EVALUATION OF DAIRY COW LOCOMOTION THROUGH TECHNOLOGY-BASED APPROACHES

BY

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ABSTRACT

Lameness is a prevalent issue within the dairy industry that has serious financial and welfare implications. The implementation of alternative gait assessment methods outside of traditional visual locomotion scoring is of interest to producers and researchers, as identifying abnormalities in locomotion early on is key to preventing severe cases of lameness. Some automated approaches are conducted via kinematic, kinetic, and accelerometric technologies. Kinematic approaches focus on how the cow moves through time and space, kinetic approaches focus on force-related measures exerted by the cow, and accelerometric approaches focus on the acceleration of the body as the cow moves.

The thesis objectives are: 1) to conduct a systematic literature review to determine the types of measures that have been recorded to assess dairy cow locomotion through technological and human observer-based approaches, and 2) to experimentally validate a kinematic system used in conjunction with two types of artificial neural networks (ANN; Convolutional Neural Network and Long Short-Term Memory model) to predict locomotor ability levels of cows according to a numeric rating system (NRS). The systematic review was conducted according to PRISMA guidelines and a final number of 34 articles were retained. Overall, similar types of measures were used to evaluate gait, but differences in types of technologies used, physical arrangements of equipment, terminology, and measure-recording approaches used make it difficult to compare these measures across studies. Use of these technologies with dairy cows is relatively novel, and more research utilizing them is needed to reach conclusions about how gait is affected by the environmental or cow-level factors being studied. Our experimental study aimed to merge the ability of these alternative, more automated technologies to provide detailed data regarding how the cow moves with the simplicity and visual approach of a commonly used, 5-point NRS. In particular, we aimed to develop a model that would be able to identify cows which exhibit gait abnormalities but which are not yet clinically lame. To validate the kinematic system, kinematic data was collected for 12 lactating Holstein dairy cows. Reflective markers were placed on cows at 20 anatomical landmarks, and video of cows walking a 7m passageway was recorded from 6 camera angles and digitized within a motion analysis software to acquire 3D coordinates of each marker. A trained observer conducted visual locomotion scoring from recorded videos. Building off previous collaborative work with the UQÀM bioinformatics lab, the kinematic data was entered into a convolutional neural network and a recurrent neural network with long short-term memory architecture. Although the tested models performed well during training, they performed poorly in the validation phase on metrics of accuracy, precision, recall, and F1-score. This was contradictory to the results of previous study testing a CNN to predict binary classification of lame vs. non-lame cows with similar kinematic data with all metrics performing above 90%. Overall locomotion score may not be ideal to provide to a model for the type of problem evaluated in the current study; next steps should involve the testing of applying scores of specific gait attributes as an alternative to overall locomotion score for machine learning, and investigate whether specific joints provide more useful kinematic data for inclusion in machine learning than others. An improved model framework predicting overall locomotor ability, or adapted to evaluate more specific aspects of gait, could eventually be used as both an on-farm and research tool as kinematic data recording systems becomes mobile with future technological advancements.

RÉSUMÉ

La boiterie est un problème à prendre au sérieux dans l'industrie laitière, en raison de sa fréquence et de son impact, financier comme sur le bien-être animal. La mise en place d'alternatives à la méthode de notation visuelle de la boiterie est d'intérêt pour les producteurs comme pour les chercheurs, puisqu'identifier plus tôt les troubles locomoteurs permettrait de mieux prévenir les cas de boiterie sévère. Quelques méthodes automatiques pourraient servir à cette fin, notamment la cinématique (qui s'intéresse au mouvement de la vache dans l'espace et au fil du temps), la cinétique (qui s'intéresse aux forces appliquées par la vache en mouvement ou à l'arrêt) et les accéléromètres (qui examinent l'accélération du corps de la vache en mouvement).

Les objectifs de ce mémoire sont : 1) déterminer quel type de mesures ont été utilisées pour évaluer la locomotion de la vache laitière, via une revue de littérature systématique examinant des approches basées sur les technologies ou sur des observations directes, dans les études se focalisant sur les facteurs affectant la locomotion de la vache; 2) valider, par le biais d'une expérience, la capacité d'un système combiné de cinématique et de deux types de réseaux neuronaux artificiels (ANN; réseau neuronal convolutif et réseau de longue mémoire à court-terme) à prédire la capacité locomotrice de vaches laitières suivant le système de notation numérique de la démarche (NRS). La revue de littérature systématique a été menée suivant les lignes directrices de PRISMA, pour une sélection finale de 34 articles. En somme, les mesures utilisées dans les diverses études pour évaluer la démarche des vaches sont similaires, mais les différences relevées quant aux technologies, au positionnement des équipements, à la terminologie, et aux approches de relevé des mesures utilisées rendent difficile la comparaison de ces mesures entre les études. L'utilisation de ces technologies chez les vaches laitières est encore relativement récente et plus de recherche est nécessaire pour arriver à conclure quant à ce comment la démarche des vaches est affectée par les différents facteurs à l'étude. Notre expérience visait à combiner ces technologies automatisées alternatives afin d'obtenir, avec la simplicité et l'approche visuelle du système NRS, des données détaillées à propos de la démarche de la vache laitière, et ainsi établir un système permettant la détection précoce de changements dans la démarche précédent l'apparition de la boiterie clinique. Afin de valider notre système de cinématique, les données de 12 vaches Holstein en lactation ont été collectées.

Vingt marqueurs réfléchissants ont été apposés sur autant de sites anatomiques, pour chacune des vaches. Des vidéos de chacune des vaches marchant dans un passage de 7m de longueur ont été enregistrées depuis 6 angles de caméras différents, puis numérisées à l'aide d'un logiciel d'analyse du mouvement pour obtenir des coordonnées 3D de chacun des marqueurs. Un observateur formé a procédé à l'analyse visuelle de la démarche (NRS) à l'aide des vidéos. En continuité d'un travail collaboratif précédent conduit conjointement avec le laboratoire de bio-informatique de l'UQÀM, les données de cinématiques ont été saisies dans un réseau neuronal doté d'une structure de longue mémoire à court-terme. Les modèles testés n'ont pas été en mesure de prédire la notation NRS avec une grande précision ce qui est en contradiction avec le modèle précédent qui prédisait une classification binaire boiteuse ou non-boiteuse avec une précision de 90%. Les limites actuelles de ce type de système de cinématique devraient être considérés au fur et à mesure que plus d'expériences seront conduites, et en fonction des prochaines avancées technologiques. Un modèle prédictif de l'aptitude locomotrice globale, ou adapté à l'évaluation d'aspects spécifiques de la démarche, pourrait éventuellement servir sur les fermes et comme outil de recherche, si la collecte de données de cinématique devient mobile dans l'avenir.

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CONTRIBUTION OF AUTHORS

This thesis contains two multi-authored manuscripts. The authors of manuscripts 1 and 2, presented in chapters 2 and 3, respectively, are as follows:

Anna Bradtmueller (primary author, both manuscripts), Elsa Vasseur (supervising author, both manuscripts), Elise Shepley (co-supervising author, both manuscripts), Amir Nejati (contributing author, manuscript 1), Gabriel Machado Dallago (contributing author, manuscript 2), Dylan Lebatteux (contributing author, manuscript 2), Amanda A. Boatswain Jacques (contributing author, manuscript 2), and Abdoulaye Baniré Diallo (supervising author, manuscript 2).

Anna Bradtmueller was the primary author of manuscripts 1 and 2. Anna conducted the search, screening, and data items extraction for manuscript 1. Anna conducted the project in manuscript 2, for which she did the video observations, processing and digitization of videos to obtain kinematic data, and preparation of data for use with the developed model. Elsa Vasseur supervised the primary author and reviewed and co-authored both manuscripts. She co-conceptualized manuscripts 1 and 2 and provided the funding and design of the validation study presented in manuscript 2. Elise Shepley co-supervised the primary author, and co-conceptualized, reviewed, and co-authored both manuscripts. Elise Shepley co-designed the experiment presented in manuscript 2. Amir Nejati co-conceptualized, reviewed, and co-authored manuscript 1. Gabriel Machado Dallago co-conceptualized the design of the model and reviewed manuscript 2. Dylan Lebatteux and Amanda A. Boatswain Jacques co-conceptualized the design of the model, wrote the code for the models used in manuscript 2, and provided detailed methodology and results of the model for manuscript 2. Abdoulaye Baniré Diallo oversaw the model development and collaboration between labs, and is a supervising author for manuscript 2.

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CHAPTER 1 – GENERAL INTRODUCTION

Lameness can be defined as "a deviation in gait resulting from pain or discomfort from hoof or leg injuries and disease" (Flower & Weary, 2009). It is a major welfare concern within the dairy industry (Whay & Shearer, 2017) and is considered the third most costly health problem after reduced fertility and mastitis (Van Nuffel et al., 2015). While estimates of lameness prevalence are high, such as a 21% herd prevalence in freestalls (Solano et al., 2015) and a 25% herd prevalence in tie-stalls (Bouffard et al., 2017) estimated by researchers in Canada, the actual prevalence of lameness within dairy herds is also frequently under-estimated (Cutler et al., 2017). This is, in part, due to producers underestimating the true extent to which lameness impacts farm profitability (Dolecheck & Bewley, 2018), and therefore not prioritizing lameness identification and reporting. While lameness contributes to more obvious expenses such as drug treatment, veterinary costs, death and culling, it also contributes to more indirect expenses such as reduced life expectancy, milk yield, and reproductive performance (Van Nuffel et al., 2015). For example, cows in Quebec who experienced a lameness event in their first lactation were found to produce 800 – 1100 kg less per lactation than cows that did not have an occurrence of lameness (Puerto et al., 2021). Lameness under-estimation on-farm is also attributed to a lack of available time and labor that must be dedicated to evaluating gait within a herd (Leach et al., 2010). Finally, lameness prevalence may also be under-estimated because producers largely rely on the presence of an easily identifiable aspect of impaired gait, such as a limp or a cow's reluctance to move, to detect lameness (Cutler et al., 2017). However, signs of more extreme locomotor impairment like limping are representative of more severe cases of lameness. To fully address the true prevalence of lameness within herds and to minimize the costs and welfare implications associated with it, detection of gait abnormalities or less obvious changes in locomotion before a severe case of lameness develops are imperative.

Traditionally, for both on-farm and research purposes, visual gait scoring systems have been a commonly used approach for detecting and assessing the severity of lameness, as they are inexpensive and relatively easy to carry out (Schlageter-Tello, Bokkers, Koerkamp, et al., 2014). However, gait assessment through visual locomotion scoring requires training (Alsaaod et al., 2019) and generally a large time commitment and dedicated labor when carried out, so is unlikely to be conducted frequently for on-farm purposes (Van Nuffel et al., 2015). Reliability between individual observers can also be problematically low due to differences between observers' training level, background experience, and interpretations of locomotion scoring system descriptions (Channon et al., 2009). Along with the inconsistencies seen between individual observers, there are also inconsistencies between visual scoring systems used. At least 25 different visual scoring systems exist (Van Nuffel et al., 2015), ranging from binary (lame vs. non-lame) to multiple point (commonly 5 or 9-point) scales to continuous analog scales (0 – 100 scale). These different scoring systems also focus on a range of different aspects or attributes of gait and postures (Schlageter-Tello, Bokkers, Groot Koerkamp, et al., 2014).

To address the issue of lameness within the dairy industry and to circumvent the limitations of traditional visual locomotion scoring, researchers have begun to develop and implement more automated approaches of evaluating locomotion through the use of technology. The types of technology which have been primarily implemented for this purpose include kinematic, kinetic, and accelerometry technologies (Nejati, 2021). Kinematic technologies focus on how the cow's body moves in terms of space and time. Kinetic technologies focus on force and force-related measures that are exerted as a cow moves or stands. Accelerometry technologies generally measure the acceleration of the cow's body or of specific parts of the body as she moves. The measures recorded through these types of technology, while overlapping with many of the aspects of locomotion that are focused on by visual locomotion scoring systems, can go a step further to provide more detailed data regarding how the cow is moving and may be able to detect more subtle changes or abnormalities in her movement that would not be possible with the human eye alone. Kinematics technologies are the most obvious overlapping starting point in transitioning from simple visual observer scoring to an automated approach of acquiring more detailed data that would reflect aspects of locomotion looked at in terms of space and time (e.g., stride length and stride duration). Data recorded through these more technological approaches could provide better insight into how a cow's locomotion has changed or become impaired, especially in earlier stages before severe lameness develops. These technologies have the potential to detect a specific aspect of locomotion that is irregular, a location on the cow's body that is affected, or a certain pattern that could be eventually associated with different causes of lameness such as specific injuries or hoof disorders.

1.1. OBJECTIVES

1.1.1. Overall objectives

The main objectives of this thesis were to: 1) determine the measures that have been recorded in research utilizing kinematic, kinetic, accelerometry, and other approaches to look at factors which influence dairy cow locomotion, and 2) validate a kinematic system used in conjunction with machine learning approaches to predict locomotor ability via a numeric rating system (NRS).

