOG) (Dalal & Triggs 2005), Scale-Invariant Feature Transform features (SIFT) (Lowe 2004), Speeded Up Robust Features (SURF) (Bay et al. 2008), DAISY (Tola et al. 2010), Local Binary Patterns (LBP) (Ojala et al. 2002) and Fast Retina Keypoint (FREAK) (Alahi et al. 2012) are examples for this category.
2. Variables describing the object's shape: an overview of the these descriptive variables can be found in Bose (2005). The simplest descriptions are the area and aspect ratio of the bounding box of the object.

Fitting a 3D model is another way to classify objects in traffic monitoring. In Messelodi et al. (2005), complex 3D models are used to classify objects into seven classes: bicycle, motorcycle, car, van, urban bus, and truck. The object description includes other visual features such as brightness and colour histograms. SVM classifiers are used to differentiate between sub-classes, such as between bicycles and motorcycles or between buses and trucks. A global detection rate as high as 92.5 % has been reported, however this value varies for the different classes. The authors found that the main sources of classification error are shadows, reflections, occlusions, and presence of pedestrian groups in the video. However the greatest problem with 3D model classifiers is partial occlusion in busy traffic scenes causing a "greater-than-real-object" silhouette detection, resulting in an overestimation in the truck class.

In Kanhere & Birchfield (2008), authors classified objects into two categories of cars and trucks, in simple highway settings and using relatively low camera angles. Using feature-based tracking mixed with background subtraction and 3D perspective mapping from the scene to the image, they succeeded in distinguishing between subsets of features which were then grouped to yield the location of the vehicles. Using the number of features making up the object height (called "unstable features", the ones that do not lie on the front of the vehicles close to the road), the overall classification accuracy of this work is reported to be over 90 %.

In Morris & Trivedi (2008), after background subtraction to detect objects, the authors extracted the standard description of blobs. Tracking objects was done using dynamic models (Kalman filter) and appearance constraints. In this work, based on the most frequent vehicle types from the 2001 National Household Travel Survey, objects were classified into different categories: sedan, pickup, SUV, van, bike, and truck. Classification was done using a weighted k-nearest neighbor classifier based on the reduced feature set. In this work, the classification accuracy ranged from 77.5 % to 94 % based on different confidence threshold values.

Although the work presented in Zhang et al. (2007) is called "unsupervised" by its authors, using k-means, it implicitly relies on prior knowledge of the road users in the scene. The description variables are the velocity of the object area, the "compactness", defined as the ratio of the object area over the square of the object perimeter (length of the path surrounding the object shape), the time derivative of the area and the angle between the motion direction and the direction of the major axis of the shape. The reported classification accuracy of this work varies between 98 % for pedestrians, 90 % for bicycles, and 97 % for vehicles.

The method to count and classify composite objects presented in Somasundaram et al. (2013a) relies on various descriptors combined in a Naïve Bayes framework or simply concatenated as inputs of a SVM classifier. In this work, SIFT, SURF, and pyramidal HOG were used as feature descriptors. The accuracy of this work for classifying objects into pedestrians and cyclists is reported to be around 92 %.

In Saunier et al. (2011), based on the discrimination of the cyclic nature of the speed profiles of each road user type, i.e. the speed movement patterns of vehicles and the ambulatory characteristics of pedestrians, objects are classified in two categories of pedestrians and vehicles. The main assumption of this technique is that vehicle movements do not have any harmonic components. The overall accuracy is reported to be approximately 90 %.

In Zaki & Sayed (2013), after tracking each moving object in the video using the feature-based tracker described in Saunier & Sayed (2006), the class of each object is predicted based on the motion pattern attributes associated with the trajectories of each road user type. Specifically, a road user is classified based on the characteristic oscillatory movements and the matching to prototype trajectories labeled by type of each road user (representing the main motion pattern for each road user type), as first introduced in Ismail et al. (2010a). In this work, classification accuracies of 94.8 % and 88.6 % are reported respectively for binary classification of motorized versus non-motorized road users and for the classification of three main types of road users: pedestrian, cyclist, and vehicle.

More recently in Hediyeh et al. (2013), using the spatiotemporal parameters of gait (step frequency and length), the authors tried to classify pedestrians based on their age and gender. The gait parameters were extracted from the trajectory and instantaneous speed of the pedestrian. Using the k-nearest neighbor classifier, they achieved classification accuracies of around 80 % and 86 % respectively for gender and age. In this work both classifiers were binary, being male and female for gender, and young (between 16 to 35 years) and old (above 55 years) for age. However the classification accuracy is not clearly reported for the age between 36 to 55 years.

One of the main problems with reporting the classification accuracy in most of the previous works is that instead of reporting confusion matrices (results per class) and accuracy of classification for each type of road user, the authors just report an overall accuracy or proportion of correctly classified objects for given time periods. The accuracy reported based on the counts over a long period of time can be prone to error, as uncertainty and randomness of over-counting and under-counting in shorter time periods do not always compensate for the effect of each other in longer time periods. Also it should be noted that none of these studies focused on busy locations such as intersections with heavy cyclist and pedestrian traffic.

Most past studies have focused mainly on obtaining data and trajectories of motor vehicles. Due to the constant change of orientation and appearance of pedestrians and cyclists, detecting and tracking them in video data is still a challenging task. This is one of the main reasons why automated data collection methods have mainly been developed to detect and track motorized traffic. Moreover, among the existing methods with the ability to classify road users in traffic videos, most of them rely on single classification cues such as speed parameters or appearance and none have tried to combine both sources of information to improve the accuracy of the classification. Due to the lack of standardized benchmarks and public implementations, it is difficult to replicate previous work since some details remain unpublished, putting the reported accuracy of these methods in question.

1.4.2. Cyclist Safety

As mentioned previously, due to challenges of automatically extracting microscopic data for cyclists, to date, most of the past studies on cyclist safety rely on either accident data or surrogate safety analysis based on manual data collection. This section of literature review is divided into two main approaches for safety analysis, whether studies are based on: 1) traditional historical accident analysis, and 2) surrogate analysis.

1.4.2.1 *Studies Based on Historical Accident Analysis*

Using historical accident data, the majority of studies have found that corridors with cycle tracks are either safer or at least not more dangerous than corridors without cycle tracks. However some of the studies concluded that although cycle tracks make the road segments safer, the presence of a cycle track at an intersection can make it more dangerous for cyclists (for example in (Gårder et al. 1994) and (Jensen 2008)).

In a review of 23 papers which examined the literature on cycle tracks from Northern European countries (with the exception of one study from Canada), it was found that one-way cycle tracks are safer than bidirectional cycle tracks and that in general, cycle tracks reduce the number of accidents involving a cyclist (Thomas & DeRobertis 2013). Another review revealed that bicycle-specific facilities (i.e. cycle tracks, bicycle lanes, and bicycle paths), compared to shared roads with vehicles or shared off-road paths with pedestrians, reduce the risk of accidents and injuries for cyclists (Reynolds et al. 2009).

A case-control study carried out in Montreal, compared cyclist injury rates on 6 bidirectional cycle tracks and compared them to that on reference streets (Lusk et al. 2011a). Bicycle flows were found to be 2.5 times greater on cycle tracks than on the reference streets and the relative risk of injury on cycle tracks was found to be 0.72 compared to the reference streets, supporting the safety effects of cycle tracks.

Looking at bicycle infrastructure in Toronto and Vancouver, Teschke et al. (2012) found that cycle tracks have the lowest injury risk compared to other types of infrastructure and with one ninth of the risk of major streets with parked cars and no bicycle infrastructure. Overall, authors found that quiet streets and bicycle facilities on busy streets provide safest passage for cyclists.

Although most studies have agreed on the safety effects of cycle tracks along road segments, some studies have found that the presence of cycle tracks at intersections is dangerous. A before-after study in Denmark found that by installing cycle tracks, bicycle flows increased by 20 % while vehicle flow decreased by 10 % (Jensen 2008). However, overall, injuries were found to increase with the implementation of cycle tracks. While injuries were reduced along road segments, the increase in injuries at intersections was greater than this decrease. The author identified that cycle tracks which end at the stop line of the intersection can be dangerous. In Gårder et al. (1994), authors found a similar conclusion in Sweden, physically separated tracks should be cut some short distance before the intersection which would not only improve visibility but also cause cyclists to feel less safe influencing them to pay greater attention at intersections.

1.4.2.2 *Studies Based on Surrogate Safety Analysis*

Cyclist safety studies based on surrogate measures of safety are beginning to gain more popularity in the literature, however very few of these studies used automated techniques for the data collection and analysis. In one of the first studies on bicycle boxes, video data was recorded before and after the installation of a bicycle box to observe cyclist behaviour and interactions with other road users (Hunter 2000). Among other results, the statistical tests in this study showed no significant reduction in the total number of violations and interactions.

In another study, the authors investigated the impact of bicycle boxes and their colour on cyclist safety (Loskorn et al. 2011). They used video footage of two intersections in Austin, Texas, collected over three time periods: before the installation of the bicycle boxes, after marking the bicycle boxes, and after adding colour to the bicycle boxes. In this study the safety indicator was the appropriate usage of the facilities, assuming that if cyclists use the facility correctly, they are behaving in a safe way. This study showed that bicycle boxes improved the safety of cyclists at intersections, however, adding colour to the bicycle boxes did not significantly increase the percentage of cyclists that used the bicycle boxes correctly. As the authors mentioned in this paper, cyclists not using the facility correctly are not necessarily behaving dangerously.

In Dill et al. (2012a), the authors manually analyzed cyclist-vehicle interactions that could potentially lead to an accident and behaviours using video data recorded before and after the installation of bicycle boxes at 10 signalized intersections. The number of interactions between cyclists and vehicles decreased, while the total number of cyclists as well as right turning vehicles at the intersections increased. Also, in terms of perceived safety, over three-quarters of the cyclists that participated in the survey stated that bicycle boxes made the intersection safer for them.

With the increase in computing power and capacity of sensors as well as the introduction of new technologies, automated studies based on surrogate safety analysis have begun to emerge in the literature. However there are still very few studies which used automated techniques for cyclist surrogate safety analysis. In a recent study, the authors used an automated video-analysis technique to identify and analyze serious events such as cyclist-vehicle interactions as well as vehicle rear-end and merging interactions (Sayed et al. 2013b). By looking at a newly installed bicycle lane at the entrance of a major bridge in Vancouver, and using time to collision as a surrogate safety indicator, a high number of traffic conflicts involving cyclists and a significant driver non-compliance rate were found.

Another recent study in Ottawa evaluated cyclist-vehicle interactions at signalized intersections based on automated video analysis techniques to extract microscopic data and post encroachment time as the surrogate safety measure (Kassim et al. 2014b). In this work, objects were classified manually and the main focus was on the methods to estimate post encroachment time automatically and accurately. At the end, no conclusions were made on the safety of cyclists at the studied intersections.

Roundabout design and the safest design for cyclists is considered in a study in Sweden (Sakshaug, Laureshyn, Å. Svensson, et al. 2010). This study was based on different sources of data: historical accident data, manually observed conflicts, and semi-automatically extracted surrogated safety measures. The findings of this study revealed that the most dangerous situations in an integrated roundabout (without separated bicycle crossing) are when a motorist enters the roundabout while a cyclist is circulating and when they are both circulating in parallel and the motorist exits. Also they found that roundabouts with separated bicycle crossing are the safest for cyclists.

1.4.3. Using Traffic Conflicts to Predict Accidents

The use of surrogate measures of safety goes back to 1967 when Perkins and Harris (1967) first proposed a simple definition of traffic conflicts: "any potential accident situation leading to the occurrence of evasive actions such as braking or swerving". The original idea of the authors was to develop an observation method to find out if the cars made by General Motors, in comparison to the cars of other manufacturers, were involved in relatively fewer unsafe traffic situations. Soon the potential for a general observation technique was recognized and led to an increase in the use of surrogate safety measures and to the development of traffic conflict techniques (Hayward 1971; Zegeer & Deen 1977; Hauer 1978b; Hauer 1978a; Glauz & Migletz 1980; Williams 1981; Hauer 1982; Shinar 1984; Hydén 1987; van der Horst 1990; Chin & Quek 1997; Sayed & Zein 1999).

In an early study (Glauz & Migletz 1980), the authors developed a standard definition of a traffic conflict and designed a manual data collection procedure that minimizes individual differences in the observation and recording of conflicts. The Swedish traffic conflict technique was developed at Lund Institute of Technology during the 1970's and 1980's and finally reached its most mature version in 1987 (Hydén 1987). The Swedish traffic conflict technique focuses on situations where two road users would have collided had neither of them made any kind of evasive maneuver. Based on this technique and using regression analysis, Hydén found that the relation between the number of observed conflicts per unit time and the number of accidents per unit time depend mainly on the types of the road users involved in the conflict and their speeds. For different situations (based on speeds, movements, and the type of intersection) and interaction types (car-

car or car-pedestrian/cyclist), he found conversion factors that could predict the number of accidents based on the number of observed conflicts.

In a study in British Colombia, to establish traffic conflict standards, the authors studied conflicts from 94 signalized and non-signalized intersections (Sayed & Zein 1999). Two trained observers watched each intersection for two days, 8 hours each day. They determined the severity of traffic conflicts by the sum of two scores: time to collision score (in three categories) and risk-of-collision score. Risk-of-collision is a subjective measure of the seriousness of the observed conflict which depends on factors such as severity of the evasive maneuver. Regression analyses have been used to develop models that relate the number of conflicts to traffic accidents. Among other results, these analyses indicated a strong relationship between conflicts and accidents for signalized intersections.

Although it is expected that traffic conflicts provide useful insight into situations that lead to accidents, the relationship between conflicts and accidents is not completely clear. In most cases, the number of accidents that occur at a location is random and even without any changes in the traffic situation, the number of accidents every year at the same place does not remain the same (Laureshyn 2010).

In El-Basyouny & Sayed (2013), the authors first employed a lognormal model to predict conflicts using traffic volume, area type and other geometric variables and then developed a conflict based negative binomial safety performance function to predict collisions from conflicts. The situations with a minimum time to collision of 1.5 seconds or less were used as conflicts. The conflict data was collected at 51 signalized intersections in British Columbia via conflict surveys conducted by the Insurance Corporation of British Columbia in partnership with BC municipalities as well as the BC Ministry of Transportation and Highways. For each studied intersection, traffic conflicts were observed for 2 days, with 8 hours of observation per day. Two trained observers were stationed at intersection locations for the 16 hours of observation. The scaled deviance and Pearson goodness of fit measures indicated the proportional relationship between the number of conflicts and accidents was significant at the 5 % level of significance.

Sacchi et al. (2013) compared the results of a collision-based evaluation with the results of a traffic conflict-based evaluation of the same treatment which was conducted in a previous study (Autey et al. 2012). The comparison showed remarkable similarity between the overall and location specific reduction in the number of conflicts. The authors showed that the reduction in the number of traffic conflicts (measured as the number of interactions with minimum time to collision value of less than three seconds) is very consistent with the reduction in the number of collisions. However, collision reduction is usually slightly higher than conflict reduction. Also the ranking of the three studied intersections according to the magnitude of the reductions is consistent between the collision-based and conflict-based studies.

In Shahdah et al. (2014), the authors proposed a framework for integrating observed accident-based and simulated conflict-based indicators to obtain the effectiveness of a safety treatment. Minimum time to collision was used as the conflict indicator with two thresholds: less than or equal to 1.5 seconds and less than 0.5 seconds. A before and after analysis was carried out for a sample of treated intersections in Toronto, where left turn signal priority had been changed from permissive to protected-permissive. This work showed that the results of the conflict-based analysis (using time to collision ≤ 0.5 s) are statistically similar to the accident-based analysis, to predict the reduction in the number of left-turn opposing accidents.

1.5. ORIGINAL CONTRIBUTIONS

This thesis contributes to the existing literature by addressing some of the shortcomings by:

- Presenting an automated classification algorithm (based on appearance, average speed, instantaneous speed in the frequency domain, and positions of each road user), capable of classifying road users, in a traffic video, into three main categories: pedestrian, cyclist, and motor vehicle.
- Proposing and evaluating the performance of the developed classification method (combined with a tracking algorithm) to count cyclists in mixed traffic environments such as intersections and road segments, where traditional technologies do not perform well.
- Investigating the safety effects of cycle tracks at signalized intersections using a control-case study methodology and a relatively large video dataset.

- Studying the safety effects of bicycle boxes at signalized intersections using a before-after approach and cyclist crossing behaviours.
- Using disaggregate exposure measures in a short period of time, separately for each road user involved in an interaction, to better understand their interactions with other road users.
- Investigating the relationship and correlation between the number of automatically detected dangerous interactions and the number of accidents.

1.6. GENERAL METHODOLOGY

This section summarizes the general methodology developed for automated road-user classification and surrogate safety analysis for non-motorized modes of transportation, especially for cyclists. After recording video from the sites of interest, the proposed methodology consists of five main steps: 1) detecting and tracking moving road users in the video, 2) predicting the class of road users, 3) selecting the desired road users and their trajectories, 4) extracting surrogate safety measures and other variables of interest, and 5) statistical analysis and modelling of extracted data. These steps are shown in Figure 1-2 and additional details are provided below:

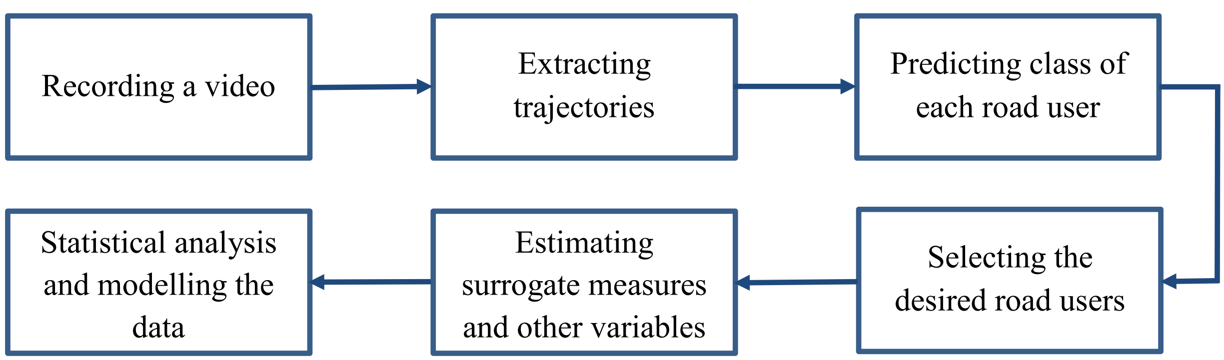


Figure 1-2. Steps involved to perform surrogate safety analysis

1.6.1. Object Tracking

In this thesis the existing tracking program, included in the open-source *Traffic Intelligence* project (Saunier n.d.), is used for tracking the objects and generating trajectory data. This algorithm uses the output of a generic feature-based moving object tracker (Saunier & Sayed 2006) and can be summarized in two steps:

1. Moving pixels are detected and tracked in each frame and recorded as feature trajectories using the Kanade Lucas Tomasi feature tracking algorithm (Birchfield 1997).
2. A moving object is composed of several features which must be grouped. Feature trajectories are grouped based on their consistent common motion. In other words, features with the same relative movements are grouped together to form one object.

The tracker output is a set of trajectories (sequence of x-y coordinates of objects in each frame) of each moving road user in the video. A calibration step is required to compute a mapping from image space to real world coordinates at ground level. The parameters of the tracking algorithm are tuned through trial and error, leading to a trade-off between over-segmentation (one object tracked as many) and over-grouping (many objects tracked as one). For more details about the tracking process, the readers are referred to Saunier & Sayed (2006).

1.6.2. Road User Classification

As one of the main contributions of this thesis, a classifier capable of classifying road users into three main road user types (pedestrian, cyclist, and vehicle) is introduced. This methodology uses four different sources of information to classify the moving road users in a traffic video: a) appearance, b) average speed, c) instantaneous speed in the frequency domain, and d) position, of each road user in the scene (Figure 1-3).

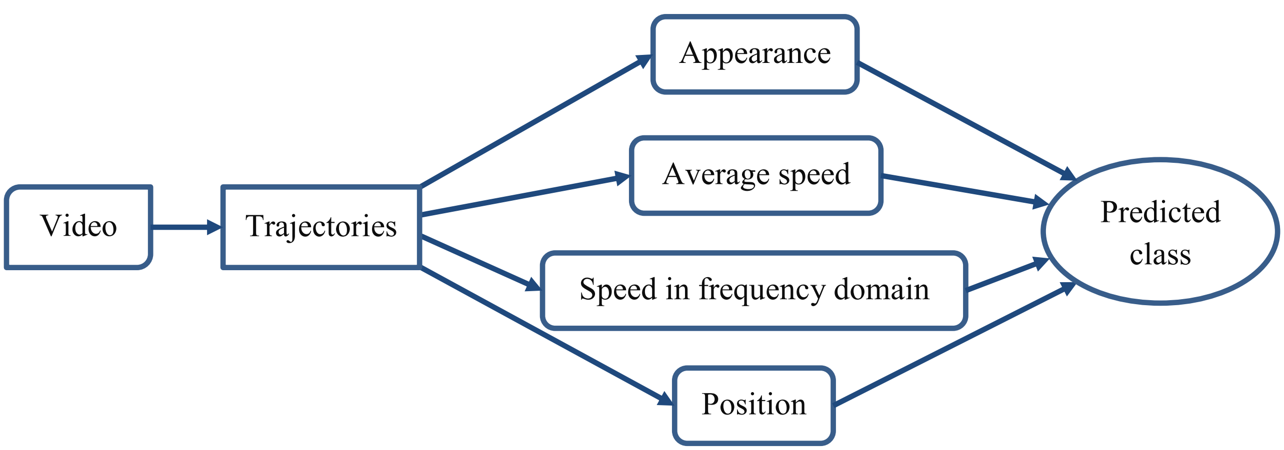
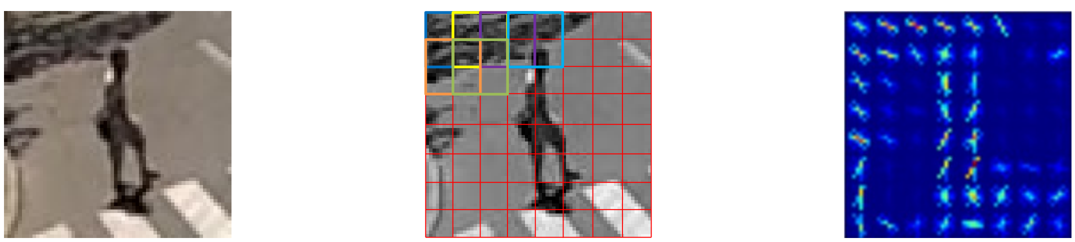


Figure 1-3. Steps involved in the class prediction of each road user

a) Appearance

To be able to classify objects based on their appearance, the first step is to find proper feature descriptors capable of discriminating between road user classes. The next step is to classify the chosen descriptors into the different road user classes to obtain the base appearance-based classifier. In this thesis histograms of oriented gradients (HOG) are used as feature descriptor with a support vector machine (SVM) as a classifier.

HOG features concentrate on the contrast of silhouette contours against the background. It works by dividing each region of interest (ROI) within the image into cells in which histograms of gradient directions or edge orientations are computed. ROI's are automatically computed using the object trajectories provided by the tracker, as the square bounding boxes of the features of each moving object. The cells making up the image can have different illumination and contrast that will be normalized. This is achieved by grouping together adjacent cells into larger connected blocks and calculating a measure of intensity for these new blocks. The individual cells within the blocks can then be normalized based on the larger block. An example of HOG for a sample image is shown in Figure 1-4.



a) Sample of image b) Dividing to cells and blocks c) Visualization of HOG

Figure 1-4. Example of HOG for an image and its visualization

After transforming the road user ROI into numerical vectors (using feature descriptors), what remain is a traditional classification problem that can be addressed using machine learning to learn discriminative models. A training algorithm builds a model of the labeled data that can then be applied to new, unlabeled input data, to predict their classes. Our appearance classification method relies on a SVM with the HOG features of an image ROI as the inputs and one of the three road user types as the output.

b) Average Speed

Aside from the appearance of a road user in the video, another criterion that can help predict the type of road user is its speed. To use speed as a criterion, one first needs to define a discriminative aggregated indicator of the instantaneous speed measurements corresponding to each frame. Since the speed given by the tracker may be noisy and the maximum and mean are more sensitive to noise, the median speed is used as the criterion for classification.

c) Speed in the Frequency Domain

The periodicity of the instantaneous speed time series of different road user types can also be a criterion to improve the classification accuracy. In other words, considering that the speed time series is periodic for pedestrians given small acceleration and deceleration at each step, i.e. using gait information, and the relative smoothness of cyclist and vehicle movements and their speeds, it is possible to find a way to fuse this information with the other sources of information to increase the accuracy of the road user classification. For this purpose the speed of each road user in the frequency domain (with the use of the discrete Fourier transform) is used as a numerical representative of the frequency of the speed signal of each object.

d) Position

The trajectory position of each road user can also provide information about the road user class. As an example, if the trajectory of a road user appears to be on a sidewalk, the chance that the road user is a vehicle or a cyclist is minor.

1.6.3. Road User Selection

After extracting the trajectory and predicting the class of each road user in a video, the next step to perform a safety analysis is to select specific road user classes and movements of interest. This can be done by defining origin and destination areas for the trajectories of the road users involved in the analysis.

1.6.4. Surrogate Safety Measures

In general, in surrogate safety analysis, the subject of analysis is traffic conflicts rather than accidents. The most common definition of a traffic conflict is an observable situation where two or more road users approach each other in time and space in a way that there is a chance of collision if they do not change their movements (Hyden & Amundsen 1977). The main surrogate safety measure that is being used in this thesis is post encroachment time (PET). The number of dangerous conflicts can be measured by the number of interactions with low PET values. PET is preferred over time to collision (TTC) to study conflicts at intersections since most of the interactions involve the road users' paths crossing one another, so that PET can always be computed. Also unlike TTC, which is based on motion prediction, PET is not sensitive to speed noise and each interaction only has one specific value.

Also in this step, other variables can be extracted for each road user to be used in the modelling. These variables include, but are not limited to, speed and traffic flow (for different road users/movements) during a short period of time before and after the arrival of each road user to the intersection.

1.6.5. Statistical Analysis and Modelling

The last step in the proposed surrogate safety analysis is to generate statistical models to find the impact of different variables on interactions and their severity, measured by PET in this study. For this purpose, the PET values are discretized. Once PET values are discretized, a random-effect ordered logit model will be applied to control for the effects of other variables such as traffic conditions as well as the random effect and unobserved variables of each site. In this model, the dependent variable is the discretized PET value and the independent variables include the short-term traffic flow (for each road user class), and other variables that may have an impact on the severity of the interactions, such as the number of lanes, the presence of any type of bicycle facility, other geometric factors, etc.

1.7. ORGANIZATION OF THE DOCUMENT

This thesis is organized into six chapters, including the introduction. Since this is a manuscript-based thesis, the following chapters, two through five, are each journal articles for which the author is the primary author. These papers are either published or under review for publication in peer-reviewed journals.

In chapter 2, an automated method for classifying moving objects in traffic video is introduced. This method is capable of classifying moving road users in a video into three main categories: pedestrian, cyclist, and vehicle. Using this method jointly with a tracking system, one can extract microscopic data from different road users in a video. An improvement of the developed classifier is presented in APPENDIX A of this thesis and is used instead of the original classifier in the following chapters.

Chapter 3 shows how the method presented in chapter 2 can be used to count different road users with different movements. Specifically, the focus of this section is on short-term counting of bicycles in a variety of environments and traffic conditions.

In chapter 4, using the automated data collection method that was presented in the previous chapters, the safety effect of cycle tracks at intersections is investigated. The main objectives of this chapter are to examine the effect of cycle tracks on the interactions between cyclists and turning vehicles, and to find the best location for bidirectional cycle tracks, whether on the left or right sides of the road. In addition, the relationship between surrogate safety measures that are used in this research with the historical accident data has been investigated in this chapter.

Chapter 5 investigates the impact of bicycle boxes on the safety of cyclists at signalized intersections. This investigation was carried out based on two different data collection methods: 1) manual, and 2) automated using the method presented in the previous chapters. The surrogate safety measures in this study include red light violations, stopping behaviours, and the PET values of the interactions.

The links between the chapters are shown in Figure 1-5. The developed methods for classification and counting from chapters 2 and 3 are used in the empirical studies in chapters 4 and 5.

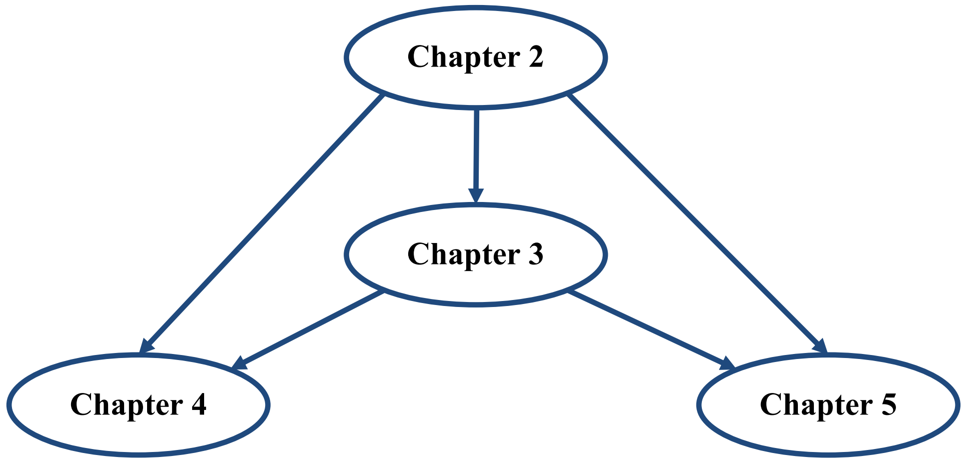


Figure 1-5. Links between the chapters of this thesis

Chapter 6 outlines a summary of conclusions and discusses some ideas for future work. Finally at the end of this thesis an appendix is provided to describe the criteria used for improving the classification algorithm.

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Chapter 2

Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application

Chapter 2: Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application

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2.1. ABSTRACT

Pedestrians and cyclists are amongst the most vulnerable road users. Pedestrian and cyclist collisions involving motor vehicles result in high injury and fatality rates for these two modes. Data for pedestrian and cyclist activity at intersections such as volumes, speeds, and space-time trajectories are essential in the field of transportation in general, and road safety in particular. However, automated data collection for these two road user types remains a challenge. Due to the constant change of orientation and appearance of pedestrians and cyclists, detecting and tracking them using video sensors is a difficult task. This is perhaps one of the main reasons why automated data collection methods are more advanced for motorized traffic. This paper presents a method based on Histogram of Oriented Gradients to extract features of an image box containing the tracked object and Support Vector Machine to classify moving objects in crowded traffic scenes. Moving objects are classified into three categories: pedestrians, cyclists, and motor vehicles. The proposed methodology is composed of three steps: i) detecting and tracking each moving object in video data, ii) classifying each object according to its appearance in each frame, and iii) computing the probability of belonging to each class based on both object appearance and speed. For the last step, Bayes' rule is used to fuse appearance and speed in order to predict the object class. Using video datasets collected in different intersections, the methodology was built

and tested. The developed methodology achieved an overall classification accuracy of greater than 88 %. However, the classification accuracy varies across modes and is highest for vehicles and lower for pedestrians and cyclists. The applicability of the proposed methodology is illustrated using a simple case study to analyze cyclist-vehicle conflicts at intersections with and without bicycle facilities.

2.2. INTRODUCTION

With the increase in computing power and capacity of sensors coupled with their decreasing economical cost, the field of Intelligent Transportation System (ITS) has seen considerable improvements in automated traffic monitoring systems. The aim is not only to collect traffic data, e.g. flow, density and average speed at specific locations in the road network, but also detailed microscopic information about each road user (position and speed) continuously and over large areas of the network. A great amount of the workload of traffic monitoring will thus shift from human operators to emerging automated systems with improved performance and the possibility to perform new tasks such as road safety monitoring (Anon 2001), leading to the development of more accurate and practical methods for data collection, safety diagnostics and evaluation of traffic engineering countermeasures at critical road facilities such as intersections.

Intersections are critical elements of the road network for safety, given that a high concentration of conflicts, crashes and injuries occurs at these locations. In cities such as Montréal, 60 % of pedestrian and cyclist injuries occur at intersections (Strauss, Miranda-Moreno, et al. 2013). Given the importance of this topic, in research and practice, several recent studies have looked at different safety issues at intersections using traditional approaches based on historical crash data (Miranda-Moreno et al. 2011) and surrogate approaches such as conflict analysis (Ismail, Sayed & Saunier 2009b). Independent of the method for road safety diagnosis, obtaining macroscopic and microscopic traffic data is fundamental. In the traditional safety approach, exposure measures are often developed based on traffic counts of each user type (e.g., vehicle, pedestrian and bicycle volumes over a given time period). In the surrogate approach, road user trajectories are necessary to compute measures such as Time To Collision (TTC), Post Encroachment Time (PET), and gap time (Saunier et al. 2010).

Road users can be detected and classified using a variety of sensors such as inductive-loops, magnetic sensors, microwave and laser radars, infrared and ultrasonic sensors (Klein et al. 2006). However, it seems that the most convenient way to obtain spatial data such as road user trajectories over a certain area, if not the only, is through video sensors. These sensors have several advantages, in particular the ability to capture naturalistic movements of road users with a small risk of catching their attention, the relative ease of installation, the richness of extracted data and the relatively low cost (Saunier et al. 2011).

The main challenge with video sensors is developing an automated process to obtain trajectories by user type (e.g. for pedestrians, cyclists and vehicles) in order to avoid manual processing that is costly and time-consuming. Automated video processing is even more complex at urban signalized intersections which have a high mix of traffic conditions where all three main road user types (pedestrians, cyclists and motorized vehicles) are present. This issue has attracted some attention in research. The need for classification algorithms has been highlighted and addressed in (Zaki & Sayed 2013), and (Ismail et al. 2010b). Tracking and collecting observational data for cyclists and pedestrians is more difficult than for vehicles because of their non-rigidity, their more varied appearances and less organized movements. In addition, they often move in groups close to each other which make them even harder to detect and track.

Accordingly, this research aims to develop an automated road user classification methodology combining a tracking algorithm and a HOG approach to obtain object appearance and speeds. Different classifiers are proposed to determine object class. Moving objects are classified into three categories: pedestrians, cyclists, and motor vehicles. The proposed methodology includes different tasks: detection and tracking of each moving object and classification according to object appearance in each frame and its speed through the video. Although this methodology may not be entirely novel in the field of computer science, this work is the first to combine and use this method in the field of transportation. An existing open-source tracking tool called Traffic Intelligence is used (Saunier n.d.). As part of this research, the accuracy of different classifiers is evaluated to show the advantages of classifiers using two sources of information for classification: the appearance and speed of an object. Finally, the proposed method is demonstrated through an example which investigates the safety effectiveness of a specific treatment at an intersection, in this case a bicycle facility. This case study aims to illustrate one of the potential applications of the developed methodology. This methodology, however, is not limited to analyzing the effectiveness of different safety treatments.

The following section provides a literature review on studies looking at object classification in traffic video, limitations and applications.

2.3. BACKGROUND

The literature on automated video data analysis for traffic operations and safety is very extensive. In this paper, the literature review is concentrated on studies looking at object tracking and classification as well as their applications in road safety. Some of the gaps in this field are also discussed.