1.1.2. Specific objectives

In contributing to the overall thesis objectives, the objectives of the systematic review within the thesis were to:

1. List the specific outcome measures of locomotion that have been recorded through use of kinematic, kinetic accelerometry, and other approaches in studies evaluating environmental or cow-level factors which influence locomotion
2. List the specific physiological and behavioral outcome measures of indirect approaches of identifying changes in locomotor ability that have been used in research
3. Determine the relationships, overlaps, and differences between the measures recorded and the approaches or technologies used to record these measures
4. Determine which environmental and cow-level factors were examined in research focusing on locomotion and understand which approaches of recording and examining the quality of locomotion have been used to study each.

The specific objective of the validation study was to:

1. Determine if 3D-scaled coordinates acquired from a kinematic system with corresponding visually observed NRS scores could be used with machine learning approaches to predict a locomotion score with high accuracy.
2. Determine if the developed model(s) could accurately predict locomotion scores representing cows which exhibit gait abnormality or subtle locomotor impairment but which are not yet designated as clinically lame.

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CHAPTER 2 – APPLICATIONS OF TECHNOLOGY TO RECORD LOCOMOTION MEASURES IN DAIRY COWS: A SYTEMATIC REVIEW

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2.1. ABSTRACT

Lameness within the dairy industry is of major concern due to its costliness and welfare implications. Visual locomotion scoring has been the most common approach used for assessing the quality of dairy cow locomotion, but is prone to low reliability and is relatively subjective compared to automated methods of assessing locomotion. Kinematic, kinetic, and accelerometry technologies are alternatives which can provide a greater number of more detailed outcome measures of locomotion than visual locomotion scores. The objectives of this review are to 1) list and determine the relationships between the measures recorded by kinematic, kinetic, and accelerometry technologies and other approaches for evaluating dairy cow locomotion and 2) evaluate how these types of measures are used in different research contexts to study factors that impact locomotor ability. A systematic literature review was conducted according to PRISMA guidelines. Two online databases were searched using for studies published from January 2000 – June 2020 using search strings developed to collect references corresponding to the review objectives. Gathered articles underwent a two-step screening process, consisting of a first step of title and abstract evaluation based on inclusion criteria and a second step of full-text assessment. A final 34 articles were retained. Technologies and human observer-based approaches used for evaluating locomotion, the specific measures recorded, and research contexts of these studies were the data items extracted. Locomotion measures recorded by the three technologies of primary interest often overlapped, but inconsistencies in types of technology used, physical arrangements of equipment, terminology, and measure-recording approaches or calculations made it difficult to compare locomotion measures across studies. Therefore, future use of these

technologies for dairy cow locomotion research may benefit from the development and implementation of standard guidelines to allow for more consistency across studies. Factors which may impact locomotion that were most frequently studied included flooring type, hoof-trimming, lameness intervention, and the presence of lameness or hoof disorders in an animal. Additional research is required to develop a more comprehensive understanding of how these specific environmental and cow-level factors specifically affect aspects of locomotion as recorded through the detailed, objective outcome measures provided by kinematic, kinetic, and accelerometry technologies.

2.2. INTRODUCTION

Reliable gait assessment of dairy cows is of major interest for both producers and researchers. Abnormalities in gait can contribute to impaired locomotion or lameness, which is defined as “a deviation in gait resulting from pain or discomfort from hoof or leg injuries and disease” (Flower & Weary, 2009). Lameness is a major welfare concern and is considered one of the costliest health problems within the dairy industry after mastitis and reduced fertility (Dolecheck & Bewley, 2018; Van Nuffel, Zwertvaegher, Pluym, et al., 2015). Early detection of lameness or gait abnormalities which may lead to lameness can help minimize the costs and welfare concerns associated with impaired locomotion (Van Nuffel, Zwertvaegher, Van Weyenberg, et al., 2015). Producers and researchers have often relied on visual locomotion scoring systems as the primary method of gait assessment, as they are non-invasive, inexpensive, and relatively easy to carry out (Schlageter-Tello et al., 2014; Van Nuffel, Zwertvaegher, Pluym, et al., 2015). Visual locomotion scoring systems typically consist of an overall value given to represent quality of gait on an analog scale (generally with a value from 0 – 100) or a scale with multiple classes (generally consisting of 3, 5, or 9 points), with prescribed aspects and quality levels of gait defined for each score. Some visual scoring systems may also focus on specific attributes of gait, such as reluctance to bear weight on a limb or asymmetry of gait, which are also generally explained for observers via detailed charts. However, aspects of these visual scoring charts may be interpreted differently between individual observers, and inconsistencies between observers can lead to low inter- or intra-observer reliabilities (Channon et al., 2009). The required training and time necessary to conduct locomotion scoring also make it less likely to be conducted frequently for on-farm purposes (Alsaaod, Fadul, & Steiner, 2019; Dolecheck &

Bewley, 2018). Therefore, lameness prevalence is often underestimated by producers (Cutler et al., 2017; Van Nuffel, Zwertvaegher, Pluym, et al., 2015). Visual scoring may be conducted by an observer with recorded video to circumvent the necessity of a live observer being physically present for long periods of time. One lameness scoring method was found to be generally comparable in levels of agreement between video and live scoring, with video scoring resulting in fewer false negatives of lameness (Palacio et al., 2017). However, recording video for the purpose of conducting gait or lameness scoring is not practical for on-farm purposes and would be a less efficient approach for producers looking to assess gait within a herd.

To move beyond the limitations of visual locomotion scoring systems, several types of technologies have been adopted to record measures of locomotion at a more detailed level and through a more automated approach (Alsaaod, Fadul, & Steiner, 2019; Schlageter-Tello et al., 2014). However, these technologies are often compared and validated against visual locomotion scoring methods, which are not an ideal reference point, as gait scoring is often prone to relatively more subjective interpretations of gait quality and low reliability within and between observers (Schlageter-Tello et al., 2014). These technologies have been developed and applied within the context of research focusing on how environmental factors, such as flooring surface (Alsaaod, Huber, et al., 2017; Flower et al., 2007; Telezhenko et al., 2017), or cow-level factors, such as the presence of hoof disorders (Blackie et al., 2013; Flower et al., 2005), may influence dairy cow locomotion.

Technologies and methods taking a more indirect approach to assessing gait quality or identifying changes in gait through the recording of physiological and behavioral measures which are associated with gait have also been used alongside visual gait scoring or other technological approaches of recording gait measures. For example, infrared thermography has been used to record hoof temperature, which is a physiological measure that may be associated with different levels of mobility due to the presence of hoof disorders affecting the temperature of the hoof (Rodriguez et al., 2016). Wearable sensors that are typically mounted on a cow's leg have been used to record behavioral measures such as activity and lying time, which may be affected by impaired locomotion (Blackie et al., 2011). These technologies and methods, which directly or indirectly evaluate gait, could provide alternative approaches to assessing locomotion from visual locomotion scoring. Currently, however, there are gaps in knowledge about what the differences within these technologies and methods are, what specific measures have been recorded across approaches used, and what potential gait-influencing factors these approaches have been applied to evaluate.

There are four literature reviews that have been conducted which focus on technologies used for gait analysis, although most of these primarily take a “lameness detection” approach. Two of these (O'Leary et al., 2020; Van Nuffel, Zwertvaegher, Van Weyenberg, et al., 2015) focused only on wearable sensor technologies. One review of manual and automatic locomotion scoring systems for dairy cows was conducted with the aim of comparing and evaluating agreement, reliability, and validity of manual and automatic locomotion scoring systems used in research (Schlageter-Tello et al., 2014). The Schlageter-Tello et al. (2014) review was also the first to highlight the issue of using visual locomotion scoring systems, which are more subjective compared to automatic systems and may have low reliability, as a reference for validating automated lameness detection systems. Another review (Alsaaod, Fadul, & Steiner, 2019) was conducted to describe the current automated systems - including kinematic, kinetic, and indirect methods - that are used for cattle lameness detection. The review conducted by Alsaaod, Fadul and Steiner (2019) focused on performance of the methods compared with a reference standard (locomotion score or lesion score) and described technical aspects of these technologies such as levels of sensor technique, validation of algorithm, performance for lameness detection, and/or decision support with an early warning system. While previous reviews focused on technical aspects of technologies used in gait analysis, the current systematic literature review aims to focus on the specific measures recorded by these different technologies and methods of assessing gait. The current review also aims to describe and draw out the relationships between specific types of measures, both those directly and indirectly assessing cow locomotor ability. The current review will also lay out how individual studies define and go about recording specific types of measures, as terms such as “step length” can often be measured with different approaches or have varying definitions between studies. Additionally, our review will be conducted from a perspective of analyzing gait at all stages of locomotor ability, rather than from a lameness detection perspective. Finally, there are no previous reviews describing, in detail, the contexts of research in which these technologies and other indirect methods of gait assessment are applied. Our review will describe the cow-level and environmental risk factors these measures are used to evaluate. A sister scoping review by (Nejati, 2021) has also been conducted with the aims of mapping research trends of quantitative bovine gait analysis, exploring the technologies that have been used to measure biomechanics parameters of gait variables in bovine species, and highlighting the current gaps in the field of cow gait analysis. The sister review additionally covers trends in the frequency of use in research that the three technologies of primary interest (kinetematics, kinetics, and accelerometry) within the current study have had since the year 2000. These aspects will therefore not be covered here.

This systematic literature review consisted of two main objectives. Objective 1 consisted of two research questions: 1) What specific measures are used by kinetic, kinematic, and accelerometry technologies to directly measure dairy cow locomotor ability? 2) What other approaches outside of these 3 technologies are used to record locomotion measures and what physiological and behavioral measures are used in other approaches to indirectly evaluate dairy cow locomotor ability? Objective 1 also aimed to describe the relationships between these different types of direct and indirect, gait-related measures. Objective 2 aimed to answer how these types of measures are used in different research contexts to study factors that impact locomotor ability.

2.3. MATERIALS AND METHODS

2.3.1. Protocol

This review was conducted using guidelines adapted from Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA, 2009).

2.3.2. Eligibility Criteria

Eligibility criteria required that studies included 2 of the 3 following levels to be considered appropriate for addressing the objectives of this review. These characteristics along with their definitions are as follows:

A. Level A: the use of one or more of the three autonomous technologies of primary interest (kinematics, kinetic, and accelerometry) used for directly evaluating gait through the recording of locomotion measures
B. Level B: the use of approaches which evaluate gait through the recording of:
    I. Locomotion measures recorded through other methods (human observer-based) or technologies (less autonomous technologies outside of kinetics, kinematics, and accelerometry)

II. Gait-associated physiological (e.g. hoof temperature, mechanical nociception threshold, muscle fatigue) or behavioral measures (e.g. activity, lying time)

C. Level C: Presence of a relevant study context: environmental or cow-level risk factor(s) that measures recorded through the Level A and B approaches are used to evaluate in research

Note for studies appearing to meet combination B + C: For purposes of study selection for this review, visual locomotion scoring conducted by humans is considered a Level B approach to assessing gait; however, studies which use only visual locomotion scoring to assess gait quality/locomotor ability when evaluating factors which may affect locomotion will not be included.

Primary research in the English language was included, and review papers and conference proceedings were excluded so that only studies with original peer-reviewed research relevant for addressing the objectives of this review would be used. Validation and technology or model development studies were excluded, as studies focusing only on technical aspects (validity, sensitivity, specificity) of technologies discussed were not relevant to the objectives of the review. Studies using certain measures, evaluation methods, or technologies that in some cases could be deemed as locomotion-related but which focused on topics other than locomotion (GPS/animal tracking, estrus detection, calving detection, behavior monitoring independent of locomotion, etc.) were also excluded due to lack of relevance. Only papers from the year 2000 and after were included because technology and methods used before that time would be outdated and no longer of use or relevance in current research. Studies were also required to use adult dairy cows as subjects, as this review focuses only on locomotion in adult dairy cows and species, animal production type, stage of life, and sex can influence locomotion of an animal.

2.3.3. Information Sources

Literature searches were conducted in two electronic databases (Scopus and Web of Science Core Collection) to obtain references.

2.3.4. Search

The final search was conducted on May 31, 2020. Search terms were designed to include all relevant keywords as to ensure results with the greatest number of possible references. To encompass both objectives of the review within one comprehensive search, four levels of search terms were developed. In the final search, only the first three levels of keywords were incorporated into search queries and the fourth level was excluded to ensure that the maximum number of relevant references resulted from the search terms. Query strings that were used in each database and the number of records that resulted from each are shown in Table 2.3.1. The "Combination 1, 2, and 3" rows contain the queries and search results that were ultimately used for the reference screening process. The final search was conducted on May 31, 2020. No search limitations were set regarding language, date, study subject, or study design to minimize bias and ensure that all relevant references could be obtained.

Table 2.3.1. The strings included in the search strategy with the number of resulting records for each string in it the Scopus database on May 31, 2020.

#	String	Records Found
#1	TITLE-ABS (cattle OR cow* OR bovine)	480,753
#2	TITLE-ABS (locomot* OR movement OR gait OR walk*)	1,223,442
#3	TITLE-ABS (kinemat* OR kinetic* OR thermography OR electromyography OR *emg OR hematology OR sensor* OR ams OR "Automatic milking system" OR "milking robot" OR accelerometer*)	2,976,033
#4	TITLE-ABS (exercise OR "outdoor access" OR pasture OR flooring OR "hoof health" OR "leg health" OR lameness OR environment* OR risk* OR hous*)	7,810,723
#1, 2, 3	TITLE-ABS (cattle OR cow* OR bovine) AND (locomot* OR movement OR gait OR walk*) AND (kinemat* OR kinetic* OR thermography OR electromyography OR *emg OR hematology OR sensor* OR ams OR "Automatic milking system" OR "milking robot" OR accelerometer*)	550
#1, 2, 3, 4	TITLE-ABS (cattle OR cow* OR bovine) AND (locomot* OR movement OR gait OR walk*) AND (kinemat* OR kinetic* OR thermography OR electromyography OR *emg OR hematology OR sensor* OR ams OR "Automatic milking system" OR "milking robot" OR accelerometer*) AND (exercise OR "outdoor access" OR pasture OR flooring OR "hoof health" OR "leg health" OR lameness OR environment* OR risk* OR hous*)	224

Additional searches were later conducted to obtain any relevant references that had not been included by the initial database searches. Supplementary searches included forward- and back-searches of references obtained from initial database searches, as well as handsearching to gather individual references missed by database searches.

2.3.5. Study Selection

All resulting references from the "Combination 1, 2, and 3" strings were imported into Endnote X8 reference management software. Duplicates were then removed, and remaining references were screened using the web application Rayyan (Rayyan, Qatar Computing Research Institute). A two-step screening process was used. The first step consisted of a screening of reference titles and abstracts to determine relevance to the review objectives and research questions, as well as other general eligibility criteria, such as language and date requirements. References incorporating at least two of the three A, B, and C eligibility levels listed above were then included in the second step of screening. The second step consisted of a full-text review to confirm that references met eligibility criteria. The study selection process is shown in Figure 2.4.1.

2.3.6. Data Collection Process, Data Items, and Summary Measures

Data extraction sheets were developed by the authors to chart literature. Screening and data extraction was conducted by an individual reviewer. Specific definitions -which are provided in the results section - for the technology categories of kinematics, kinetics, and accelerometers were determined by the reviewers before the data extraction process. Uncertainties regarding the review process or protocol were discussed with the review team to minimize human error. The initial data extraction sheet consisted of the headings: reference, direct measure(s) of locomotor ability, technology category for direct measure(s) (kinetic, kinematic, accelerometer), indirect measure(s) associated with locomotor ability, factor investigated (cow-level or external factor), methodology, country where the study was conducted, non-locomotion related measurements, recording interval/duration, number of animals, number of farms, treatment/comparisons, difference(s) between treatments/comparisons, p-value, conclusions, and limitation(s)/critique(s). Additional charts corresponding to each objective and research question were later developed to organize data further.

A narrative synthesis and organization of tables based on research questions of the review were used to summarize and present data. Tables and/or narrative descriptions were developed for each objective and its subsequent research questions. Definitions and categorization terms were developed by the review team to ensure consistent and thorough description of measures used. Data relevant to objective 1 were organized based on types of technologies and methods used for gait analysis. A visual diagram was developed to display the connections and relationships between types of measures used by different technologies and methods of gait assessment. Data relevant to the objective 2 section were organized based on research contexts of studies.

2.4. RESULTS

2.4.1. Study Selection

A total of 550 references in Scopus and 635 references in Web of Science resulted from the combination of search strings 1, 2, and 3. After deduplication was conducted, 835 references remained for title and abstract screening. An additional 5 references were found from hand searching. Based on a lack of relevance to bovine locomotion and obvious discordance with eligibility criteria, 782 papers were excluded. Fifty-eight references remained for full-text screening. Through full-text examination, 28 references were excluded leaving a final number of 34 references. Figure 2.4.1 shows the PRSIMA flow diagram for the selection and screening process of the review.

PRISMA 2009 Flow Diagram

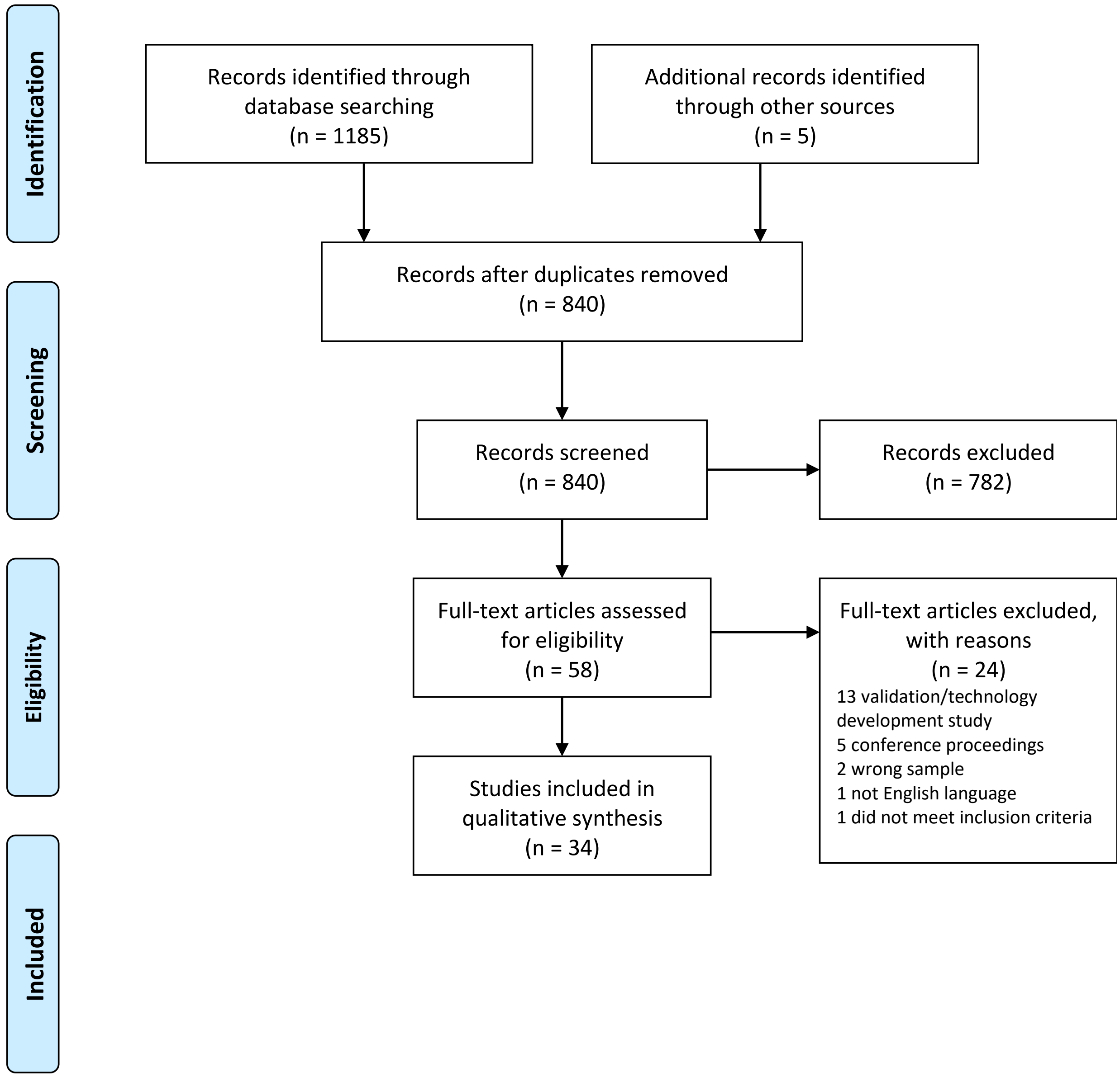

Figure 2.4.1. PRISMA flow diagram for systematic review detailing the selection and screening of literature.

2.4.2. Approaches to recording and analyzing gait in dairy cows: categorizations and definitions

In research that evaluates factors that may impact dairy cow locomotion, kinematics, kinetics, and accelerometry are the three main categories of technologies that have been used to record direct measures of locomotion (Nejati, 2021). These types of technologies are generally more autonomous and provide measures of locomotion in greater detail than other types of technology that have been used for similar purposes. Therefore, in this review, these three technologies are of primary interest, as are the locomotion measures that they record. Measures recorded by one type of technology but whose definitions may be associated with another type of technology will be organized and described under the section of technology by which they are recorded.

Other methods outside of these three technology types have also been used to record measures of locomotor ability. In this review, gait or gait-associated measures recorded via technologies or other methods aside from kinetics, kinematics, and accelerometers are be categorized as “Level B”, with sub-categories detailing how they approach recording locomotion or gait-associated measures. For example, Level B encompasses methods such as “manual kinematics”, which involve the recording of kinematic-type measures through software that is not specifically designed for gait analysis have been used with the goal of recording locomotion measures. The use of image analysis software or custom-written code generally requires a greater amount of manual human work to obtain kinematic measures than the gait analysis-specific software encompassed within Level A that allow for easier, automated “tracking” of movement, and therefore can be viewed as their precursor. Additionally, even simpler approaches, or “human-recorded locomotion variables” for recording kinematic-type measures have been used. Human observations - live or via video recordings – have been conducted to record easily identifiable measures such as the number of steps taken within a passage or given amount of time to complete a gait passage. Stopwatches or timers have been used for recording the time taken for a cow to walk a known distance to allow for a simple approach to calculating walking speed. Finally, methods involving human observations for looking at overall locomotor ability or specific gait characteristics, such as scores from numeric rating scales or analog locomotion-rating scales, have been commonly used.

2.4.3. Kinematics

Kinematics is a subdivision of the study of biomechanics which involves observable aspects of motion, such as space and time (Basic Biomechanics, Susan Hall, 2011) and, thus, measures recorded by kinematic technology generally fall under the categories “spatial” and “temporal.” Spatial measures provide information as to how the body is moving within space, and temporal measures provide information as to how the body is moving in time. The type of technology that has mainly been used to record kinematic measures in research which evaluates factors affecting dairy cattle locomotion is the combination of video cameras used alongside commercially available motion analysis software. These video and software systems, which are designed specifically for motion analysis, are the sole technology to be considered as “kinematic” technology in this review. However, other types of technologies which are designed to record kinetic measures have also been used to record kinematic measures. In this review, these kinetics-focused technologies and all the measures which they record will be discussed under the “kinetics” technology section. Additionally, three studies included in this review have used accelerometers in conjunction with a specific pedogram designed to extract certain temporal measurements. While temporal measures would generally fall under the category of kinematics, these three studies will be discussed under the “accelerometry” technology section of the review.

The Level A type of kinematic technology used for recording spatial and temporal measures in these studies involved the use of commercially available motion tracking or motion image analysis software specifically designed for analysis of kinematics. Details regarding the technology used in these studies are provided in Table 2.8.1. These studies used these technologies with only a single camera to record video, which means that only one side and one angle of the cow is visible as the cow’s gait is recorded on video. Three different software programs were used within these studies, and all required markers to be attached to the cow. This type of system allows for 2D kinematic analysis, where the marker movement is “tracked” to provide data which then can be extracted and interpreted as specific spatial and/or temporal measures or variables. The use of this technology allows for the recording of detailed, quantitative gait measures, such as stride time, which can then be compared between cows or between an individual cow’s gait cycles, gait change over time, or contralateral limb movements. While commonly used, visual locomotion scoring may identify when a cow experiences a deviation from “normal” gait or may be able to pinpoint a deviation from what would be “normally” expected regarding a specific gait characteristic, these more detailed and quantitative measures can go a step further and provide data representing motion trajectories of specific points on the cow’s body through which patterns can be detected and a potential cause of gait impairment could be inferred. Additionally, recording multiple interconnected spatial and temporal measures for multiple body parts at once can provide a clearer picture of a cow’s locomotion overall as well as what is occurring at different phases within the gait cycle.

2.4.3.1. Measures Recorded

Spatial measures recorded by kinematic technologies used in dairy cow locomotion research generally look at the distance between two points – either between two points on the cow or between the floor and a point on the cow – or at the range of movement of a particular part of the body. Studies using the above video and motion analysis software systems to evaluate dairy cow locomotion have used spatial measures of stride length, tracking distance, the length of particular regions of the spine, range of movements for different joints, head position, and measures which describe the maximum height a particular point on the cow reaches during locomotion (specific definitions for each variable detailed in Table 2.4.1). All five studies measured stride length, 3 measured hoof height, and 3 measured tracking. For these measures, definitions and approaches used to record them were similar. Only one study recorded the spatial posture measures of head position, spine markers height, spine length, thoracic region length, and lumbar region length, with each being recorded during a frame of video when the cow was seen to be bearing weight on the right foot. These measures were recorded to provide information regarding the posture of the cow. Blackie et al. (2011) and (Blackie et al., 2013) both recorded hock ROM and fetlock ROM. Blackie et al. (2011) was the only study which recorded rotation of movement (ROM) of the knee.