For a general survey on object tracking, one can refer to (Yilmaz et al. 2006). According to (Forsyth et al. 2005), the different approaches for the detection and tracking of road users are classified into:

- ✓ Tracking by detection: in many cases, especially if the objects are well separated, this approach works well. Detection of objects is done using background modeling and subtraction with the current image (Antonini et al. 2006) or deformable templates, i.e. a model of image appearance using colour distribution, edge characteristics or texture (Gavrila & Munder 2006). Image classifiers can be trained on labeled data to detect road users (Wu & Nevatia 2007; Dalal & Triggs 2005).
- ✓ Tracking using flow: when a deformable template specifying the appearance of an object is available, pixels in successive images can be matched. This approach is also called feature-based tracking and has been applied to traffic monitoring in (Saunier & Sayed 2006).
- ✓ Tracking with probability: it is convenient to see tracking as a probabilistic inference problem in a Bayesian tracking framework. In simple cases, independent Kalman filters can be run successfully for each target (Hsieh et al. 2006a), but this approach will fail in scenes where the objects interact and occlude each other. This is called the data

association problem and can be solved using particle filters and Markov chain Monte Carlo methods for sampling.

Although significant progress has been made in recent years, tracking performance is difficult to report and compare, especially when the systems are not publically available, and when benchmarks are rare and not systematically used.

Similar to object detection and tracking, significant progress has been made in object classification for images in recent years, but generic multi-class object classification is still a challenging task. Most of the research focuses on the design and extraction of the best features or variables to describe the objects in the images. There are two main classes of description variables:

1) Variables describing the object's appearance, i.e. the pixels. New features have successfully been developed which are invariant to various image transformations such as translation, rotation and scaling. Among these are the Histogram of Oriented Gradients features (HOG) (Dalal & Triggs 2005), Scale-Invariant Feature Transform features (SIFT) (Lowe 2004), Speeded Up Robust Features (SURF) (Bay et al. 2008), DAISY (Tola et al. 2010), Local Binary Patterns (LBP) (Ojala et al. 2002) and Fast Retina Keypoint (FREAK) (Alahi et al. 2012).
2) Variables describing the object's shape or contour. A good overview of the use of this description variable can be found in (Bose 2005). The simplest descriptions are the area and aspect ratio of the bounding box of the object.

Once object instances are turned into numerical vectors (using description variables), this becomes a traditional classification problem that can be addressed using machine learning or other techniques to learn generative or discriminative models. A popular state of the art technique is Support Vector Machines (SVM), readers are referred to (Dalal & Triggs 2005) for an example. There is also a renewed interest in nearest-neighbor techniques for object classification (Morris & Trivedi 2008; Hasegawa & Kanade 2005).

Road user classification is a useful addition to traffic monitoring systems and efforts have already been done in this area. One of the first methods was proposed in a simple system (Lipton et al. 1998) to classify and then track vehicles and pedestrians. The classification was done using a Mahalanobis-based distance and a classification accuracy of 86.8 % and 82.8 % was achieved for vehicles and pedestrians, respectively.

Fitting a 3D model is another way to classify objects in traffic monitoring. Complex 3D models are used in (Messelodi et al. 2005) to classify vehicles into seven classes. The object description includes other visual features such as brightness and colour histograms. A SVM classifier can also be used to differentiate between sub-classes, such as between bicycles and motorcycles or between buses and trucks. A global detection rate as high as 92.5 % has been reported, however this value varies for different classes. In (Kanhere & Birchfield 2008), in simple highway settings, using feature-based tracking as well as the number of features making up the object's height, over 90 % of road users were correctly classified. The work presented in (Morris & Trivedi 2008) extracts the standard description of blobs by simple morphological measurements and targets real-time traffic monitoring on highways. Its performance is not clear as it reports results for different confidence levels. Although the work presented in (Zhang et al. 2007) is called "unsupervised" by its authors, using k-means, it implicitly relies on prior knowledge of the road users in the scene. The description variables are the velocity of the object area, the "compactness", defined as the ratio of the object area over the square of the object perimeter, the time derivative of the area and the angle between the motion direction and the direction of the major axis of the shape. It should be noted that none of these studies focused on busy locations such as intersections with heavy cyclist and pedestrian traffic.

The method to count and classify composite objects presented in (Somasundaram et al. 2013a) relies on various descriptors combined in a Naïve Bayes framework or simply concatenated as inputs of a SVM classifier. The reported classification accuracy is 92 % and the counting accuracy is 95 %. In (Zaki & Sayed 2013), after tracking each moving object in video, the type is classified based on speed profile information, such as maximum speed and stride frequency. In this work, a classification accuracy of 94.8 % and 88.6 % are reported respectively, for binary classification of motorized versus non-motorized road users and for the classification of three main types of road users.

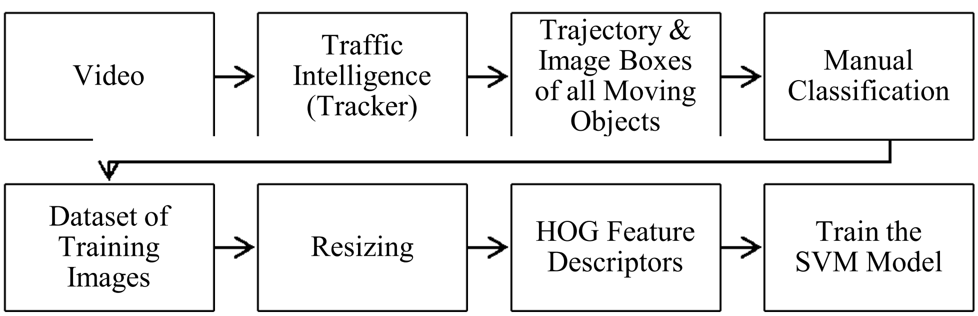
Finally, the use of multiple detections provided by a tracking system in each frame is one of the commonalities in this literature. By integrating the instantaneous classification, the system achieves more robust performance, see (Hsieh et al. 2006a) for some quantitative results that illustrate this point.

Very few methods in the current literature have shown the ability to collect microscopic data separately for different road users, specifically for pedestrians and cyclists. Most past studies focus mainly on obtaining data and trajectories of motor vehicles. Due to the constant change of orientation and appearance of pedestrians and cyclists, detecting and tracking them in video data is a difficult task. This is perhaps one of the main reasons why automated data collection methods have mainly been developed to detect and track motorized traffic. Moreover, among the existing methods with the ability to classify road users in traffic videos, most of them use simple classification methods based on speed or appearance and none have tried to combine both using different criteria to improve the accuracy of the classification. Due to the lack of standardized benchmarks and public implementation, it is difficult to replicate previous work since some details remain unpublished, causing the accuracy of these methods to be questioned. Also there are very few studies that have applied their methods to the safety of non-motorized modes and therefore have not considered all modes and all stages: data collection, trajectory extraction, classification and surrogate analysis.

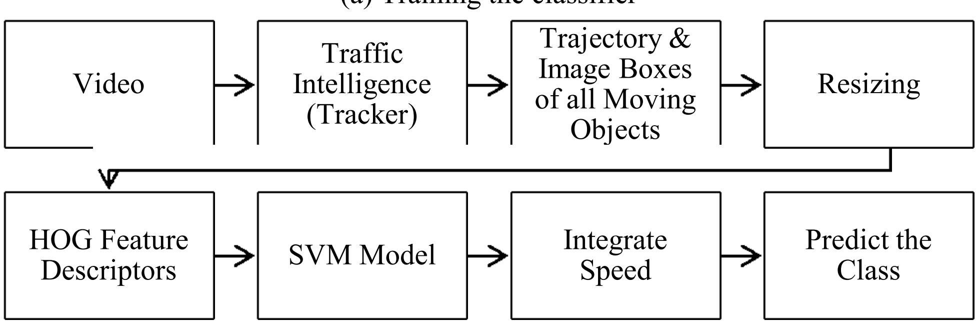
In recent years, non-motorized safety issues have attracted a lot of attention. One particular subject of interest is investigating the safety effectiveness of engineering treatments such as, bicycle boxes at intersections, the presence of bicycle facilities, curb extensions, etc. Typically two approaches have been used for evaluating safety and treatment effectiveness: traditional crash-based studies and surrogate safety methods. Despite the popularity of traditional crashed-based studies, a general shortcoming is the need to wait for crashes to occur over several years before and after the treatment's installation and at control group sites. Implementation of traditional before-after studies can take a long time and demands considerable resources, in particular for active transportation with low crash frequency. Also, the effectiveness over time can change due to road user adaptation. Longitudinal crash-based safety studies require even more years of data, which makes them infeasible. Because of the lack of data such as cyclist-vehicle crash history as well as cyclist volumes before and after the installation of treatments, surrogate safety analysis seems to be more suitable. Surrogate measures do not need to wait for accidents to occur and allows for quicker evaluation of treatments and adjustments if its performance is not satisfactory. An example of this type of analysis has been shown in (St-Aubin et al. 2013).

2.4. METHODOLOGY

This research presents a methodology based on histograms of oriented gradients (HOG) to extract features of an image box containing the tracked object and on a support vector machine as a classifier, to classify moving objects in traffic scenes with motorized and non-motorized modes. Our method classifies moving objects into three main types of road users: pedestrians, cyclists, and motor vehicles. The methodology consists of several steps: i) tracking each moving object in the video, ii) classifying its appearance in each frame, and iii) computing the probability of belonging to each class based on its appearance and speed over time. For this purpose, several classifiers are used to fuse appearance and speed to predict the class of each object. For the first step, classifiers have to be calibrated (trained) before they can be applied to classify road users. All the different steps in our methodology are shown in Figure 2-1.



(a) Training the classifier



(b) Predicting the object class

Figure 2-1. Steps involved in (a) training the classifier and (b) predicting the class of each object

The only prior knowledge used for designing the classifiers are the speed distributions per type of road user and the dataset containing images for each type of road user, gathered by automated tracking and labeled manually. Using the same parameters and methods described in this section, it is expected that one can replicate the same results. Additional details of each component in the methodology are presented as follow:

2.4.1. Sample Dataset for Appearance Classification

A dataset containing images for each type of road user to classify pedestrians, cyclists and vehicles, is used as prior knowledge to train and test the appearance-based classifiers. Using the object trajectories provided by the tracker, the square bounding boxes of the features of each moving object are automatically computed. The region of interest within the bounding box is saved and then manually classified into three groups: pedestrian, cyclist, and motor vehicle (1500 bounding box for each user type). It is worth mentioning that:

- The videos used for extracting training data are different from the videos used to test the algorithm's performance.
- For the training dataset, two different cameras with different resolutions and view angles were used in locations different from where the testing videos were recorded, as can be seen in Figure 2-2a for a sample of train video and Figure 2-2b for a sample of test video. This implies that the algorithm does not have a high sensitivity to camera resolution or angle as well as to the site under study.
- The tracker does not necessarily track the entire object. It is possible that parts of the pedestrian, cyclist or vehicle are not within the extracted image box. In this case, only part of a pedestrian's body or a wheel or bumper of a vehicle is being tracked. Since this situation will occur also during prediction, these object portions are added to the training dataset as well (Figure 2-2c and d).

(a) Training video sample, resolution of 800x600

(b) Testing video sample, resolution of 1280x960

(c) Sample of complete objects

(d) Sample of objects which do not include the entire road user

Figure 2-2. Sample of extracted road user images used for training and testing

2.4.2. Feature Descriptor

The first element to select in an appearance-based classifier is the description feature or descriptor best suited to discriminate between road user classes. Among the many image descriptors documented in the literature, HOG is used since it has been applied with success to object classification, in particular pedestrian detection in static images (Dalal & Triggs 2005) and vehicle detection (Kembhavi et al. 2011). HOG features concentrate on the contrast of silhouette contours against the background. It works by dividing each image into cells in which histograms of gradient directions or edge orientations are computed. The cells making up the image can have different illumination and contrast which can be corrected by normalization. This is achieved by grouping together adjacent cells into larger connected blocks and calculating a measure of intensity for these new blocks. The individual cells within the block can then be normalized based on the larger block. The implementation of the HOG algorithm used in this work is part of an open source computer vision and machine learning library for the Python programming language (available at http://scikit-image.org/).

2.4.3. Feature Classification

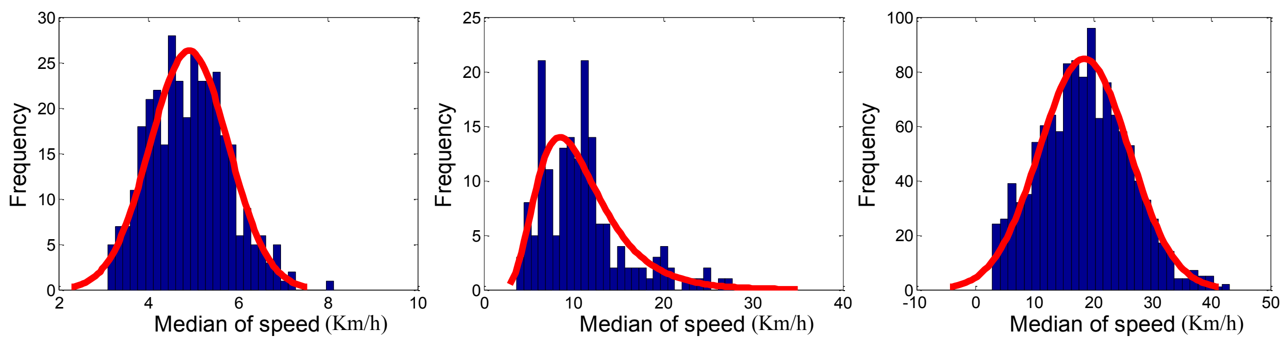
The next step is to classify the chosen descriptors into the different road user classes to obtain the base appearance-based classifier. Supervised learning methods are used for classification tasks where the classes are known and labeled instances can be obtained (Aha et al. 1991). In this work, the instances are the HOG features computed over an image sub-region, and their labels correspond to the road user type (pedestrian, cyclist, and vehicle). A training algorithm builds a model of the labeled data that can then be applied to new, unlabeled input data, to predict their class. Artificial neural networks (White 1989), K-Nearest Neighbors (KNN) (Hastie & Tibshirani 1996) and Support Vector Machine (SVM) (Burges 1998) are well-known supervised classifiers. Among the many methods and models developed in the field of machine learning, SVMs are one of the most commonly used classifiers as they have good generalization capabilities (Burges 1998). The method presented in this paper relies on a SVM with the HOG features of an image sub-region as the inputs and one of the three road user types as the output.

A SVM is by nature a binary classifier. For multi-class problems, several strategies exist in the literature, such as “one versus rest” where a classifier is trained for each class, or “one versus one” where a classifier is trained for each pair of classes. The SVM algorithm used in this work is the open source implementation LibSVM (Chang & Lin 2011) available in the OpenCV library which uses the “one versus one” strategy: the final class is decided by majority vote of the underlying binary SVMs. This appearance-based classifier is called HOG-SVM.

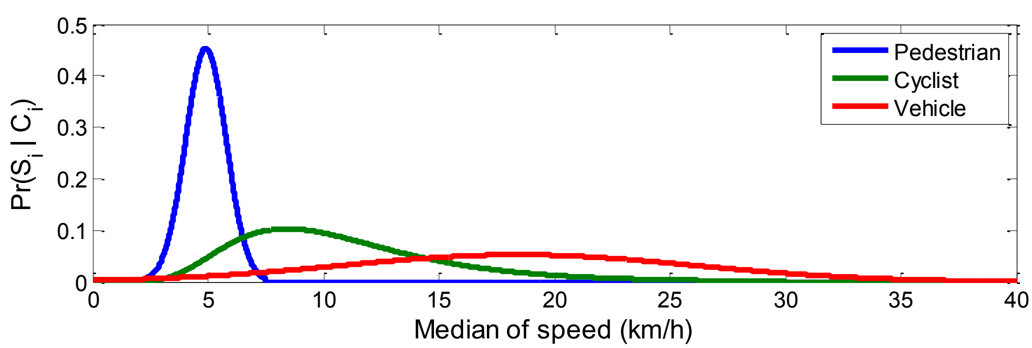
2.4.4. Speed Information

Aside from the appearance of an object in the video, another criterion that can help predict the type of object is its speed (Ismail, Sayed & Saunier 2009a). Instantaneous speed measurements can be aggregated over time and compared to a threshold to eliminate a possible object type. For example, it is nearly impossible for a pedestrian to walk at a speed of 15 km/h. Speed can also be combined with other information, such as appearance, using probability principles to increase the classification accuracy. In this study, alternative methods to combine criteria are used to design and test different classifiers.

To use speed as a criterion, one first needs to define a discriminative aggregated indicator of the instantaneous speed measurements made in each frame. The usual aggregation functions are: maximum, mean, median or percentiles of the speed measurements (e.g., 85th). Since the speed given by the tracker may be noisy and the maximum and mean are sensitive to noise, the median speed is used. From this point forward, the speed S_i of object *i* refers to the median of each road user's instantaneous speed. The speed distributions of each of the three road user classes are considered as prior knowledge and are gathered through automated tracking and manual object classification in the sample videos (Figure 2-3). Other distribution types and parameters were tested to find the best representative types of distributions for the speeds.



(a) Distribution of pedestrian speed (b) Distribution of cyclist speed (c) Distribution of vehicle speed



(d) Probability function of $Pr(S_i \mid C_i)$

Figure 2-3. Speed distribution and probability functions of each object type used for classifiers' design

2.4.5. Classifier Design

Based on the two criteria, the median of the speed measurements and the classification of the HOG-SVM in each frame, the following classifiers are derived:

Classifier I: this is the simplest and relies on two speed thresholds to predict the type of each object. These two speed thresholds are extracted from empirical speed distributions for the different types of road users. For this study, based on Figure 2-3d, the pedestrian-cyclist speed threshold Th_{pc} is 6.5 km/h and the cyclist-vehicle speed threshold Th_{cv} is 14.5 km/h (intersection points of pedestrian/cyclist and cyclist/vehicle speed distributions, respectively). Classification is performed following:

$$\begin{cases} If\ 0 \leq S_i \leq Th_{pc}, & classify\ as\ pedestrian \\ Else\ if\ Th_{pc} < S_i \leq Th_{cv}, & classify\ as\ cyclist \\ Else, & classify\ as\ vehicle \end{cases}$$

Classifier II: this classifier only uses the appearance of each object through the video to predict its type (with HOG-SVM). A method is needed to decide based on the multiple predictions made for each frame in which the object is tracked. The proportion of frames in which the object is classified can be considered as the class probability, denoted as: $\Pr(C_i|A_i)$, where C_i and A_i stand for class (pedestrian, cyclist or vehicle) and appearance of object i (constituted by all the image boxes extracted during its tracking), respectively:

$$\Pr(C_i|\ A_i) = \frac{\text{Number of frames that the object image box was classified as } C_i}{\text{Number of frames that the object appears in the video}}$$

Finally, the most likely class (the class with the highest number of detections) is the predicted type for the object.

Classifier III: this classifier combines both appearance-based and speed-based classifiers based on a simple algorithm illustrated below to switch between the following three possible situations. Speed thresholds are chosen as the 99th percentile so that very few road users (less than 1 %) of a certain type may have a median speed above the selected threshold. The thresholds are 7.5 km/h for Th_{pc}^{99} and 30 km/h for Th_{cv}^{99} and the algorithm is:

$$\begin{cases} If\ 0 \leq S_i \leq Th_{pc}^{99}, & apply\ three\ class\ HOG - SVM\ (pedestrian, cyclist, vehicle) \\ Else\ if\ Th_{pc}^{99} < S_i \leq Th_{cv}^{99}, & apply\ two\ class\ HOG - SVM\ (cyclist, vehicle) \\ Else, & classify\ as\ vehicle \end{cases}$$

1) In the first case, the speed of the tracked object is lower than the pedestrian-cyclist speed threshold: the object can either be a pedestrian, a cyclist, or a vehicle. In this situation a HOG-SVM classifier trained for the three classes is used.
2) In the second case, the speed of the tracked object is lower than the cyclist-vehicle speed threshold but higher than the pedestrian-cyclist speed threshold. It is very unlikely that the object is a pedestrian: it can either be a cyclist or a vehicle. In this situation a binary HOG-SVM classifier trained for the two classes, cyclist and vehicle, is used. In this situation it is expected that a binary classifier outperforms a multi-class classifier.
3) The speed of the tracked object is higher than the cyclist-vehicles speed threshold. In this situation the object can only be a vehicle and no classifier is needed.

Classifier IV: this classifier combines the probability of each class given the speed and appearance information using Bayes' rule and the naïve assumption of independence of these two pieces of information used for classification. Although this assumption is probably not true, the resulting classifier shows good performance empirically, similarly to the naïve Bayes classifiers that can still be optimal as (Domingos & Pazzani 1997) suggested, even when the assumption of independence is violated. To obtain this classifier, consider the typical Bayesian classifier given by the posterior distribution (likelihood × prior). This is formulated as:

$$\Pr(\mathrm{C_i}\ |\mathrm{S_i}\ , \mathrm{A_i}) = \frac{\Pr(\mathrm{C_i})}{\Pr(\mathrm{S_i}, \mathrm{A_i})} \Pr(\mathrm{S_i}, \mathrm{A_i}\ |\mathrm{C_i})$$

where C_i, S_i and A_i stand for class, speed and appearance of object *i*, respectively. Then, by the assumption of independence of speed and appearance:

$$\Pr(C_i \mid S_i, A_i) = \frac{\Pr(C_i)}{\Pr(S_i)P(A_i)} \Pr(S_i|C_i)\Pr(A_i|C_i) \qquad (1)$$

Also, using conditional probability, one can write:

$$\Pr(A_i|C_i)\Pr(C_i) = \Pr(C_i|A_i)\Pr(A_i) \qquad (2)$$

Replacing (1) into (2), gives:

$$\Pr(C_i \mid S_i, A_i) = \frac{\Pr(C_i|A_i)}{\Pr(S_i)} \Pr(S_i|C_i)$$

Finally, given that $P(S_i)$ is independent of the classes, it can be said that:

$$\Pr(C_i \mid S_i, A_i) \propto \Pr(C_i|A_i) \Pr(S_i|C_i)$$

$\Pr(C_i| A_i)$ is the probability of each class obtained from classifier III. $\Pr(S_i|C_i)$ is estimated through distributions fitted to the empirical speed distributions of the three road user classes, gathered through manual object classification in sample videos and shown for this study in Figure 2-3 a, b, c. The speed distributions of pedestrians and vehicles are fitted to normal distributions and the speed distribution of cyclists is fitted to a lognormal distribution.

The parameters of these speed distributions (Figure 2-3) are the following:

1) Pedestrian speed distribution: normal distribution with mean of $\overline{S_p}$ = 4.91 km/h and standard deviation of s_p = 0.88 km/h.
2) Cyclist speed distribution: log-normal distribution with location parameter of $\overline{\mu_c}$ = 2.31 (mean of $\overline{S_c}$ = 11.00 km/h) and scale parameter of ς_c = 0.42 (standard deviation of s_c = 4.83 km/h)
3) Vehicle speed distribution: normal distribution with mean of $\overline{S_v}$ = 18.45 km/h and standard deviation of s_v = 7.6 km/h

Finally, the class of the object is selected as the one with the highest $\Pr(C_i \mid S_i, A_i)$. For more information about naïve Bayes classifiers and the naïve assumption of independence of information please refer to (Domingos & Pazzani 1997; Friedman et al. 1997). It is expected that using speed for classifying objects increases the classification accuracy under normal conditions (pedestrians have lower speeds than cyclists and cyclists have lower speeds that vehicles) but decreases the accuracy under abnormal conditions such as running pedestrians with high speeds, very fast cyclists or very slow vehicles.

The video data used in this paper are available upon request. The implementations of the classifiers, as well as the training and testing functions are available under an open source license on the Traffic Intelligence project website:
https://bitbucket.org/Nicolas/trafficintelligence/wiki/Road%20User%20Classification.

2.5. RESULTS

In the first part of this section, the accuracy of the classification method is evaluated. In the second part, the applicability of our methodology is illustrated showing the entire process (data collection and processing, classification and analysis).

2.5.1. Accuracy

For training the HOG-SVM classifier, a dataset containing 1500 square bounding boxes for each road user type (pedestrian, cyclist, and vehicle) is used. Videos from intersections of Rue Milton / Rue University and Rue Saint-Urbain / Rue Villeneuve, in Montréal, were selected to constitute the training dataset (for more detail please refer to section 2.4.1). To test the accuracy of the designed classifiers, two videos taken at two different sites from the training phase were used. The first video was recorded at the signalized intersection of Avenue des Pins / Rue Saint-Urbain in Montréal during peak hours for 232 minutes and a total of 4,756 objects were manually classified to create the ground truth. To show the independence of the proposed method to the tested condition and viewpoint, a second video was recorded from another intersection (signalized intersection of Avenue du Mont-Royal / Rue Saint-Urbain in Montréal, Figure 2-7b) during peak hours (for a total of 154 minutes). In this video, a total of 2,909 objects were manually classified to create the ground truth. The predicted class (obtained from each automated classifier) and the ground truth (observed, manually labelled) were then compared to compute the accuracy of each classifier.

For classification problems, it is crucial to report performance measures for each class and not only the global accuracy. The components of the confusion matrix c_{ij} are the number of objects of true class i predicted in class j. The performance measures are thus defined globally and for each class k:

$$Recall_k = \frac{c_{kk}}{\sum_j c_{kj}} \qquad Precision_k = \frac{c_{kk}}{\sum_i c_{ik}} \qquad Accuracy = \frac{\sum_k c_{kk}}{\sum_i \sum_j c_{ij}}$$

The results of classification for the video recorded from intersection of Avenue des Pins / Rue Saint-Urbain are shown in Table 2-1. Classifier IV has the best recall for pedestrians and the best precision for cyclists and vehicles, while classifier III has the best recall rate for vehicles and cyclists and the best precision for pedestrians. Overall classifier IV has the best accuracy among the tested classifiers. In the first test video the majority of the traffic was motorized vehicles (around 68 %) with fewer pedestrians (around 22 %) and cyclists (around 10 %). In order to estimate the performance of the best designed classifiers if the traffic had the same number of road users in each class, the performance for a balanced number of observations of each user type (400 observations for each user type) is also shown in Table 2-1. This illustrates that the accuracy changes when the class distribution changes, and also illustrates that the precision for cyclists is low in part because of relatively few cyclists in the video.

Table 2-1. Confusion matrices showing each classifier's performance for the intersection of Avenue des Pins / Rue Saint-Urbain

			Ground Truth					Accuracy
			Pedestrian	Cyclist	Vehicle	Total	**Precision**	
Predicted	**Classifier I**	Pedestrian	946	86	277	1309	72.3 %	**72.4 %**
		Cyclist	77	324	793	1194	27.1 %	
		Vehicle	0	78	2175	2253	96.5 %	
		Total	1023	488	3245	4756		
		Recall	92.5 %	66.4 %	67.0 %			
	Classifier II	Pedestrian	742	191	584	1517	48.9 %	**75.9 %**
		Cyclist	121	244	37	402	60.7 %	
		Vehicle	160	53	2624	2837	92.5 %	
		Total	1023	488	3245	4756		
		Recall	72.5 %	50.0 %	80.9 %			
	Classifier III	Pedestrian	726	43	64	833	87.2 %	**86.3 %**
		Cyclist	131	373	177	681	54.8 %	
		Vehicle	166	72	3004	3242	92.7 %	
		Total	1023	488	3245	4756		
		Recall	71.0 %	76.4 %	92.6 %			
	Classifier IV	Pedestrian	969	53	180	1202	80.6 %	**88.5 %**
		Cyclist	42	371	198	611	60.7 %	
		Vehicle	12	64	2867	2943	97.4 %	
		Total	1023	488	3245	4756		
		Recall	94.7 %	76.0 %	88.4 %			
	Classifier IV (balanced observation)	Pedestrian	374	40	23	437	85.6 %	**86.4 %**
		Cyclist	20	308	22	350	88.0 %	
		Vehicle	6	52	355	413	86.0 %	
		Total	400	400	400	1200		
		Recall	93.5 %	77.0 %	88.8 %			

The classification results for the second video, recorded from intersection of Avenue du Mont-Royal / Rue Saint-Urbain (with use of classifier IV) are shown in Table 2-2. From this table it can be seen that with this dataset, the accuracy of classifier IV is greater than 93 %. Note that due to a higher percentage of vehicle traffic in the second video compared to the first video (75 % versus 68 % of road users respectively for the second and the first video), accuracy of classification for the second video is higher than the one for the first video. However the accuracy for the balanced observation (200 observations for each user type) remains the same, around 86 %.

Table 2-2. Confusion matrices showing the performance of classifier IV for the intersection of Avenue du Mont-Royal / Rue Saint-Urbain

			Ground Truth					**Accuracy**
			Pedestrian	Cyclist	Vehicle	Total	**Precision**	
Predicted	**Classifier IV**	Pedestrian	424	23	41	488	86.9 %	**93.3 %**
		Cyclist	44	160	30	234	68.4 %	
		Vehicle	28	30	2132	2190	97.4 %	
		Total	496	213	2203	2912		
		Recall	85.5 %	75.1 %	96.8 %			
	Classifier IV (balanced observation)	Pedestrian	172	20	5	197	87.3 %	**86.0 %**
		Cyclist	17	151	2	170	88.8 %	
		Vehicle	11	29	193	233	82.8 %	
		Total	200	200	200	600		
		Recall	86.0 %	75.5 %	96.5 %			

It is worth mentioning that misclassification occurred in cases where multiple objects were tracked as a single object (caused by over-grouping in the tracker output) or when only a portion of an object was tracked (caused by over-segmentation in the tracker output). A sample of these situations is shown in Figure 2-4.

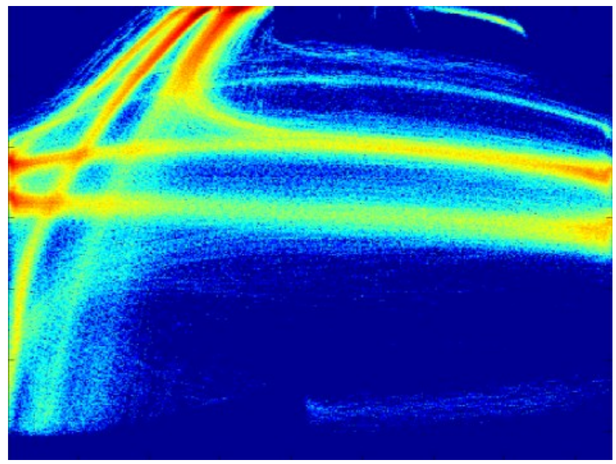
Figure 2-4. Example of tracked objects that are hard to classify

Despite the satisfactory performance of the classifiers, the classification of cyclists is the most challenging and has the lowest precision and recall. This clearly shows the challenge of cyclist classification, since the cyclist can look like a pedestrian and move at vehicular speeds.

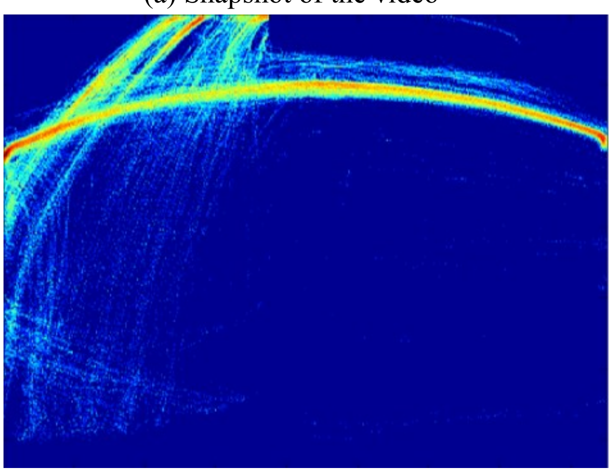
The performance of all classifiers relies on that of the tracker and therefore any tracking error may lead to error in the classification process. If the tracker fails to track certain moving objects, these objects are lost from the dataset and never get classified, affecting the ability to obtain precise flow counts and trajectories. In most cases, even when the tracker only identified part of a pedestrian, cyclist or vehicle, the classifiers were still able to classify the objects correctly.

Another way to visualize the results of the proposed classifier is through heat-maps (number of positions in discretized two-dimensional space bins) for the three road user classes (Figure 2-5). The heat-maps show the good performance of classifier IV since the trajectories of the different road user types are overall in the expected locations: pedestrians are on the sidewalks and crosswalks, cyclists are mostly in the bicycle facility, and vehicles are on the road, in the lanes. Through the heat-maps it is also easy to identify where the classifier makes errors. For example a few cyclists in the bicycle facility have been classified as vehicles or there are some vehicles at the top of the camera view which are classified as pedestrians or cyclists.

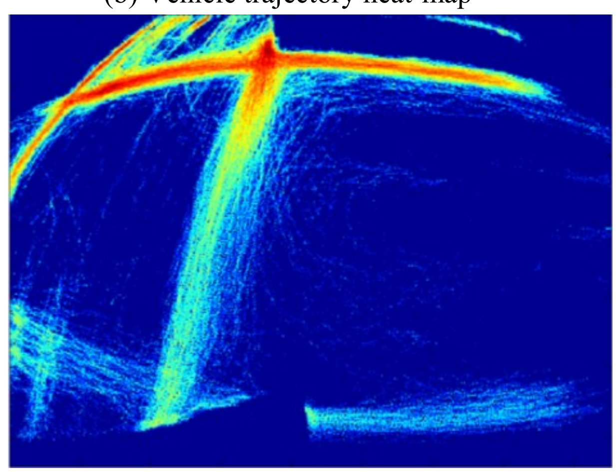
(a) Snapshot of the video



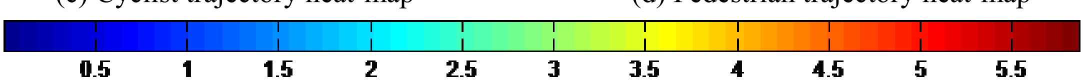
(b) Vehicle trajectory heat-map



(c) Cyclist trajectory heat-map



(d) Pedestrian trajectory heat-map



(e) Scale used for trajectorie heat-maps (log-scale)

Figure 2-5. Snapshot of video and position heat-maps for the three road user types (classified by Classifier IV). The most and least used map locations are respectively red and blue (heat-map colours range from blue to red, passing through cyan, yellow, and orange) (the resolution of each heat-map cell is 3x3 pixels in image space)

Due to the number of parameters for each classifier, performance comparison between different classifiers is not straightforward and can be biased by poor choices of parameters. The Receiver Operating Characteristic (ROC) (Fawcett 2006) curve is a tool to compare different methods over several parameter settings. Although ROC was originally designed for binary classification, it can be modified for three-class classification. A ROC curve is a graphical plot of true positive rate (true positives out of all the positives, i.e. the recall rate) versus false positive rate (false positives out of all the negatives) for different parameter settings. If, again, the components of the confusion matrix c_{ij} are the number of objects of true class i predicted in class j, true positive rate and false positive rate for each class k are defined as:

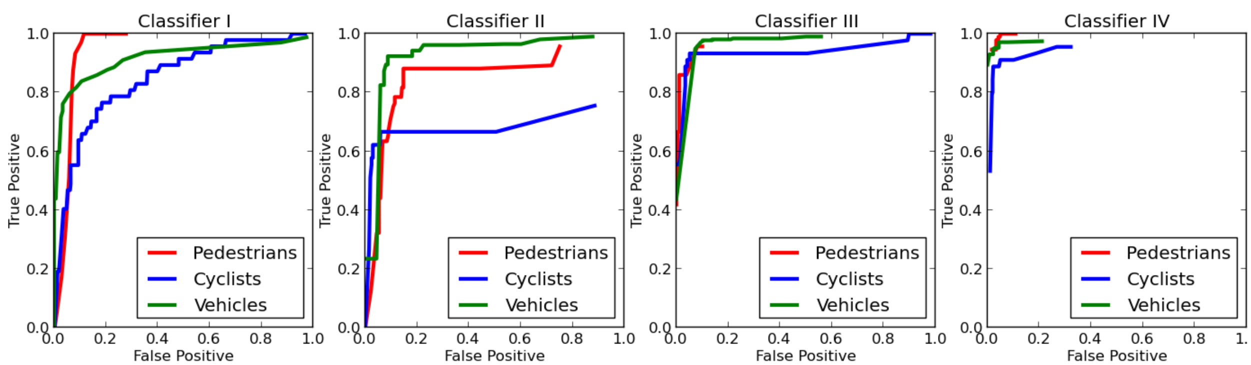
$$True\ Positive\ Rate_k = Recall_k = \frac{c_{kk}}{\sum_j c_{kj}}$$

$$False\ Positive\ Rate_k = \frac{\sum_{i,i\neq k} c_{ik}}{\sum_{i,i\neq k} \sum_j c_{ij}}$$

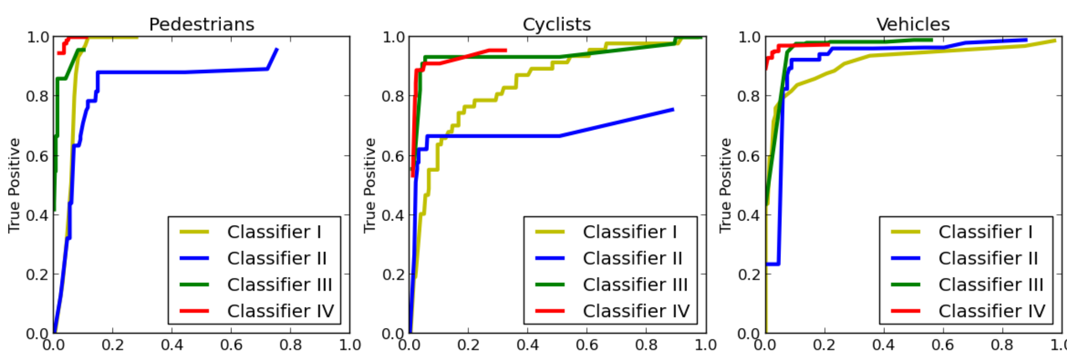
One point in a ROC space is better than another if it is closer to the top left corner (higher true positive rate with lower false positive rate). Figure 2-6a shows ROC curves separately for the four different classifiers while Figure 2-6b shows the ROC curves separately for the three classes. The parameter ranges used for each classifier to produce the ROC curves are presented in Table 2-3. Figure 2-6 shows that classifying cyclists is the hardest among the three classes and classifier IV has the best performance of all four classifiers. Note that only the convex hull of all the points (false positive rate, true positive rate) is plotted for clarity.