Temporal measures which have been recorded by these studies include durations of specific parts of the gait cycle. Three studies measured stride duration, stance duration, and swing duration. Definitions and approaches used for these measures were relatively similar (Table 2.4.1). Only one study recorded triple support. The walking speed of the cow can also be calculated based on recorded kinematic variables. Three studies using automatic motion tracking software – as opposed to the Level B kinematic approaches of “manual kinematics” or “human-recorded kinematics" – recorded walking speed, although two of these did so by calculating the walking speed based of the stride duration divided by the stride time, and the third did not provide a definition as to how walking speed was calculated (Table 2.4.1).

Table 2.4.1. Locomotion measures recorded and analyzed using a camera and a kinematic motion analysis software.

Measure Category	General Measure	Measure Definition/Approach	Reference
Spatial: Limb Movement	Stride length	Horizontal displacement between 2 consecutive hoof strikes of the same hoof	Flower et al., 2005; Flower et al., 2007
		Distance between 2 consecutive hoof strikes for the same hoof (right side of cow only)	Franco-Gendron et al., 2016
		Distance between cannon appearing straight and next occurrence of cannon being straight for the fore and hind limbs	Blackie et al., 2011; Blackie et al., 2013
	Hoof height	Maximum vertical displacement between 2 consecutive hoof strikes of the same hoof	Flower et al., 2005; Flower et al., 2007
		Maximum vertical distance at which the hoof is lifted while the cow is walking	Franco-Gendron et al., 2016
	Maximum fetlock height	Highest distance from the floor to the fetlock marker that weas seen during the stride	Blackie et al., 2013
	Maximum hock height	Highest distance from the floor to the hock marker that was seen during the stride	Blackie et al., 2013
	Tracking	Horizontal distance between front hoof strike and subsequent ipsilateral rear hoof strike	Flower et al., 2007
		Distance between the fore foot being placed on the ground and the ipsilateral hind foot being placed on the ground	Blackie et al., 2011; Blackie et al., 2013
	Hock range of motion (ROM)	Difference between minimum and maximum hock angles calculated from tracking of the hind fetlock, hock, and stifle markers	Blackie et al., 2011; Blackie et al., 2013
	Fetlock ROM	Difference between minimum and maximum fetlock angles calculated from tracking the fetlock marker, knee marker, and elbow marker	Blackie et al., 2011; Blackie et al., 2013
	Knee ROM	Difference between minimum and maximum knee angles calculated from tracking the fore fetlock marker, knee marker and elbow marker	Blackie et al., 2011

Spatial : Posture	Head position	Distance from bottom of cow's nose to floor (measured when front right foot first observed to bear weight)	Blackie et al., 2013
	Spine markers height	Distance from the spine markers to the floor (assessed when cow was seen to be bearing weight on front right foot)	Blackie et al., 2013
	Spine length	Distance between markers at T3 and TA (assessed when cow was seen to be bearing weight on front right foot)	Blackie et al., 2013
	Thoracic region length	Distance between markers at T3 and L1 (assessed when cow was seen to be bearing weight on front right foot)	Blackie et al., 2013
	Lumbar region length	Distance between markers at L1 and SA (assessed when cow was seen to be bearing weight on front right foot)	Blackie et al., 2013
Temporal: Individual Limb	Stride duration	Time interval between 2 consecutive hoof strikes of the same hoof	Flower et al., 2005; Flower et al., 2007
		Not described	Blackie et al., 2013
	Stance duration	Time the hoof is in contact with the ground (interval between hoof strike and following hoof-off) (right side of cow only)	Flower et al., 2005; Flower et al., 2007
		Period of time when a cow's hoof is on the ground during a stride	Franco-Gendron et al., 2016
	Swing duration	Time the hoof is not in contact with the ground (interval between toe-off and following hoof strike)	Flower et al., 20117
		Period of time when a cow's hoof is on the ground during a stride (right side of cow only)	Franco-Gendron et al., 2016
Temporal: Overall	Walking speed	Stride length ÷ stride duration	Flower et al., 2005; Flower et al., 2007
		Not described	Blackie et al., 2011
	Triple support	Time spent with 3 hooves in contact with the ground; calculated as (sum of intervals between toe-off and subsequent contralateral hoof strike ÷ stride duration) x 100	Flower et al., 2007

2.4.4. Kinetics

Kinetics is a subdivision in the study of biomechanics that focuses on the forces associated with motion (Basic Biomechanics, Susan Hall, 2011). In research evaluating dairy cattle locomotion, technologies using kinetic measures can be divided into three general categories: force platforms (FP), pressure mapping systems (PMS), and weight distribution platforms

(WDP) (Nejati, 2021). Force platforms and pressure mapping systems may be used independently or in a system where the two are combined to record simultaneously. All three types of these kinetics-focused technologies may record “static” measures, or measures taken as the cow is standing in place over the platform. However, force platforms and pressure mapping systems are generally used to record “dynamic” measures, or measures taken as the cow walks over the platform. While kinetic technologies primarily focus on measuring kinetic (force-related) measures, FP and PMS may also record kinematic-type spatial or temporal measures. Kinematic-type measures which have been recorded using kinetic technologies in studies evaluating dairy cow locomotion will be discussed in this section. Details of the measures recorded by these 3 technologies are provided in Table 2.4.2. Details of each of the types of kinetic technologies used are provided in Table 2.8.2.

Table 2.4.2. Locomotion measures recorded and analyzed using force platforms, pressure mapping systems, and weight distribution platforms.

Technology Type	**Measure Category**	**General Measure**	**Measure Description/Approach**	**Reference**
-Force Platform	Force-related	ground reaction force (GRF)	Average ground reaction force normalized by the animal’s dynamic weight of a tested limb	Liu et al., 2011
			vertical GRF exerted to the lateral and medial claw (parameters analyzed for five moments (heel strike, maximum braking, midstance, maximum propulsion, and push off) of stance phase for the left and right limbs)	Van der Tol et al., 2003
			vertical (Fv), longitudinal (Fl), and mediolateral (Fm) ground reaction forces	Thorup et al., 2014
		Maximum/peak force	maximum force per lateral and medial claw (used for analysis deceleration, midstance, and acceleration positions)	Carvahlo et al., 2005
			maximum force per foot (used for analysis deceleration, midstance, and acceleration positions)	Carvahlo et al., 2005
			peak GRF normalized by the animal’s dynamic weight of a tested limb	Liu et al., 2011
			symmetry index for peak GRF (a pelvic limb symmetry variable)	Liu et al., 2011
			positive cranio-caudal peak force	Walker et al., 2010
			negative cranio-caudal peak force	Walker et al., 2010
			vertical peak 1 (fore and hind limbs)	Walker et al., 2010

			vertical peak 2 (hind limb parameter only)	Walker et al., 2010
			vertical peak 3 (hind limb parameter only)	Walker et al., 2010
		Force asymmetry	symmetry index for average GRF (a pelvic limb symmetry variable)	Liu et al., 2011
			Symmetry parameters calculated for vertical (Fv), longitudinal (Fl), and mediolateral (Fm) ground reaction forces to compare entire stance phase curves of the left and right legs; 0 to 100 scale signifying stance phase curve symmetry (lower values signifying better symmetry/more parallel left and right leg curves)	Thorup et al., 2014
		GRFω	area under the Fourier transformed curve of a GRF signature normalized by the animal's dynamic weight	Liu et al., 2011
			symmetry index GRFω (pelvic limb symmetry variable)	Liu et al., 2011
		Impulse	the integral of the GRF normalized by the animal's dynamic weight with respect to time	Liu et al., 2011
			symmetry index for vertical impulse (a pelvic limb symmetry variable)	Liu et al., 2011
			positive cranio-caudal impulse	Walker et al., 2010
			decelerative impulse	Walker et al., 2010
			accelerative impulse	Walker et al., 2010
		moment of force (torque)	moment of vertical (Fv), longitudinal (Fl), and mediolateral (Fm) ground reaction forces	Thorup et al., 2014
	Kinematic: Temporal	stance time	time a limb is in contact with the floor	Liu et al., 2011
		stance time asymmetry	symmetry index for stance time (a pelvic limb symmetry variable)	Liu et al., 2011
		Zero Crossing	% stance	Walker et al., 2010
		Stride frequency	Not provided	Walker et al., 2010
		Swing time	Not provided	Walker et al., 2010
		Walking speed	calculated from the GRF data using timing information (frame number) and COP co-ordinates corresponding to forelimb mid-stance on two different force plates; calculate speed (in m/s) divided by distance between COP location in stride one and stride two by the difference in time, calculated from the difference in frame numbers divided by the sample rate (200 Hz)	Walker et al., 2010
		Duty factor	Not provided	Walker et al., 2010

Pressure Mapping System	Force-related	Force	Force for left/lame foot and right/non-lame foot (to compare)	Kleinhenz et al., 2019
			force for each foot (4) (basic gait, within-imprint variable)	Van Nuffel et al., 2013
			static vGRF (while cow is standing)	Oehme et al., 2018
			dynamic vGRF (while cow is walking)	Oehme et al., 2019
				Oehme et al., 2019
			total vertical force during locomotion (relative value as a percentage of hoof strike average)	Ouweltjes et al., 2009
			corrected mean vertical force claw-floor interactions during locomotion (per footprint double-support phase time average)	Ouweltjes et al., 2009
			shapes of force-time curves assessed for local maxima and where they were in the stance phase	Oehme et al., 2019
		force asymmetry	symmetry in force between left and right limbs	Van Nuffel et al., 2009
				Van Nuffel et al., 2013
		maximum force	maximum vertical force per sensor	Ouweltjes et al., 2009
		Impulse	impulse for both the lame/left and non-lame/right feet (to compare)	Kleinhenz et al., 2019
		Weight Distribution	calculated using at least eight pairs of vertical impulses from steady state locomotion recordings of each cow; hind limb vertical impulse was then expressed as a percentage of forelimb impulse for each plate; mean of all the ratios was calculated to determine mean weight distribution across all cows	Walker et al., 2010
		Contact Area	dynamic overall loaded area (while cow is walking)	Oehme et al., 2019
			claw-floor contact area during locomotion (relative value as a percent of hoof strike average)	Ouweltjes et al., 2009
			mean claw-floor contact area during locomotion (per footprint double-support phase time average)	Ouweltjes et al., 2009
			A_{zone}: the loaded area per zone relative to the total zone area	Oehme et al., 2018
			static total loaded area/overall contact area (while cow is standing)	Oehme et al., 2018
				Oehme et al., 2019
		Pressure	static mean pressure (while cow is standing)	Oehme et al., 2018
				Oehme et al., 2019

			dynamic mean pressure (while cow is walking)	Oehme et al., 2019
			Pav: average pressure per foot at five moments of stance phase (heel strike, maximum braking, midstance, maximum propulsion, and push off)	Van der Tol et al., 2003
			contact pressure for both the left/lame and right/non-lame feet (to compare)	Kleinhenz et al., 2019
			COPx: center of pressure in a lateromedial direction	Ouweltjes et al., 2009
			COPy: center of pressure in a craniocaudal direction	Ouweltjes et al., 2009
			vGRF per loaded area per zone (Pzone) (describes the pressure in each zone)	Oehme et al., 2018
		Maximum pressure	static maximum pressure (while cow is standing)	Oehme et al., 2018
				Oehme et al., 2019
			dynamic maximum pressure (while cow is walking)	Oehme et al., 2019
			Pmax: maximum pressure per foot at five moments of stance phase (heel strike, maximum braking, midstance, maximum propulsion, and push off)	Van der Tol et al., 2003
	Kinematic: Spatial	stride length	not described	Kleinhenz et al., 2019
			not described	Van Nuffel et al., 2009
			distance between two consecutive imprints of the same hoof	Van Nuffel et al., 2013
		step length asymmetry	step length symmetry between left and right limbs	Van Nuffel et al., 2013
		Tracking	step overlap or tracking up	Van Nuffel et al., 2009
			the lengthwise distance between the front hoof imprint and a subsequent imprint of the hind hoof on the same side	Van Nuffel et al., 2013
		Abduction	the sideways distance between the front hoof imprint and a subsequent imprint of the hind hoof on the same side	Van Nuffel et al., 2013
		step width asymmetry	step width symmetry between left and right limbs	Van Nuffel et al., 2009
			mean difference in step width between left and right hoof imprints	Van Nuffel et al., 2013
		distance between hoof imprints	Ax: relates to the distance between hoof imprints along the X dimension	Van Nuffel et al., 2009
			A_Y: relates to the distance between hoof imprints along the Y dimension	
			A_T: relates to the distance between hoof imprints along the t dimension	
		distance within hoofprints	B_X: relates to the distance within hoof imprints along the X dimension	Van Nuffel et al., 2009
			B_Y: relates to the distance within hoof imprints along the Y dimension	

			B_T: relates to the distance within hoof imprints along the t dimension	
	Kinematic: Spatio-Temporal	transversal deviations for each foot	relative location and timing of imprints in X direction (between-imprint variable)	Van Nuffel et al., 2013
		coefficients of variation of transversal deviations for each foot	represent stride to stride fluctuation of transversal deviations for each food (an inconsistent gait variable)	Van Nuffel et al., 2013
		longitudinal deviations for each foot	relative location and timing of imprints in Y direction (between-imprint variable)	Van Nuffel et al., 2013
		coefficients of variation of longitudinal deviations for each foot	represent stride to stride fluctuation of longitudinal deviations for each foot (an inconsistent gait variable)	Van Nuffel et al., 2013
		step time (T)	relative location and timing of imprints in the T direction/dimension	Van Nuffel et al., 2013
		CV for step time		Van Nuffel et al., 2013
	Kinematic: Temporal	stance time	time during one stride that the hoof is on the floor	Van Nuffel et al., 2009
			stance time symmetry between left and right limbs	Van Nuffel et al., 2013;
		stance time asymmetry	stance time symmetry between left and right limbs	Van Nuffel et al., 2009
			Not described	Van Nuffel et al., 2013
		stride time	Not described	Van Nuffel et al., 2009
				Van Nuffel et al., 2013
		step time	Not described	Van Nuffel et al., 2009
			step time symmetry between left and right limbs	Van Nuffel et al., 2013
		step time asymmetry	Not described	Van Nuffel et al., 2009
Weight Distribution Platforms	Weight distribution	limb weight ratio	ratio of weight placed on legs (maximum weight asymmetry)	Pastell et al., 2010
			ratio of weight on hind legs	Netchanisky et al., 2016
				Chapinal et al., 2010
		mean limb difference	Δweight(%): mean weight difference across the healthy and the lame limb within the affected limb pair	Netchatsky et al., 2016; Buisman et al., 2018; Alsaaod et al., 2019
		Limb weight	mean weight applied on each limb	Netchansky et al., 2016; Buisman et al.,

				2018; Alsaaod et al., 2019
			mean percentage of weight applied on each limb	Neveux et al., 2006
			mean percentage of weight distributed on front pair and back pairs of legs	Neveux et al., 2006
		mean variation	mean variation of weight distributed on each limb	Neveux et al., 2006
		standard deviation of weight applied on limb	a measure to determine weight shifting between hind limbs	Netchansky et al., 2016; Buisman et al., 2018; Alsaaod et al., 2019
		mean standard deviation of weight applied	mean SD of weight applied to all 4 legs	Pastell et al., 2010
			mean SD of weight applied to rear legs and mean SD of weight applied to front legs	Chapinal et al., 2010

2.4.4.1. Force Platforms

Five studies included in this review have used FP technology for dairy cow locomotion analysis. Recording of force-related measures may provide insight into the cow's gait by primarily focusing on differences in force applied between legs as the cow steps. The presence of hoof disorders or injuries on a particular leg make it likely that the cow will load less weight on that hoof, and therefore step down on the hoof with less force as compared to the hoof of her contralateral limb. Differences between forcefulness of steps on contralateral limbs is also a method for evaluating gait symmetry. Three of the studies used force plates independently to record force-related measures. Force plates used alone were supported by load cells, placed in pits to be level with the ground of the surrounding walkway, and were covered with rubber mats to provide additional friction to the walking surface. Liu et al. (2011) and Thorup et al. (2014) had FP systems arranged so that two force plates were parallel and could record both sides of the cow's body, with dimensions allowing for 2 to 4 stances to be recorded on each plate. Walker et al. (2010) alternatively created a 3m-long, 0.9m-wide walkway using 5 smaller force plates arranged in a row with the goal of collecting data from a pair of limbs on one side of the body.

Two studies used FP technology in conjunction with pressure mapping systems. Carvalho et al. (2005) mounted a PMS on top of a force platform consisting of a metal base plate with load cells at the corners supporting a top metal plate. The PMS and force platform both had the same dimensions so that the FP could measure the correct force under any individual limb and then that force could be used to calibrate the PMS. Van Der Tol et al. (2003) used a Kistler force plate placed underneath a PMS. They sampled simultaneously so that the force plate could output a vertical ground reaction force which could be used for calibration of the PMS. The total force measured by the FP was also used to adjust the sum of vertical forces that were applied to the individual sensors of the PMS.

2.4.4.1.1. Measures Recorded

Studies using FP technology primarily recorded the measure of GRF, which are the vertical or 3-dimensional ground reaction forces applied of the surface of the platform, and measures related to GRF, such as pressure and moment of force. Details regarding the definitions of each of these measures and the approach used to record them are shown in Table 2.4.4. However, these measures are often organized as some type of more specific variable, usually consisting of a calculation involving multiple sub-measures, to investigate the aspect of locomotion that is of interest. Studies using FP technologies independently (without a PMS) were only used to record dynamic measures, which were primarily organized into variables or scales focusing on gait symmetry. Liu et al. (2011) presented measures recorded by the StepMetrix system as “limb movement variables,” and reported the force-related measures of peak ground reaction force, average ground reaction force, vertical impulse, and GRFω. Thorup et al. (2014) measured vertical, longitudinal, and mediolateral ground reaction forces as well as their associated moments (torque). Both studies used force measures to evaluate gait symmetry. Liu et al. (2011) developed a symmetry index for average GRF to evaluate pelvic limb symmetry, while Thorup et al. (2014) developed symmetry parameters calculated for GRFs in each dimension to compare entire stance phase curves between the left and right legs. Thorup et al. (2014) used a scale from 0 – 100 to represent stance phase curve symmetry, with lower values signifying more parallel left and right leg curves and thus better symmetry. Walker et al. (2010) recorded several types of peaks of GRF curves, as well as three types of impulse measures. Weight distribution was also calculated from a minimum of eight pairs of vertical impulses from steady state locomotion recordings of each cow. The two studies using FP in conjunction with PMS (Carvalho et al., 2005; Van Der Tol et al., 2003) primarily relied on PMS to record kinetic measures, with the FP used as an accessory technology. The kinetic measures recorded in these studies will be described in the following PMS section. Two studies used force plates to record kinematic-type measures looking at temporal aspects of gait. Liu et al. (2011) measured stance time and developed a symmetry index for stance time to evaluate pelvic limb symmetry. Walker et al. (2010) measured stride time, stride frequency, swing time, walking speed, and zero crossing.

2.4.4.2. Pressure Mapping Systems

Eight studies included in the review used pressure mapping systems (PMS). Pressure mapping systems are unique as a kinetic technology, as they are the only technology which have a network of sensors allowing identification of multiple hoof-prints of different limbs during one passage, as opposed to FP, which can only record the sum of force occurring on one platform/sensor. This allows PMS to record a broader range of both kinematic and kinetic measures. Carvalho et al. (2005) and Kleinhenz et al. (2019) used the Matscan pressure measuring system (Tekscan Inc., South Boston, MA, USA. Oehme et al. (2018) and Oehme et al. (2019) used the Hoof™System (M3200E, Tekscan Inc., Boston, MA, USA), a foil-based piezoresistive pressure measurement system. It is important to note the difference between the two studies in which Hoof™System was used, as Oehme et al. (2018) used amputated hooves attached to a load applicator to press down on the film, while Oehme et al. (2019) cut the pressure film to be in the shape of claw and fitted the insoles into leather claw shoes. Van Nuffel et al. (2013) was the only study included in the review which used the GAITWISE system, which was developed by Maertens et al. (2011) and has a greater length (6m) that allows for data to be recorded for up to three consecutive gait cycles. Van Nuffel et al. (2009) used a permanently installed pressure distribution plate which was a precursor to the later-developed GAITWISE system. Van Der Tol et al. (2003) and Ouweltjes et al. (2009) both used Footscan pressure distribution plates (RsScan International, Olen, Belgium); however, Van Der Tol et al. (2003) used the pressure distribution plate overtop Kistler force plate (Kistler Corp, Winterthur, Switzerland) while Ouweltjes et al. (2009) used the Footscan 2D-box system (RsScan International, Olen, Belgium), which is used independently of a force plate. Carvalho et al. (2005) also used a force plate underneath the Matscan system.

2.4.4.2.1. Measures Recorded

Pressure mapping systems used in conjunction with force plates may record force through their associated force plates, while PMS used independently can extrapolate force based on the pressure and contact area measured. Five of the seven studies using PMS included in the review recorded measures of force, although different approaches were used across studies. Oehme et al. (2019) recorded both “static” and “dynamic” force, while Oehme et al. (2018) recorded only a static measurement of force as it was an ex-vivo study using an amputated hoof attached to a load-applicator. Van Nuffel et al. (2009) and Van Nuffel et al. (2013) both recorded variables looking at asymmetry of force. Five studies using PMS recorded some type of measure of pressure and four recorded contact area. Kleinhenz et al. (2019) was the only study using PMS to record impulse.

In addition to recording force-related measures, PMS are also used to record spatial and temporal measures of gait. Although PMS is a kinetic-type technology, timing, and distance of hoofprints upon the platform can be used to calculate kinematic measures. Spatial measures which have been measured by PMS include stride length, tracking up, abduction, and asymmetry variables relating to spatial measures. Van Nuffel et al. (2009) also recorded measures looking at distance within hoofprints and distance between hoofprints in different spatial dimensions. Temporal measures which have been recorded by PMS include stride time, stance time, and step time. Van Nuffel et al. (2009) and Van Nuffel et al. (2013) also recorded stance time symmetry between left and right limbs. Further details on measures recorded through PMS are shown in Table 2.4.2.

2.4.4.3. Weight Distribution Platforms

Weight distribution platforms are technologies which measure weight distribution to evaluate aspects of locomotion, especially with regards to lameness detection. WDP technologies are more frequently being utilized within milking robots as automated milking systems (AMS) grow in popularity, although none of the studies included in this review involve a WDP within an AMS. Compared to other kinetic technologies, WDPs are more limited in the types of measures they can provide, as they only record “static” measures – measures while the cow stands – of weight distribution across limbs. They may measure weight distribution within one instant, or across a short period of time to evaluate shifting of weight between limbs. Thus, they provide an objective alternative to the subjective, visual observation of a cow’s reluctance to bear weight on a particular limb, which is commonly used when an overall gait score or the specific gait characteristic of limping is considered.

Two types of WDPs technologies have been used in research evaluating factors that may influence dairy cattle locomotion. The first is an Itin+Hotch weighing platform (Futterungstechnik, Liestal, Switzerland) consisting of 4 independent recording units with one hermitically sealed load cell (HBM, Volketswil, Switzerland) each, which has been used in four studies (Alsaaod, Fadul, Deiss, et al., 2019; Buisman et al., 2018; Nechanitzky et al., 2016; Neveux et al., 2006). The second is a Pacific Industrial Scale weighing platform (Richmond, British Columbia, Canada) consisting of 4 independent recording units each containing 4 hermetically sealed load cells (Anyload LLC, Santa Rosa, CA, USA, which has been used in two studies (Chapinal et al., 2010; Pastell et al., 2010).

2.4.4.3.1. Measures Recorded

Studies using weighing platforms to evaluate aspects of dairy cattle locomotion have recorded several different types of specific measurements relating to weight distribution among the cow’s legs. Limb weight ratio among either all four legs or between only the hind legs has been used as a measure of maximum weight asymmetry in several studies. The mean limb difference, which describes the weight difference across a healthy and a lame limb within a pair of limbs, has also been recorded. Other measures used include the mean weight applied on each limb and the standard deviation of weight applied on individual limbs, which allows for the determination of weight shifting between hind limbs. Finally, the mean standard deviation of weight applied to multiple limbs - either to all four, to the rear legs, or to the front legs – has also been recorded. Details of the measures recorded are shown in Table 2.4.2.

2.4.5. Accelerometry

Accelerometers are used in biomechanics for the purpose of recording acceleration. While accelerometry is a kinematic-related technology, the purpose of accelerometers is to primarily measure acceleration. Acceleration as a measure can be compared between limbs to identify an impaired limb or an abnormality in gait. Other kinematic-type variables can also be extrapolated from the recorded acceleration. For the purposes of this review, accelerometers are considered their own category of gait-assessing technology, as they are used differently and generally with greater ease and fewer limitations than kinematic technologies or PMS used to record kinematic-type measures. Accelerometers that have been used to evaluate aspects of animal behavior, rather than to evaluate locomotion specifically, will be discussed in the gait-associated measures section.

One type of accelerometer that has been used to record acceleration for the purpose of cow locomotion analysis is the Hobo Pendant G Acceleration Data Logger (Onset Computer Corp., Bourne, MA, USA). Chapinal et al. (2011) used five of these accelerometers, with 4 attached to the lateral side of each leg above the fetlock and one attached to the right of the dorsal midline. Franco-Gendron et al. (2016) used 2 of these accelerometers, which were each attached to a rear leg above the fetlock. One study, which aimed to measure acceleration of the whole cow rather than of individual legs, used the acceleration sensing system Vibration Measurement Pack MVP-A3 (MicroStone, Nagano, Japan). The sensor was placed at the posterior end of the thoracic vertebrae of the cow to measure vertical, forward, and lateral acceleration. A specific software (Vibration Measurement Pack1.7.5, MicroStone) was used to manage the system, and the storage device for the sensor was attached to the collar of the cow. Finally, several studies have used a USB Accelerometer X16-4 (GulfCoast Data Concept, Waveland, USA) along with the Cow-Gait-Analyzer, a pedogram developed by Alsaaod, Kredel, et al. (2017). For these studies, instead of focusing on acceleration as the outcome measure, the Cow-Gait-Analyzer is designed to extract kinetic and kinematic gait cycle variables from the acceleration data. Details of all accelerometer technologies used to record locomotion measures are shown in Table 2.8.3.