Table 2-3. Parameter range for each classifier to produce ROC curves

	Number of tested parameters	**Parameters**
Classifier I	273	Th_{pc} range from 0 to 12 (km/h) Th_{cv} range from 0.5 to 29 (km/h)
Classifier II	66	"Rescaled image size" range from 25x25 to 100x100 pixels "Cells per block" in {1, 2, 4} "Pixels per cell" in {4, 8, 12}
Classifier III	109	Th_{pc}^{x} range from 6 to 15 (km/h) Th_{cv}^{x} range from 25 to 35 (km/h) "Rescaled image size" range from 40x40 to 80x80 pixels "Cells per block" in {1, 2, 4} "Pixels per cell" in {4, 8}
Classifier IV	184	Th_{pc}^{x} range from 6 to 9 (km/h) Th_{cv}^{x} range from 25 to 30 (km/h) "Cells per block" in {2, 4} "Pixels per cell" in {4, 8} Pedestrian speed standard deviation s_p range from 0.7 to 1.05 "Cyclist speed scale parameter" range from 0.34 to 0.5 Vehicle speed standard deviation s_v range from 6 to 9.1



(a) ROC curves for four different classifiers and three classes



(b) ROC curves for three classes and four different classifiers

Figure 2-6. ROC curves showing true positive rate versus false positive rate for different parameter settings, for all classifiers and road user types

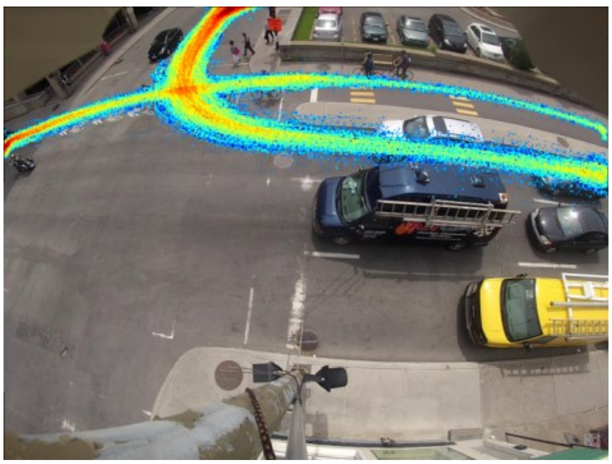
Since in Figure 2-6a the deviation from the top left corner of the ROC curve for classifier IV is less than the others, intuitively, it can be concluded that classifier IV is the least sensitive to its parameters compared to the other proposed classifiers.

2.5.2. Application – Case Study on Cyclist Safety

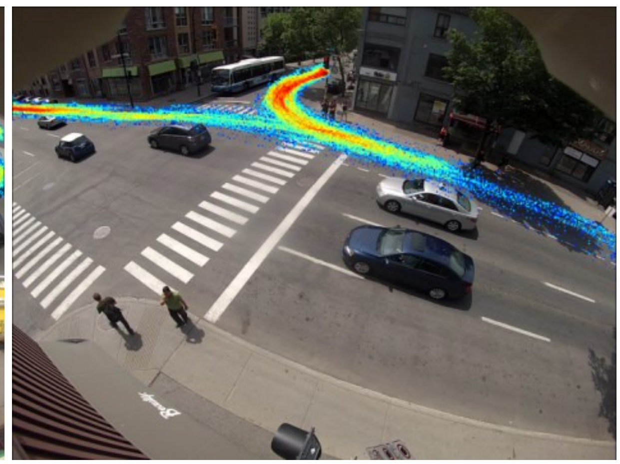
As an example of the applicability of the entire process, a simple case study is presented here showing all the steps from data collection to surrogate safety analysis. The aim is to carry out a comparative analysis between two intersections: an intersection with a bicycle facility and another without a bicycle facility, but with similar traffic and geometric characteristics. The objective of this application is to investigate the safety effect of a bicycle facility on cyclists at intersections based on interactions between cyclists and right-turning vehicles (an interaction is constituted by each pair of cyclist in the bicycle facility or lane and right-turning vehicle existing simultaneously in the scene) according to two surrogate conflict measures. For the intersection with a bicycle facility we chose the intersection of Rue Saint-Urbain / Avenue des Pins and for the intersection without a bicycle facility we chose Rue Saint-Urbain / Avenue du Mont-Royal (Figure 2-7 a and b). Specific trajectories of objects can be isolated based on their origins and destinations and then classified to obtain trajectory heat-maps for cyclists passing through and for right-turning vehicles (Figure 2-7 c and d). These figures show the strengths of the isolation and classification methods. These heat-maps can also be used to identify conflict areas at intersections as well as the potential collision angle between cyclists and right-turning vehicles.

(a) Intersection with a bicycle facility

(b) Intersection without a bicycle facility



(c) Heat-map of cyclists and right-turning vehicles at an intersection with a bicycle facility



(d) Heat-map of cyclists and right-turning vehicles at an intersection without a bicycle facility

Figure 2-7. Chosen intersections for studying the effectiveness of bicycle facilities (a, b) and heat-maps of the trajectories of cyclists and right-turning vehicles at these intersections (c, d)

The most common definition of a traffic conflict is “an observable situation in which two or more road users approach each other in time and space to such an extent that there is a possibility of collision if their movements remain unchanged” (Hyden & Amundsen 1977). As surrogate measures of safety, the classical time to collision (TTC) measure as well as the post-encroachment-time (PET) are used for comparison purposes. TTC is defined at each instant as the time until two objects would collide if their “movements remain unchanged”: this depends on predicting the road users’ future positions, which is generally done at constant velocity. For a detailed discussion and comparison of motion prediction methods, the readers are referred to (Mohamed & Saunier 2013). PET is defined as the observed time between the departure of the encroaching cyclist from the conflict point and the arrival of the first vehicle to the conflict point at the intersection or vice versa (Gettman & Head 2003). TTC and PET are computed for all interactions. TTC is then aggregated over time to produce a single indicator summarizing the interaction severity: a percentile of the distribution (the 15th percentile, TTC^{15}) is chosen over the minimum TTC to avoid sensitivity to noise. Based on these two measures, dangerous conflicts are defined as an interaction with TTC^{15} or PET below 1.5 seconds. Conflict rates (for conflict with TTC^{15} or PET below 5 seconds) and dangerous conflict rates are defined as follows:

$$TTC\ Conflict\ Rate = \frac{\left(Interactions\ with\ TTC^{15}\ less\ than\ 5\ seconds,\ \ per\ Hour\right) * 10^6}{(Tracked\ Cyclists\ per\ Hour) * (Tracked\ Vehicles\ per\ Hour)}$$

$$TTC\ Dangerous\ Conflict\ Rate = \frac{\left(Interactions\ with\ TTC^{15}\ less\ than\ 1.5\ seconds,\ \ per\ Hour\right) * 10^6}{(Tracked\ Cyclists\ per\ Hour) * (Tracked\ Vehicles\ per\ Hour)}$$

$$PET\ Conflict\ Rate = \frac{(Interactions\ with\ PET\ less\ than\ 5\ seconds,\ \ per\ Hour) * 10^6}{(Tracked\ Cyclists\ per\ Hour) * (Tracked\ Vehicles\ per\ Hour)}$$

$$PET\ Dangerous\ Conflict\ Rate = \frac{(Interactions\ with\ PET\ less\ than\ 1.5\ seconds,\ \ per\ Hour) * 10^6}{(Tracked\ Cyclists\ per\ Hour) * (Tracked\ Vehicles\ per\ Hour)}$$

The units are in conflicts per million potential conflicts (the number of potential conflicts is defined as the total number of cyclists in the bicycle facility/lane per hour multiplied by the total number of right-turning vehicles per hour).

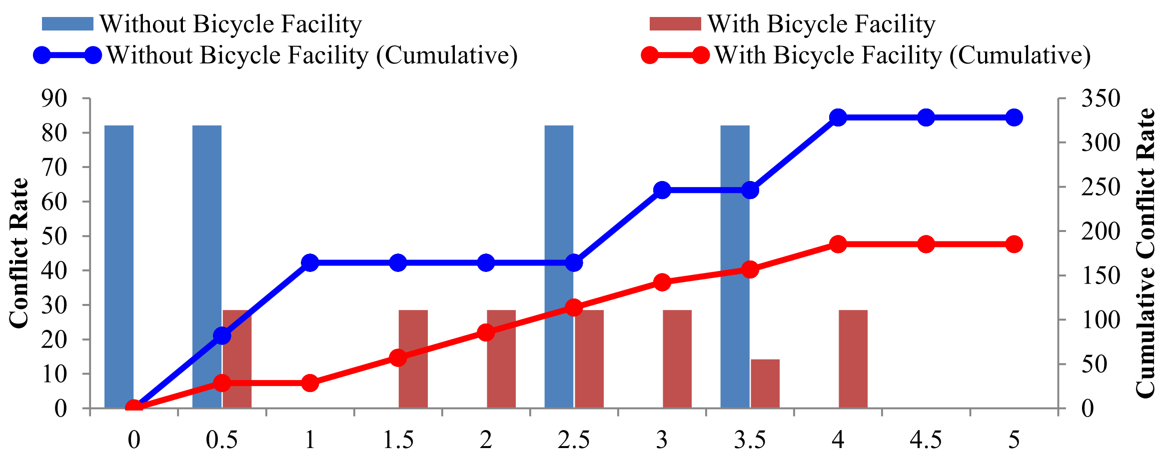
Unlike TTC based on motion prediction at constant velocity, PET is not sensitive to speed noise and each conflict only has one specific value. The number of tracked cyclists and right-turning vehicles as well as TTC^{15} and PET for each pair of cyclists and right-turning vehicles were derived automatically from the classified road user trajectories. Results are reported in Table 2-4.

Table 2-4. Surrogate measures for the intersections with and without a bicycle facility

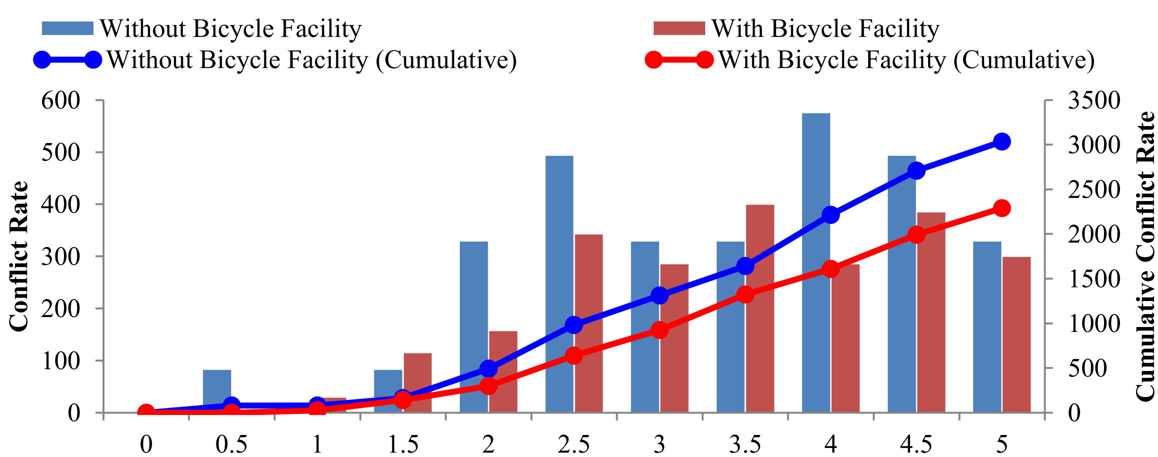
	Hours of Video	Cyclists	Right-Turning Vehicles	Average Cyclist Speed	Average Vehicle Speed	TTC^{15} < 5 seconds	TTC^{15} < 1.5 seconds	PET < 5 seconds	PET < 1.5 seconds	TTC Conf. Rate*	TTC Dang.* Conf. Rate	PET Conf. Rate*	PET Dang.* Conf. Rate
Without bicycle facility	2.57	119	263	11.8	12.3	4	2	37	2	328	164	3038	164
With bicycle facility	3.88	438	622	15.2	13.7	13	4	161	10	185	57	2293	142

* Conflicts per million potential conflicts

The distributions of TTC^{15}, PET and their cumulative distributions (the ones less than 5 seconds) for both intersections are shown in Figure 2-8.



(a) TTC^{15} (seconds)



(b) PET (seconds)

Figure 2-8. TTC^{15} (a) and PET (b) distributions for the intersections with and without a bicycle facility

Both TTC[15] and PET results suggest that the intersection with a bicycle facility is safer than the one without a bicycle facility (Figure 2-8). Due to the effect of speed noise on the computation of TTC[15] based on motion prediction at constant velocity and the availability of more data for PET (by definition of right turning interactions, it is possible that one conflict does not have TTC[15] but still has PET, this can be seen in TTC[15] and PET distributions in Figure 2-8), it seems logical to consider PET as a better surrogate safety measure in this study and rely more on its results.

This case study shows one of the applications of our methodology but does not intend to draw conclusions about the effectiveness or safety of bicycle facilities at intersections. To obtain conclusive results, data for a representative sample of intersections both with and without bicycle facilities are needed.

2.6. FINAL DISCUSSION

Since the tested classifiers have different precision and recall rates, the choice of the best classifier depends on the application and preference for missed detections or false alarms for one class or another. For example, if it is important to detect as many pedestrians as possible at the expense of other road users being classified as pedestrian, classifier IV is the best (recall rate of 94.7 % for pedestrians). On the other hand, if it is important that no other road user other than pedestrian is classified as pedestrian then classifier III is the best (precision of 87.2 % for pedestrians). Overall, classifier IV (accuracy of 88.5 %) has the best performance among the tested classifiers, showing the advantage of methods using both sources of information for classification: object's appearance and speed. There are several ways to improve the accuracy of the designed classifiers:

1) Using video data from different viewpoints to train the classifier. Using this approach, the classifier is generalized for different camera angles. One question is whether the performance will break down if the viewpoints become too different. The question of using more consistent viewpoints with the same angle is also raised as it may improve appearance-based classification by reducing the variability of object appearance.

2) As discussed previously, the classifier accuracy relies on the performance of the tracker algorithm: a way to improve classification accuracy is therefore to improve the tracking algorithm. These are some ideas that can help improve the tracking performance:
   - Increase the camera angle to see objects separate from each other in crowded scenes since one of the major issues of the tracker is over-grouping in dense traffic.
   - Compensate the fisheye effect of the camera lens. A camera with a fisheye lens was used to cover as much of the intersection as possible. However, fisheye lenses produce strong visual distortion at the corners of the video frame (Figure 2-2b). This effect reduces the accuracy of the tracker to map the position of objects in real world coordinates and speed estimation. By correcting for the fisheye effect of the camera, the usage of position and speed of an object will be more reliable for classification.
3) In this paper HOG and SVM with a radial basis function were used as feature descriptor and classifier. Other feature descriptors and classifiers should be tested to see if better accuracy can be achieved.
4) Background subtraction is another possible way to increase the performance of the classifiers, especially to obtain more precise images of each object (more precisely around its contour), although this will not help if road users overlap.
5) Since the appearance of each object in the center of video is richer than its appearance in the edge of the video (mostly due to viewpoint and fish eye effect of the camera), assigning more value and weight to the classified frames of each object in the center of the video can possibly improve the overall accuracy of classification.

2.7. CONCLUSION

The need of microscopic data (trajectories, speeds, counts) classified by user type is more and more recognized in the transportation literature in general and in traffic safety in particular. This research presents a novel methodology to design, integrate and combine classifiers capable of classifying moving objects in crowded traffic video scenes (for example at intersections) into three main road user types: pedestrians, cyclists, and motor vehicles. Given the limitations of single classification methods based on speed or appearance, this research combines these methods through several classifiers in order to improve the classification performance.

Among the four tested classifiers, the one that combines the probability of both the object's appearance and speed achieved systematically better performance (classifier IV) than the other tested classifiers. Overall the accuracy of the best classifier (Classifier IV) is greater than 88 %. Due to the similarity in appearance between pedestrians and cyclists (a cyclist consists of a bicycle and a human who rides a bicycle) and of the large range of cyclist speed, cyclists are the most difficult road user to classify. False positive rates for the best classifier are 19.4 % for pedestrians, 39.3 % for cyclists, and 2.6 % for vehicles, while the rates for false negative are 5.3 %, 24.0 %, and 11.6 %, respectively. However due to the lack of available benchmarks and accessibility to other methods, comparison with other classification methods is not possible. To address this issue, a software implementation of the methods presented in this work is available as open source software.

As part of the contributions, the entire process is illustrated, from video data collection to surrogate safety analysis, using cyclist-vehicle interactions at intersections as an application environment. Our methodology integrates a set of open-source tracking codes that have been used in previous work and extended for the current application. The applicability of our methodology is illustrated for automated surrogate analysis in situations with crowded and mixed traffic.

As part of the future work, different bicycle/pedestrian treatments will be evaluated such as bicycle boxes and curb extensions using surrogate measures. The methodology can be also improved according to the points highlighted in section 2.6. Alternative video sensors can also be tested such as thermal cameras to deal with some of the limitations of the regular video cameras in low light conditions, shade, adverse weather, and occlusion in high density conditions.

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Link between chapter 2 and chapter 3

In the previous chapter, a novel methodology for classifying moving objects in crowded traffic video scenes was proposed to classify road users into three main categories: pedestrians, cyclists, and vehicles. The proposed classifiers, which are combined with a tracking system, give the capability of collecting microscopic data for each road user class separately. The collected microscopic data can be used for several purposes but not limited to: 1) counting different road users and different their movements in traffic videos, 2) safety analysis of different road users in different situations, and 3) collecting information about speed and position density of road users.

The classification method proposed in chapter 2 is extended to automatic counting. In the next chapter a method for counting specific road users with specific movements is proposed and its accuracy for counting bicycles in different environments is evaluated. This method consists of several steps: recording video, tracking and classifying objects in the video, and defining origins and destinations of movements subject to counting. Not only are counts useful information for planning and designing projects, but also it is an important piece of information for safety studies to generate exposure measures or safety performance functions. It is worth mentioning that automated counting based on video data has several advantages and is a highly accurate technique for gathering short-term bicycle counts in locations where traditional technologies such as loop detectors and pneumatic tubes do not work well. In addition, this method has a considerably lower cost than the other methods (such as use of loop detectors) and does not need intrusive installation.

Please note that an improvement of the developed classifier is presented in the appendix of this thesis and is used as the classifier in the rest of this research.

Chapter 3

Video-Based Automatic Counting for Short-Term Bicycle Data Collection in a Variety of Environments

Chapter 3: Video-Based Automatic Counting for Short-Term Bicycle Data Collection in a Variety of Environments

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3.1. ABSTRACT

Short-term and long-term bicycle counts are important sources of information for researchers and practitioners in the transportation field. In comparison with other road users, automated data collection for cyclists is a challenging task. This paper presents and evaluates an automated video-based method for counting bicycles in different environments such as intersections and road segments. The method consists of three different elements: mobile video-camera-mast hardware, moving road user detection and tracking techniques, and classification-counting algorithms. The results indicate that the method is highly accurate at gathering short-term bicycle counts in locations where traditional technologies such as loop detectors and pneumatic tubes do not work properly. One of the main advantages of the method is its ability to count cyclists flow for different movements with different origins and destinations, even in complex environments with mixed traffic such as intersections. In addition to counting cyclists, the trajectory data gathered through this method can be used for a variety of purposes such as cyclist behaviour and road safety studies. For 5 minute interval counts, the accuracy of the proposed method ranged from 66 % for intersections without a cycle track to 92 % for road segments with a cycle track, while for 15 minute interval counts, the accuracy ranged from 81 % for intersections without a cycle track to 94 % for road segments with a cycle track.

3.2. INTRODUCTION

Bicycle data, in particular cyclist counts at a set of locations (intersections, bicycle facilities, etc.), is an important piece of information for both practitioners and researchers in transportation. For instance, this type of information is typically required for road safety studies to generate exposure measures or safety performance functions (Strauss, Miranda-Moreno, et al. 2013). During planning and designing projects, bicycle counts are necessary to estimate bicycle activity (ridership) and infrastructure needs. Counts are also required to quantify ridership growth over time after interventions and installing bicycle facilities (Buehler & Pucher 2011). In fact, in a recent research review published by the group Active Living Research on bicycle counting technologies and the state of cycling research, it was remarked that some governments are even beginning to consider bicycle count data when allocating funds for certain parks and evaluating potential projects (Ryan & Lindsey 2013). This increased awareness has led to new research efforts to improve how counting data can be used such as the development of extrapolation factors to estimate long-term trends based on short-term data. Data collection is not always an easy task because it can be time consuming and costly, particularly when counts have to be collected for a large sample of sites or when counts have to be taken over long periods of time. Several data collection methods have been used in an effort to increase spatial and temporal coverage. Short-term counting over a large set of locations in a timeframe of hours is a typical data collection strategy that is combined with long-term count data coming from fewer permanent stations. That is, municipalities and cities are increasingly adopting strategies which involve obtaining short-term counts over large areas while at the same time having a large temporal coverage with permanent counting stations. From this, one can classify counting methods based on long-term and short-term durations, where long-term counting efforts vary from a few months to many years (long-temporal coverage) and short-term counting typically take place over a few hours during a single day (e.g., 2-8 hours of counting) and involve many sites (large-spatial coverage) (Nosal et al. 2014).

Count data collection methods can be automatic or manual. Automatic counts are often derived from technologies such as loop detectors, infrared sensors, pneumatic tubes, video recordings, etc. Manual counts can be obtained directly in the field or by manually processing video data. Although there are many technologies available for long-term automatic counting in lanes, little research has been conducted regarding automatic count data collection at intersections and wide roadway sections. Pneumatic tubes or loop detectors are not designed to count in open spaces or at intersections. These traditional technologies can also fail to accurately collect data in very wide roadway sections (with several road lanes) in which under-passing problems occur and vehicular traffic intensity is high. In addition, given the installation, maintenance and acquisition costs for the equipment involved, these techniques are not practical for short-term data collection campaigns. Recently, video-based short-term data collection methods have emerged through research and private efforts; as an example one can refer to the technologies offered by a company named MioVision (Anon n.d.). However, their video-processing methods have not been well documented making it difficult to judge whether or not a fully automated method is used. While video counting does offer a number of important advantages such as low cost, multiple variable data collection, and non-intrusive installation, its use has generally been limited to good lighting conditions and low intensity traffic. It performs fairly well in counting objects, but work on determining how to categorize those objects is relatively new and untested. Most video counting methods also tend to require large amounts of calibration.

This paper presents and evaluates an automated video-based method for counting bicycles in different environments such as intersections and road segments. This method consists of three different elements: mobile video-camera-mast hardware, moving road user detection and tracking techniques, and classification-counting algorithms. This method offers a large degree of flexibility because the camera-sensor can be installed on existing infrastructure which enables one to collect data in places where traditional technologies cannot be implemented or do not typically work well. In addition to all of the mentioned advantages, trajectory data gathered through this method can be used for other purposes such as behaviour and road safety studies.

3.3. LITERATURE REVIEW

Cyclists may be counted in a variety of ways, depending on their movements and the temporal data requirements. The technologies and methods will depend on the type of counting specified by the researchers.

3.3.1. Technologies for Counting Cyclists

There is an ever increasing need to develop and test pedestrian and cyclist counting techniques in order to better understand their importance in the urban transportation field (Ryan & Lindsey 2013). Some of the most common techniques include on-site manual counting, manual video analysis, automated video analysis, active and passive infrared counting, inductive loops, and pneumatic tubes. In a research review on counting methods, Ryan and Lindsey (2013) remarked that while manual counting methods have an accuracy rate ranging from 75 % to 99 %, it is an expensive technique that cannot serve as a practical means for long-term counting efforts. The authors found that results from infrared technology can provide anywhere from 5 % to 50 % error, primarily due to object clustering. It was also noted that most studies tend to indicate that the accuracy of count data is higher at roadway and sidewalk segments compared to intersections, mainly because of the high number of turning movements.

Nordback and Janson (2010) tested the long-term accuracy of inductive loop detectors installed in 1998 on multi-use paths for cyclists by comparing automated results with manual counts. The 1.5 to 1.75 hour long manual counting sessions took place over 6 days in March of 2009 in the City of Boulder, Colorado, and were conducted with two observers performing manual counts over 15 minute intervals in order to ensure the quality of the data. The results of the study indicated that the loop detectors typically under-detected cyclists by an average of 4 %. Of the 22 out of 24 detector channels or loops abled to be analyzed, 68 % of the channels were found to be accurate where an accurate channel was defined as a channel having an absolute percent difference of less than 15 %. The authors attributed a large majority of these errors to such things as improper installation and paving of the road. It is also interesting to note that the study found a 6 % average absolute difference with a 6 % standard deviation between the separate manual counts.

Hyde-Wright et al. (2014) compared the accuracy of pneumatic tubes designed specifically for cyclists and pneumatic tubes designed to count cyclists and motor vehicles. The study used three general purpose counters (GPC) from MetroCount and one bicycle-specific counter (BSC) from Eco-Counter. The readings from the tubes were compared to over 2,000 manual counts collected over 17.25 hours. The study found that the one BSC was between 94 % to 95 % accurate up to a distance of 27 feet (8.23 meters) away from the counter, but only around 57 % accurate for a distance between 27 feet and 33 feet (10.06 meters). The best GPC had a high accuracy of around 95 % for only up to a distance of 4 feet (1.22 meters). The accuracy from 4 feet to 27 feet and 27 feet to 33 feet were roughly 55 % and 60 %, respectively.

Brewer et al. (2007) tested the counting accuracy along with other characteristics such as ease of installation of three pedestrian and cyclist counters. The study was conducted at three sites over 4 hour long study periods. Ground truth data was established through manual video-based analysis. The overall error rate of the best tested sensor in this study for counting cyclists was reported to be 26 %.

3.3.2. Methods for Video-based Counting

According to a report by Ryan and Lindsey (2013), one can see that although many of the traditional methods perform reasonably well in terms of accuracy and cost, it is clear that automated video analysis offers the most benefits in regards to the data types it can generate such as speed, volume, and trajectory. Two other important advantages are that they do not require any physical alteration to the road surface and they are more discreet.

The three fundamental tasks of all video tracking systems are to detect, track and classify the type of objects (Hsieh et al. 2006b). However, when these systems were first introduced, similar to loop detectors, they just collected basic vehicle data such as speed and volumes, at specific points on the road without tracking them (Coifman et al. 1998). These systems known as 'tripwire systems' essentially look at specific points along a road segment and count whenever the image intensity changed. Newer systems also track vehicles and provide engineers with microscopic data for individual vehicles such as acceleration and deceleration patterns (Oh et al. 2009). The primary issues of detecting and tracking vehicles or any other road user are related to visibility, or lack thereof due to poor weather and lighting conditions, congested traffic, occlusion of complete or partial vehicle segments, and vehicle shadows (Coifman et al. 1998). In particular, for congested conditions and instances where the sun creates vehicle shadows, most systems have issues with identifying individual vehicles and often group several vehicles and their shadows into large masses. These issues are even more prevalent for pedestrian and cyclist tracking systems because of high user variability in both appearance and movement (Zangenehpour, Miranda-Moreno, et al. 2014).

Other imaging technologies have also been developed and tested. One promising solution in the cases of poor lighting and shadows is the use of infrared thermal imaging, particularly for monitoring traffic nighttime conditions (Chen et al. 2008; Iwasaki et al. 2011). The contrast between the typically low thermal background signature of the road and high thermal foreground signature of the vehicle makes it easier to identify moving vehicles especially in bad weather conditions. However, this contrast is heavily dependent on weather and temperature conditions, with worse performance in warm weather. Although infrared technology has already been extensively used for military purposes such as weapon guidance systems, it is yet to gain prominence in the field of traffic monitoring.

The four main tracking techniques are model-based, region-based, active contour-based, and feature-based tracking (Coifman et al. 1998). Model-based tracking functions by matching an approximate model, typically a wire-frame model, to the detected road user shapes through proper scaling and orientation (Baker & Sullivan 1992). The second tracking technique, region-based tracking, works by identifying road users pixel groups often called blobs typically using background subtraction. This technique works well when few road users are present on the road. However, in situations of congestion, road users too close to each other may be accidentally grouped together and tracked as a single large object. Similarly to the previous method, active contour-based tracking identifies road users by their borders or contours. Although it is computationally less intensive than region-based tracking, it suffers from the same issue of occlusion. In these first three techniques, the road user detection (characterized by 3D model, shape or contour) is then updated using a specified filtering technique to estimate its new position based on its velocity and angle. The fourth is feature-based tracking which works by identifying distinct points or features such as corners to track (Coifman et al. 1998; Guo et al. 2007). The most important advantage of this technique is that vehicles may be tracked even in cases of partial occlusion (Coifman et al. 1998). It is also advantageous to use in varying lighting conditions because it focuses on identifying the most obvious features that can be used to identify a vehicle. Classification can then be performed on the output to distinguish between vehicles, pedestrians and cyclists such as in the case of intersections with mixed traffic (Zangenehpour, Miranda-Moreno, et al. 2014).

Among the recent studies evaluating the counting performance of video analysis, Zaki et al. (2013) focused on collecting cyclist count and speed data from a single roundabout located at one of the entrances to the University of British Columbia campus using an automated computer vision technique. The study consisted of two twelve hour recordings taking place over two consecutive days in March 2011. In regards to counting, the results of the study were found to be over 84 % accurate when compared to a manual video analysis. It was noted that the accuracy of counts depended on the camera position relative to the four screen line positions evaluated. Similarly, Somasundaram et al. (2013b) presented a number of computer vision methods to deal with the issue of classifying objects as pedestrians or cyclists. Some of the methods included were individual in nature such as, bag-of-visual-words (BoVW), bag of salient words, and classification with discriminative dictionaries while others were simply a combination of individual approaches such as a combined naïve Bayes method and a combined histogram method. The study tested the different techniques along with other techniques described in the literature on two video sets which featured a cycling path with a high percentage of cyclists and a university walkway with a high percentage of pedestrians in Minneapolis. The results found that the combined approach described in the paper produced the most accurate results in regards to frame-by-frame classification (92 %) and counting (95 %). A study by Belbachir et al. (2010) focused on testing an event-based 3D vision system to classify 128 test trips along a path designated for pedestrians and cyclists only. The system functioned by first clustering similar objects and then classifying them based on length, width, and time. The results of the study indicate that the system was more than 92 % accurate in classifying an object as a riding cyclist, walking cyclist or pedestrian.

Very few studies tested automated video-based technologies for counting cyclists in mixed environments such as intersections. The most important shortcoming of previous works involved the reporting of the accuracy of the counting method over the entire study period. Accuracy values reported for long periods of time can be subject to uncertainty and randomness as over-counting and under-counting errors in shorter time periods do not always compensate for the effect of each other in longer time periods.

3.4. METHODOLOGY

This section describes the proposed methodology for the automated bicycle counting technique. The methodology can be broken down into three steps:

1) Site selection and video collection
2) Data processing
3) Assessing counting accuracy

3.4.1. Site Selection and Video Collection

For investigating the bicycle counting accuracy of the proposed method, a set of sites with different environment types and volume intensities were selected in Montréal. The sites consisted of intersections and road segments with or without cycle tracks. In each site, several hours of video were recorded:

- Two road segments with separated cycle tracks (7 hours)
- Five intersections with separated cycle tracks (14 hours)
- Three road segments without a cycle track (6.5 hours)
- Three intersections without a cycle track (8.5 hours)

All the videos were recorded during the weekday and afternoon peak hours (3pm to 6pm) in the summer in order to ensure significant count variability. In addition, videos were collected in good weather conditions, since issues related to bad weather were not the focus of this paper. Figure 3-1 shows the locations of the selected sites.

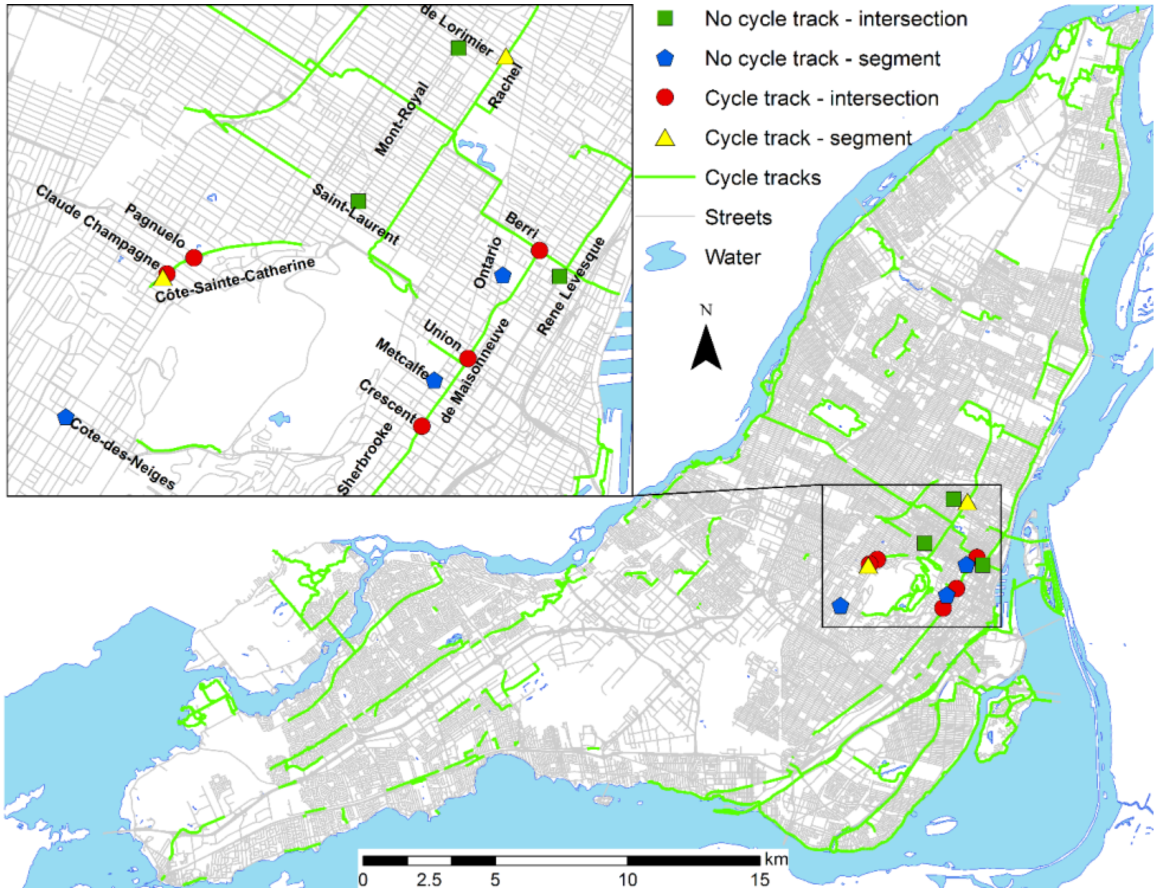


Figure 3-1. Location of sites selected for recording video in Montréal

In regards to video data collection, GoPro's Hero 3+ Black Edition cameras were used to record video in high definition (HD) at 15 frames per second. With each single charge of the camera (including standard external "battery BacPac"), around 3.5 hours of video could be recorded. These cameras were mounted on tall adjustable poles which were then installed next to an existing pole at an intersection to provide support and stability in order to prevent the camera view from changing throughout the video. The camera angle was adjusted for each site in order to optimize the viewing of the site. Depending on the width of the road, the location of an appropriate pole as well as other obstacles, the camera setup differed for each site.

3.4.2. Data Processing

Data processing involves three steps: detecting and tracking moving objects in the video, classifying the tracked objects into road users of different types (pedestrian, cyclist or vehicle), and selecting the trajectories associated with the road users subject to count (in this study, cyclists in each direction).

3.4.2.1 *Tracking Objects in Video*

An existing feature-based tracking tool from the open-source project called Traffic Intelligence (Saunier n.d.) was used for detecting and tracking the road users in each video. The proposed approach uses the output of the moving object tracker (Saunier & Sayed 2006). This algorithm can be summarized in two steps:

3. Individual pixels are detected and tracked from frame to frame and recorded as feature trajectories using the Kanade Lucas Tomasi feature tracking algorithm (Birchfield 1997).
4. A moving object is composed of many features which must be grouped. Feature trajectories are grouped based on consistent common motion. In other words, features that have relatively the same movements will be grouped together to form an object.

The tracker output is a set of trajectories (sequences of object positions at each frame) of each moving object in a video. The parameters of this algorithm are calibrated through trial and error, leading to a trade-off between over-segmentation (one object being tracked as many) and over-grouping (many objects tracked as one). Readers are referred to (Saunier & Sayed 2006) for more details.

3.4.2.2 *Object Classification*

In traffic videos with different road user types, object classification is needed, especially when the subject of study is the interaction between two different road user types. In this paper, a previously developed method for object classification in video (Zangenehpour, Miranda-Moreno, et al. 2014) was modified for use. Classification is done based on the object appearance in each frame combined with its aggregated speed and step frequency (one of the gait parameters). The overall accuracy of this classification method at intersections with high volumes and mixed road user traffic is more than 90 %. The classifier is capable of classifying objects into three main road user types: pedestrians, cyclists, and motor vehicles. For more details regarding the original classification method, readers are referred to (Zangenehpour, Miranda-Moreno, et al. 2014).

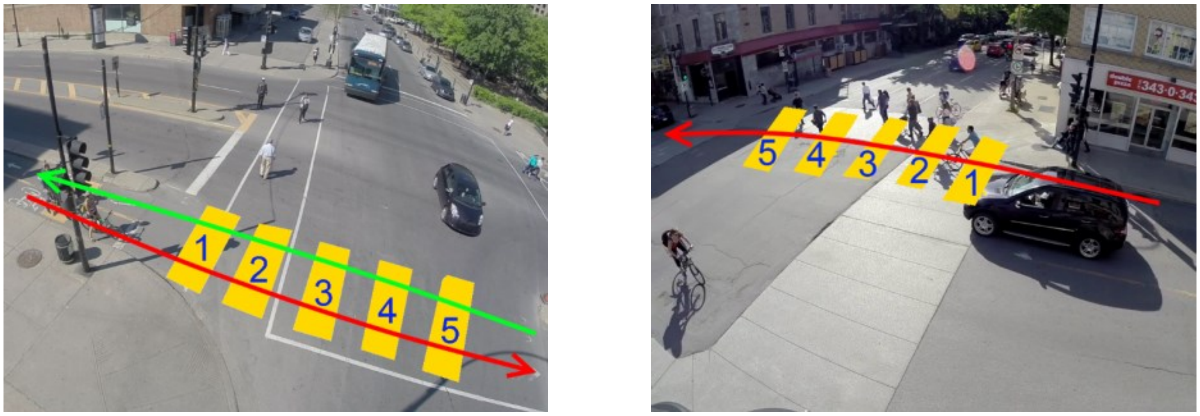
3.4.2.3 *Selecting What is Counted*

The next required step is to define what is counted, i.e. for which pairs of origin and destination zones the cyclists were counted. This step is done by defining separate origin and destination areas for cyclists, for each movement, in a video. Since it is possible that an object trajectory appears or disappears somewhere in the middle of the camera view (for example if it stops and then starts moving, or as a result of problems with tracking or the quality of the video), five areas for origins and destinations are defined (instead of just one origin and one destination). This increases the chance of a cyclist being detected and counted. The origins and destinations are defined in a way to count specific movements of cyclists. By changing the position, shape or size of these areas, it is possible to count the cyclists of another movement. A trajectory is counted as a cyclist if:

1) the moving object is classified as a cyclist
2) it passes through one of the origin areas defined for each movement
3) after it passes through one of the origin areas, it passes through one of the destination areas defined for that movement.

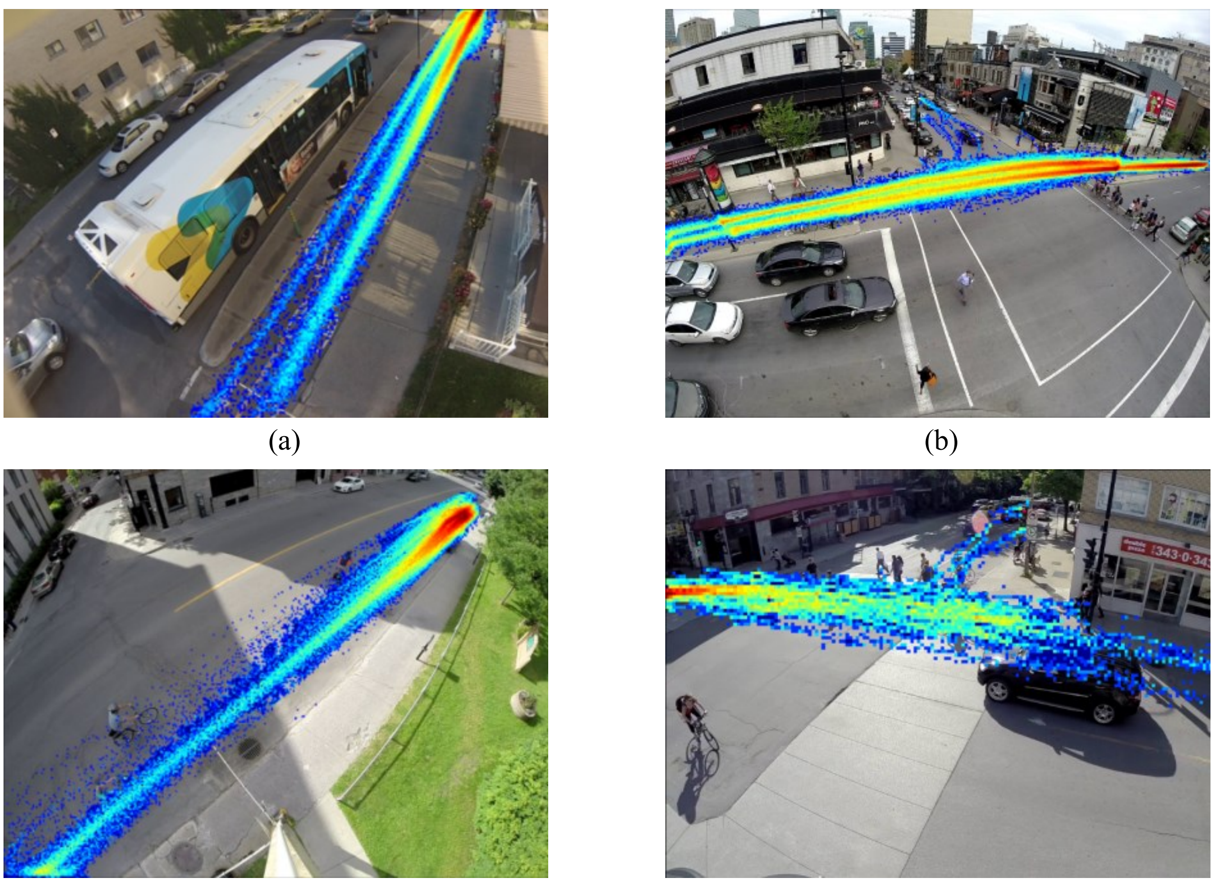
For example in Figure 3-2, to be counted as a cyclist in the movements indicated by the red arrows, a cyclist has to first appear in one of the yellow areas (origin) and then appear in another yellow area with a higher number (destination). Even if a cyclists passes through multiple origins and destinations it is counted as one cyclist. Figure 3-2a shows an intersection with two directions subject to counting (counting in the direction of movement represented by the green arrow is different from the opposite direction by differentiating whether the destination areas have lower or higher numbers than the origin areas), while Figure 3-2b shows another intersection with only one direction subject to counting, since the origin of the other movement is not visible in the camera's field of view.

Samples of the density maps derived from the trajectories extracted and filtered by this algorithm are shown in Figure 3-3. These heat-maps are useful to see the most used locations of the map by the counted cyclists. Note that due to lens distortion and the fisheye effect of the camera, the image borders always appear to be denser.



(a) (b)

Figure 3-2. Examples of origins and destinations for (a) an intersection with two directions for counting, and (b) an intersection with only one direction for counting



(a) (b)

(c) (d)

Figure 3-3. Densities of the positions of the counted cyclists for different environments (the most and least used map locations are respectively red and blue; heat-map colours range from blue to red, passing through cyan, yellow, and orange): (a) road segment with a cycle track, (b) intersection with a cycle track, (c) road segment without a cycle track, and (d) intersection without a cycle

3.4.2.4 *Measuring Counting Accuracy*

Sources of error in the proposed automated counting method can be grouped into four main categories:

1) Objects not being tracked: this error mostly happens when the quality of the recorded videos is too low and the tracker cannot properly track the moving features in the video. This error may also occur when cyclists are occluded in the video by a larger vehicle.
2) One object being tracked as two or more objects: this type of error is not common in counting cyclists, since it happens when the features of one object are far from each other (it is problematic for larger objects).
3) Two or more objects tracked as one object: this type of error is more common in situations where cyclists arrive simultaneously in the video and move together.
4) Misclassification of objects: this type of error is more common in environments with mixed traffic, such as intersections which have mixed high volume traffic.

To test both the accuracy and precision of the proposed automatic bicycle counting method, five measures are computed: the R squared of the best linear fit, the Root Mean Square Deviation (RMSD), the Mean Absolute Percentage Deviation (MAPD), the Standard Deviation of Percentage Deviations (SDPD), and the Weighted Mean Absolute Percentage Deviation (WMAPD).

RMSD, a frequently used measure of accuracy, is the difference between predicted values and the actual observed values. RMSD can be computed as:

$$RMSD = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(AC_t - MC_t)^2}$$

where, AC_t stands for the automatic counts for each time interval *t*. MC_t stands for the manual counts during the same time interval, *n* stands for the number of time intervals.

MAPD is a relative measure of accuracy and can be defined as follows:

$$MAPD = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{AC_t - MC_t}{MC_t}\right|$$

SDPD is the standard deviation of MAPD and can be calculated as:

$$SDPD = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left[\left(\frac{AC_t - MC_t}{MC_t}\right) - MAPD\right]^2}$$

WMAPD is expected to give more meaningful results than MAPD since the time periods with low volumes will not bias the measure by having the same weight as higher volume periods:

$$WMAPD = \sum_{t=1}^{n}\left(\left|\frac{AC_t - MC_t}{MC_t}\right| * \frac{MC_t}{\sum_{i=1}^{n} MC_i}\right)$$

3.5. RESULTS

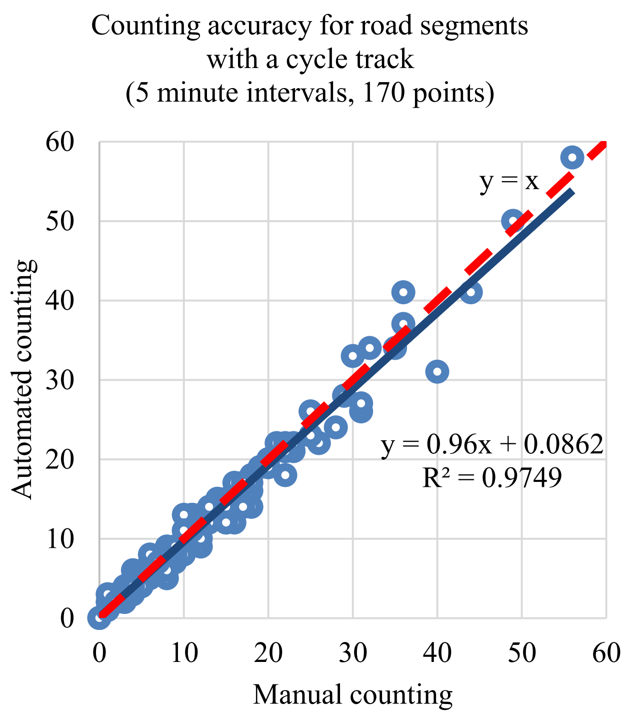
The proposed automated counting method was applied to the selected sites and compared to the manual counts from the videos. From the selected sites, the views at five sites were not adequate enough to count bicycle flows traveling in both directions (either because of the high fish eye effect of the camera at the edges of the field of view or because the counting area was not fully in view, e.g. the origin or destination area was not visible). In such cases, the automated counts were obtained for only one direction (Figure 3-2).

On average, the number of cyclists was higher on road segments and intersections with cycle tracks. Cyclist flow per direction ranged from as low as 8 cyclists on average per hour where there was no cycle track to as high as 464 cyclists on average per hour where there was a cycle track (see Table 3-1). A simple, but naïve way to show the overall accuracy of the automated counting method is to find the ratio of the overall counts generated by the automated method to the overall manual counts. Based on this measure, the automated count to manual count ratios ranged from 0.73 to 1.04 for different environment types. A summary of the analyzed videos, flows, and aggregated automated to manual count ratio results are presented in Table 3-1.

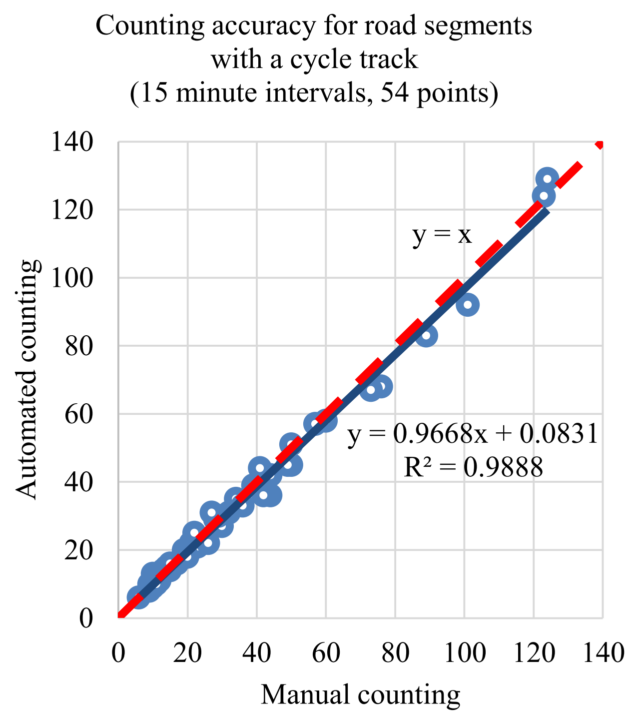
Table 3-1. Summary of the analyzed videos for bicycle counts and aggregated performance

Environment type	Site	Hour	Travel direction	Manual bicycle count	Automated bicycle count	Manual bicycle count per hour	Automated bicycle count per hour	Automated to manual ratio
Road segment with cycle track	Cote Sainte Catherine/ Claude Champagne (at bus stop)	5.28	East	599	587	113	111	0.98
			West	612	563	116	107	0.92
	Rachel / Messier (at bus stop)	1.75	West	533	530	305	303	0.99
			East	145	148	83	85	1.02
Intersection with cycle track	Berri / Maisonneuve	1.21	South	170	130	140	107	0.76
			North	561	487	464	402	0.87
	Cote Sainte Catherine / Claude Champagne	3.5	East	182	164	52	47	0.90
			West	489	433	140	124	0.89
	Cote Sainte Catherine / Pagnuelo	3.95	East	235	204	59	52	0.87
			West	287	266	73	67	0.93
	Maisonneuve / Crescent	3.5	West	1083	901	309	257	0.83
			East	772	674	221	193	0.87
	Maisonneuve / Union	1.8	West	393	404	218	224	1.03
			East	521	468	289	260	0.90
Road segment without cycle track	Ontario / Bullion	3.44	East	714	703	208	204	0.98
	Sherbrooke / Metcalfe	1.05	East	129	134	123	128	1.04
	Cote Sainte Catherine / Cote des Neiges	2.06	East	16	14	8	7	0.88
Intersection without cycle track	Mont Royal / Lorimier	2.88	West	116	109	40	38	0.94
	Mont Royal / Saint Laurent	2.71	East	115	119	42	44	1.03
			West	73	53	27	20	0.73
	Saint Denis / Rene Levesque	3	West	81	69	27	23	0.85
Road segments with cycle track		7.03		1889	1828	269	260	0.97
Intersections with cycle track		13.96		4693	4131	336	296	0.88
Road segments without cycle track		6.55		859	837	131	128	0.97
Intersections without cycle track		8.59		385	364	45	42	0.95

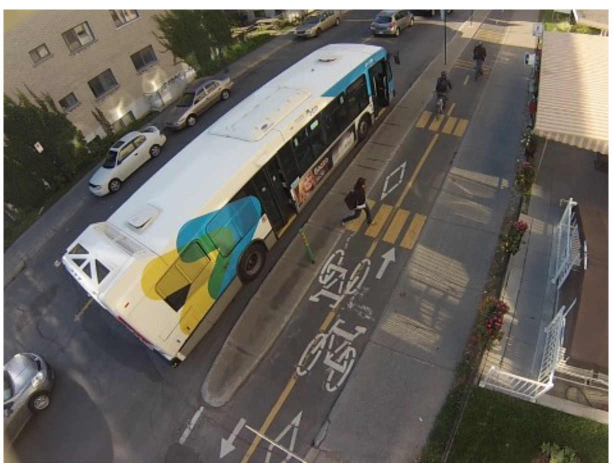
To visually evaluate the quality of the proposed automatic counting method and explore the effect of the temporal aggregation, x-y plots between automatic and manual counts were generated at 5 and 15 minutes intervals. In Figure 3-4 to Figure 3-7 points corresponding to the counting accuracy for 5 and 15 minutes intervals pooled for different environments are shown. Each figure shows the automated counts versus manual counts for all the sites and directions in that category. In these figures, the dashed red line shows the ideal counts: "y=x" or "manual counting = automated counting" and the blue line represents the best linear fit. The R^2 precision measure is also shown for each figure.



(a)



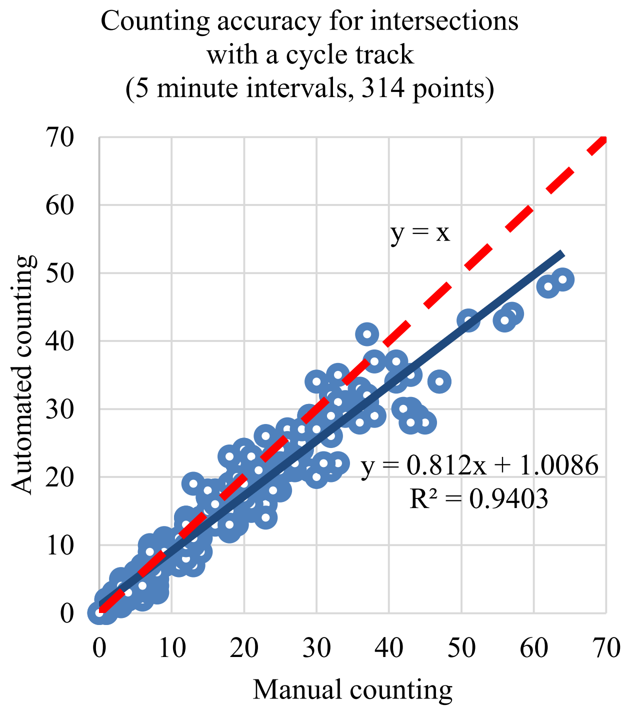
(b)



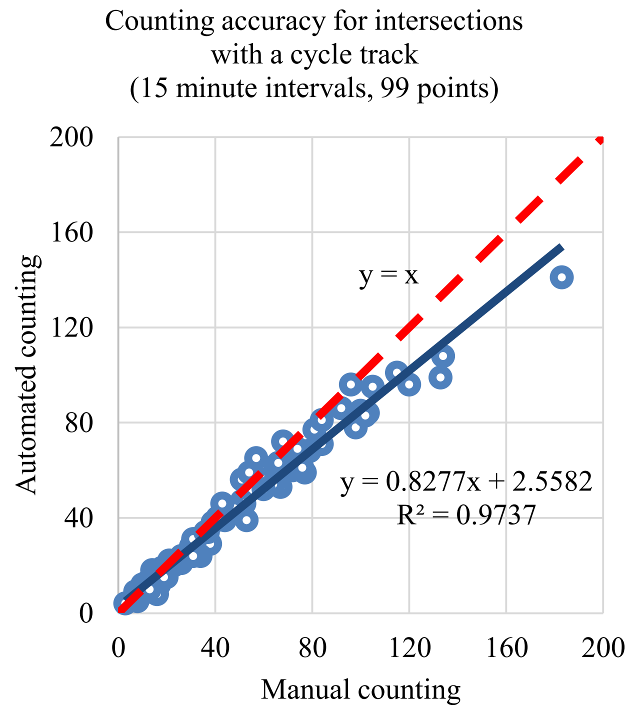
(c)

(d)

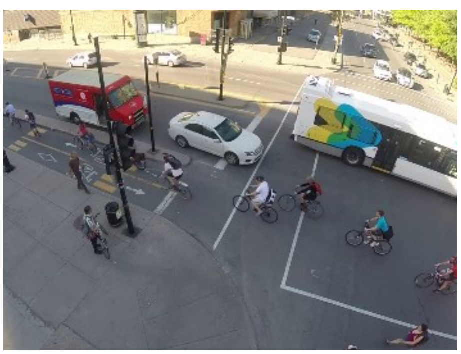
Figure 3-4. Bicycle counting accuracy for road segments with a cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d) show the field of views of the corresponding sites



(a)



(b)

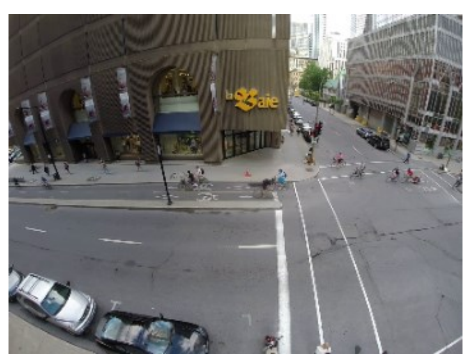


(c)

(d)

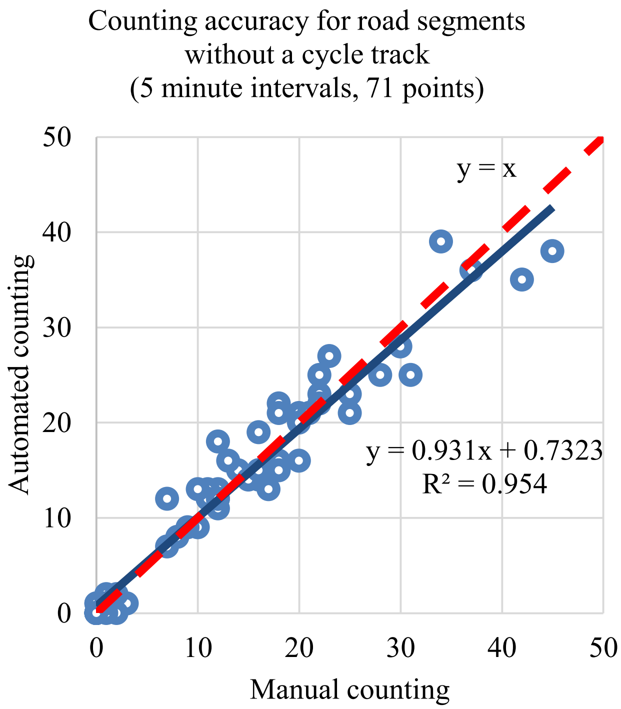
(e)

(f)

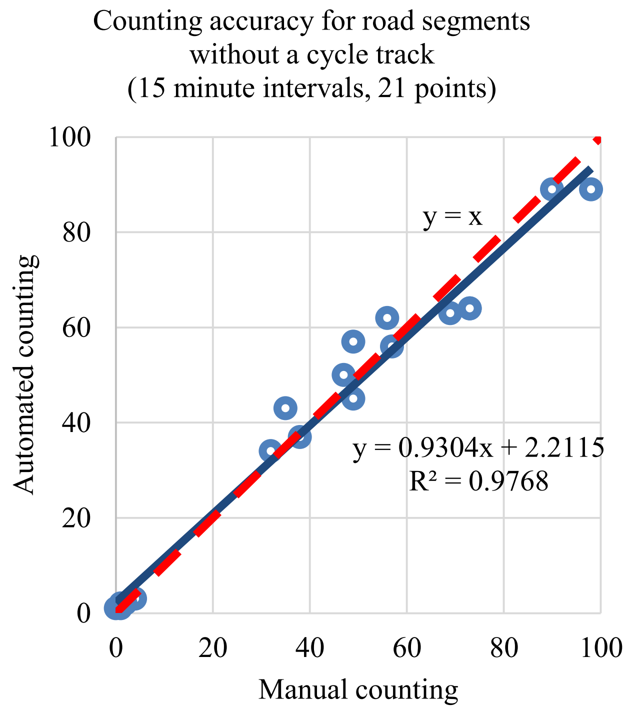


(g)

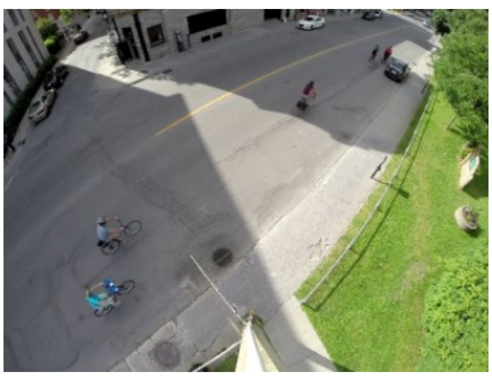
Figure 3-5. Bicycle counting accuracy for intersections with a cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d, e, f, g) show the field of views of the corresponding sites



(a)

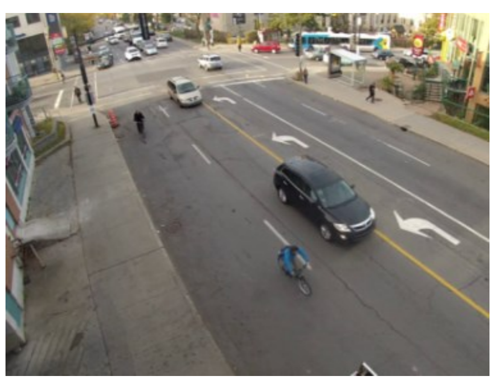


(b)



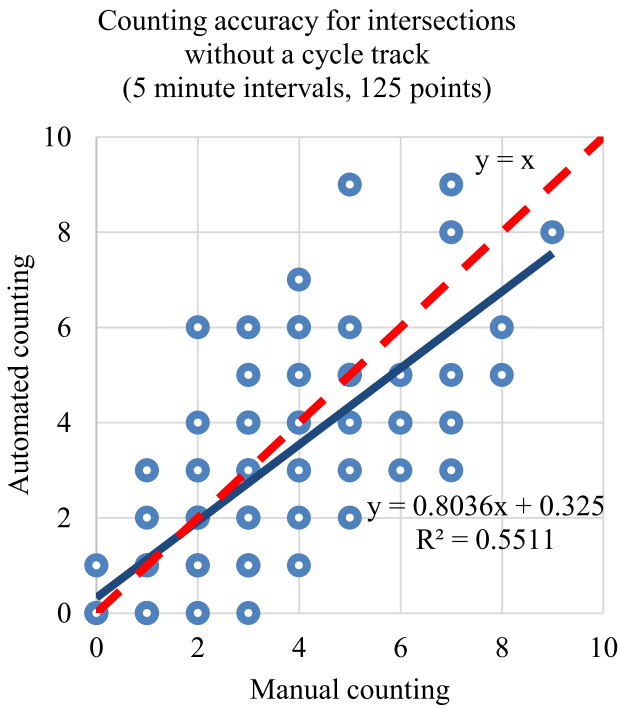
(c)

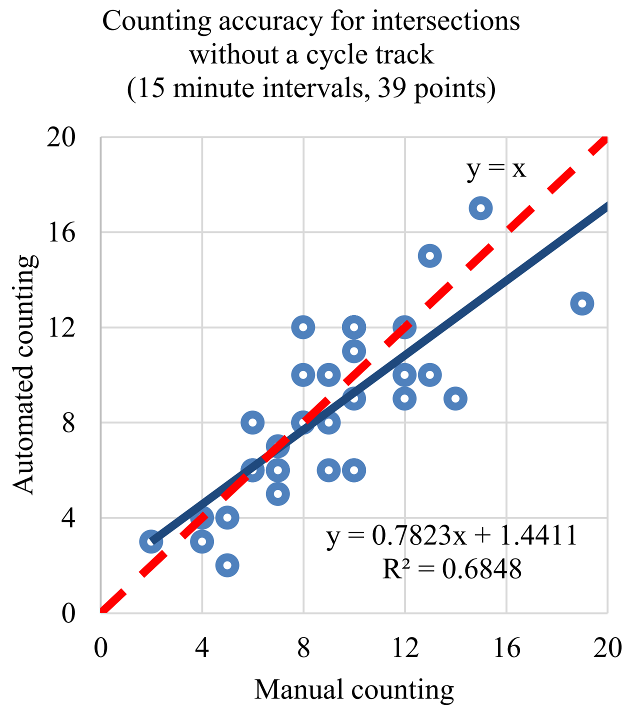
(d)



(e)

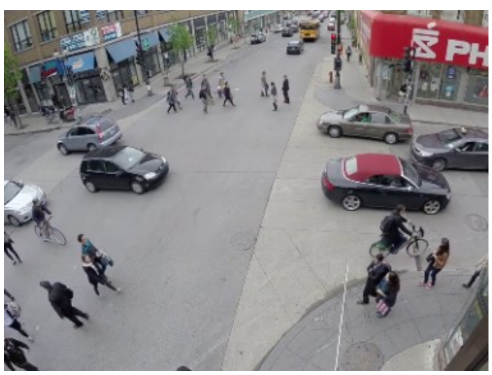
Figure 3-6. Bicycle counting accuracy for road segments with no cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d, e) show the field of views of the corresponding sites





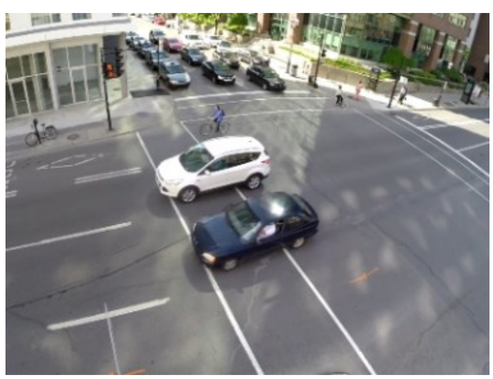
(a)

(b)



(c)

(d)



(e)

Figure 3-7. Bicycle counting accuracy for intersections with no cycle track. (a) for 5 minutes intervals, and (b) for 15 minutes intervals. (c, d, e) show the field of views of the corresponding sites

Table 3-2 shows the acceptable performance of the proposed methodology for counting bicycle flows in different environments. Based on the WMAPD, for 5 minutes interval counts, the accuracy ranged from 66 % for intersections without a cycle track to 92 % for road segments with a cycle track. With the same measure, for 15 minutes interval counts, the accuracy ranged from 81 % for intersections without a cycle track to 94 % for road segments with a cycle track. RMSD describes the absolute error value for each type of environment, meaning that the count given by the automated method has the absolute average error of RMSD. Since this is not a normalized value, RMSD tended to be higher for situations with a higher number of cyclists, such as at intersections with a cycle track. Regarding the time interval of the counts, due to the possibility of under-counting in one time interval being compensated by over-counting in another, the accuracy of the counts was higher for the longer time intervals (15-min vs 5-min).