2.4.5.1. Measures Recorded

In studies using accelerometers to measure acceleration directly, the measurements used were mean acceleration and the asymmetry of variance of acceleration, which is meant to represent how irregular stepping patterns for the rear limbs were (Chapinal et al., 2011; Franco-Gendron et al., 2016). Tanida et al. (2011) measured the mean acceleration and variance of acceleration separately for the vertical, lateral, and forward directions. For studies using accelerometers in conjunction with the Cow-Gait-Analyzer pedogram, the kinematic outcomes were gait cycle duration, relative stance phase duration, and relative swing phase duration. The kinetic outcomes were foot load and toe-off, which are the maximum acceleration of the initial ground contact of the claw and of the termination of the ground contact of the tip of the claw, respectively (Alsaaod, Huber, et al., 2017). In two studies, these measures extracted from the Gait-Analyzer pedogram were used alongside measures of weight distribution recorded via WDP to evaluate how gait changed after lameness intervention surgery (Buisman et al., 2018) and after an analgesic to alleviate pain from lameness (Alsaaod, Fadul, Deiss, et al., 2019). The combination of these technologies allowed for both static and dynamic kinetic measures of locomotion along with the kinematic outcome measures of the pedogram, providing multiple approaches for recognizing how lameness was specifically impacted in these intervention studies. Details regarding locomotion measures recorded via accelerometers are shown in Table 2.4.3.

Table 2.4.3. Locomotion measures recorded and analyzed using accelerometers independently and accelerometers in conjunction with a validated pedogram.

Technology Type	Measure Category	General Measure	Measure Description/Approach	Reference
Accelerometer	Acceleration	Acceleration	Mean acceleration	Chapinal et al., 2011; Franco-Gendron et al., 2016
			Forward lateral and vertical acceleration (to describe pattern of acceleration of whole body of cow)	Tanida et al., 2011 (Trial 2)
		Acceleration variance	Mean variance in acceleration of cows' backs before and after hoof trimming	Tanida et al., 2011 (Trial 2)
		Acceleration asymmetry	Asymmetry of acceleration variance (%)	Chapinal et al., 2011; Franco-Gendron et al., 2016
Accelerometer + Pedogram	Kinematic	Gait cycle duration	interval between 2 consecutive foot load peaks	Alsaaod, Huber, et al., 2017
		Stance phase duration	percentage of time claw is in contact with the ground relative to the total gait cycle	Alsaaod, Huber, et al., 2017; Buisman et al., 2018; Alsaaod et al., 2019
		Swing phase duration	percentage of time in swing phase relative to total gait cycle	Alsaaod, Huber, et al., 2017; Alsaaod et al., 2019
	Kinetic	Foot load	maximum acceleration of the initial ground contact of the claw	Alsaaod, Huber, et al., 2017; Buisman

		Toe-off	maximum acceleration of the termination of the ground contact of the tip of the claw	et al., 2018; Alsaaod et al., 2019

2.4.6. Other Approaches to Recording Locomotion Measures

"Manual kinematic" approaches often involve the use of software outside of those that are focused on gait analysis, such as software that allow for processing of images from a recorded video of a cow walking. For example, Tanida et al. (2011) calculated the range of vertical and forward movement of each limb by looking at the difference in the maximum and the minimum value of pixels in the x- and y-axes. Manual kinematic analysis may also involve the use of various types of software to calculate walking speed of a cow within a video by recording the time taken for the cow to walk between two points of a known distance (Chapinal et al., 2010; Walker et al., 2010). Additionally, variables like walking speed, step speed, and number of strides per passage have also been recorded by humans via live observations with stopwatches or observations as cows pass between two physical markers in video recordings. Several studies have used these "manual kinematic" or objective "human observed locomotion variable" approaches along with measures of locomotion recorded by the Level A kinematic, kinetic, or accelerometer technologies (Franco-Gendron et al., 2016; Tanida et al., 2011; Walker et al., 2010). In some cases, these measures were used as a way to validate measures being recorded via Level A technologies, while in other cases they were used as an additional method for recording a locomotion measure which was not recorded via other technologies being used.

Visual locomotion scoring was a frequently used method of providing an overall score for gait or for providing scores of individual characteristics or attributes of gait, such as joint flexion. Twenty-four studies in this review used locomotion scoring (also termed gait, mobility, or lameness scoring) to assess the locomotor ability of cows, with several more studies use locomotion score in the process of selecting animals to be included in studies. Multiple types of numeric rating systems, most commonly 3- or 5-point scales, and analog scales, typically marked on a line representing values from 0 – 100, were used. Additionally, defining gait characteristics which were scored or used to determine an overall gait score varied between scoring approaches used.

2.4.7. Approaches for Recording Physiological and Behavioral Gait-Associated Measures

Multiple approaches have been used to record measures which do not directly focus on gait characteristics but rather may be associated with changes in locomotor ability or factors which may contribute to impaired locomotor ability. Sensors, accelerometers, and live observations have been used for recording behavioral measures, as measures which provide information as to how the cow is distributing her time (e.g. lying time vs. time spent active) may provide insight into a cow's locomotor ability (Blackie et al., 2011). Although these behavioral measures are often recorded via accelerometer technology, they are considered "gait-associated" measures, as they are not direct measures of locomotion. Approaches using surface electromyography (SEMG), infrared thermography (IRT), pain measurement devices, ultrasonography, and hematology have been used for recording physiological measures. Additionally, hoof disorder identification and scoring methods have been commonly used to subjectively record the presence and severity of various hoof pathologies. These "gait-associated" measures have been used in addition to locomotion measures recorded through Level A technologies or independently of locomotion measures for purposes of comparing or exploring relationships between multiple types of potentially gait-associated measures. The categorizations and relationships of gait-focused and gait-associated measures and the technologies and methods used to record them are shown in Figure 2.4.2. Finally, the hoof and leg injuries or disorder which often cause locomotor impairment may be associated with other types of measures relating to the general health of the cow. Studies in this review which recorded general health measures generally focused on those relating to stress or immunology.

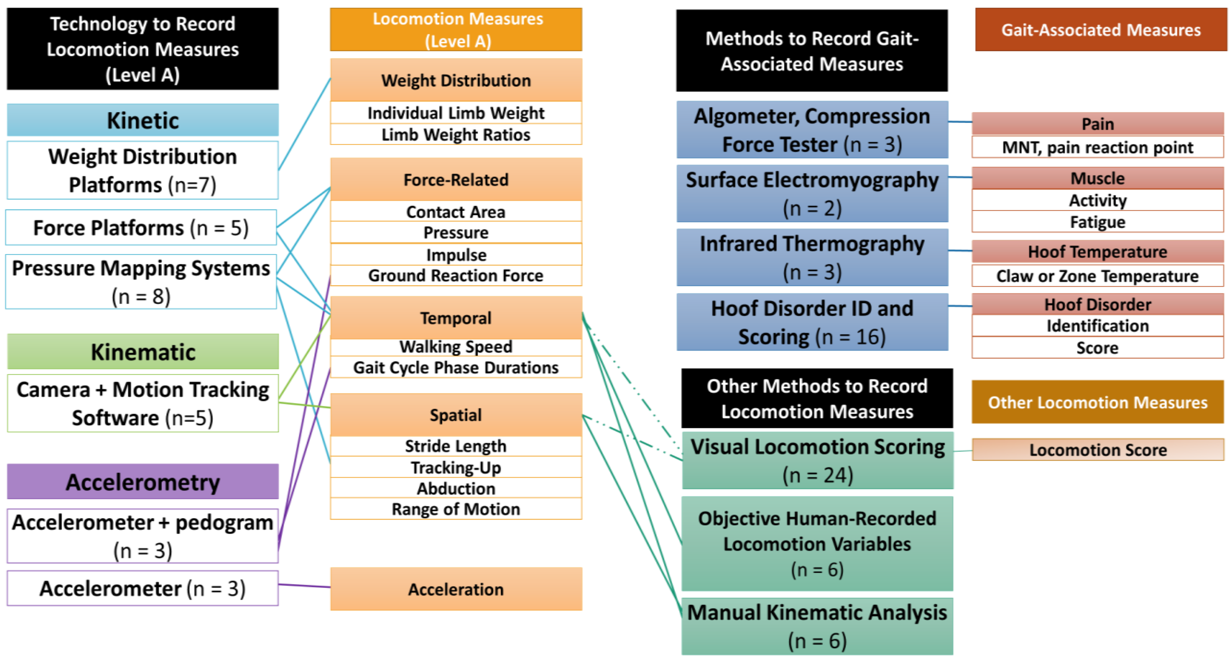

Figure 2.4.7. Relationship diagram of types of measures recorded by studies in this literature review and the methods used to record them. (Note: not all measures are listed for each measure category. Examples of common measures are displayed. Additionally, types of behavioral, gait-associated measures and the approaches for recording them are not included, but are explained in the text of section 2.4.7)

Factors that have been evaluated through the use of Level A kinematic, kinetic, and accelerometer technologies to record measures of gait fall into the two broad categories of environmental factors and cow-level factors. For the purposes of this review, all factors that involve the housing and management of cows, including health and maintenance procedures that are performed on them, were considered “environmental” factors. Factors intrinsically related to the cow’s body, such as the presence of hoof disorders or lameness itself, were considered “cow-level” factors.

2.4.7.1. Approaches used to record locomotion measures when evaluating environmental factors

The most commonly studied environmental factor was flooring type or walking surface. In the ten studies that evaluated flooring, all three “direct” technology approaches to recording gait measures as well as methods for recording gait-associated measures were used. Two studies used kinematic technology (Flower et al., 2007; Franco-Gendron et al., 2016) to record kinematic gait measures, and one (Telezhenko et al., 2017) used a manual kinematic approach. Three studies used kinetic technology to record kinetic measures of gait. Ouweltjes et al. (2009) used kinetic technology to record kinematic-type measures, as well. Kinetic technologies used to evaluate flooring in some cases focused only on the interaction of the type of surface itself with a hoof via static measures, while others focused on the interactions of the surface with the hooves as the cow walked over it via dynamic measures. Oehme et al. (2018) used a load applicator with amputated limbs to look at pressure distribution on different types of rubber mats, so only static kinetic measures were recorded. Oehme et al. (2019) recorded both static and dynamic kinetic measures, and Ouweltjes et al. (2009) recorded only dynamic kinetic measures. Three studies used accelerometer technology: two studies (Chapinal et al., 2011; Franco-Gendron et al., 2016) used accelerometers to record acceleration, while one study (Alsaaod, Huber, et al., 2017) used accelerometers in conjunction with a pedogram to extract kinematic- and kinetic-type outcome measures. Two studies (Rajapaksha & Tucker, 2015; Schutz et al., 2018) used only gait-associated measures, and primarily focused on measuring muscle activity and fatigue via surface electromyography along with number of steps taken via a live human observer as cows were standing over different flooring surfaces simultaneously placed under different hooves.

The second most studied environmental factor was hoof trimming. In the five studies evaluating how hoof trimming affected gait, gait measures would either be recorded and compared from before and after hoof trimming, or gait measures would be recorded and compared between cows who underwent different types of hoof trimming methods. Three studies (Carvalho et al., 2005; Ouweltjes et al., 2009; Thorup et al., 2014) used kinetic technologies to record kinetic gait measures, and Ouweltjes et al. (2009) additionally used kinetic technology to record kinematic-type measures. Two studies looking at effects of hoof trimming on gait used accelerometers. Alsaaod, Huber, et al. (2017) used accelerometers in conjunction with a pedogram to extract kinematic- and kinetic-type measures. Tanida et al. (2011) looked at the overall acceleration as the cow walked with an accelerometer attached over her thoracic vertebrae, and used the manual kinematic approach of image analysis to look at kinematic measures involving range of motion of limbs.

Three studies evaluated how some type of lameness intervention affected gait. Alsaaod et al. (2019) used accelerometers along with a pedogram to obtain kinematic- and kinetic-type outcome measures as well as a WDP to measure weight distribution when evaluating the effects of an analgesic on cows who had limb pathologies. Buisman et al. (2018) used the same approach with an accelerometer used with a pedogram and a WDP to evaluate gait after foot surgery to address foot pathologies. Kleinhenz et al. (2019) used kinetic technology to evaluate effects of an analgesic on gait of cows with clinically induced lameness. Finally, one study (Yamamoto et al., 2014) investigated how diet supplementation with trace minerals affected kinematic gait parameters as measured through a manual kinematic approach.