Table 3-2. Performance measures of automated counting

Environment type	Counting interval (minutes)	Average flow	Linear coef., a*	Linear const., b*	Linear R^2	RMSD	MAPD	SDPD	WMAPD
Road segments with cycle track	5	11.3	0.96	0.09	0.97	1.59	10 %	4 %	8 %
	15	33.8	0.97	0.08	0.99	3.10	7 %	0.3 %	6 %
Intersections with cycle track	5	15.0	0.81	1.01	0.94	3.92	17 %	3 %	16 %
	15	44.3	0.83	2.56	0.97	9.33	12 %	1 %	13 %
Road segments without cycle track	5	12.3	0.93	0.73	0.95	2.40	13 %	5 %	12 %
	15	40.8	0.93	2.21	0.98	4.77	11 %	4 %	9 %
Intersections without cycle track	5	3.1	0.80	0.33	0.55	1.47	37 %	18 %	34 %
	15	9.4	0.78	1.44	0.68	2.32	19 %	2 %	19 %

* in "Manual count = a * Automated count + b"

The counting accuracy was higher for roads and intersections with separated bicycle flow (with cycle track) compared to those with mixed traffic (without cycle track). Due to less mixed movements at road segments (and fewer pedestrians) the counting accuracy was higher than for intersections. The only source of error for the road segments with a cycle track was misclassification of the pedestrians who had to cross the cycle track to get on or off a bus at bus stop. Due to the high accuracy of the classifier to distinguish pedestrians from cyclists, the counting accuracy for road segments with separated cycle tracks was very high (Figure 3-4). The main source of error in the videos of the intersections with a cycle track was the camera angle which could have caused cyclists to be occluded by larger vehicles, resulting cyclists to be partially or completely hidden in the video. Another source of error was the high amount of road user interactions at intersections and cyclists stopping at intersections which can cause disruptions in the tracking (Figure 3-5). In road segments and intersections without a cycle track compare to the ones with a cycle track, the classifier had less accuracy (Figure 3-6 and Figure 3-7). Examples of this misclassification include a vehicle or pedestrian being classified as a cyclist (over-counting) or a cyclist being classified as a vehicle or as a pedestrian (under-counting).

3.6. CONCLUSION

In this paper, an automatic method for counting cyclists at road segments and intersections was proposed. The results indicated that this method was a feasible and highly accurate technique for gathering short-term bicycle counts in locations where traditional technologies such as loop detectors and pneumatic tubes do not work well. The proposed method consisted of several steps: recording video, tracking and classifying objects in the video, and defining origins and destinations for movements subject to counting.

One of the main advantages of this method was its ability to count cyclist flow for different movements with different origins and destinations, even in complex environments with mixed traffic such as intersections. In addition, the cyclists trajectories derived from this method for different movements can be used for other purposes such as road safety studies (Zangenehpour, Strauss, et al. 2014).

One of the shortcomings of most previous works was reporting the accuracy for the entire period of the data collection or for a long period of time. Since over-counting and under-counting errors in shorter time periods cannot always compensate for the effect of each other, accuracy reported for longer periods of time can be subject to uncertainty and randomness. In order to address this issue, the accuracy of the proposed method was reported for two short time intervals of 5 and 15 minutes. Using WMAPD as an accuracy measure, road segments with cycle tracks had the least error (8 % for 5 minutes intervals and 6 % for 15 minutes interval). Road segments without a cycle track had the second best accuracy, 12 % and 9 % error for 5 and 15 minutes intervals respectively. Due to the complex movements at intersections, the accuracy for bicycle counts at these environments was relatively lower compared to road segments. 16 % and 13 % were the errors associated for intersections with a cycle track respectively for 5 and 15 minutes intervals, while 34 % and 19 % were the errors associated for intersections without cycle track respectively for 5 and 15 minutes intervals.

Several factors can cause the proposed method to be inaccurate such as camera angle, distance between camera and cyclists subject to count, bad weather conditions, presence of shadows, and movements of two or more cyclists next to each other. These factors can affect the accuracy of counting cyclists in different environments by different magnitude, making counting in road segments with a cycle track and at intersections without a cycle track the best and worst environments for which to accurately count cyclists.

In regards to future developments, one can improve the accuracy of the used tracker and classifier to reduce the error in tracking, grouping, and classifying moving objects in a video. Alternative video sensors can also be used such as thermal cameras, to deal with some of the limitations of the regular cameras in low light, shade, and adverse weather conditions. Changing the camera angle by using a taller pole or mounting the camera to a drone can mitigate the problem of occlusion in high density conditions. In addition, installing multiple cameras at intersections to capture all the possible movements, origins and destinations, can be a useful addition to the current method.

3.7. ACKNOWLEDGMENTS

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Link between chapter 3 and chapter 4

Chapter 3 presented a counting method derived from the classification method developed in chapter 2. This technique is capable of collecting microscopic data separately for each category of road users as well as computing exposure measures for safety studies by counting different road users. By integrating different techniques, the focus of the fourth chapter is on investigating the effect of cycle tracks on cyclist safety at signalized intersections. More specifically, in this chapter we look at the interactions between cyclists and turning vehicles traveling in the same direction. The results of chapter four suggest that intersections with cycle tracks on the right side are safer than intersections with no cycle track. However, intersections with cycle tracks on the left side compared to no cycle tracks were not found to be significantly safer. Also the relationship between the surrogate safety measure used in this thesis and accident data has been investigated in this chapter.

Chapter 4

Are Signalized Intersections with Cycle Tracks Safer? A Case-Control Study Based on Automated Surrogate Safety Analysis using Video Data

Chapter 4: Are Signalized Intersections with Cycle Tracks Safer? A Case-Control Study Based on Automated Surrogate Safety Analysis using Video Data

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4.1. ABSTRACT

Cities in North America have been building bicycle infrastructure, in particular cycle tracks, with the intention of promoting urban cycling and improving cyclist safety. These facilities have been built and expanded but very little research has been done to investigate the safety impacts of cycle tracks, in particular at intersections, where cyclists interact with turning motor-vehicles. Some safety research has looked at injury data and most have reached the conclusion that cycle tracks have positive effects of cyclist safety. The objective of this work is to investigate the safety effects of cycle tracks at signalized intersections using a case-control study. For this purpose, a video-based method is proposed for analyzing the post-encroachment time as a surrogate measure of the severity of the interactions between cyclists and turning vehicles traveling in the same direction. Using the city of Montreal as the case study, a sample of intersections with and without cycle tracks on the right and left sides of the road were carefully selected accounting for intersection geometry and traffic volumes. More than 90 hours of video were collected from 23 intersections and processed to obtain cyclist and motor-vehicle trajectories and interactions. After cyclist and motor-vehicle interactions were defined, ordered logit models with random effects were developed to evaluate the safety effects of cycle tracks at intersections. Based on the extracted data from the recorded videos, it was found that intersection approaches with cycle tracks on the right are safer than intersection approaches with no cycle

track. However, intersections with cycle tracks on the left compared to no cycle tracks seem to be significantly safer. Results also identify that the likelihood of a cyclist being involved in a dangerous interaction increases with increasing turning vehicle flow and decreases as the size of the cyclist group arriving at the intersection increases. The results highlight the important role of cycle tracks and the factors that increase or decrease cyclist safety. Results need however to be confirmed using longer periods of video data.

4.2. INTRODUCTION

In recent years, cities throughout North America have begun to follow Europe and Asia's lead and have started to build bicycle infrastructure. Until recently, some North American cities (e.g., Montréal, Portland, Ottawa, etc.) have been building and expanding their cycle track network but have not carried out many in-depth analyses to quantify their effects on cyclist safety, specifically at intersections where over 60 % of cyclist injuries occur (Strauss, Miranda-Moreno, et al. 2013). Now that cyclist numbers are on the rise, cyclist safety concerns at bicycle facilities have become an important issue. In the US and in Canada, some cities have implemented cycle tracks which are physically separated from vehicle traffic by concrete medians or bollards, as well as bicycle lanes delineated from vehicles by painted lines or simple sharrows (shared lane markings) along the roadway for vehicles and cyclists to share the same road. Facilities of these types can be found in cities such as Montréal, Canada. Despite their increasing popularity, few studies have investigated whether or not cycle tracks are the appropriate solution and more specifically, how safe intersections with cycle tracks are for cyclists with respect to intersections without cycle tracks.

Previous studies have investigated the safety effects of cycle tracks using historical cyclist injury data also referred to as motor-vehicle-bicycle crash data (Thomas & DeRobertis 2013; Reynolds et al. 2009; Lusk et al. 2011a; Teschke et al. 2012). Overall, the recent literature has identified some safety benefits for corridors with cycle tracks. However, these studies have not been able to fully answer the question of whether or not intersections with cycle tracks are safer than similar intersections without cycle tracks. Given the limitations of the crash data, these studies have not looked at cyclist injuries microscopically focusing on interactions between vehicles and cyclists as well as the geometry of the intersection. Only few studies have used surrogate safety measures or have relied on manual or semi-automated methods (Afghari et al. 2014; Sayed et al. 2013b). Also, past surrogate studies have involved one or very few locations (Afghari et al. 2014; Sayed et al. 2013b) and most have been carried out in Europe (Laureshyn et al. 2009; Phillips et al. 2011; Vogel 2003). Overall the previous literature has not investigated the specific question: what is the effect of cycle tracks on cyclist safety and more specifically what effect does building them on the right or left sides of the road have on safety.

In this work, we tackle the shortcomings in the current literature by developing an automated surrogate safety method, based on video data, to characterize cyclist-vehicle interactions. This method begins with video data extraction and ends with modeling cyclist-vehicle interactions. The proposed method is used to investigate the safety effects of cycle tracks at intersections focusing on interactions between turning vehicles and cyclists traveling in the same direction. For this purpose, a sample of intersections with cycle tracks (referred to as treated sites) and without cycle tracks (referred to as control sites) are carefully selected in the city of Montréal, Canada. This study is expected to provide additional insight into the risk of collision (in terms of probability) of bidirectional cycle tracks at intersections. Also, we expect that the proposed method is easily transferable and can be replicated in other cities.

A sample of 23 intersections were selected and categorized into 3 different groups. In total, more than 90 hours of video data was collected and processed to obtain the cyclist and vehicle trajectories. From the videos, post encroachment time (PET) measures are computed automatically for each cyclist as a surrogate safety indicator. It is worth mentioning that among the advantages of surrogate analysis, is that interactions with different levels of severity can be observed, even in the short-term (hours), as opposed to the traditional approach (with crash data), where no or very few accidents are observed over a long period of time (months and years). Another advantage of the video-based surrogate safety method is its ability to extract information about the factors influencing interactions, such as bicycle and motor-vehicle flows at different levels of aggregation (as is desired) (Zangenehpour, Romancyshyn, et al. 2015).

This paper is divided into several sections. First a review of the literature on cyclist safety at cycle tracks, surrogate safety measures as well as automated methods is provided. This is followed by a detailed description of the proposed automated video based methodology. The paper then presents and discusses the modelling results and finally provides the conclusions that are drawn from this study and future work.

4.3. LITERATURE REVIEW

Several studies have been published in recent years on cyclist safety in urban environments. In particular, some of these studies have investigated cyclist injury risk and its associated factors. Given the rising popularity of cycle tracks, few studies have investigated cycle tracks to identify and quantify their safety effectiveness. The majority of recent studies have concluded that corridors with cycle tracks are either safer or at least not more dangerous than corridors without cycle tracks. We can refer to the literature review of Thomas and deRobertis (2013) which examined the literature on cycle tracks from different countries mostly in Northern Europe and one study in Canada. Overall, it was found that one-way cycle tracks are safer than bidirectional cycle tracks and that in general, cycle tracks reduce collisions and injuries when effective intersection treatments are also implemented. Another review of the literature by Reynolds et al. (2009), revealed that bicycle-specific facilities, not shared roads with vehicles or shared off-road paths with pedestrians, reduce both the risk of accidents and injuries. Also, of the 23 studies reviewed in (Reynolds et al. 2009), eight examined safety at intersections which were for the most part roundabouts.

To investigate the effectiveness of safety treatments, road safety studies can be divided into: i) cross-sectional studies in which data from a sample of locations or intersections with different geometry and built environment characteristics are used (Strauss, Miranda-Moreno, et al. 2013; Miranda-Moreno et al. 2011; Wang & Nihan 2004), ii) before-after studies, in which data from before and after treatment implementation is available from a sample of treated and non-treated locations (Dill et al. 2012b; Gårder et al. 1998; S. U. Jensen 2008; Zangenehpour 2013; S. Jensen 2008), and iii) case-control studies in which data from a sample of intersections contains two subsets: a subsample of intersections in which the treatment exists and a subsample of intersections with very similar characteristics (same traffic intensity, geometry) but without treatment (Lusk et al. 2011a; Chen et al. 2012).

A case-control study carried out in Montréal (Lusk et al. 2011a), compared cyclist injury rates on six bidirectional cycle tracks and compared them to that on reference streets. Bicycle flows were found to be 2.5 times greater on tracks than on the reference streets and the relative risk of injury on tracks was found to be 0.72 compared to the reference streets, supporting the safety effects of cycle tracks. A study looking at bicycle infrastructure in Toronto and Vancouver found that cycle tracks have the lowest injury risk compared to other infrastructure types and with one ninth of the risk of major streets with parked cars and no bicycle infrastructure (Teschke et al. 2012). Overall quiet streets and bicycle facilities on busy streets provide safest passage for cyclists. An older before-after study in Denmark found that cycle tracks increased bicycle flows by 20 % while decreased vehicle mileage by 10 % (Jensen 2008). However, overall, injuries were found to increase with the implementation of cycle tracks. While injuries were reduced along links, the increase in injuries at intersections was greater than this decrease. The author identified that cycle tracks which end at the stop line of the intersection are dangerous. A decade prior, Gårder et al. (1994) came to a similar conclusion in Sweden, that physically separated tracks should be cut some short distance before the intersection which would not only improve visibility but also cause cyclists to feel less safe influencing them to pay greater attention at intersections.

In this emerging literature, it is worth highlighting that most empirical evidence about the effectiveness of cycle tracks are based on historical crash data, referred to as the traditional safety approach. Studies using surrogate safety measures are beginning to gain popularity in the bicycle literature (Sayed et al. 2013b; Afghari et al. 2014). However, surrogate safety analysis looking specifically at the effects of cycle tracks are rare in the current literature. In addition, most surrogate safety studies consider only one or a small sample of intersections.

Automated methods for surrogate safety analysis have begun to emerge in the literature (Sayed et al. 2013b; Kassim et al. 2014b; Sakshaug, Laureshyn, A. Svensson, et al. 2010). A recent study in Vancouver presented the use of an automated method to obtain Time To Collision (TTC) to identify the severity of cyclist interactions at one busy intersection (Sayed et al. 2013b). Another recent study in Ottawa evaluated cyclist-vehicle interactions at signalized intersections based on post encroachment time (PET) (Kassim et al. 2014b). These studies however have not looked at the effectiveness of cycle tracks.

4.4. METHODOLOGY

This section describes the methodology which consists of the following steps: i) site selection and video data collection, ii) data processing and iii) statistical analysis. Additional details for each step are provided as follows.

4.4.1. Site Selection and Video Collection

To investigate the safety effects of cycle tracks, more than 90 hours of video were recorded from intersections both with and without cycle tracks, all of them in Montréal. A sample of sites with cycle tracks on the right side of the road, on the left side of the road and control sites without cycle tracks (or any other bicycle facilities) were carefully selected. It is worth mentioning that all the studied cycle tracks in this paper are bidirectional. External sources of bicycle and vehicle traffic flow data helped us identify sites with and without cycle tracks with high levels of bicycle flow providing a large number of cyclists to study. All intersections in this study are four-legged and signalized where at least one approach is defined as an arterial or a collector. Due to summer road closures and construction, in some cases, alternate sites had to be selected. For each cycle track on the right, video was collected the exact same day and time at a control site. The control sites were selected on parallel streets but without any bicycle infrastructure. Where possible, parallel streets were selected since these streets provide an alternative route for cyclists who do not wish to ride along the street with a cycle track. Also, the control sites were selected to have similar vehicle traffic conditions. No control sites were selected for cycle tracks on the left since streets without cycle tracks on the left would have cyclists riding on the right and therefore this type of interaction does not exist anywhere but where the cycle track is on the left.

For the video data collection, GoPro Hero 3+ Black Edition cameras were used in HD resolution at 15 frames per second. These cameras were mounted on tall poles which are then installed next to an existing pole at the intersection to support and provide stability for the pole to prevent the camera view from changing during the video recording. Where possible, these poles were set up on the approach opposite and facing the interaction area. In some cases, alternate poles and locations were necessary since there was no pole at some intersections or the location of the traffic signals prevented the camera from being mounted in the ideal location. Using available bicycle flow data from automatic counters, we were able to identify the peak cycling hours. For this data collection, evening peak was selected as the study period in order to ensure a sufficient number of cyclists to study. Videos were collected on weekdays during the evening peak period from 15:00 to 19:00 for two to four hours with few exceptions. The camera angle differed for each site since the angle was selected to provide the best view of the interaction area and the cyclists and vehicles entering and leaving the interaction area to accurately obtain their trajectories. Depending on the width of the road, the location of an appropriate pole as well as other obstacles, the camera setup differed between sites.

4.4.2. Data Processing

Data processing includes four steps: detecting and tracking moving road users in the video, classifying the road users into their road user types (pedestrian, cyclist or vehicle), selecting the road users involved in the interactions under study, and computing the surrogate safety measures for each cyclist-vehicle interaction (Zangenehpour, Miranda-Moreno, et al. 2015). Further details are provided as follows.

4.4.2.1 *Tracking Road users in Video*

An existing feature-based tracking tool from an open-source project called Traffic Intelligence (Saunier n.d.) is used for detecting and tracking the road users in the video. The proposed approach uses the output of the moving object tracker (Saunier & Sayed 2006).

The tracker output is a set of trajectories (sequence of road user's position in each frame) of each moving road user in the video. The parameters of this algorithm are tuned through trial and error, leading to a trade-off between over-segmentation (one road user tracked as many) and over-grouping (many road users tracked as one). Readers are referred to (Saunier & Sayed 2006) for more details.

4.4.2.2 *Road User Classification*

At intersections with different road user types, road user classification is needed, especially when the focus of the study is on the interactions between two different road user types. In this paper, a modification of the previously developed method for road user classification in video (Zangenehpour, Miranda-Moreno, et al. 2014) has been used. Classification is achieved based on the road user's appearance in each frame combined with its aggregated speed and speed frequency (or gait parameters). The overall accuracy of this classification method at intersections with high volumes and mixed road user traffic is around 93 % (a 5 % point improvement from the original classification method presented in (26)). The classifier is capable of classifying road users into three main road user types: pedestrian, cyclist, and motor-vehicle. For more details regarding the original classification method, readers are referred to (Zangenehpour, Miranda-Moreno, et al. 2014).

4.4.2.3 *Selecting Trajectories*

Only the interactions between cyclists and turning vehicles traveling in the same direction, are of interest in this study. Interacting cyclists and turning vehicles are selected by defining origin and destination areas in the field of view. A trajectory will be selected as a desired cyclist (or vehicle) if:

1- the road user is classified as a cyclist (or vehicle)
2- the road user passes through the origin area defined for cyclists, B1 (or vehicles, V1) (Figure 4-1)
3- after the road user passes through the origin area, it passes through the destination area defined for cyclists, B2 (or vehicles, V2) (Figure 4-1)

One sample of a density map derived from the trajectories (both cyclists and turning vehicles) extracted and filtered by this algorithm is shown in Figure 4-1. This density map is useful to see the most used locations of the map by the cyclists and turning vehicles.

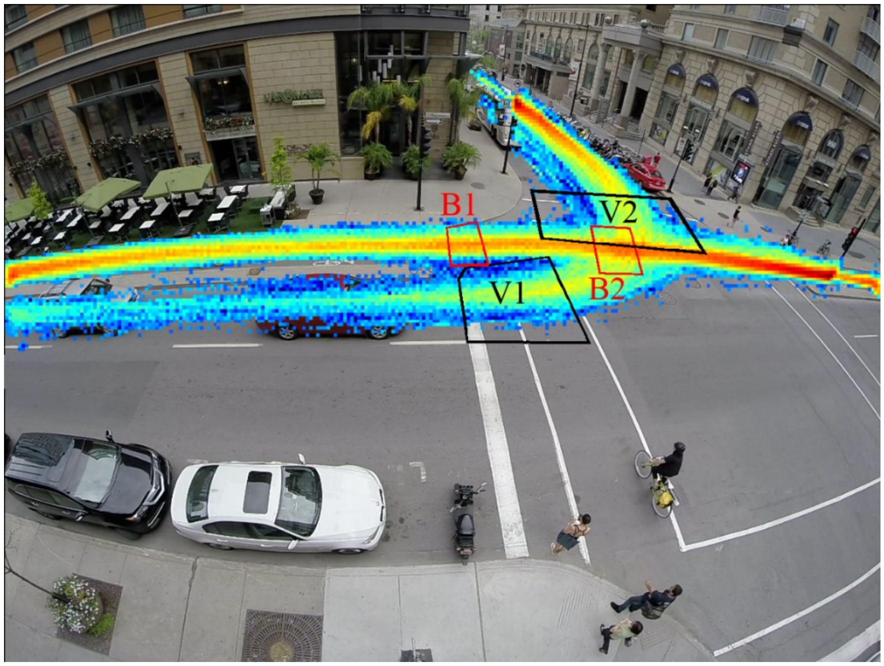


Figure 4-1. Position density map of the studied cyclists and turning vehicles in a sample video[1]

4.4.2.4 *Surrogate Safety Indicator*

The surrogate measure of safety used in this study to evaluate the severity of each interaction is PET. This measure is the time between the departure of the encroaching cyclist from the potential collision point (at the intersection of the two trajectories) and the arrival of the first vehicle at the potential collision point at the intersection, or vice versa (Gettman & Head 2003; Laureshyn et al. 2010). PET is preferred over TTC in this study since all interactions of interest involve the road users' paths crossing one another, so that PET can always be computed. TTC is a widely used surrogate safety measure that depends on the choice of a motion prediction method. The most common motion prediction is constant velocity, which is inappropriate in many practical cases, in particular if the interactions under study involve turning movements as it does in this study. Several methods exist to alleviate this issue (Mohamed & Saunier 2013), but PET was found to be sufficient for this study.

[1] The most and least used map locations are respectively red and blue, density map colours range from blue to red, passing through cyan, yellow, and orange. B1 and V1 are the origin areas while B2 and V2 are the destination areas for cyclists and vehicles, respectively.

Once the desired trajectories are extracted (the ones for cyclists and turning vehicles), PET can be calculated using the time difference between the instants the two road users (one cyclist and one turning vehicle) pass through the point where their trajectories intersect. Since the position of each road user is identified by its center point, PET is computed based on the time difference between the instants at which the road users are within a threshold distance of the trajectory crossing points (selected as one meter). PET is selected for each cyclist as the minimum PET value for each cyclist with each turning vehicle which turned either before or after the cyclist crossed the intersection.

4.5. STATISTICAL MODELING

For the analysis, two approaches are used: raw-risk estimates and statistical models. For the raw-risk estimates, interaction rates and dangerous interaction rates at intersections with cycle tracks and intersections without cycle tracks are compared. These rates are defined as follows:

$$IR_t = \frac{(NPET_t) \ * \ 10^6}{(Cyclists\ per\ hour) \ * \ (Turning - Vehicles\ per\ hour)} \tag{1}$$

where in (1):

- IR_t is the interaction rate for a predefined PET threshold value denoted by t.
- $NPET_t$ is the number of cyclists with at least one interaction with PET below t, per hour. It is possible that the same cyclist has interactions with more than one vehicle but in this work we just consider the most dangerous interaction (with the lowest PET).
- t is a predefined PET threshold value, 1.5 seconds for dangerous interactions and 5 seconds for interactions.

The definition of t has been arbitrary selected and is in agreement with the thresholds used in the literature (Sayed et al. 2013c). It is worth mentioning that other t values have been tested and the results were found to be robust.

In the second analysis, a statistical modeling approach is used. For this purpose, the PET value of each individual cyclist arriving to the intersection with the turning vehicle that turns closest in time to the cyclist (the one that provides the minimum PET for the cyclist) is used as the dependent variable. Only the cyclists riding parallel to the motor-vehicles, in the same direction (prior to turning), are the focus of this study, as shown in Figure 4-2. In order to provide meaningful results, PET values (for each cyclist) are discretized into four categories, defined as:

1. PET ≤ 1.5 seconds, considered as a very dangerous interaction,
2. 1.5 seconds < PET ≤ 3 seconds, considered as a dangerous interaction,
3. 3 seconds < PET ≤ 5 seconds, considered as a mild interaction, and
4. PET > 5 seconds, considered as no interaction.

Note that as a sensitivity analysis, other thresholds for defining the categories have been tested; however small changes in the threshold values did not significantly change the results. Once PET is discretized, random effects ordered logit models are applied to control for the effects of other variables such as traffic conditions and road geometry as well as the random effect and unobserved variables of each intersection. The random effect ordered logit model is one of the most commonly used statistical models for crash severity analysis. For more details about the random effect ordered logit model, please refer to (Crouchley 1995). In this model, $y_{ij} = \beta x_{ij} + \varepsilon_{ij} + \delta_j$, where y_{ij} is the PET latent variable for observation i at site j, x_{ij} is the vector of attributes for interaction i at site j, β is the vector of unknown parameters, ε_{ij} is the individual error term for each observation and δ_j is the random effect at the intersection level considering that measurements obtained from the same intersections are nested. The dependant variable, y_{ij}, is bound by unknown cut-offs, which define the alternatives.

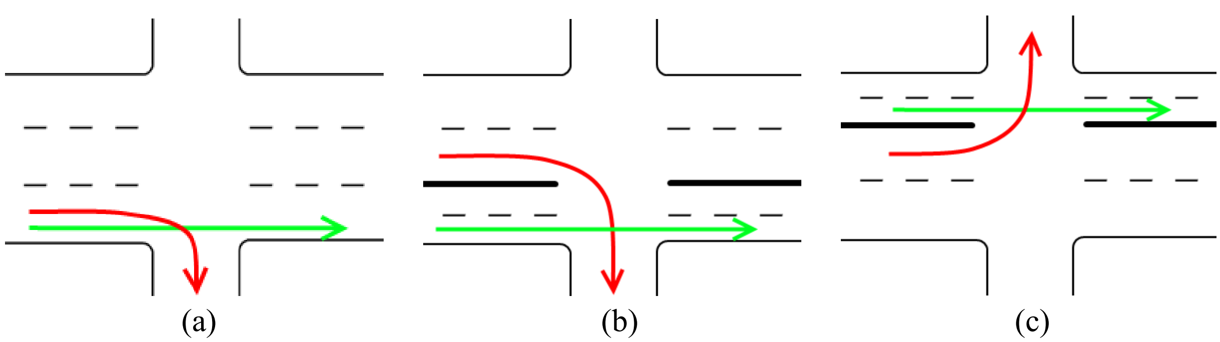


Figure 4-2. Studied interactions for three different types of intersections: (a) cyclists and right-turning vehicles at intersections without cycle track, (b) cyclists and right-turning vehicles at intersections with cycle track on the right, and (c) cyclists and left-turning vehicles at intersections with cycle track on the left. Red and green arrows show turning vehicles and cyclists respectively

Several variables were generated and tested as potential independent variables associated with the severity of interactions, including:

- Cycle track on the right side of the road (dummy variable).
- Cycle track on the left side of the road (dummy variable).
- Number of lanes on the approach where the vehicles is turning from, parallel to where cyclists are riding.
- Number of lanes on the approach where vehicles turn into.
- Presence of bus stops at the intersection (dummy variable).
- One way street (dummy variable).
- Turning vehicle and cyclist flows per hour.

Disaggregate exposure measures are also considered in the proposed modeling approach, such as the number of cyclists and turning vehicles arriving before and after the arrival of each individual cyclist. Considering cyclist i (C_i) arrives at time t_i, these variables are defined individually for cyclist i as:

- Bicycle flow before C_i = number of cyclists arriving between t_i - t_b and t_i.
- Bicycle flow before and after C_i = number of cyclists arriving during $t_i \pm t_{ba}$.
- Vehicle flow before C_i = number of turning vehicles between t_i - t_b and t_i.
- Vehicle flow before and after C_i = number of turning vehicles arriving during $t_i \pm t_{ba}$.

Where t_b represents a predefined time interval before the arrival of cyclist i of 10, 30, or 60 seconds and t_{ba} represents a predefined time interval before and after the arrival of cyclist i of 5, 15, or 30 seconds. Different time intervals were selected and tested to determine which has the greatest effect on cyclist safety with respect to turning vehicles at intersections. The proposed method for counting cyclists in different movements has been shown in (Zangenehpour, Romancyshyn, et al. 2015) to provide acceptable counting accuracy.

Using the variables defined previously, different models were proposed to investigate the safety effect of cycle tracks on interactions between cyclists and turning vehicles. Three sets of models are developed to compare:

1- Intersections with a cycle track on the right side to intersections without a cycle track.
2- Intersections with a cycle track on the left side to intersections without a cycle track.
3- Intersections with a cycle track on the right side to intersections with a cycle track on the left side.

4.6. VALIDATION OF THE ACCURACY OF PET MEASURES

The use of automated video analysis for detecting conflicts and extracting surrogate measures of safety is not new. The accuracy of the video analysis algorithms integrated in "Traffic Intelligence" has been validated in previous studies; for instance one can refer to (St-Aubin et al. 2015) in regards to its tracking accuracy, (Zangenehpour, Romancyshyn, et al. 2015) in regards to its accuracy in counting cyclists in various conditions, and (Anderson-Trocmé et al. 2015) in regards to its accuracy in measuring speed.

In order to show the accuracy of the automated method to estimate the PET category of each interaction, 50 samples (based on the automated method) from each category were randomly selected and reviewed manually by the authors (Table 4-1). The overall classification acuracy of the automated method is determined to be 88 %.

Table 4-1. Confusion matrix showing the accuracy of the method to estimate PET categories

		Manual					
		$PET \leq 1.5$	$1.5 < PET \leq 3$	$3 < PET \leq 5$	$PET > 5$	Total	Precision
Automated	$PET \leq 1.5$	42	6	1	1	50	84 %
	$1.5 < PET \leq 3$	1	44	3	2	50	88 %
	$3 < PET \leq 5$	0	3	46	1	50	92 %
	$PET > 5$	0	0	6	44	50	88 %
	Total	43	53	56	48		
	Recall	98 %	83 %	82 %	92 %		88%

4.7. DATA AND RESULTS

Video and geometry data were obtained for a sample of 23 intersections. More specifically, a total of over 90 hours of video data was collected, from which around 31 hours of video were collected from intersections with no cycle track (8 sites), around 37 hours for intersections with cycle track on the right side of the road (8 sites) and more than 22 hours for intersections with cycle track on the left side of the road (7 sites). Figure 4-3 provides the locations of these intersections.

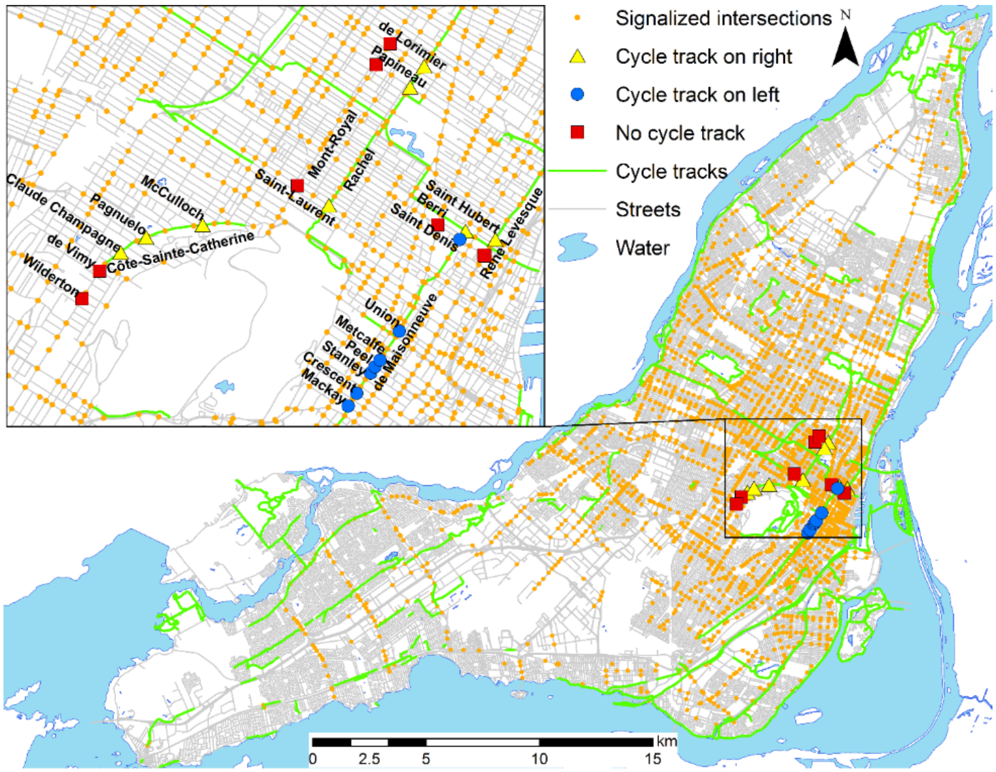


Figure 4-3. Location of sites selected for recording video in Montréal

A summary of the video analysis for the recorded video is shown in Table 4-2 which shows that:

- Bicycle flow is higher at intersections with a cycle track, an average of 18 cyclists per hour for intersections without a cycle track, 63 for intersections with a cycle track on the right side and 191 for intersections with a cycle track on the left side (all the cycle tracks on the left side are on Maisonneuve Boulevard which is one of the busiest cycle tracks in Montréal). This shows that either cyclists prefer to use roads with cycle tracks, or cycle tracks were implemented on roads that have more bicycle flow.
- Looking at the averages at the bottom of the table, the average cyclist speeds are found to be similar across site subgroups. Speed is only slightly higher at intersections with cycle tracks where cyclists feel safe and are provided with their own space to bike at their

desired speed. Additionally, as expected, average cyclist speed is greater for cyclists riding in the downhill direction at intersections (such as on Cote Sainte Catherine).

- The number of interactions and dangerous interactions per hour are on average greater at intersections with cycle tracks. However, accounting for bicycle and turning vehicle flows, the rate of dangerous interactions is lower for intersections with cycle tracks, as illustrated in Figure 4-4.
- Figure 4-5 shows the position density maps for cyclists and turning vehicles for three different intersection types. These density maps show the acceptable accuracy of detecting, tracking, and classifying road users in the videos. In addition, it shows the average distance between cyclists and turning vehicles at intersections, which can also be related to safety.

Table 4-2. Summary of the processed videos, counts and speeds for cyclists and vehicles

	Intersection	Hours of video	Number of Bicycles	Number of Vehicles	Cyclist Average Speed (km/h)	Vehicle Average Speed (km/h)	PET ≤ 5	PET ≤ 1.5	Cyclists per Hour	Vehicles per Hour	PET ≤ 5 per Hour	PET ≤ 1.5 per Hour	Interaction Rate*	Dangerous Interaction Rate*
No Cycle Track	Cote Sainte Catherine / Vimy	6.54	56	323	14.3	18.9	6	2	8.6	49.4	0.9	0.3	2169.4	723.1
	Cote Sainte Catherine / Wilderton	8.32	90	843	12.6	9.8	13	2	10.8	101.3	1.6	0.2	1425.6	219.3
	Mont Royal / Lorimier	2.88	106	66	10.9	12.6	4	2	36.8	22.9	1.4	0.7	1646.7	823.3
	Mont Royal / Papineau	1.74	48	50	13.8	10.4	5	2	27.6	28.7	2.9	1.1	3625.0	1450.0
	Mont Royal / Saint Laurent	2.71	53	150	10.4	8.2	6	3	19.6	55.4	2.2	1.1	2045.3	1022.6
	Rene Levesque / Saint Denis	2.8	116	237	10.5	9.3	19	2	41.4	84.6	6.8	0.7	1935.1	203.7
	Saint Denis / Ontario	2.95	43	62	10.1	12.3	2	0	14.6	21.0	0.7	0.0	2213.1	0.0
	Saint Denis / Rene Levesque	2.98	46	328	12.2	14.1	9	3	15.4	110.1	3.0	1.0	1777.6	592.5
Cycle Track on Right	Berri / Maisonneuve	2.89	188	90	8.7	8.4	11	0	65.1	31.1	3.8	0.0	1878.8	0.0
	Cote Sainte Catherine / Claude Champagne	8.28	436	153	18.1	17.8	27	1	52.7	18.5	3.3	0.1	3351.3	124.1
	Cote Sainte Catherine / Mcculloch	7.14	236	125	18.8	18.9	7	0	33.1	17.5	1.0	0.0	1694.2	0.0
	Cote Sainte Catherine / Pagnuelo	8.08	383	340	10.0	13.8	29	1	47.4	42.1	3.6	0.1	1799.4	62.0
	Rachel / Lorimier	2.5	142	63	11.8	11.0	12	0	56.8	25.2	4.8	0.0	3353.5	0.0
	Rachel / Papineau	2.1	226	390	11.7	12.3	16	9	107.6	185.7	7.6	4.3	381.2	214.4
	Rachel / Saint Laurent	2.98	106	350	10.7	9.8	23	6	35.6	117.4	7.7	2.0	1847.4	481.9
	Rene Levesque / Saint Hubert	2.98	605	175	15.7	13.1	76	4	203.0	58.7	25.5	1.3	2139.1	112.6
Cycle Track on Left	Maisonneuve / Crescent	3.5	787	558	14.2	13.7	245	17	224.9	159.4	70.0	4.9	1952.7	135.5
	Maisonneuve / Makay	3.33	476	291	12.5	12.2	82	9	142.9	87.4	24.6	2.7	1971.3	216.4
	Maisonneuve / Metcalfe	3.28	820	358	13.3	12.1	163	15	250.0	109.1	49.7	4.6	1821.2	167.6
	Maisonneuve / Peel	3.48	500	222	13.2	10.4	68	8	143.7	63.8	19.5	2.3	2131.9	250.8
	Maisonneuve / Saint Denis	3.22	398	219	14.2	12.3	73	4	123.6	68.0	22.7	1.2	2696.8	147.8
	Maisonneuve / Stanley	3.32	956	247	12.6	12.4	135	12	288.0	74.4	40.7	3.6	1898.1	168.7
	Maisonneuve / Union	2.09	308	147	14.3	15.5	30	0	147.4	70.3	14.4	0.0	1384.8	0.0
Total	No Cycle Track	30.92	558	2059	11.7	11.9	64	16	18.0	66.6	2.1	0.5	1722.4	430.6
	Cycle Track on Right	36.95	2322	1686	14.0	12.9	201	21	62.8	45.6	5.4	0.6	1897.1	198.2
	Cycle Track on Left	22.22	4245	2042	13.4	12.7	796	65	191.0	91.9	35.8	2.9	2040.4	166.6

* Computed based on equation (1)

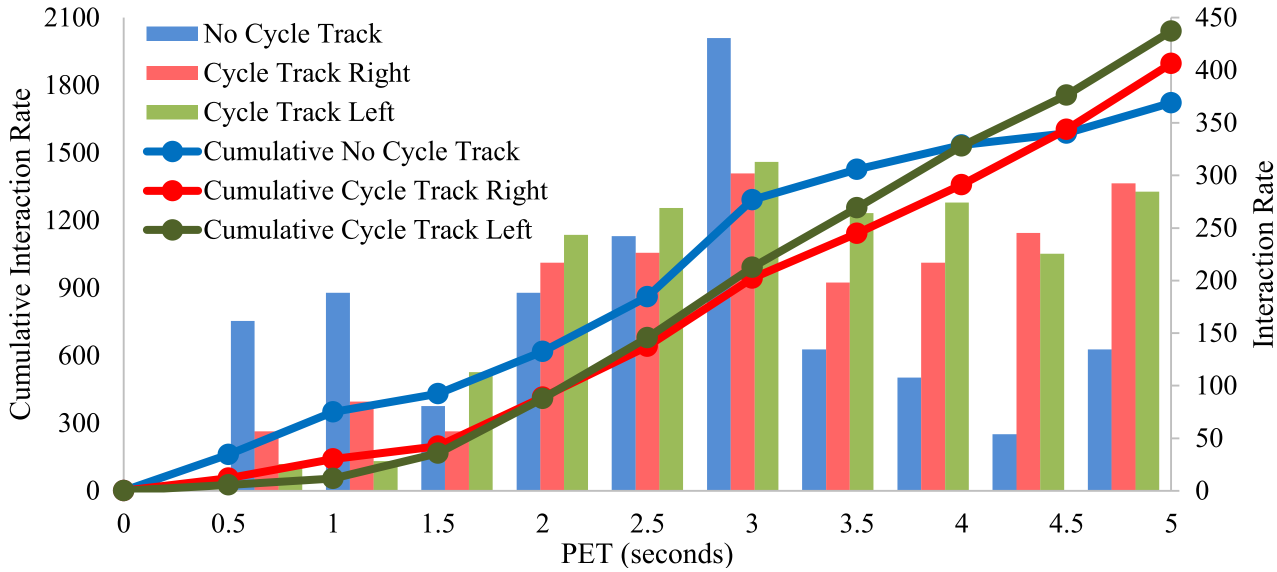
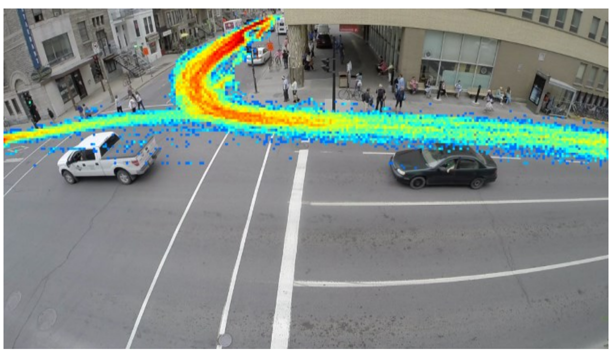
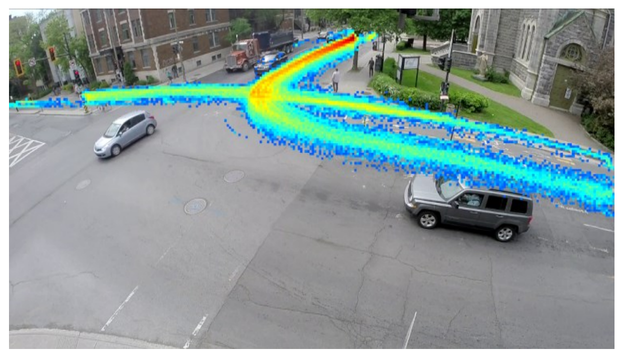


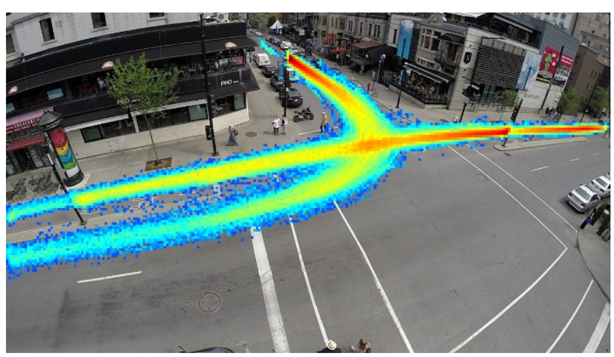
Figure 4-4. Interaction rate and cumulative interaction rate per PET interval



(a)



(b)



(c)

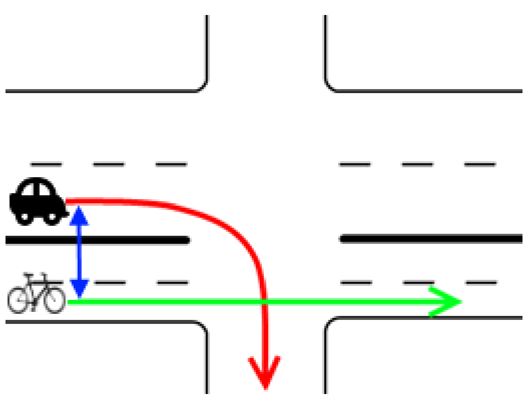
Figure 4-5. Position density map of cyclists and turning vehicles for three sample intersections, intersection with no cycle track (a), intersection with a cycle track on the right side of the road (b), and intersection with a cycle track on the left side of the road (c).

The final random effects ordered logit modelling results for PET values are shown in Table 4-3. Note that different combinations of variables were used to find the best model, and only variables significant to the 95 % confidence level, which do not have high correlation with any other variable, are introduced and presented in the final models.

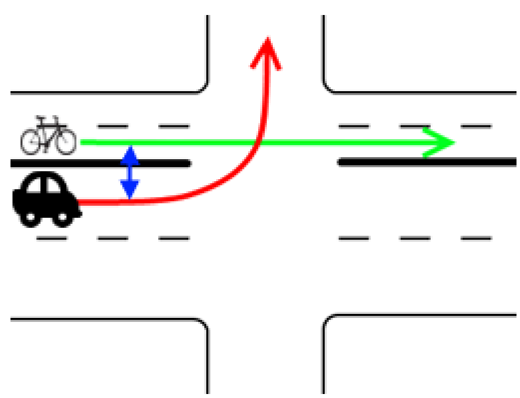
Table 4-3. Model results for interactions between cyclists and turning vehicles

	Model I. Cycle track on the right vs. no cycle track			**Model II. Cycle track on the left vs. no cycle track**			**Model III. Cycle track on the right vs. cycle track on the left**		
	Coef.	Std. Err.	Sig.	Coef.	Std. Err.	Sig.	Coef.	Std. Err.	Sig.
Cycle Track on Right	0.395	0.181	0.03	-	-	-	-	-	-
Cycle Track on Left	-	-	-	Not Significant			-0.513	0.131	0.00
Bicycle Flow for 5s before to 5s after	Not Significant			0.088	0.038	0.02	0.066	0.034	0.05
Turning vehicle Flow for 5s before to 5s after	-2.771	0.132	0.00	-3.265	0.090	0.00	-3.131	0.080	0.00
Number of Lane on the Main Road	-0.151	0.078	0.05	Not Significant			Not Significant		
Number of Lane on the Turning Road	Not Significant			0.324	0.146	0.03	0.457	0.178	0.01
Cut-off 1	-6.599	0.353	0.00	-7.372	0.301	0.00	-7.621	0.323	0.00
Cut-off 2	-4.233	0.273	0.00	-3.807	0.223	0.00	-4.125	0.265	0.00
Cut-off 3	-3.150	0.256	0.00	-2.102	0.211	0.00	-2.479	0.258	0.00
Number of Observations	2880			4803			6567		
Log likelihood	-804			-1876			-2330		

The main goal of this regression analysis is to complement and confirm the observed safety effects of cycle tracks based on interaction rates between cyclists and turning vehicles. The advantage of regression analysis is that one is able to simultaneously control for geometry and traffic conditions while the raw-risk estimates (interaction rates) assume that the number of interactions is a linear function of the number of cyclists and vehicles involved. Not surprisingly, the results of the regression analysis are in the same direction and show that intersections with cycle tracks on the right are safer for cyclists compared to intersections without cycle tracks (Model I). Based on the predictions made by this model, and with the assumption that all the relevant variables are included in the models, if cycle tracks (on the right side of the road) are built at all the intersections which currently do not have any cycle track, while keeping all else constant, the expected number of dangerous interactions (interactions with PET $\leq$ 3 seconds) does not change but the number of interactions (interactions with PET $\leq$ 5 seconds) is expected to decrease by around 40 % (from 1.07 to 0.65 interactions per hour). However, intersections with cycle tracks on the left side (all on Maisonneuve Boulevard) are not significantly safer than intersections without cycle tracks (Model II). Another finding is that cycle tracks on the right are safer than cycle tracks on the left side (Model III). This may be due to the lateral distance between cyclists and vehicles. At intersections with cycle tracks on the right (Figure 4-6a), the lateral distance between a cyclist and a vehicle in the same direction is greater than at intersections with cycle tracks on the left (Figure 4-6b). This means that cyclists and drivers have a greater chance of seeing one another and avoiding dangerous interactions. If cycle tracks are moved from the left side to the right side of the intersection, while keeping all else constant, based on the predictions made by this model, the expected number of dangerous interactions (interactions with PET $\leq$ 3 seconds) does not change but the number of interactions (interactions with PET $\leq$ 5 seconds) is expected to decrease by around 25 % (from 32.5 to 24.7 interactions per hour). These elasticities were computed based on each individual cyclist and with the assumptions of building cycle tracks at the intersections currently without cycle tracks in Model I, and changing the position of cycle tracks at the intersections with cycle tracks on the left to the right side in Model III. Note that these elasticities were computed based on the assumption that all the relevant variables have been included in the models. It is possible, however, that some relevant variables cannot be measured or quantified and therefore included in the models. Such variables include cyclists' and drivers' gender, age, and experience as well as their personality and their level of aggression.



(a)



(b)

Figure 4-6. Interaction between cyclists and turning vehicles (the red arrows show a trajectory sample of turning vehicles, the green arrows show a trajectory sample of cyclists and the blue arrow shows the lateral distance between cyclists and vehicles), for intersections with a cycle track on the right side (a), and for intersections with a cycle track on the left side (b).

Results also show that the number of turning vehicles is the main factor associated with intersections being dangerous for each individual cyclist. Higher turning vehicle flow at the time that a cyclist is crossing the intersection provides smaller gaps for the cyclist crossing the intersection and increases the chance of a cyclist being involved in a more dangerous interaction with one of the turning vehicles.

Another variable that makes an intersection dangerous for cyclists is the number of lanes on the main road (the road that vehicles are turning from), meaning that the more lanes on the main road, the more dangerous it is for cyclists on that road (just for Model I).

The bicycle flow before and after C_i, defined as the number of cyclists arriving at the intersection between $t_i - 5$ and $t_i + 5$, reduces the risk for each individual cyclist. This means that as the arrival rate of cyclists increases, the chance of being seen by drivers also increases. This variable represents the safety effect of group arrivals and can also be seen as the "safety in numbers" effect (Jacobsen 2003). Note that this variable was not significant for comparing intersections with cycle tracks on the right to intersections with no cycle track (Model I).

The higher the number of lanes on the road that vehicles turn into is another variable that can make intersections safer for cyclists. More lanes on the road, on to which vehicles turn, means that turning vehicles have more manoeuvering options for their turning radius to avoid interactions with cyclists. This variable was not significant for comparing intersections with cycle tracks on the right to intersections with no cycle track (Model I).

It is worth mentioning that a sensitivity analysis was carried out to ensure that the results are independent of the threshold values chosen to discretize the PET values. Several different thresholds ({1, 1.2, 1.6, 1.7} s, {2, 2.5, 3.5, 4} s, and {4, 4.5, 6, 7} s for first, second and third threshold, respectively) were tested and all the parameter estimates were found to be consistent.

4.8. VALIDATION OF SURROGATE SAFETY MEASURES

To validate the relationship of the surrogate safety measure used in this study with actual safety, we compared the rankings of the 23 studied intersections based on historical accident data to the rankings based on the surrogate safety measure. The historical accident data came from ambulance services in Montreal over a six year period from 2007 to 2012. At locations with cycle tracks, in order to look at the accidents potentially caused by the presence of cycle tracks, only accidents that occurred after the track was built were considered. Also, the accident data used is for the entire intersection, considering total vehicle and bicycle flows, and not specifically for the cyclists traveling straight and turning vehicles. This analysis therefore assumes that the ratio of total accidents to total flows can be used as a proxy for the ratio of accidents between cyclists traveling straight and vehicles turning to their respective flows. In the accident database, accidents were considered as having occurred at an intersection if they were within fifteen meters of the centre point of the intersection. Although ambulance data may be biased towards more severe injuries, in Montreal, this source of data identified more cyclist injuries than police reports (Strauss, Miranda-Moreno, et al. 2013).

For ranking the intersections based on safety, equation (2), which has been widely accepted and used in the literature (Strauss, Miranda-Moreno, et al. 2013), was applied:

$$Accident\ Rate = \frac{Accident\ per\ year * 10^6}{AADB * 365} \qquad (2)$$

, AADB is the average annual daily bicycle volume achieved by combining smartphone GPS and manual count data in Montréal (Strauss et al. 2015). Other exposure measures were used in the rest of this paper to correlate the interaction and accident rate.

For the ranking based on interactions, equation (1) was used with t equal to 1.5 seconds in order to identify only very dangerous interactions. The summary of accident, flow and interaction data for the 23 studied intersections is presented in Table 4-4.

Table 4-4. Summary of accident, flow and surrogate measure of safety

Intersection	Observed accidents	Years of data	Number of accidents per year	AADB	Accident rate*	Surrogate dangerous rate**	Accident rank	Surrogate dangerous rank
Mont Royal / Papineau	13	6	2.17	898	6.608	1450	1.0	1.0
Cote Sainte Catherine / Vimy	1	6	0.17	319	1.433	723	2.0	4.0
Cote Sainte Catherine / Claude Champagne	5	3	1.67	4437	1.030	124	3.0	16.0
Mont Royal / Lorimier	3	6	0.50	1768	0.775	823	4.0	3.0
Mont Royal / Saint Laurent	2	6	0.33	2180	0.419	1023	5.0	2.0
Maisonneuve / Crescent	7	5	1.40	9674	0.397	136	6.0	15.0
Saint Denis / Rene Levesque	1	6	0.17	1330	0.342	593	7.5	5.0
Rene Levesque / Saint Denis	1	6	0.17	1330	0.342	204	7.5	11.0
Maisonneuve / Mackay	5	5	1.00	8277	0.332	216	9.0	9.0
Cote Sainte Catherine / Pagnuelo	2	3	0.67	5590	0.326	62	10.0	18.0
Maisonneuve / Peel	5	5	1.00	9662	0.285	251	11.0	7.0
Maisonneuve / Saint Denis	6	5	1.20	11803	0.279	148	12.0	14.0
Cote Sainte Catherine / Mcculloch	1	3	0.33	4023	0.227	0	13.0	21.0
Maisonneuve / Stanley	4	5	0.80	11142	0.197	169	14.0	12.0
Rachel / Saint Laurent	5	6	0.83	13331	0.173	482	15.0	6.0
Maisonneuve / Union	7	5	1.40	32997	0.115	0	16.0	21.0
Rachel / Papineau	7	3	2.33	67336	0.096	214	17.0	10.0
Rachel / Lorimier	7	6	1.17	68256	0.047	0	18.0	21.0
Saint Denis / Ontario	2	6	0.33	24554	0.038	0	19.0	21.0
Rene Levesque / Saint Hubert	1	6	0.17	20165	0.022	113	20.0	17.0
Berri / Maisonneuve	3	5	0.60	83130	0.019	0	21.0	21.0
Cote Sainte Catherine / Wilderton	0	6	0.00	318	0.000	219	22.5	8.0
Maisonneuve / Metcalfe	0	5	0.00	11475	0.000	168	22.5	13.0

* accident per million cyclists

** dangerous interactions per million potential interactions

Figure 4-7 visually shows the relationship between the ranking based on the accident data and the ranking based on the surrogate measure used in this study.

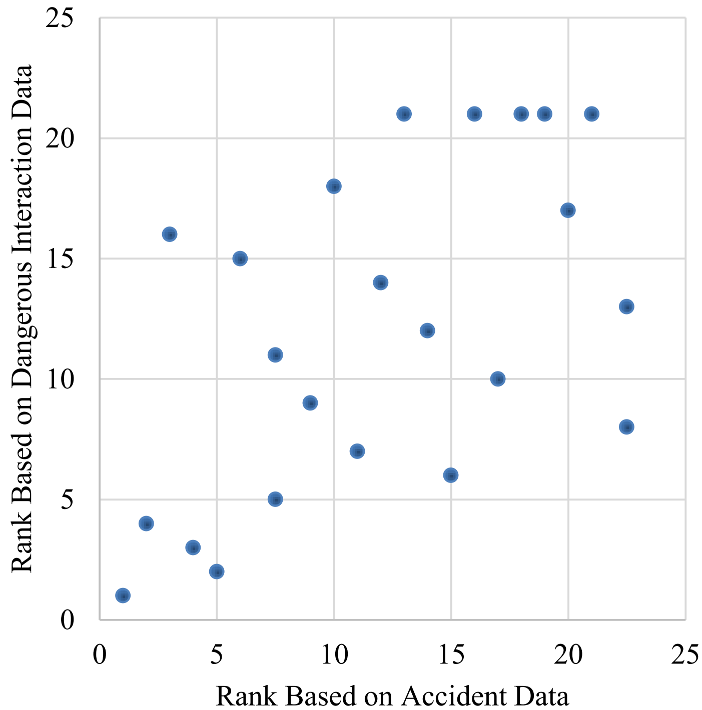


Figure 4-7. Comparison between the ranking based on accident data and surrogate measure

Spearman's rank correlation coefficient is a nonparametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function. A perfect Spearman correlation of +1 or −1 occurs when each of the variables is a perfect monotone function of the other. Spearman's rank correlation can be computed as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \tag{3}$$

where n is the number of samples and d_i is the difference between the ranks for measure (site) i based on the two safety measures. Note that identical values (rank ties or value duplicates) are assigned a rank equal to the average of their positions in the ascending order of the values. Using this definition, Spearman's correlation between the ranks based on accident data and dangerous interaction data was 0.55 which shows promising correlation between accident data and dangerous interactions.

Other than using just AADB in equation (2), other values such as AADB multiplied by AADT and AADB multiplied by AADTT were applied, where AADT is the average annual daily vehicle traffic and AADTT is the average annual daily turning vehicle traffic at an intersection. In addition to using t equal to 1.5 seconds, t equal to five seconds was also tested to find the best surrogate measure (Table 4-5). Furthermore, using AADB and the Empirical Bayes (EB) estimation of accidents in equation (2), resulted in a correlation of 0.55 with ranks based on interactions with surrogate measures with t equal to 1.5 seconds. Although all of these results had relatively acceptable correlation values, the use of t equal to 1.5 seconds in equation (1), and using just AADB as the exposure measure in equation (2), resulted in the highest correlation value.

Table 4-5. Spearman's rank correlation for different interactions and exposure measures

Exposure measure / Interaction in surrogate data	AADB	AADB * AADT	AADB * AADTT
NPET with t = 1.5 s	0.55	0.40	0.45
NPET with t = 5 s	0.35	0.33	0.45

Also a linear correlation of 0.4 between the number of accidents per year and the hourly number of very dangerous interactions (with PET lower than 1.5 s) is obtained. This again shows some evidence about the relationship between reported accidents and the surrogate safety indicator used in this study. This relationship however needs more investigation using more data (longer periods of time and more sites).

4.9. CONCLUSION AND FUTURE WORK

This research investigated the safety effectiveness of cycle tracks using a cyclist-vehicle interaction methodology based on an automated video process. PET is used as a surrogate safety measure for defining the severity of interactions between cyclists and turning vehicles. The proposed methodology consisted of three main steps: i) video data collection at the selected treated and control sites, ii) automatic road user detection, tracking and classification, as well as the computation of PET between cyclists and turning vehicles, and iii) statistical modeling of PET values to identify the effects of cycle tracks and other variables on cyclist safety.

Empirical evidence is generated based on a relatively large sample of intersections with many hours of video data. A total of 23 intersections were involved, eight with a cycle track on the right side, seven with a cycle track on the left side, and eight without a cycle track. From over 90 hours of video, over 7,000 cyclists were recorded and used in this study. Each cyclist and its interaction with turning vehicles represents an observation in the random effects ordered logit modeling framework. Different models were fitted to the data in order to compare the safety effects of intersections in the presence and absence of cycle tracks. In addition to presence of cycle tracks and their locations, measures of traffic conditions and geometry were also evaluated using statistical analysis.

Among other results, interaction rates estimated from the raw data showed that intersections with cycle tracks on the right or left side appear to be safer than no cycle track. However, these results do not account for disaggregate traffic flow conditions and geometry characteristics. Therefore, a regression analysis was executed. Based on the recorded video data and our analysis, it seems that intersections with cycle tracks on the right, compared to intersections with no cycle track are safer. By adding a cycle track to the right side of intersections currently without a cycle track, interactions (with PET $\leq$ 5 s) are expected to drop by around 40 %. However, cycle tracks on the left did not show any significant decrease in the probability of interactions compared to no cycle tracks. Cycle tracks on the right are then recommended, from a safety perspective, over cycle tracks on the left. Building cycle tracks on the right side is associated with 25 % fewer interactions (with PET $\leq$ 5 s) than on the left side. Ideally intersection treatments should be implemented as well, in addition to having cycle tracks, to ensure the safety provided by cycle tracks along road segments is not overruled by interactions and the potential for collisions they may cause at intersections.

Other factors such as bicycle and turning vehicle flows in the few seconds before and after the arrival of each cyclist to the intersection were shown to have a statistically significant effect on interactions between cyclists and turning vehicles. These micro-level exposure measures provide a better understanding of cyclist behaviours and interaction mechanisms. For instance, the effect of cyclists arriving alone or in a group was evaluated. Interaction severity was found to reduce as cyclist presence increases (size of group arriving at the intersection). An opposite effect was observed for turning vehicles, more traffic results in a higher probability of serious interactions.

Some geometry factors such as the number of lanes were also shown to be statistically significant. More lanes in the vehicle approach result in more dangerous situations for cyclists. This means that in addition to the installation of right-side cycle tracks, the reduction of vehicle turning movements and geometry changes could represent additional safety benefits. These results highlight the important role that cycle tracks play in cyclist safety and reinforce the findings reported using the traditional safety approach.

It is also important to recognize that a before-after observational approach is more suitable than control case-studies to evaluate safety treatments. However, the before-after approach is difficult to implement when safety treatments have already been implemented and when no data from the before period is available – which is the case in this research. As part of the future work, the effectiveness of cycle tracks needs to be evaluated using longitudinal before-after surrogate approach. Another limitation of this work is the small number of hours of recorded video from each site. By recording video for longer periods of time from fewer intersections, the safety effect of cycle tracks can be confirmed.

Also, as part of future work, the safety effect of cycle tracks at non-signalized intersections will be investigated. Other interactions will also be examined such as cyclist-vehicle rear-end interactions and pedestrian-cyclist interactions in shared spaces. The proposed methodology could also be replicated to validate the safety effectiveness of different bicycle facility designs (bidirectional vs unidirectional, bicycle lanes, etc.). This could also involve different cities and longitudinal video data. This will help provide a more general and transferable results about the safety effectiveness of bicycle facilities. In addition, by recording video for a longer period of time, one will be able to investigate the safety effect of cycle tracks for different times of the day (including nighttime). To test the accuracy of surrogate safety measures as an indicator of accidents and injuries, these results will be compared to historical accident and injury data. Another study will be carried out to compare the safety effects of unidirectional versus bidirectional cycle tracks. Also the safety effect of different signal phasing, including advanced green light for cyclists and pedestrians, will be investigated.

4.10. ACKNOWLEDGMENTS

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Link between chapter 4 and chapter 5

In the previous chapters, first by tracking and classifying moving objects in traffic video, we introduced an accurate automated method to collect microscopic data separately for each road user category. Then we showed how the mentioned method can be used for counting cyclists and their different movements. In the previous chapter we illustrated how safety analysis can be done using this method. The first example of this kind of safety analysis was the effect of cycle tracks and their different designs on the safety of cyclists at signalized intersections. As shown in the chapter four, surrogate safety measures that are used in this thesis have high correlation with accident and injury data and can be good indicators of safety. The main focus of chapter four is investigating the impact of bicycle boxes on cyclist safety at intersections, using surrogate safety measures. In this chapter, data is collected through two separate methods, manual and automated (improved version of the classifier) to illustrate how these two different data collection methods complement each other by covering variables that the other one cannot easily or accurately cover.

Chapter 5

Impact of Bicycle Boxes on Cyclist Behaviour and Safety: A Surrogate Study Using Manual and Automatic Video-Data Measures

Chapter 5: Impact of Bicycle Boxes on Cyclist Behaviour and Safety: A Surrogate Study Using Manual and Automatic Video-Data Measures

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5.1. ABSTRACT

To improve cyclist safety and comfort at intersections, different engineering countermeasures have been recommended and implemented, such as the installation of bicycle boxes. In recent years, cities throughout North America have begun to follow Europe's lead and have started to build bicycle boxes. These facilities have been built, but very little research has been done to investigate their impact on road user behaviour and safety. The main objective of this study is to investigate the safety effects of bicycle boxes at signalized intersections. For this purpose, two video data collection methods, one manual and one automated, are proposed. This data is used to extract surrogate safety measures to analyze the safety effects of bicycle boxes at signalized intersections. The secondary objective of this paper is to illustrate how manual and automated data collection methods complement each other by obtaining variables that the other one cannot easily or accurately provide. Using the city of Montréal as the case study, a sample of intersections with and without bicycle boxes was selected. A total of 29 hours of video were collected and processed in order to obtain cyclists' behaviour and their interactions with vehicles. After these behaviours and interactions were detected, multinomial logit and random-effect ordered logit models were developed to evaluate the safety effects of bicycle boxes, as measured by the violation behaviour with respect to the red light as well as the post encroachment time

(PET) for the cyclist interaction with the closest crossing vehicle. The results show that age, gender, group arrival, helmet, and the presence of bicycle box, influence cyclist safety. In addition, the magnitudes of bicycle and vehicle flows during a short period before the arrival of each individual cyclist affect the probability of the cyclist being involved in a more severe interaction (with a lower PET) with vehicles. The findings of this paper support the effectiveness of bicycle boxes in reducing interactions with vehicles.

5.2. INTRODUCTION

As urban cycling gains momentum, cyclist safety concerns have increased for governments and societies in North America. Cyclist fatalities in North America, especially in United States, are 11 times higher than car fatalities per kilometer traveled (Pucher & Dijkstra 2000), emphasizing the importance of cyclist safety when encouraging active transportation. As recently found in (Strauss et al. 2014), the risk of being involved in an accident at signalized intersections is 12 times higher for a cyclist compared to a motor vehicle occupants. To improve cyclist safety at intersections, different engineering countermeasures have been recommended, such as the installation of bicycle boxes, also known as Advanced Stop Box (ASB). Although these facilities have been used for over 20 years in many Northern European countries and in the United Kingdom, so far only a few cities have implemented this kind of treatment in North America (Dill et al. 2012a), such as Portland, Vancouver, Ottawa and recently Montréal. At intersections with bicycle boxes, cyclists have a legal way to bypass the first stop line and place themselves in front of vehicles during the red signal phase. Among the advantages of bicycle boxes in the literature, one can mention the improvement of driver awareness of cyclists, the increase of cyclists' comfort, the decrease in cyclists' exposure to the direct exhaust of vehicles, the reduction of interactions between cyclists and vehicles, etc. (Atkins Services 2005).

Despite the increasing popularity of bicycle boxes, very little research has been done to evaluate their effectiveness, especially in the North American context. To our knowledge, no traditional safety studies based on historical crash data are available. This is likely due to the lack of historical cyclist-vehicle accident data and the lack of site-specific characteristics as well as bicycle volumes before and after the installation of any treatment. Also, a general shortcoming of traditional before-after studies is the need to wait several years for accidents to occur in both the before and after periods of the installation of the treatment. Implementation of traditional before-after studies can take a long time and can demand many resources. In addition, the effectiveness of the treatment over time can change due to road user adaptation. Longitudinal traditional safety studies would require even more years of data, making them almost infeasible.

To overcome these issues, surrogate safety analysis can be used instead of the traditional accident based approaches. It can be argued that surrogate safety analysis is more suitable since it allows for quicker evaluation of the treatment and adjustment if the performance of the treatment is not satisfactory. Despite the growing literature, very few studies have investigated the impact of bicycle boxes using before-after video data and surrogate safety measures. Also very few studies have dealt with the impact of bicycle boxes in terms of cyclists' red light violations. It could be hypothesized that by increasing the comfort and allowing cyclists to wait in front of vehicles in a designated space, more cyclists are willing to stop and wait for the green light. In other words, improving cyclists' comfort may lead to them adopting safer behaviours by decreasing the proportion of red light violations.

Accordingly, the main objective of this study is to introduce a surrogate video-based methodology to investigate the safety effects of bicycle boxes before and after their installation at intersections and the changes they cause on road users' behaviour. Different behavioural and surrogate safety measures are used for this purpose: cyclists' red-light violations, cyclists' stopping before crossing the intersections, and cyclist-vehicle interactions. For analyzing red-light violations and stopping behaviour of cyclists, video data were collected and processed manually for before and after the installation of the bicycle boxes at two intersections and for two other control intersections. Red-light violations and stopping behaviours are then segmented in different types and modeled as a function of several characteristics such as gender, age, group arrival, helmet use, etc. In addition, cyclist-vehicle interactions are automatically detected and measured using computer vision techniques. Interactions are segmented based on their severity (using pre-defined threshold values) and modeled as a function of different factors such as disaggregated vehicle and bicycle flows, red-light timing, etc.

This paper is divided into several sections. First a background on bicycle boxes and their safety effects, surrogate safety measures as well as automated analysis methods is provided. This is followed by a detailed description of the proposed methodologies and the data extracted from these methods. The modelling framework and the results of the models are presented next. The paper finally provides the conclusions that are drawn from this study and future work.

5.3. BACKGROUND

In recent years, cyclist mobility and safety have attracted a lot of attention. Several recent studies have tried to document the factors associated with cyclist injury risk, in particular road and built environment factors such as cycle tracks (Lusk et al. 2011b) or bicycle boxes (Dill et al. 2012a). Despite the increasing popularity of bicycle boxes, few studies have looked at their safety effects at intersections in the United States and Canada. One of the first studies on bicycle boxes was carried out in Oregon in 1998 at a busy downtown intersection with two one-way streets (Hunter 2000). In this study, video data was recorded before and after the installation of the bicycle box to observe cyclist behaviour and interactions with vehicles as well as other cyclists and pedestrians. Additional information was also collected through a short survey. Among other results, the statistical tests in this study showed no significant reduction in the total number of violations and interactions. The author suggests that this result could have been due to a high percentage of vehicles encroaching into the bicycle box.

More recently, Dill et al. (2012a) analyzed cyclist-vehicle conflicts and behaviours using video data recorded before and after the installation of bicycle boxes at 10 signalized intersections in Portland, Oregon. For each location and time period (before and after) videos were recorded during two peak periods and one off-peak period for a total of 6 hours. A high rate of compliance and understanding of the markings was found in the analysis. The number of conflicts between cyclists and vehicles decreased, while the total number of cyclists as well as right turning vehicles at the intersections increased. For identifying conflicts, authors reviewed video data. A conflict was defined as a series of events that potentially could lead to a collision: precautionary/emergency braking/change of direction or full stop by the cyclist or vehicle. Also, in terms of perceived safety, over three-quarters of the cyclists that participated in the survey stated that bicycle boxes made the intersection safer for them.

Another American study on bicycle boxes was done by Loskorn et al. (2011) which investigated both the impact of bicycle boxes and their colour on cyclists' safety. They used video footage of two intersections in Austin, Texas, for three time periods: before the installation of the bicycle boxes, after marking the bicycle boxes, and after adding colour to the bicycle boxes. In this study the safety indicator was the appropriate usage of the facilities, assuming if cyclists use the facility correctly, they are behaving in a safe way. Among other findings, this study showed that bicycle boxes improved the safety of cyclists at intersections. In addition, it was found that adding colour to the bicycle box did not significantly increase the percentage of cyclists that used the bicycle box correctly, but it did make drivers more aware of the presence of cyclists. As the authors mentioned in this paper, cyclists not using the facility correctly are not necessarily behaving dangerously.

Some limitations in the studies evaluating bicycle boxes can be mentioned. Although several behavioural measures have been proposed as a surrogate safety indicator (e.g., violations and interactions), only manual techniques have been used to process video data. Also, in most of the past studies, simple statistical analyzes have been used to evaluate the safety impact, without controlling for cyclists' profiles (e.g. gender, age, helmet usage) and traffic conditions.