2.4.7.2. Approaches used to record locomotion measures when evaluating cow-level factors

Twelve studies recorded measures which evaluated how lameness or how known sources of lameness, such as hoof pathologies, affected gait. These studies primarily used kinematic or kinetic technologies to record measures of gait. However, several studies only used physiological gait-associated measures such as hoof temperature measured via thermal imaging (IRT) of pain as measured by hoof-testers or algometers as approaches evaluate locomotor ability beyond visual locomotion scoring. One study (Oikonomou et al., 2014) had an objective of determining if digital cushion thickness influenced sole temperature as measured by IRT. One study (Dyer et al., 2007) focused on pain as recorded via algometer and hoof testers as a measure of how hoof disorders can influence gait, and two studies (O'Driscoll et al., 2015; O’Driscoll et al., 2009) also focused on how other health-related measures, such as leukocyte profile, gene expression, and metabolite status were associated with the presence of hoof disorders. The majority of these studies recorded a visual locomotion score, an identification and subjective severity scoring of hoof pathologies, or both. Studies which focused more on gait-associated measures and did not use a direct technology approach for recording gait measures relied on subjective gait scoring to record measures which provided information about cows’ gait. One study (Van Nuffel et al., 2009) focused on if human observers were able to detect differences in gait due to hoof disorders or lameness via locomotion scoring as compared to kinematic measures recorded by a PMS. Another study (Van Nuffel et al., 2013) focused on variation of measures of specific gait variables when looking at early signs of lameness measured via a PMS.

2.5. DISCUSSION

Technologies used in dairy cattle gait analysis to record measures of locomotion have been adapted from technologies and research methods which were initially developed for use in horses and humans. The intended use and application of these technologies with these species may differ from how they are used in research with cows, where locomotion is typically assessed for the purpose of identifying lameness or impairment since lameness is of major concern within the dairy industry (Nejati, 2021). This may explain the differences in specific types of technology used and how technology set-ups are different in areas designated for recording gait. The results of objective 1 of this review indicate that a wide variety of approaches have been used to record similar types of gait measures across multiple technologies and other approaches. If one were to go a step further to conduct meta-analyses with data from these types of studies, a number of factors regarding (i) differences in the technologies used, (ii) approaches taken, (iii) equipment arrangements, (iv) technical aspects of equipment used, and (v) terminology of outcome measures would need to be taken into consideration. Additionally, the research contexts outlined in the objective 2 results of this review would need to be considered, as the environmental or cow-level factors influences which approaches of recording and analyzing gait measures are used.

The studies in this review using video recordings and motion analysis-specific software had cameras arranged usually only to view one side of the body, which, in some cases, allowed for kinematic measures to be recorded for only two ipsilateral limbs. Cameras were often placed at different distances from the “walkways,” which also had varying dimensions between studies. As all these studies within this review used only one camera, only 2D kinematic analysis could be performed, therefore making it difficult to minimize the effects of the differences between camera and walkway setup and camera differences, such as lens thickness and recording rate (frames/s recorded at). Types of markers used as well as their attachment locations on the cow were different between studies. However, within the studies using direct kinematic technology approaches for recording kinematic measures, definitions between studies remained fairly consistent. For studies using only manual kinematic approaches to record kinematic measures, differences between how different types of software used work and how images or videos are processed between studies could result in greater inconsistencies in what could otherwise appear to be similar types of measures.

Studies in this review which used kinetic technologies had greater overall variation in terminology and approaches taken to recording specific measures, as well as differences between technology types and physical arrangements of platforms used. In studies using FP technology, two were used in conjunction with PMS, for primarily calibration and PMS measure adjustment purposes, while the other three studies used them independently. For studies using FP or PMS technologies, platforms could be arranged in parallel or with several in a row. However, dimensions of platforms in studies using a parallel arrangement were generally consistent, being around 2m in length. In one study, pressure film was placed inside a shoe worn on the hoof of the cow. These differences in arrangements meant that some studies only recorded data from one pair of limbs during a gait cycle while others recorded data for all four limbs.

Both FP and PMS studies recorded force-related measures; however, FP technologies could only record the sum of force on a platform, while PMS could calculate force based on the pressure applied over a number of sensors within the platform. PMS studies which recorded kinematic-type measures often used the same terminology as studies using kinematic visual motion-tracking approaches to recording kinematic measures, although clear definitions and calculations used to obtain these measures were not always provided. One study (Van Nuffel et al., 2009) also used unique terminology with a set of spatio-temporal measures acquired via PMS, which would be difficult to directly compare to the more straightforward spatial and temporal types of measures reported by other studies. For all studies using kinetic technologies, differences such as thickness in rubber mats placed over platforms, recording frequency, and filters or adjustments made to raw recordings should be taken into account. Studies using WDP used two brands of commercially available WDP across 6 studies. While recording frequency sometimes varied, all these studies had the goal of measuring weight distribution amongst limbs, and therefore calculated ratios which could be more easily compared across studies than those measures recorded studies using FP or PMS technologies.

In studies using accelerometers to record acceleration or to extrapolate other gait measures through use of a pedogram, different types of accelerometers with different recording frequencies were used. However, two studies used the same brand of accelerometer, same recording frequency, and same or similar placement of the sensor on the cow to measure acceleration. One study used an independently developed sensor and, after validation with use on the limbs, placed it at the cow's thoracic vertebra with the goal of measuring the acceleration of the cow's body overall. In the three studies using the accelerometer in conjunction with the validated pedogram from Alsaaod, Kredel, et al. (2017), the technology and approach used were all the same. While these extrapolated kinematic and kinetic outcome measure would be comparable between studies using this approach, they could not be directly compared to measures from studies which recorded kinematic- and kinetic-type measures through kinematic-focused or kinetic-focused technologies.

In studies using kinematic or kinetic technologies, factors such as the size, body shape/breed, and weight of the cow may influence measures, and therefore have been reported in some cases. In some studies in which kinematic technology was used, measurements of specific body parts of the cow were manually recorded and used as a calibration measurement within a motion analysis software. However, some studies have provided additional details regarding morphometric features of cows which may influence outcome measures such as claw dimensions, for which interactions were checked when looking at the effects of hoof trimming and different flooring types as measured by PMS (Ouweltjes et al., 2009).

Finally, many of these studies compare gait measures recorded through these direct technology approaches to aspects of gait that are recorded through subjective locomotion scoring systems. Locomotion scores or specific gait attribute scores within locomotion scoring methods are also often used supplementary to these measures acquired through direct approaches. In studies which focused more on physiological or behavioral measures which were associated with gait as a method of measuring factors affecting locomotion, locomotion scoring was used as the primary approach to recording gait-measures. While locomotion scoring is a more convenient approach to evaluating gait that does not require extra materials or technology, it is difficult to compare as an actual measure across studies. Visual locomotion scoring is still comparatively subjective, with often low intra- and inter-observer reliability, and multiple methods which may focus on different aspects of gait exist (Schlageter-Tello et al., 2014). Additionally, locomotion scores as a comparison provide a very general idea of a cow's gait and lack the ability to provide an actual objective value for a more specific type of measure. For example, many numeric rating scales used for locomotion may focus on "asymmetry" as an aspect of gait that is evaluated by an observer. However, when we look at studies using direct technologies, many of them look at differences between more specific types of measures like stride duration, stride length, or acceleration between contralateral limbs as an approach for measuring asymmetry. When a locomotion scoring method simply instructs an observer to look at "asymmetry" without additional details, it is understandable to see how many different interpretations as to what part of the cow or what exact aspect of movement (differences in spacing or in timing) should be focused on could arise. Despite differences in technical aspects, physical arrangements, and approaches involved when using kinematic, kinetic, and accelerometer technologies, the amount of data they record allows for much more specific outcome measures to be obtained. These measures and their results can then be more easily compared across studies, especially when detailed terminology and methodology is provided.

2.6. CONCLUSION

The use of automated locomotion or lameness assessment technologies is of great interest to both producers and researchers. Accurate and early detection of signs of locomotor impairment that would not require the training, time commitment, and sometimes low reliability of visual locomotion scoring would be beneficial for on-farm practical purposes as well as to use in research focusing on a range of factors which may influence dairy cattle locomotion. Kinematic, kinetic, and accelerometry technologies are alternative approaches that can evaluate specific aspects of locomotion with a greater level of detail and provide a greater number of outcome measures than visual locomotion scoring. However, the inconsistencies in how these technologies are set up to record locomotion measures and how such measures are defined in research settings demonstrates that kinematic, kinetic, and accelerometry technologies are still in relatively early stages of use in dairy cow locomotion research. Reaching conclusions about specific factors which influence locomotion through the outcome measures of these three technologies across all studies which have used them is not yet feasible, as there is not currently enough overlap between the types of technologies and measure-recording approaches used. The inconsistencies in technology use and lack of overlap between studies also highlights the need for a set of standard guidelines to be developed future use with these technologies in research. The multiple other methods for evaluating locomotion which have been used to circumvent the limitations of these technologies, such as the recording of physiological or behavioral measures associated with gait or more manual methods of recording locomotion measures, also encompass a wide range of measure types and approaches which are difficult to compare across studies. These other approaches also do not provide the straightforward, detailed locomotion measures which are possible through kinematics, kinetics, and accelerometry. Additional research using these three technologies, as well as technical advancements and the development of strategies to overcome their current limitations, are needed to fully evaluate how environmental and cow-level factors of interest may specifically change dairy cow movement.

2.7. SUPPLEMENTARY MATERIAL

Supplementary Table 2.7.1. Details of the kinematic gait-analysis software and cameras used from section 2.4.3. (fps = frames/s)

Software	**Camera Details**	**Distance/#Strides Recorded per passage**	**Markers**	**Reference**
PEAKMotus version 3.2 (Peak Performance Technologies, Inc., Englewood, CO, USA)	One camera (Panasonic AG_195MP, Matsushita Electric, Mississauga, ON, Canada); 60 fps; 6.75m placement distance; left-side view	7.05m long; at least 2 consecutive strides	One reflective marker made of tape (0.04 x 0.22m) backed with back cloth (0.15 x 0.22m) wrapped around circumference of each leg directly above metacarpo- and metatarsophalangeal joints	Flower et al., 2005
PEAKMotus version 7.1.1 (Peak Performance Technologies, Inc., Englewood, CO, USA)	One camera (Panasonic AG_195MP, Matsushita Electric, Mississauga, ON, Canada); 9.6m placement distance; right-side view	7.4m long; at least 2 consecutive strides		Flower et al., 2007
Simi Motion Analysis software (Simi Reality Motion Systems GmbH, Unterschleißheim, Germany)	One Camera (Canon PAL MV690; Canon UK Ltd., Borehamwood, UK); 15m placement distance, 4.5m field of view	1.6m	Yellow, cardboard markers (3cm diameter) glued with contact adhesive (Evo-stick 528) onto left side of cow at fore coffin, fore fetlock, knee, elbow, hind coffin, hind fetlock	Blackie et al., 2011
	One Camera (Canon PAL MV690; Canon UK Ltd., Borehamwood, UK); 7m placement distance	1.6m wide; 1 stride analyzed per passage	Above details (right side only) + speherical orange table tennis balls (4cm diameter) attached to skin over thoracic vertebrae 3 and 7 (T3 and T7), Lumbar vertebrae 1 and 4 (L1 and L4), the cranial end of the sacral vertebrae (SA) and on the TA	Blackie et al., 2013
MoviAs Pro tracking program (version 1.63g: 3D, NAC Image Technology, SimiValley, CA, USA)	One camera (uEye UI-1225LE-C, Imaging Development Systems GmbH, Obersulm, Germany) with 4.8mm lens (Pentax CCTV C418DX, 1:1.8, Pentax Ricoh Imaging Amercas Corporation, Denver, CO, USA); right-side view; 9.7m and 11.8m placement distances from corridor 1 and 23, respectively	Digitalized 3 or 4 strides at 30 fps	2 reflective plastic ball markers (3.18 cm; B & L Engingeering, Santa Ana, CA, USA) sewn onto 12cm-wide adjustable black elastic band placed on the metatarsal and metacarpal regions of right limbs; 2 reflective plastic balls placed on floor (8.57m apart) for reference	Franco-Gendron et al., 2016

Supplementary Table 2.7.2. Locomotion measures recorded and analyzed using force platforms, pressure mapping systems, and weight distribution platforms.