Surrogate safety measures such as TTC (Time to Collision), PET (Post Encroachment Time), GT (Gap Time), and DST (Deceleration to Safety Time) can be computed automatically to estimate the safety of road users, as demonstrated in various studies for analyzing pedestrian and bicycle safety, such as (Gettman & Head 2003). To date, surrogate safety and video-analysis techniques with various levels of automation have been extensively used in pedestrian-vehicle interaction studies (Ismail, Sayed, Saunier, et al. 2009; Brosseau et al. 2013). Using a direct observation approach and video data for validation, Brosseau et al. (2013) investigated the impact of different variables on pedestrians' violation of traffic lights and dangerous crossing at signalized intersections. After analyzing data from 13 intersections with similar geometry in Montréal, several variables were determined to influence violations and dangerous crossings. These variables include age, gender, group size, conflicting vehicle flow, presence of pedestrian signal as well as maximum waiting time (red phase), and intersection clearing time.

Automated video-processing methods to track and classify road users in different environments have also been recently proposed, e.g., (Zangenehpour, Miranda-Moreno, et al. 2015). In a recent study (Zangenehpour, Strauss, et al. 2014), authors looked at the safety effect of cycle tracks at signalized intersections with respect to cyclists conflicting with turning vehicles. PET was the surrogate safety measure used in this study. Using 90 hours of video from 23 intersections in Montréal, it was found that intersections with cycle tracks on the right side of the road are safer than intersections with no cycle track; however, intersections with cycle tracks on the left side of the road were not found to be significantly safer than intersection with no cycle track. Overall this study showed that cycle tracks on the right are preferred, from a safety perspective, to no cycle track or to cycle tracks on the left side of the road.

In another recent study, Sayed et al. (2013d) used automated video-analysis technique to identify and analyze cyclist-vehicle interactions as well as vehicles rear-end and merging interactions. This study was based on the TTC surrogate safety indicator at a newly installed bicycle lane in Vancouver, Canada. The results showed a high exposure of cyclists to traffic conflicts and a significant driver non-compliance rate.

5.4. METHODOLOGY

This section describes the data collection procedure as well as the two approaches for processing video data which are manual and automated methods.

5.4.1. Site Selection and Video Recording

Two types of intersections are used in this study: treated intersections with bicycle boxes and non-treated intersections without bicycle boxes. Both types of intersections are selected with similar traffic conditions, and all intersections are four-legged and signalized. The treated sites are the intersections of: i) Milton Street and University Street, and ii) Saint-Urbain Street and Villeneuve Street. These two intersections are the locations of the first bicycle boxes built in Montréal. Two similar sites were selected as control intersections without bicycle boxes, intersections of: i) Saint-Laurent Boulevard and Villeneuve Street and ii) Saint-Urbain Street and Mont-Royal Avenue. Detailed descriptions of these four intersections are provided in Table 5-1.

For the video data collection, a mobile video-camera system (Jackson et al. 2013), developed by the transportation research group at McGill (with SVGA resolution), and a GoPro Hero 3 Black

Edition camera (with HD resolution) were used at 15 frames per second. These cameras were mounted on tall poles which are then installed next to an existing pole at the intersection to support and provide stability for the pole to prevent the camera view from changing throughout the video. For this study, more than 29 hours of video were recorded (all on weekdays) before and after the installation of the bicycle boxes at the two mentioned intersections, as well as the two other intersections without bicycle boxes. From the recorded videos, only 22 hours had a good view of the intersections and were used for the automated data collection method.

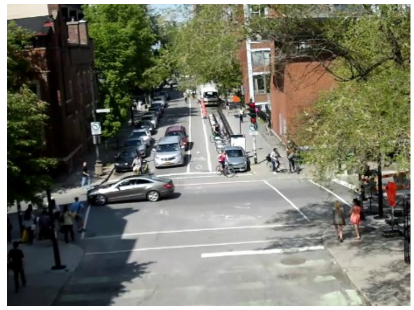
5.4.2. Manual Data Collection

This approach is required to detect and measure each cyclist's personal characteristics such as gender, age group, helmet usage, and arrival pattern. By manually observing video, each individual cyclist who passed through the intersections was classified according to the following variables:

- Gender
- Age group (an approximate measure of age), which is divided into:
    - Very young (under 18)
    - Young adult (18 to 35)
    - Middle age (35 to 60)
    - Old (over 60)
- Helmet use
- Arrival pattern: single or group arrival

In addition to personal characteristics, cyclist behaviours when arriving at an intersection were observed and classified using the flow chart represented in Figure 5-1.

Table 5-1. Description of the selected sites with the number of hours of collected video data

	Characteristics	**Without bicycle box (before condition)**	**With bicycle box (after condition)**
Milton Street and University Street	Four-legged with two bicycle facilities. Both streets are unidirectional. On University Street, a cycle track was installed two years before the installation of the bicycle box. Milton Street has a bicycle lane running in the opposite direction of vehicle traffic. Due to its proximity to McGill University, thousands of cyclists pass through this intersection during the cycling season (April to November).	 4.7 hours of video data	 7.3 hours of video data
Saint-Urbain Street and Villeneuve Street	Four-legged with two bicycle boxes on Villeneuve Street where the bicycle lanes reach the intersection. Saint-Urbain Street is one-way running southbound and Villeneuve Avenue is one-way on the east approach and two-way on the west approach. On Saint-Urbain Street there is a bicycle lane running in the same direction as vehicles while on Villeneuve Street there are two bicycle lanes, one running eastbound and the other westbound.	 2.5 hours of video data	 5.5 hours of video data
Saint-Laurent Boulevard and Villeneuve Street	Four legged without any bicycle facility. Saint-Laurent Boulevard is one-way heading northbound and Villeneuve Street is one-way heading westbound.	 5.4 hours of video data	-
Saint-Urbain Street and Mont-Royal Avenue	Four-legged. Saint-Urbain Street is one-way heading southbound, with a bicycle lane running in the same direction as vehicle traffic. Mont-Royal Avenue is a two-way street.	 3.8 hours of video data	-

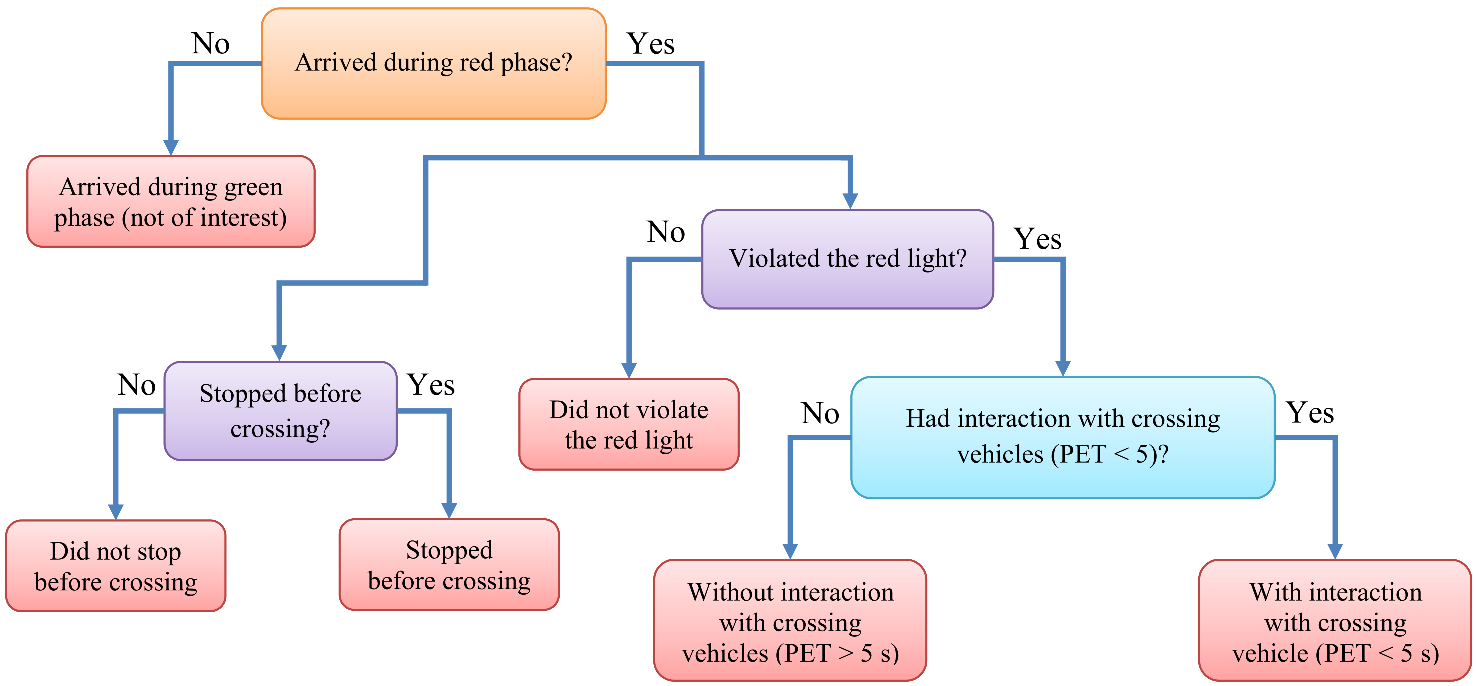


Figure 5-1. Flow chart for the behaviour of a cyclist arriving at an intersection

Each individual cyclist is first grouped based on if she/he arrived at the intersection during the green or red phase (only those arrived during red phase are the subject of this study). From the cyclists who arrived during the red phase, two behaviours are of interest in this part: i) stopping behaviour, and ii) violation behaviour. Regarding the stopping behaviour, a cyclist can either stop or not stop before crossing the red light (regardless of if she/he violates the red light, since a cyclist can first stop for the red light and after a while and finding a gap, can violate the red light). Regarding the violation behaviour, a cyclist can either wait for the green light or violate the red light. The behaviour of cyclists who violate the red light are categorized into two subgroups: a) dangerous violation (with PET less than 5 seconds), and b) mild violation (with PET greater than 5 seconds). PET is computed as the time between the departure of the cyclist from the crossing zone and the arrival of the first crossing vehicle, from the perpendicular approach to the crossing zone in the intersection or vice versa. Note that in this part, the PET values are estimated manually by reviewing the videos.

5.4.3. Automated Data Collection

The automated video-analysis and data collection techniques consist of four main steps: i) detecting and tracking moving objects in the video, ii) classifying each object into three main classes of road users (pedestrian, cyclist and vehicle), iii) selecting the desired objects (the ones that are subject of this study) and their trajectories, and iv) computing surrogate measures and other variables of interest.

5.4.3.1 *Object Tracking*

For this work, an existing open-source tracking software included in the *Traffic Intelligence* project (Saunier n.d.) is used for tracking the objects and generating trajectory data. The proposed approach uses the output of a generic feature-based moving object tracker (Saunier & Sayed 2006). The output of the tracker is the trajectory (x-y coordinates of objects at each frame) of each moving object. A calibration step is required to compute a mapping from image space to real world coordinates at ground level. The algorithm parameters are tuned by trial and error, leading to a trade-off between over-segmentation (one object being tracked as many) and over-grouping (many objects tracked as one). For more details about the tracking process, the readers are referred to (Saunier & Sayed 2006).

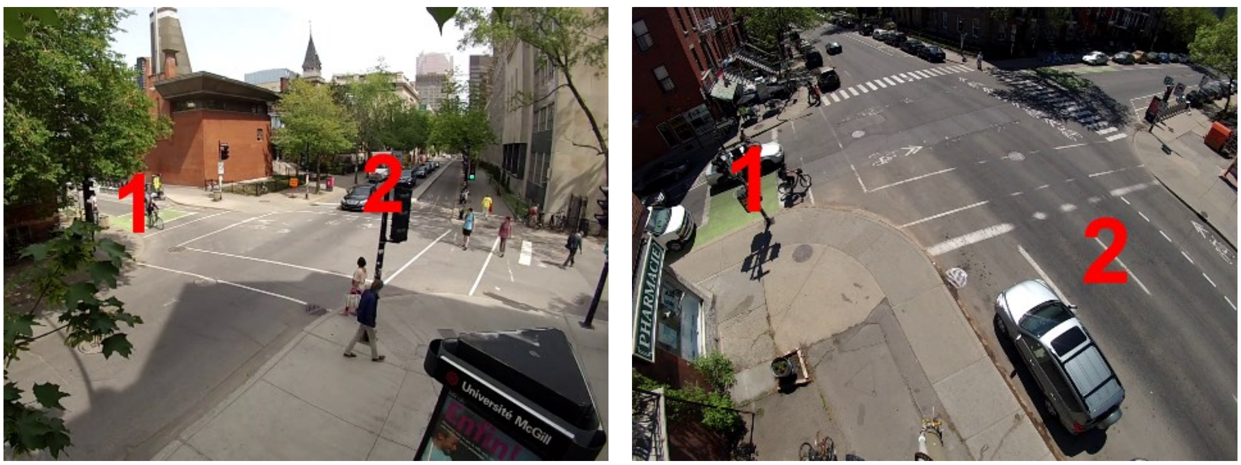
5.4.3.2 *Object Classification*

After tracking all the moving objects in the video, object classification is required to obtain the information separately for each road user type. For this purpose, an improved version of our initial algorithm for object classification (Zangenehpour, Miranda-Moreno, et al. 2014) is used. Classification is done based on object appearance in each frame combined with its aggregated speed and speed frequency (or gait parameters). The tested overall accuracy of this modified classification method at intersections with high and mixed road user traffic is more than 93 % (a 5 % point improvement from the original classification method presented in (Zangenehpour, Miranda-Moreno, et al. 2014)). The classifier is capable of classifying objects into three main road user types: pedestrian, cyclist, and vehicle. For more detail regarding the classification method, the readers are referred to (Zangenehpour, Miranda-Moreno, et al. 2014).

5.4.3.3 *Road User Selection*

The cyclists of interest are the ones whose origin of movement is graphically represented by a “1” in Figure 5-2, representing the approach which has a bicycle box (for the two intersections that have one). Also two types of vehicles (based on the approach that they enter the intersection) are of interest in this study: i) vehicles of type 1, which enter the intersection from the same approach and move parallel to the cyclists through the intersection (origin represented by a “1” in Figure 5-2), and ii) vehicles of type 2, which enter the intersection from a perpendicular approach to the cyclists (origin represented by a “2” in Figure 5-2). Note that cyclists and vehicles can go straight or turn. A road user will be selected for further analysis if:

- The road user is classified as a cyclist or a vehicle.
- The origin of the cyclist’s trajectory in the video is area “1”.
- The origin of the vehicle’s trajectory in the video is area
    a. “1” for a vehicle of type 1.
    b. “2” for a vehicle of type 2.



a) Intersections with a bicycle box: Milton & University (left) and Saint-Urbain & Villeneuve (right)

b) Intersections without a bicycle box: Saint-Laurent & Villeneuve (left) and Saint-Urbain & Mont-Royal (right)

Figure 5-2. Snapshots of videos recorded from intersections with and without a bicycle box. Area “1” is the origin of the cyclists and vehicles of type 1, and area “2” is the origin of vehicles of type 2

5.4.3.4 *Extracting Variables*

After finding and selecting the desired road users in the video, the following variables are computed for each individual cyclist:

- Bicycle flow (number of cyclists) during the 30 seconds before the arrival of the cyclist.
- Vehicle flow of type 1, during the 30 seconds before the arrival of the cyclist.
- Vehicle flow of type 2, during the 30 seconds before the arrival of the cyclist.
- PET of the cyclist with the vehicle originating from area 1 that is closest in time to the cyclist (the vehicle that provides the minimum PET for the cyclist, crossing its path before or after the cyclist goes through the intersection)
- PET of the cyclist with the vehicle originating from area 2 that is closest in time to the cyclist (the one that provides the minimum PET for the cyclist)

The proposed automated video analysis technique for counting the objects, in particular for counting cyclists, in different environments has been tested in (Zangenehpour, Romancyshyn, et al. 2015) and revealed acceptable counting accuracy.

5.5. DATA

A summary of the data extracted from the manual video observations is presented in Table 5-2. A total of 3,460 cyclists arrived during the periods of video recording (more than 29 hours of video in total), from which about 66 % (2,291 cyclists) arrived during the red phase. Note that this is due to the fact the red phases for the studied approaches are approximately two times longer than green phases. Of the cyclists arriving to the intersections during the red phase, 47 % violated the red light. The gender distribution of the cyclists remained almost consistent across all data collection periods and sites, with a proportion of around 60 % male to 40 % female. In total, over 87 % of the cyclists who passed through the intersection were estimated to be young adults. At the intersection of Milton Street & University Street, due to the proximity to McGill University, the proportion of young adults is higher than at the other intersections. Using the raw data from Table 5-2, it is difficult to draw strong conclusions about the safety behaviours (stop before crossing, violation and dangerous violation) as they do not exhibit clear trends for intersections with and without (before and after the installation of) bicycle boxes.

Table 5-2. Summary of the data collected manually from the videos

Variable			Milton & University		Saint-Urbain & Villeneuve		Saint-Laurent & Villeneuve	Saint-Urbain & Mont-Royal	Total	
			Before	**After**	**Before**	**After**	**No Bicycle Box**	**No Bicycle Box**	**With Bicycle Box**	**Without Bicycle Box**
Hours of video			4.7	7.3	2.5	5.5	5.4	3.8	12.8	16.4
Number of cyclists			594	845	518	737	167	599	1,582	1,878
Characteristics	Male		62 %	62 %	59 %	56 %	63 %	58 %	59 %	60 %
	Young adult		94 %	91 %	80 %	86 %	75 %	86 %	89 %	86 %
	Group arrival		41 %	48 %	47 %	26 %	30 %	25 %	38 %	37 %
	Helmet use		35 %	38 %	46 %	42 %	31 %	48 %	40 %	42 %
Behavioural	Cyclists arriving during red light		461	654	344	488	112	232	1,142	1,149
	Of cyclists arriving on red	Stop before crossing	73 %	73 %	80 %	75 %	84 %	86 %	74 %	79 %
		Violation	60 %	53 %	43 %	46 %	35 %	19 %	50 %	44 %
		Dangerous violation	4 %	6 %	10 %	6 %	6 %	2 %	6 %	6 %

A summary of the raw data extracted by the automated video-analysis method is provided in Table 5-3. Note that from the 29 hours of videos recorded, only around 22 hours had a proper view of the intersections and were used for the automated data collection method. In addition, since not all directions were fully visible for the automated process, fewer cyclists were detected and tracked compared to the manual process. A total of 1,054 cyclists, 3,364 vehicles of type 1, and 17,090 vehicles of type 2 were detected and tracked in the recoded videos. A summary of the processed videos are provided in Table 5-3.

Table 5-3. Summary of the data collected automatically from the videos

	Intersection	Date	Hours of video	Cyclists	Vehicles type 1	Vehicles type 2	Cyclist avg. speed (km/h)	Vehicle type 1 avg. speed (km/h)	Vehicle type 2 avg. speed (km/h)
Without Bicycle Box	Saint-Laurent & Villeneuve	2012-06-07	2.7	34	180	2423	10.21	16.15	26.91
	Saint-Laurent & Villeneuve	2013-06-03	2.7	48	243	3386	9.08	15.68	20.71
	Saint-Urbain & Mont-Royal	2013-06-20	3.8	154	1667	1085	11.86	22.20	20.89
	Saint-Urbain & Villeneuve	2012-06-01	2.5	160	284	1862	11.32	20.22	28.19
With Bicycle Box	Milton & University	2012-06-18	2.9	127	167	794	10.54	15.79	23.20
	Milton & University	2013-05-28	1.7	96	99	538	10.60	17.36	28.59
	Saint-Urbain & Villeneuve	2013-05-08	2.8	208	335	4134	8.83	13.47	22.21
	Saint-Urbain & Villeneuve	2013-05-30	2.7	227	389	2868	8.83	14.20	28.21
Total	**Without Bicycle Box**		11.7	396	2374	8756	11.16	20.84	24.04
	With Bicycle Box		10.1	658	990	8334	9.42	14.54	24.78

5.6. MODELLING

After extracting the desired variables from the videos, statistical modelling approaches are adopted in order to identify the effect of bicycle boxes, controlling for other factors. That is, to identify the factors associated with cyclist behaviour and the magnitude of their effects. For the manually collected data, a multinomial logistic regression approach is used. In this model, the utility function is defined as:

$$U_i = \beta_{i,0} + \beta_{i,1}x_1 + \beta_{i,2}x_2 + \cdots + \beta_{i,n}x_n + \varepsilon_i \qquad 1 \le i \le m \tag{1}$$

where m is the number of alternatives for the dependant variable and n is the number of independent variables. U_i represents the utility function of each alternative i, $\beta_{i,j}$ with $1 \le j \le n$ is a vector of coefficients, x_j is the j^{th} independent variable and ε_i is the error of each utility function which is assumed to follow a Gumbel distribution. In a multinomial logit regression model, the

$\beta_{i,j}$ are unknown coefficients that must be found which optimize the maximum likelihood. The final probabilities of the different alternatives *i,* (P_i) are computed from the following equation:

$$P_i = \frac{\exp(U_i)}{\sum_{\forall k} \exp(U_k)} \tag{2}$$

The elasticity (also known as marginal effect) of an independent variable, x_j, is the change in the probability function, P_i, with respect to a relative change in x_j, while keeping all other independent variables constant at their mean values. Elasticity for multinomial logit model can be defined as the partial derivation of P_i with respect to x_j:

$$Elastisity\ of\ x_j = \frac{dP_i}{dx_j} \tag{3}$$

For dummy variables, the elasticity is computed as the change in the probability function when the dummy variable changes from 0 to 1, keeping all other independent variables constant at their mean values. For a more detailed explanation of multinomial logistic regression, readers are referred to (Koppelman & Bhat 2006).

In the second approach and for modelling the automatically collected data, since the exact PET values are available (not just a dummy variable as in the manual approach), PET values are discretized into four categories:

5. PET ≤ 1.5 seconds, considered as a very dangerous interaction,
6. 1.5 seconds < PET ≤ 3 seconds, considered as a dangerous interaction,
7. 3 seconds < PET ≤ 5 seconds, considered as a mild interaction, and
8. PET > 5 seconds, considered as no interaction.

Once PET values are discretized, a random-effect ordered logit model is applied to control for the effects of other variables such as traffic conditions as well as the random effect and unobserved variables of each intersection. This model is one of the most commonly used statistical models for crash severity analysis. More details about this model can be found in (Crouchley 1995). In this model, $y_{ij} = \beta x_{ij} + \varepsilon_{ij} + \delta_j$, where y_{ij} is the PET latent variable for observation *i* at site *j*, x_{ij} is the vector of attributes for interaction *i* at site *j*, β is the vector of unknown parameters, ε_{ij} is the individual error term for each observation and δ_j is the random effect at the intersection level with the assumption that measurements obtained from the same intersection are nested. The dependant variable, y_{ij}, is bound by unknown cut-offs, which define the alternatives. For the random-effect ordered logit model the elasticity represents the percent change between categories while changing the independent variables one at a time for each observation.

5.7. RESULTS

The modelling results for finding the effect of bicycle boxes on the safety of cyclists at signalized intersections, based on two data collection approaches, are presented in this section.

5.7.1. Models Based on Manual Data Collection

The safety of cyclists could be represented by the following measures: the proportion of cyclists stopping before crossing, the proportion of violations, and the proportion of dangerous violations. In Table 5-2, the changes in cyclists' behaviour for the mentioned characteristics are shown (note that these percentages are only for the cyclists who arrived during the red light and had a decision to make: stop before crossing the red light or not, violate the red light or wait for the green light). From these raw observations, it is difficult to draw any conclusions about the behaviours as they do not exhibit clear trends for intersections with and without bicycle boxes.

For analyzing the effect of each variable and simultaneously accounting for the effect of others, regression analysis is necessary. In each of the following regression analyses, all the variables collected for each cyclist who arrived during the red light were tested to find the best variables for modelling. Three behavioural outcomes (surrogate measures), which are a priori related to cyclists' safety, are the subjects of modelling:

1- Red light violation
2- No stop before crossing the red light
3- Dangerous violation (the violations with PET less than 5 seconds)

Although all the variables and their different combinations were tested to obtain the best models with the highest log-likelihood, only the variables with significant effects (p-values less than 0.05) are used in the models and presented in the following tables. The final results are shown for three sets of models: before-after study for the intersection of Milton & University (Table 5-4), before-after study for the intersection of Saint-Urbain & Villeneuve (Table 5-5), and for the combination of all intersections with and without bicycle boxes (Table 5-6). Note that in these tables, positive coefficient values correspond to dangerous behaviours.

Table 5-4. Models for the intersection of Milton & University, before-after study, 1115 observations

Explanatory variables	**Violation**			**No stop before crossing**			**Dangerous violation**		
	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*
Constant	0.532	0.00	-	-1.724	0.00	-	-3.237	0.00	-
Male	0.330	0.01	8 %	0.380	0.01	7 %	0.959	0.00	4 %
Young adult	Not Significant			0.924	0.01	15 %	Not Significant		
Wear helmet	-0.466	0.00	-11 %	Not Significant			-0.790	0.01	-3 %
Group arrival	-0.308	0.01	-8 %	-0.825	0.00	-15 %	-1.077	0.00	-4 %
Bicycle box	-0.251	0.04	-6 %	Not Significant			0.578	0.04	2 %
Percentage of positive obs.	56 %			27 %			5 %		
Log-likelihood	-747.71			-626.13			-218.73		

* Change of dummy variable from 0 to 1

Table 5-5. Model for the intersection of Saint-Urbain & Villeneuve, before-after study, 832 observations

Explanatory variables	**Violation**			**No stop before crossing**			**Dangerous violation**		
	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*
Constant	-1.107	0.00	-	-2.064	0.00	-	-3.176	0.00	-
Male	0.770	0.00	19 %	0.807	0.00	13 %	0.790	0.01	5 %
Young adult	0.839	0.00	19 %	0.928	0.00	12 %	0.951	0.05	4 %
Wear helmet	Not Significant			-0.505	0.00	-8 %	Not Significant		
Group arrival	-0.782	0.00	-19 %	-0.823	0.00	-13 %	-0.842	0.01	-5 %
Bicycle box	Not Significant			Not Significant			-0.796	0.00	-5 %
Percentage of positive obs.	45 %			23 %			8 %		
Log-likelihood	-536.87			-419.12			-212.73		

* Change of dummy variable from 0 to 1

Table 5-6. Model for all the intersections with and without a bicycle box, 2291 observations

Explanatory variables	**Violation**			**No stop before crossing**			**Dangerous violation**		
	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*
Constant	-0.605	0.00	-	-1.740	0.00	-	-3.772	0.00	-
Male	0.569	0.00	13 %	0.565	0.00	10 %	0.839	0.00	4 %
Young adult	0.725	0.00	17 %	0.801	0.00	14 %	1.088	0.01	6 %
Wear helmet	-0.330	0.00	-8 %	-0.285	0.01	-5 %	-0.548	0.01	-3 %
Group arrival	-0.440	0.00	-10 %	-0.794	0.00	-14 %	-0.888	0.00	-5 %
Control intersection	-1.238	0.00	-28 %	-0.733	0.00	-13 %	-0.744	0.02	-4 %
Bicycle box	Not Significant			Not Significant			Not Significant		
Percentage of positive obs.	47 %			24 %			6 %		
Log-likelihood	-1487.72			-1191.36			-479.85		

* Change of dummy variable from 0 to 1

In Tables 5-4,5,6, no red light violation, stop before crossing the red light, and having enough gap (PET higher than 5 seconds) are the base alternatives (all the dependent variables representing them are set to zero) respectively for the "Violation", "No Stop Before Crossing", and "Dangerous Violation" models, i.e. a positive coefficient indicates an association with an unsafe behaviour.

As initially suspected, and in accordance with previous studies (e.g. (Brosseau et al. 2013), for pedestrian behaviours), males and young adults have a higher probability of violations, not stopping before crossing the red light, and dangerous violations. However, helmet usage decreases the likelihood of these mentioned unsafe behaviours. It is hypothesized that cautious cyclists with less risky behaviour are those who wear helmets. In other words, helmet usage (which is not mandatory in Montréal) can be seen as a proxy for risk-taking. Group arrival is another variable that reduces the probability of violations, not stopping before crossing the red light, and dangerous violations. This point has also been highlighted in past research on pedestrian behaviour (e.g. (Rosenbloom 2009) and (Brosseau et al. 2013)), where it has been found that being in a group positively influences its members to obey the law. The effects of these four variables (age, gender, helmet usage, and group arrival) are consistent in all three sets of models; however the presence of a bicycle box does not show consistent effects throughout these models. The presence of the bicycle box at the intersection of Milton & University (Table 5-4) is shown to decrease the probability of violations, while it increases the probability of dangerous violations and does not have a significant effect on the probability of not stopping before crossing the red light. At the intersection of Saint-Urbain & Villeneuve (Table 5-5), the bicycle box does not have a significant effect on the probability of violations and not stopping before crossing the red light but it significantly reduces the probability of dangerous violations. This highlights the heterogeneity across sites in terms of the effectiveness of the treatment. Finally, a regression model was fitted using all the data, both before and after the installation of the bicycle boxes and the two control intersections. The results (Table 5-6) suggest that bicycle boxes do not have any significant effect on violation, not stopping before crossing or dangerous violations. Due to the inconsistent effects of bicycle boxes in these models, based on the data gathered manually, it is difficult to generalize conclusions about the effectiveness of the bicycle box treatment.

5.7.2. Models Based on Automated Data Collection

Using the data collected automatically, two types of interactions are analyzed to explore the safety effect of bicycle boxes: i) interactions between cyclists and vehicles of type 1 (interaction type 1), and ii) interactions between cyclists and vehicles of type 2 (interaction type 2). Several variables have been extracted and tested to obtain the best random-effect ordered logit models for the behaviour of each cyclist arriving at the intersections. These variables are:

- Presence of bicycle box at the intersection (dummy variable)
- Presence of any other bicycle facility at the intersection, such as bicycle lane (dummy variable)
- Number of lanes
- Duration of the red and green phases of the traffic signals
- Control or treated intersection (dummy variable)
- Bicycle flow during the 30 seconds before the arrival of the cyclist at the intersection
- Vehicle flow during the 30 seconds before the arrival of the cyclist at the intersection (for both types of vehicle)

The final modelling results using the best variables with significant effects (p-values less than 0.05) are presented in Table 5-7. Note that in these models, the alternatives range from 1) very dangerous, to 2) dangerous, to 3) mild, to 4) no interaction, where a positive coefficient indicates an association with safe behaviour.

Table 5-7. Model for automated data collection, 1054 observations

Explanatory variables	Interaction type 1			Interaction type 2		
	Coef.	p-val.	Elas.*	Coef.	p-val.	Elas.*
Bicycle flow during 30s before	-0.440	0.00	-3 %	0.524	0.01	0.8 %
Vehicle flow 1 during 30s before	-0.065	0.00	-0.4 %	-0.055	0.01	-0.1 %
Vehicle flow 2 during 30s before	0.078	0.00	0.5 %	-0.117	0.00	-0.2 %
Presence of bicycle box	0.843	0.00	6 %**	0.605	0.02	0.9 %**
Cut-off 1	-2.154			-4.867		
Cut-off 2	-1.272			-3.547		
Cut-off 3	-0.412			-2.786		
Log-likelihood	-787.08			-346.75		

* Change from category “very dangerous interaction” to other categories
** Change of dummy variable from 0 to 1

The results show that the presence of bicycle boxes at intersections play an important role in reducing the severity of the interactions between cyclists and vehicles. Bicycle flow during the 30 seconds before the arrival of the cyclist increases the probability of severe interactions of type 1 for that cyclist while it reduces the probability of severe interactions of type 2. Vehicle flow of type 1 during the 30 seconds before the arrival of the cyclist increases the probability of severe interactions of both type 1 and 2. Vehicle flow of type 2 during the 30 seconds before the arrival of the cyclist decreases the probability of severe interactions of type 1 for the cyclist but at the same time increases the probability of severe interactions of type 2.

The other tested variables (including control intersection) did not show any significant effects on the severity of the interactions. The analysis with data collected automatically strongly supports the effectiveness of bicycle boxes on reducing the severity of both types of interaction between cyclists and vehicles. Results from Table 5-7 show that not only does the presence of bicycle boxes significantly reduce the severity of the interactions of type 2 (which is the subject of the first part of the study using manually collected data), but also significantly reduces the severity of interactions of type 1 (interactions between cyclists and vehicles traveling in parallel and in the same direction). Based on the elasticities in Table 5-7, by installing a bicycle box at an intersection, the most severe interactions (category very dangerous interaction, with PET equal or less than 1.5 seconds) of type 1 are expected to be reduced by 6 %, while situations considered as very dangerous interactions of type 2 are expected to be reduced by around 1 %.

5.8. CONCLUSION AND FUTURE WORK

This study presented two different approaches to extract data from video and investigate the safety effect of bicycle boxes at signalized intersections. The main purpose of this study was not to compare two types of data collection methods but to show how they complement each other by obtaining and analyzing variables that the other one cannot easily and accurately provide. Manual data collection can provide age, gender, and helmet variables, while automated analysis can more easily provide disaggregate bicycle and vehicle flows and microscopic interactions.

Over 29 hours of video were recorded at busy intersections, with and without bicycle boxes, in Montréal, Canada. For the first part, data was extracted manually while for the second part, an automated video-analysis method was used to extract data from the videos. Based on statistical methods and by using surrogate safety measures (red light violation, not stopping before crossing the red light and dangerous violation for the first analysis, and PET for the second analysis), cyclists' behaviour at the studied intersections was investigated.

Using manual data collection, all the variables (including age, gender, violation and dangerous violation, etc.) were estimated by the authors and are subject to their judgments. However data collection for the second part was completely automated and can be considered as more objective. In terms of time, reviewing and extracting the data from each hour of video in the manual data collection, depending on the flow of cyclists, took between 1 to 3 hours; while for automated data collection (after all the necessary calibrations), took around 20 minutes.

The results of the models in the first part showed that age, gender, group arrival, wearing a helmet, and the presence of a bicycle box all influence cyclist safety and red light violations. From these variables, young adults and males are more likely to violate the red light, not stop before crossing the red light or end up in dangerous situations, while group arrival and helmet usage have positive impacts on cyclist safety. However, due to inconsistent results from the three sets of models based on manual data collection, the effect of bicycle boxes on these behaviour measures is not completely clear and no strong conclusions can be made.

On the other hand, the modelling results in the second part strongly support the effectiveness of bicycle boxes on reducing the severity of interactions between cyclists and vehicles originating from the same or different approaches, respectively moving parallel or perpendicular to one another. Based on these models, by installing a bicycle box at an intersection, very dangerous interactions (with PET equal or less than 1.5 seconds) between cyclists and vehicles originating from the same approach, are expected to be reduced by 6 %. Also, very dangerous interactions (with PET equal or less than 1.5 seconds) between cyclists and vehicles originating from different approaches are expected to be reduced by around 1 % at intersections if bicycle boxes are added. Other variables that affect the severity of these interactions for each individual cyclist are the magnitude of bicycle and vehicle flow during the 30 seconds before the arrival of the cyclist.

It is worth mentioning that the use of these two data collection approaches is not limited to study the safety effects of bicycle boxes and can be used to evaluate the effectiveness of other safety treatments. As part of future work, we will combine both sources of data, by assigning each variable that is collected by the manual method to the corresponding cyclist detected by the automated method, to generate more comprehensive models. Also, we will apply these methods to study the safety effects of other bicycle safety treatments such as bicycle paths and cycle tracks.

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Chapter 6

Conclusions and Future Work

Chapter 6: Conclusions and Future Work

6.1. GENERAL CONCLUSIONS

Worldwide more than 1.2 million people lose their life in road traffic accidents every year, meaning that more than two people die because as a result of road accidents every second. The fact that road design is mostly optimized for motorized modes, in addition to the vulnerability of pedestrians and cyclists with less physical protection, they are victim of 27 % of all the road casualties. Considering the ratio of accidents and casualties involving pedestrians and cyclists, addressing their safety is critical to reduce the total number of road traffic fatalities and successfully encourage more people to walk or bike. Despite the extensive literature on road traffic safety, few studies have looked at the safety of non-motorized road users. Arguably, the key factor that makes studying non-motorized safety challenging and rare in the literature, is the difficulty in collecting appropriate data for pedestrians and cyclists. To address this gap in the literature, we developed a novel methodology (based on an existing open-source object tracker) capable of extracting microscopic data separately for each road user type especially at urban intersections with high and mixed traffic conditions.

More specifically, chapter two presented a novel methodology to design, integrate and combine classifiers capable of classifying moving objects in crowded traffic video scenes into three main road user types: pedestrian, cyclist, and vehicle. Given the limitations of single classification methods based on road user appearance or speed, we combined these sources of information through several classifiers in order to improve the classification performance. Among the tested classifiers, the one combining the probability of both the object's appearance and speed achieved systematically better performance than the other tested classifiers. Overall the accuracy of the best classifier was higher than 88 %. Due to the similarity in appearance between pedestrians and cyclists (a cyclist consists of a bicycle and a human who rides a bicycle) and of the large range of cyclist speed, cyclists were the most difficult type of road user to classify. False positive rates for the best classifier were 19.4 % for pedestrians, 39.3 % for cyclists, and 2.6 % for vehicles, while the missed detection rates were 5.3 %, 24.0 %, and 11.6 %, respectively. However due to the lack of available benchmarks and accessibility to other methods, comparison with other classification methods in the literature was not possible. To address this issue and in order to make a benchmark for future researches, a software implementation of the developed classifier was made available as open source software. In addition, in Appendix A, by adding two more criteria to the classification algorithm, speed frequency and position, the performance of the classifier was further improved. The improved classifier that uses four sources of information for classification reaches an overall accuracy of around 96 %. Also this classifier has false positive rates of 8.6 % for pedestrians, 12.4 % for cyclists, and 1.9 % for vehicles, while the missed detection rates of this classifier are 3.6 %, 20.6 %, and 2.3 %, respectively.

Counts (traffic flows) are important pieces of information for any safety study to generate exposure measures or safety performance functions. In the third chapter, the proposed methodology was applied to automatically count cyclists at road segments and intersections. The results of this chapter showed that the proposed method could be used and was highly accurate for gathering short-term bicycle counts in locations where traditional technologies such as loop detectors and pneumatic tubes do not work well. This technique consisted of several steps: recording video, tracking and classifying objects in the video, and defining origins and destinations for movements subject to counting. One of the main advantages of this method is its ability to count cyclist flow for different movements with different origins and destinations. One of the shortcomings of most previous work was reporting the accuracy only for the entire period of the data collection or for a long period of time. In order to address performance over-estimation caused by over- and under-counting in shorter time periods, the accuracy of the proposed method was reported for two short time intervals of 5 and 15 minutes. The counting in road segments with physically separated cycle tracks had the smallest error, 8 % in 5 minute intervals and 6 % for 15 minute intervals. Road segments with mixed traffic had the second best accuracy, 12 % and 9 % error for 5 and 15 minute intervals respectively. Due to the complex movements at intersections, the accuracy for bicycle counts in these environments was relatively lower compared to road segments. 16 % and 13 % were the errors associated with intersections with a physically separated cycle track, respectively for 5 and 15 minute intervals, while 34 % and 19 % were the errors associated with intersections with mixed traffic, respectively for 5 and 15 minute intervals.

The fourth chapter of this thesis investigated the safety effectiveness of cycle tracks at signalized intersections using the proposed automated video processing method. Post encroachment time was used as a surrogate safety measure for determining the severity of interactions between cyclists and turning vehicles. A total of 23 intersections were involved in this study, 8 with a cycle track on the right side of the road, 7 with a cycle track on the left side of the road, and 8 without a cycle track. From over 90 hours of recorded video, over 7,000 cyclists were observed and used in this study. Each cyclist and its interaction with turning vehicles represented an observation in the modeling framework. Among other results, it was found that intersections with cycle tracks on the right compared to intersections with no cycle track are safer. Adding a cycle track to the right side of intersections currently without a cycle track, is associated with 40 % decrease in the number of interactions (with PET $\leq$ 5 seconds). However, the presence of cycle tracks on the left side was not associated with any significant decrease in the probability of interactions compared to no cycle tracks. From a safety perspective, cycle tracks on the right side are recommended over cycle tracks on the left side. Moving a cycle track from the left side of the road to the right side is associated with a reduction in the number of interactions (with PET $\leq$ 5 seconds) by 25 %. Other factors such as bicycle and turning vehicle flows in the few seconds before and after the arrival of each cyclist to the intersection were shown to have statistically significant effects on interactions between cyclists and turning vehicles. These micro-level exposure measures provide a better understanding of cyclist behaviours and interaction mechanisms. For instance, the effect of cyclists arriving alone or in a group was evaluated. Interaction severity was found to decrease as cyclists arrive to the intersection in groups. An opposite effect was detected for turning vehicles, more turning traffic is associated with a higher probability of serious interactions with cyclists. Some geometric factors such as the number of lanes were also shown to be statistically significant. More lanes in the vehicle approach are associated with more dangerous situations for cyclists. This means that in addition to the installation of cycle tracks on the right side of the road, the reduction of vehicle turning movements and geometry changes could represent additional safety benefits for cyclists.

The fifth chapter of this research aimed at studying the safety effect of bicycle boxes at signalized intersections. For this purpose, over 29 hours of video were recorded at busy intersections, with and without bicycle boxes. Data was extracted from the videos by two different methods, first by manual observation and then by use of the developed automated video analysis method. Based on statistical methods and using surrogate safety measures (red light violation, not stopping before crossing the red light and dangerous violation, as well as post encroachment times), cyclist behaviour at the studied intersections was investigated. Manual data collection provided information about age, gender, and the presence of helmet, while automated data collection extracted disaggregate bicycle and vehicle flows and microscopic interactions from the videos. The results of the models based on the manual data collection showed that age, gender, group arrival, wearing a helmet, and the presence of a bicycle box all influence cyclist safety and red light violations. From these variables, young adults and males are more likely to violate the red light, not stop before crossing the red light or end up in dangerous situations after violating a red light, while group arrival and helmet use are associated with improvements in cyclist safety. However, due to inconsistent results from the different models based on manual data collection, the effect of bicycle boxes on these behaviour measures was not completely clear and no strong conclusions could be made. On the other hand, the modelling results based on automated data collection supported the effectiveness of bicycle boxes on reducing the severity of interactions between cyclists and vehicles originating from the same or different approaches, respectively moving parallel or perpendicular to one another. Based on these models, a 6 % elasticity is observed between installing a bicycle box at an intersection and reduction of the number of very dangerous interactions (with PET equal or less than 1.5 seconds) between cyclists and vehicles originating from the same approach. Other variables that were found to have an association with the severity of interactions for each individual cyclist were the magnitude of bicycle and vehicle flows during the short period of time before the arrival of the cyclist.

6.2. FUTURE WORK

Future work can be grouped into two main categories: methods to improve the accuracy of data collection, and expanding the use of the developed data collection method to study other safety treatments and interactions.

In this research the accuracy of all the analyses, including counting and safety studies, is highly correlated with the accuracy of the data collection method, which includes two main steps: tracking and classification. As a result, any increase in the accuracy of the tracking and classification methods will result in more accurate results and more confidence in their outcomes.

Other than the problems with the tracking algorithm (which is not in the scope of this thesis), several factors can cause the classification method to be inaccurate such as camera angle, distance between camera and subjects of study, presence of shadows, and movements of two or more objects next to each other. Alternative video sensors can also be used such as thermal cameras, to deal with some of the limitations of regular cameras in low light, shade, and adverse weather conditions. Changing the camera angle by using a taller pole or mounting the camera to a drone can mitigate the problem of occlusion in high density conditions. In addition, installing multiple cameras at intersections to capture all the possible movements from different views can be a useful addition to the current method. Combining both sources of data, by assigning each variable that is collected by the manual method to the corresponding road user detected by the automated method can also be a good addition to the developed method to generate more comprehensive models. Furthermore, adding more road user classes (such as, scooter, motorcycle, truck, bus, tram, etc.) to the classification algorithm will add more capability to the developed methodology to study more types of road users and their interactions.

As part of future work and by using the developed methodology for data collection, other engineering safety treatments can be evaluated such as curb extensions, bicycle paths, unidirectional cycle tracks, etc. Also other types of interactions between different road users can be studied such as cyclist-vehicle rear-end interactions and pedestrian-cyclist interactions in shared spaces. The presented analyses could also be replicated to validate their results by adding more data from different cities, using a case-control or before-after surrogate safety analysis. From this, we could provide more general and transferable results for the effectiveness of different engineering safety treatments across cities. Another potential application of this automated data collection method is to calibrate and validate microscopic traffic simulation models, using video data.

6.3. PUBLICATIONS

6.3.1. Refereed Journals

Brosseau, Marilyne, Sohail Zangenehpour, Nicolas Saunier, and Luis Miranda-Moreno. 2013. “The Impact of Waiting Time and Other Factors on Dangerous Pedestrian Crossings and Violations at Signalized Intersections: A Case Study in Montréal.” Transportation Research

Part F: Traffic Psychology and Behaviour 21:159–72. Retrieved (http://dx.doi.org/10.1016/j.trf.2013.09.010).

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. “Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application.” Transportation Research Part C: Emerging Technologies 56:161–76. Retrieved (http://linkinghub.elsevier.com/retrieve/pii/S0968090X15001448).

Fu, Ting, Sohail Zangenehpour, Paul St-Aubin, Liping Fu, and Luis F. Miranda-Moreno. 2015. “Using Microscopic Video Data Measures for Driver Behavior Analysis during Adverse Winter Weather: Opportunities and Challenges.” Journal of Modern Transportation. Retrieved (http://link.springer.com/10.1007/s40534-015-0073-3).

Zangenehpour, Sohail, Jillian Strauss, Luis Miranda-Moreno, and Nicolas Saunier. 2015. “Are Signalized Intersections With Cycle Tracks Safer? A Control-Case Study Based On Automated Surrogate Safety Analysis Using Video Data.” Accident Analysis & Prevention, 86:161-172 (doi:10.1016/j.aap.2015.10.025)..

Zangenehpour, Sohail, Taras Romancyshyn, Luis Miranda-Moreno, and Nicolas Saunier. 2015. “Video-Based Automatic Counting For Short-Term Bicycle Data Collection in a Variety of Environments.” Journal of Intelligent Transportation Systems; Technology, Planning, and Operations, under review for publication.

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. “Impact of Bicycle Boxes on Cyclist Behaviour and Safety: A Surrogate Study Using Manual and Automatic Video-Data Measures.” Transportation Research Part F: Traffic Psychology, under second review for publication.

6.3.2. Conference Papers

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2013. “Impact of Bicycle Boxes on Safety of Cyclists: A Case Study in Montréal.” *Transportation Research Board 92nd Annual Meeting*.

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2014. “Automated Classification in Traffic Video at Intersections with Heavy Pedestrian and Bicycle Traffic.” *Transportation Research Board 93rd Annual Meeting*.

Zangenehpour, Sohail, Luis F. Miranda-Moreno, and Nicolas Saunier. 2014. "Automated Classification Based on Video Data at Intersections with Heavy Pedestrian and Bicycle Traffic: Methodology and Application." *24th Canadian Multidisciplinary Road Safety Conference*.

Zangenehpour, Sohail, Taras Romancyshyn, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. "Video-Based Automatic Counting For Short-Term Bicycle Data Collection in a Variety of Environments." *Transportation Research Board 94th Annual Meeting*.

Zangenehpour, Sohail, Jillian Strauss, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. "Are Intersections With Cycle Tracks Safer? A Control-Case Study Based On Automated Surrogate Safety Analysis Using Video Data." *Transportation Research Board 94th Annual Meeting*.

Zangenehpour, Sohail, Jillian Strauss, Luis F. Miranda-Moreno, and Nicolas Saunier. 2015. "Are Intersections With Cycle Tracks Safer? A Control-Case Study Based On Automated Surrogate Safety Analysis Using Video Data." *25th Canadian Association of Road Safety Professionals*.

Stipancic, Joshua, Sohail Zangenehpour, and Luis F. Miranda-Moreno. 2015. "Segmented Ordered Logit Analysis Of Gender Impacts On Bicycle-Vehicle Conflict Occurrence At Urban Intersections." *Transportation Research Board 94th Annual Meeting*.

Fu, Ting, Joshua Stipancic, Sohail Zangenehpour, Luis F. Miranda-Moreno, and Nicolas Saunier. 2016. "A Comparison of Regular and Thermal Cameras for Traffic Data Collection under Varying Lighting and Temperature Conditions in Multimodal Environments." *Transportation Research Board 95th Annual Meeting*.

APPENDIX A

For increasing the accuracy of the road user classification, aside from the appearance and speed of each object, two more criteria were added to classifier IV to make classifier V. These criteria are speed frequency (one of the gait parameters) and travel area of each road user in a video.

A.1 SPEED FREQUENCY CRITERION

Gait parameters such as step length and frequency can provide good criteria for detecting pedestrians and estimating their attributes such as age and gender. The smoothness difference of pedestrians' movement (caused by step length and step frequency) compared to cyclists' and vehicles' movement can be used to improve the accuracy of road user classification. Speed time series of a road user and its speed in the frequency domain can be used to derive the step frequency.

The discrete Fourier transform can be used to transfer instantaneous speed of a road user from the time domain to the frequency domain:

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-i2\pi kn/N}, \qquad k \in \boldsymbol{Z} \text{ (integers)}$$

where N is the number of frames that the road user appears in the video, x_n is the n^{th} speed measurement for a given road user from its first frame detected in time domain, and X_k is a complex number that shows amplitude and phase of k^{th} element in frequency domain.

By definition of the discrete Fourier transform, the first element (k=0) of transformed signal in frequency domain is a real number equal to the sum of that signal in the time domain. Since each road user appears in a video for different periods of time (N is different for each object), the frequency elements and their amplitudes are biased. The longer a road user appears in a video, the bigger its frequency amplitudes will be.

To solve this problem, a normalization factor (X_0) has been used and all the frequency amplitudes are divided by this normalization factor. After this normalizitation, X_0 for each road user is equal to 1 and the rest of the frequency values of different objects can fairly (without the effect of the time period that they appear in the video) be compared to each other and help improve the classification. From this point we call X_k the normalized amplitude.

To illustrate the difference between normalized amplitudes of different road users, an example of these values for three road user types (manually classified, 1062 pedestrians, 503 cyclists, and 3278 vehicles) are shown in Figure 7-1.

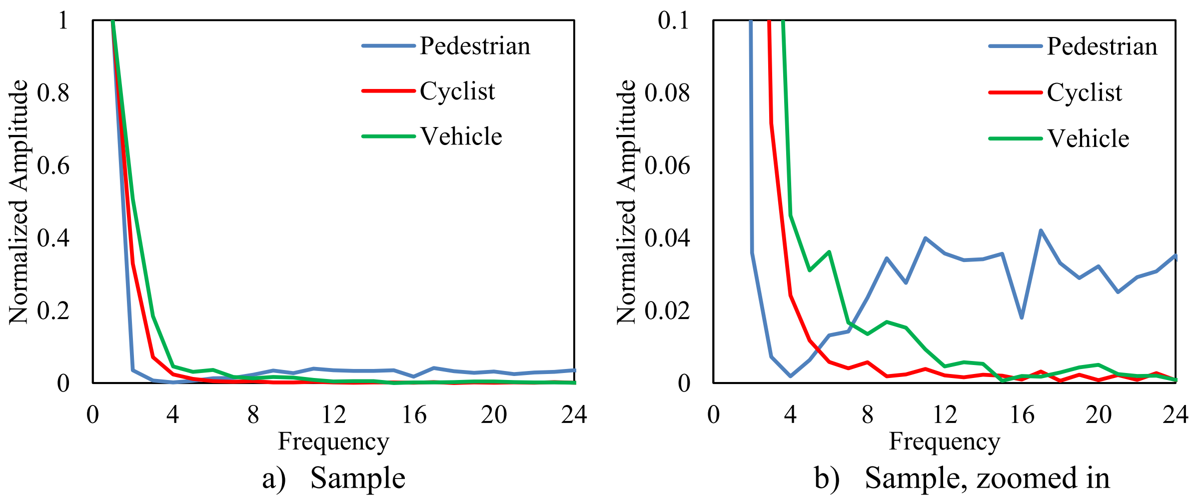


Figure 7-1. Normalized amplitude values for different road users

Based on Figure 7-1, and after trying different combinations, the speed frequency criterion (SFC) has been defined as:

$$\text{SFC} = Average(X_{19}, \ldots, X_{24}) / X_1$$

Note that all the videos that are used in this thesis were recorded in 15 frames per second. Observed density and cumulative density of the SFC for different road users (manually classified) are shown in Figure 7-2a and Figure 7-2b, respectively. In Figure 7-2c and Figure 7-2d log-normal distributions are used to fit to the observed densities. The parameters of these log-normal distributions are presented in Table 7-1.

Table 7-1. Parameters used for log-normal distributions

	Location parameter (μ)	Scale parameter (σ)
Pedestrian	-1.726	0.893
Cyclist	-3.137	0.731
Vehicle	-3.306	0.668

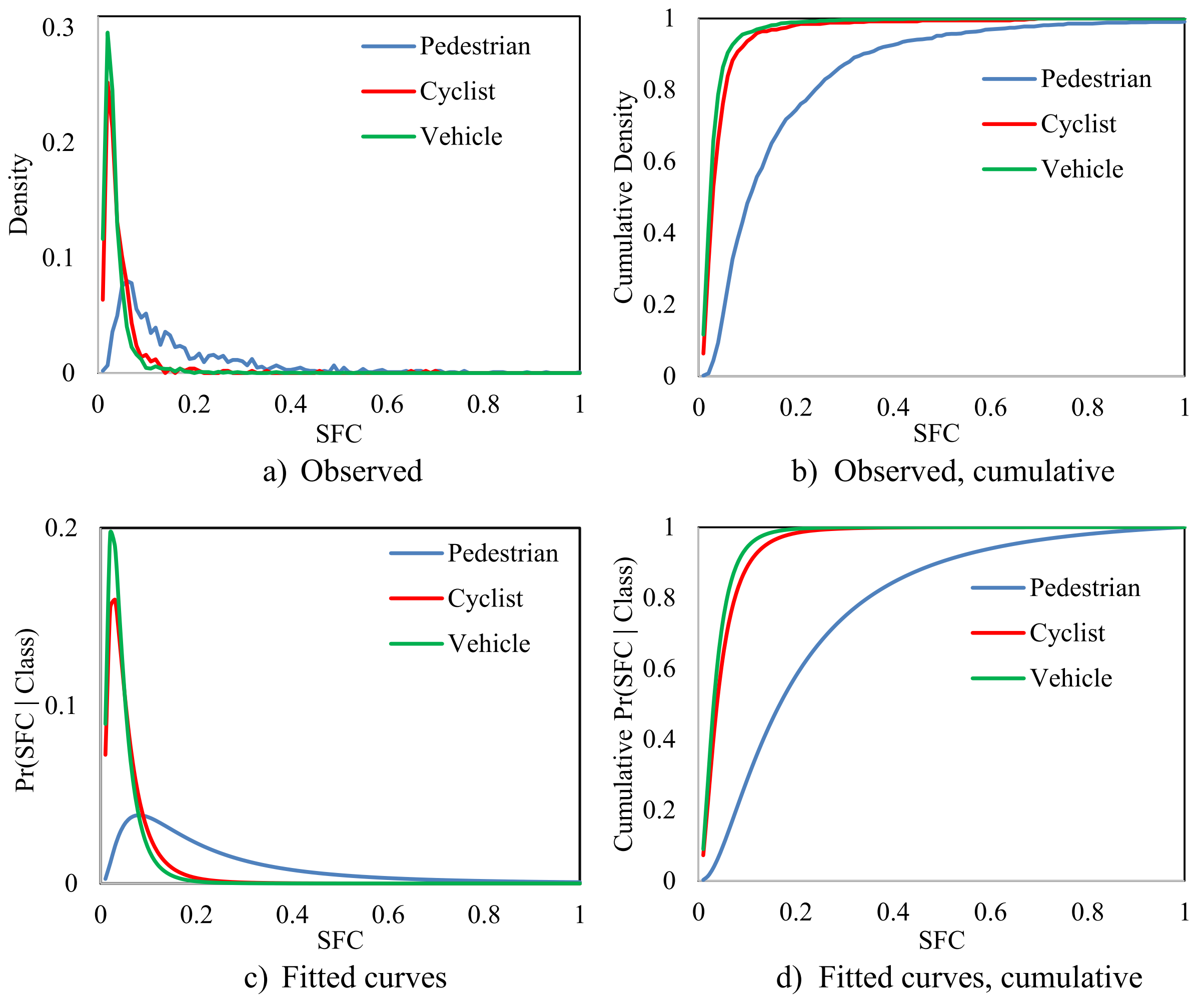


Figure 7-2. Density of the speed frequency criteria for different road users

SFC can be used alongside speed and appearance criteria to improve the accuracy of the classifier. To obtain this classifier, consider the typical Bayesian classifier given by the posterior distribution (likelihood × prior). This is formulated as:

$$\Pr(C_i \mid S_i, A_i, SFC_i) = \frac{\Pr(C_i)}{\Pr(S_i, A_i, SFC_i)} \Pr(S_i, A_i, SFC_i \mid C_i)$$

where C_i, S_i, A_i and SFC_i stand for class, speed, appearance and speed frequency criteria of road user i, respectively. By the assumption of independence of speed, appearance and speed frequency criteria:

$$\Pr(C_i \mid S_i, A_i, SFC_i) = \frac{\Pr(C_i)}{\Pr(S_i)P(A_i)\Pr(SFC_i)}\Pr(S_i|C_i)\Pr(A_i|C_i)\Pr(SFC_i|C_i) \qquad (1)$$

Also, using conditional probability, one can write:

$$\Pr(A_i|C_i)\Pr(C_i) = \Pr(C_i|A_i)\Pr(A_i) \qquad (2)$$

Replacing (1) into (2), gives:

$$Pr(C_i \mid S_i, A_i, SFC_i) = \frac{\Pr(S_i|C_i)\Pr(C_i|A_i)\Pr(SFC_i|C_i)}{\Pr(S_i)\Pr(SFC_i)}$$

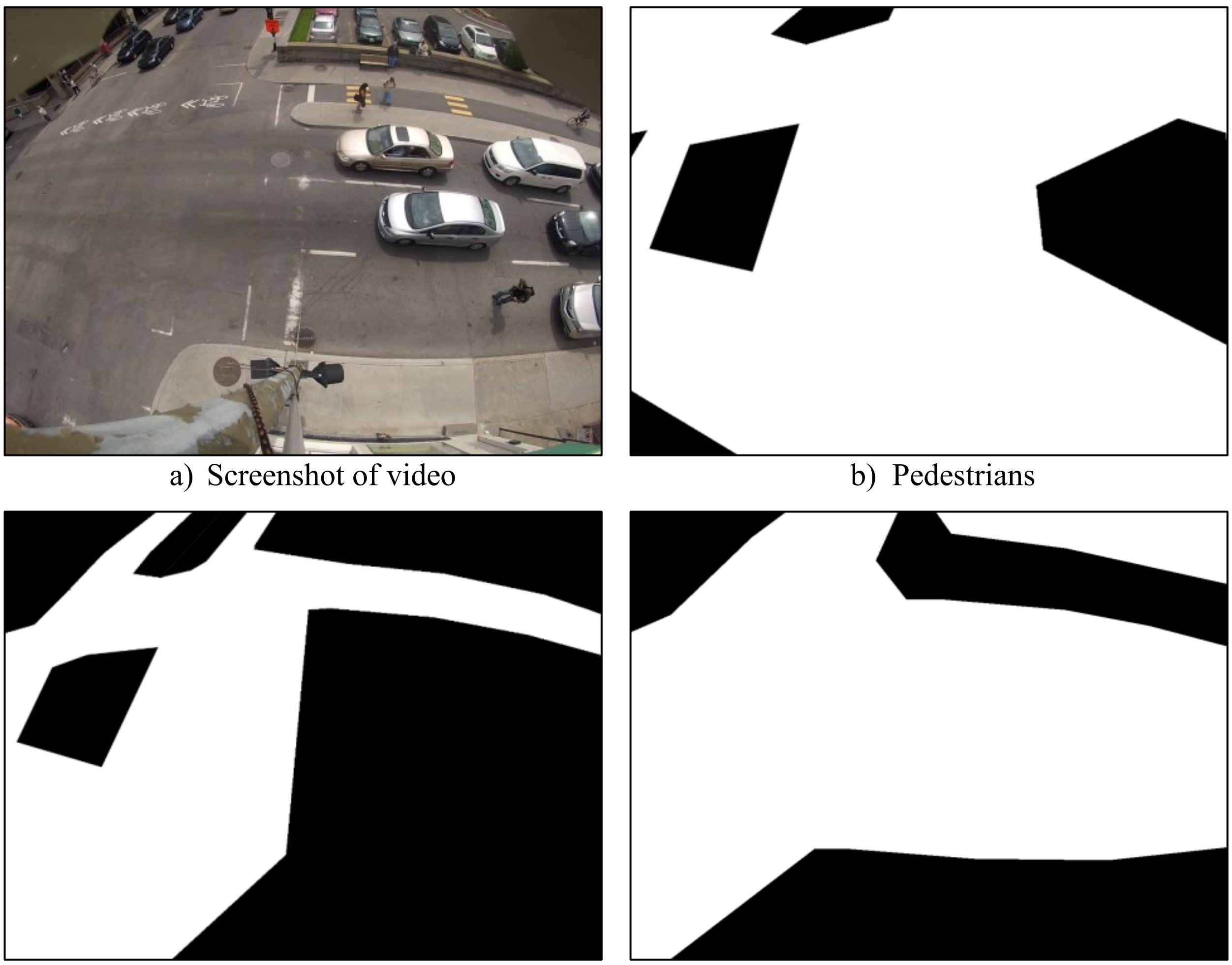
Finally, given that $\Pr(S_i)$ and $\Pr(SFC_i)$ are independent of the classes, it can be written that:

$$Pr(C_i \mid S_i, A_i, SFC_i) \propto \Pr(S_i|C_i)\Pr(C_i|A_i)\Pr(SFC_i|C_i)$$

$\Pr(C_i| A_i)$ is the probability of each class obtained from classifier III. $\Pr(S_i|C_i)$ and $\Pr(SFC_i|C_i)$ are estimated through distributions fitted to the empirical median speed and speed frequency criteria distributions of the three road user classes, gathered through manual road user classification in sample videos. The class of the road user is selected as the one with the highest $\Pr(C_i \mid S_i, A_i, SFC_i)$.

A.2 TRAVEL AREA CRITERION

In addition to speed frequency criteria of the instantaneous speed of each road user, travel area criteria is also used to improve the classification. Based on this criteria, for each road user to be classified in a class, its trajectory has to remain in a predefined area (maually defined by user, for that class) for at least 90 % of its presence in the video. For instance, if the trajectory of a road user is within the predefined area for pedestrians for less than 90 % of its presence in the video (while its trajectory is within the area for cyclists and vehicles for more than 90 % of the time), that road user can only be a cyclist or a vehicle. In this situation the classification algorithm just uses the binary HOG-SVM trained for two classes: cyclist and vehicle. It is obvious that if the trajectory of a road user is within the predefined area of just one class for more than 90 % of the time, without using any other criteria, that road user will be classified into that class. An example of these predefinedareas for different road users at one sample intersection is shown in Figure **7-3**.



a) Screenshot of video b) Pedestrians

c) Cyclists d) Vehicles

Figure 7-3. Predefined area for different road users

Classifier V is the name of the new classifier that uses four criteria: speed, appearance, speed frequency and travel area. The algorithm to decide the class of each road user based on classifier V is below:

If $TAC_{i,p}$ & $TAC_{i,c}$ & $TAC_{i,v} \geq 90$ %:

If $S_i \le Th_{pc}^{99}$:	use three class (pedestrian, cyclist, vehicle) to find the highest $\Pr(C_i \mid S_i, A_i, SFC_i)$
Else if $Th_{pc}^{99} < S_i \le Th_{cv}^{99}$:	use two class (cyclist, vehicle) to find the highest $\Pr(C_i \mid S_i, A_i, SFC_i)$
Else:	classify as vehicle
Else if $TAC_{i,p}$ & $TAC_{i,c} \ge 90$ %:	
If $S_i \le Th_{pc}^{99}$:	use two class (pedestrian, cyclist) to find the highest $\Pr(C_i \mid S_i, A_i, SFC_i)$
Else:	classify as cyclist
Else if $TAC_{i,p}$ & $TAC_{i,v} \ge 90$ %:	
If $S_i \le Th_{pc}^{99}$:	use two class (pedestrian, vehicle) to find the highest $\Pr(C_i \mid S_i, A_i, SFC_i)$
Else:	classify as vehicle
Else if $TAC_{i,c}$ & $TAC_{i,v} \ge 90$ %:	
If $S_i \le Th_{cv}^{99}$:	use two class (cyclist, vehicle) to find the highest $\Pr(C_i \mid S_i, A_i, SFC_i)$
Else:	classify as vehicle
Else if $TAC_{i,p} \ge 90$ %:	classify as pedestrian
Else if $TAC_{i,c} \ge 90$ %:	classify as cyclist
Else if $TAC_{i,v} \ge 90$ %:	classify as vehicle

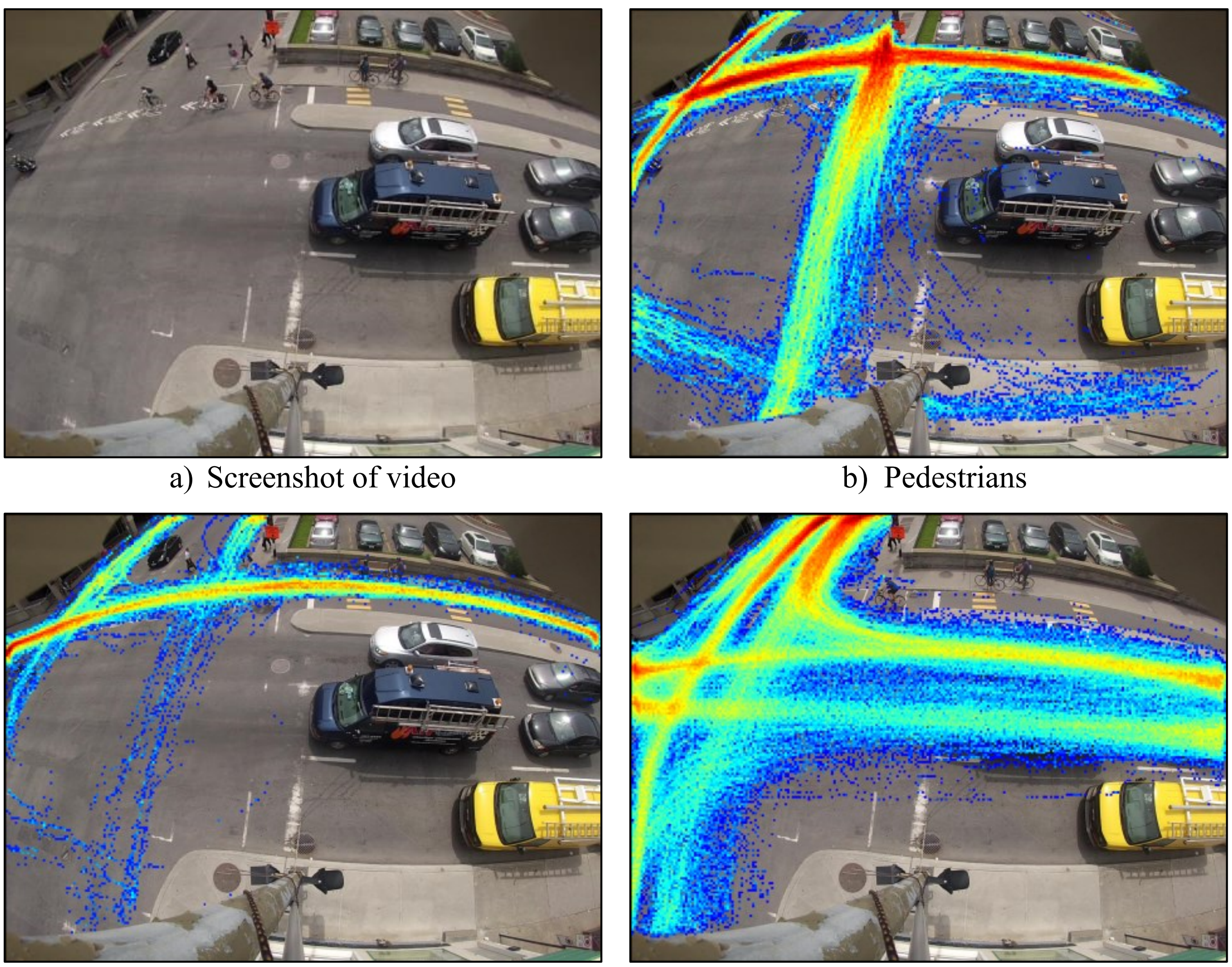
Where $TAC_{i,p}$, $TAC_{i,c}$ and $TAC_{i,v}$ are the percentage of presence of trajectory of road user i within the predefined areas for pedestrians, cyclists and vehicles, respectively.

The result of classification for the video recorded at the intersection of Avenue des Pins and Rue Saint-Urbain is shown in Table 7-2. Classifier V compared to classifier IV shows 7.2 % points improvement (from 88.5 % in Table 2-1 to 95.7 % in Table 7-2) in overall accuracy. This improvement is more noticeable in precision rate of pedestrians: 10.8 % points (from 80.6 % in Table 2-1 to 91.4 % in Table 7-2), precision rate of cyclists: 26.9 % points (from 60.7 % in Table 2-1 to 87.6 % in Table 7-2), as well as recall rate of vehicles: 9.3 % points (from 88.4 % in Table 2-1 to 97.7 % in Table 7-2).

Trajectory heat-maps of the different road users are shown in Figure 7-4. By comparing these heat-maps to the ones from classifier IV, the superiority and higher accuracy of classifier V can be seen.

Table 7-2. Confusion matrices showing the performance of classifier V

			Ground Truth					Accuracy
			Pedestrian	Cyclist	Vehicle	Total	**Precision**	
Predicted	**Classifier V**	Pedestrian	986	57	36	1079	91.4 %	**95.7 %**
		Cyclist	15	387	37	439	87.6 %	
		Vehicle	22	44	3172	3238	98.1 %	
		Total	1023	488	3245	4756		
		Recall	96.4 %	79.4 %	97.7 %			
	Classifier V (balanced observation)	Pedestrian	388	44	4	436	89.0 %	**91.5 %**
		Cyclist	5	318	4	327	97.2 %	
		Vehicle	7	38	392	437	89.7 %	
		Total	400	400	400	1200		
		Recall	97.0 %	79.5 %	98.0 %			



a) Screenshot of video

b) Pedestrians

c) Cyclists

d) Vehicles

Figure 7-4. Trajectory heat-maps for different road user types