Technology Category	Technology Type	Dimensions and Technical Aspects	Additional Technology Used	Reference
Force platforms	Step Metrix (Bou-Matic, LLC, Madison WI, USA)	2 metal, parallel biomechanical force plates supported by 4 load cells; 200 Hz frequency; 5mm rubber mat		Liu et al., 2011
	custom-designed 3D strain gauge force plates (Bertec Corp., Columbus, OH)	2 parallel plates; 2 kHz frequency; force signals low-pass-filtered at cut-off 5 Hz frequency; 13mm rubber mat	custom-made data acquisition system (Mr. Kick, Knud Larsen, Aalborg University, Denmark, based on National Instruments technology, Austin, TX); fourth-order, zero-lag Butterworth filter (Matlab 2006, The MathWorks Inc., Natick, MA)	Thorup et al., 2014
	Kistler force plate (Kistler Corp, Winterthur, Switzerland)	600 mm × 900 mm; 250 Hz frequency; 5-6mm rubber mat		Van der Tol et al., 2003
	custom-made AMTI (Advanced Mechanical Technology Inc.) Hall effect force plates	5 plates (0.6 x 0.9m); three-axis, twelve channel plates; 200 Hz frequency	Custom made software written in MATLAB (R14, The Mathsworks INC., Natick, MA, US) used to record GRF data in raw binary format	Walker et al., 2010
	force platform (metal base plate; details not provided)	1112 N load cells at corners supporting top plate		Carvahlo et al., 2005
Pressure Mapping System	MatScan system (MatScan, Tekscan, Inc., South Boston, MA.)	2288 sensels; spatial resolution of 1.4 sensel/cm2; customized to a pressure range of 1 - 10,350 kPa; 40 Hz frequency		Carvahlo et al., 2005
		244 x 45 cm^2	software (HUGEMAT Research 5.83, Tekscan, Inc.),	Kleinhenz et al., 2019
	Hoof™System (M3200E, Tekscan Inc., Boston,	0.15 mm thick sensors; cut in shape of claw and fitted into leather claw shoes	HoofSCAN Research software (version 6.85, Tekscan Inc., Boston, MA, USA)	Oehme et al. 2018

	MA, USA) foil-based piezoresistive pressure measurement system	0.23 mm thick sensor foils; 167.6 x 167.6 mm sensor matrix; 3.9 sensels/cm^2 resolution	HoofSCAN Research software (version 6.85, Tekscan Inc., Boston, MA, USA)	Oehme et al., 2019
	Footscan (RsScan International, Olen, Belgium)	976 x 325 mm^2 surface; contains 8.192 conductive polymer sensors, 5 x 7.6 mm2 each	Footscan 2D box;	Ouweltjes et al., 2009
				Van der Tol et al., 2003
	GAITWISE system (developed by Maertens et al., 2011)	consists of Gaitrite sensor (CIR Systems Inc., Havertown, PA, USA);		Van Nuffel et al., 2013
	pressure-sensitive mat (Maertens et al 2008)	0.61 m wide x 4.88 m long surface; 48 x 384 sensor elements array, each 1266 cm2; 2D; 60 Hz frequency		Van Nuffel et al., 2009
Weight Distribution Platform	Itin+Hotch weighing platform (Futterungstechnik, Liestal, Switzerland)	4 independent recording units (0.78 × 0.55 meach) with one hermitically sealed load cell (HBM, Volketswil, Switzerland); 1.94 × 1.06 m; covered with 1 cm-thick individual rubber mats; 10 Hz frequency		Alsaood et al., 2019
				Buisman et al., 2018
				Netchanitsky et al., 2016
		4 independent recording units (each 56 × 91 cm) fitted in a 1.9 × 1.3m enclosure; 2 singlepoint load cells (Vishay Tedea-Huntleigh model 1250; Vishay, Selb, Germany) in each recording unit; load cells mounted off-center at either end of each unit; 3.8 cm rubber mats (under some hooves for some treatments)	FieldPoint acquisition hardware (National Instruments, Austin, TX)	Neveux et al., 2006
	Pacific Industrial Scale weighing platform (Richmond, British Columbia, Canada);	4 independent recording units (12 cm high × 59 cm wide × 99 cm long) each containing 4 hermetically sealed load cells (Anyload LLC, Santa Rosa, CA, USA); data transmitted to computer at a rate of 14 readings/s; covered with 1.5-cmthick revulcanized rubber mats	software (CowWeigh.exe version 2.2, Pacific Industrial Scale Co. Ltd.) to provide real-time display of the weight applied	Chapinal et al., 2010

		4 independent recording units (each 56 × 91 cm) fitted in 1.9 × 1.3m enclosure; 6 Hz frequency		Pastell et al., 2010

Supplementary Table 2.7.3. Locomotion measures recorded and analyzed using accelerometers, either independently or in conjunction with a pedogram.

3D Accelerometer Type	Recording Frequency	Number and Location	Reference
Hobo Pendant G Acceleration Data Logger (Onset Computer Corp., Bourne, MA, USA)	33.3 Hz	5 total ; 4 attached to lateral side of each leg above fetlock; 1 attached to right of dorsal midline	Chapinal et al., 2011
	33 readings/s	2 total (each attached to a rear leg above fetlock)	Franco-Gendron et al., 2016
Vibration Measurement Pack MVP-A3 (MicroStone, Nagano, Japan) + software (Vibration Measurement Pack1.7.5, MicroStone)	Not provided	Sensor placed at posterior end of thoracic vertebrae	Tanida et al., 2011(trial 2)
USB Accelerometer X16-4 (GulfCoast Data Concept, Waveland, USA) + pedogram (Cow-Gait-Analyzer; developed by Alsaaod, Huber et al., 2017)	400 Hz	2 total; fitted at the level of mid metatarsus/metacarpus to both hind or fore limbs of affected limb pair	Buisman et al., 2018
		2 total; fitted at level of either both metatarsi or both metacarpi, depending on location of pathology	Alsaaod et al., 2019
		2 total; fitted level of the metatarsus to both hind limbs	Alsaaod, Huber, et al., 2017

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CONNECTING TEXT

Chapter 2 provided a review of the studies evaluating factors that influence gait quality through kinematic, kinetic, or accelerometry technologies or through alternative approaches. The specific measures that had been recorded by these technologies were listed in detail and relationships between the types of measures recorded and technologies or methods used to record them were drawn out. Studies were also grouped by the environmental and cow-level factors they evaluated. Similarities and differences in terms of measures recorded and technologies or methods used between studies evaluating the same factors were discussed. It was determined that, overall, factors regarding (i) differences in the technologies used, (ii) approaches taken, (iii) equipment arrangements, (iv) technical aspects of equipment used, and (v) terminology of outcome measures make comparison of locomotion measures between these studies difficult. These inconsistencies also demonstrate that use of these technologies for the evaluation of dairy cow gait is still in relatively early stages; technological advancements, methods to overcome the current limitations of these studies, and a greater amount of research using these technologies would be needed to provide more overlap of these detailed types of locomotion outcome measures across studies. Studies using kinematic technology to assess locomotion had more consistency in the approaches and definitions used across measures than studies using kinetic or accelerometry technologies. In comparing measures recorded used by the technologies of primary interest to traditional gait scoring systems, we could demonstrate that while similar aspects of gait are evaluated through both methods, the kinematic technologies provide more detailed information at a greater level that allows further insight to the reason behind the changes or abnormalities in a cow's gait.

Chapter 3 consists of an experimental study with the goal of validating a kinematic system used in conjunction with machine learning approaches to predict a commonly used numeric rating system (NRS) locomotion score. The kinematic system, consisting of 6 cameras and a motion tracking software, was used to acquire 3D-scaled coordinates of trajectories of specific joints on the cow as she walked. Locomotion scores were determined for each individual passage recorded by the kinematic system. Kinematic data and the corresponding locomotion score for each passage were then used to train a convolutional neural network (CNN) and a recurrent neural network with long short-term memory (LSTM) architecture. Both model types were tested with data from a separate set of passages (individual recordings of a cow walking the duration of the designated path). A high accuracy in the predictions of the model(s) would show that the level of locomotor ability that is visually observable is reflected - in greater detail - in the kinematic data.

CHAPTER 3 – Using 3D-kinematics in conjunction with machine learning approaches to predict dairy cow locomotor ability via a numeric rating system

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3.1. ABSTRACT

Lameness, or impaired gait, is a prevalent issue within the dairy industry that has serious financial and welfare implications. Traditional visual locomotion scoring systems provide a simple way to assess dairy cow gait but are prone to low reliability and are relatively subjective compared to more automated approaches. In this validation study, a kinematic system and motion tracking software able to acquire 3D-scaled coordinates of 20 specific joints on a cow as she walks were used in conjunction with machine learning approaches to evaluate if a locomotion score could be predicted from kinematic data with high accuracy. Building off previous work using similar data with a Convolutional Neural Network (CNN), the objective of the study was to develop a model with Long Short-Term Memory (LSTM) architecture that could predict dairy cow locomotion score based off of kinematic data. Kinematic data was acquired through processing of videos of cows walking within a motion tracking software. The hypothesis was that kinematic data would reflect what was visually observable by a trained individual conducting locomotion scoring. Seventy-four cow-passages with 4 consecutive classes of gait in the middle of the range of the 9-classes NRS scores (5 point scale with 0.5 intervals) were kept for analysis. The hypothesis was rejected, and the best performing model (LSTM) achieved an average accuracy of only 38%. Previous work using a CNN to classify lame and non-lame cows, upon which the current CNN was based, yielded an average accuracy of over 90%. Three-dimensional kinematic data had better predictive potential for binary classification

compared to the scale encompassing 4 locomotion scores used in the current study. Future work will incorporate additional visually observed scores for specific gait attributes (tracking up of hind limbs, joint flexion, etc.) to help improve model performance. As technology for recording 3D kinematics advances, camera system mobilization will allow for widespread, on-farm application. This technology, in conjunction with appropriate neural network approaches, could eventually eliminate the need for gait scoring altogether. Such technology would help identify changes in gait early on in cows with more subtle forms of locomotor impairment to help reduce cases of severe lameness, contributing to improved management and better cow welfare.

3.2. INTRODUCTION

Lameness in cattle, which results from pain or discomfort due to hoof or leg injuries and disease (Flower & Weary, 2009), is a prevalent issue within the dairy industry. It is a serious welfare concern and is considered the third most costly health issue for dairy cows after mastitis and reduced fertility (Dolecheck & Bewley, 2018). Early detection of lameness or gait abnormalities which may lead to lameness is crucial for minimizing the costs and welfare concerns associated with impaired locomotion (Van Nuffel, Zwertvaegher, Van Weyenberg, et al., 2015).

Visual locomotion scoring systems have been commonly used among both researchers and producers because they are non-invasive, inexpensive, and relatively easy to carry out (Schlageter-Tello, Bokkers, Koerkamp, et al., 2014). They typically consist of an overall value given to represent gait quality on a scale with multiple classes (commonly 3, 5, or 9 classes) or on an analog scale (0-100), often with prescribed aspects and quality levels of gait defined for each score. Some visual scoring systems also incorporate additional scores for specific attributes of gait, such as reluctance to bear weight on a limb or asymmetry of gait, which are typically provided for observers through detailed charts. While the simplicity of visual scoring makes it a practical choice for researchers and producers, it is not ideal as a gold standard because it is prone to low reliability within and between observers (Channon et al., 2009). At least 25 different visual scoring systems exist (Van Nuffel, Zwertvaegher, Pluym, et al., 2015), encompassing a wide range of numeric scales and different attributes of gait and postures focused on (Schlageter-Tello, Bokkers, Groot Koerkamp, et al., 2014). Aspects of these visual scoring charts can also be interpreted differently between individual observers, leading to inconsistency between scores (Channon et al., 2009). These inconsistencies make it difficult for locomotion scores to be used as comparable outcome measures across studies. Additionally, the traditional method of identifying impaired gait on-farm through visual locomotion scoring is time consuming and requires training of observers, making producers less likely to dedicate time and labor towards conducting this type of gait assessment (Alsaaod et al., 2019; Dolecheck & Bewley, 2018). This contributes to lameness prevalence being often underestimated by producers (Cutler et al., 2017). Therefore, researchers have begun testing alternative, automated methods of gait assessment which could provide more detailed measures regarding locomotion (O'Leary et al., 2020; Van De Gucht et al., 2017) to allow for easier comparison across research and for earlier detection of changes in gait that may be identified and treated before more severe lameness develops.

One of those alternative approaches using automated technology is the use of kinematics. Kinematics is a sub-category of biomechanics which focuses on how a body moves through space and time. Kinematic technologies have been previously used to study gait in humans and horses but are relatively novel in research evaluating dairy cow gait (Nejati, 2021). Technologies to evaluate kinematics are most commonly vision-based, as spatial and temporal aspects of motion are visually observable. Kinematic systems used in research typically consist of cameras used for video recording, in arrangements that allow for either 2- or 3-dimensional motion analysis, and a method for image processing or video analysis. Studies using vision-based kinematics for gait analysis also commonly use some form of marker attached to the cow at anatomical landmarks. Image processing approaches to kinematics used with dairy cows have typically only focused on one anatomical region for identifying lameness (such as focusing of the spine to determine back position or focusing on hoof position to determine step length), which may be limiting because lameness can manifest in multiple parts of the body and affect multiple aspects of gait (Nejati, 2021). For example, Abdul Jabbar et al. (2017) recorded video with an overhead depth camera and used 3D-depth images to track the height of specific regions on the cow's back such as the hooks and the spine. Nevertheless, image processing approaches to kinematics have the potential to be used as automated systems for on-farm lameness detection when combined with machine learning (ML). Wu et al. (2020) implemented the YOLOv3 deep learning algorithm with recorded video of cows walking to obtain the size of steps taken by the front and rear legs, and was able to identify lame and non-lame cows with a 98% accuracy using a long short-term memory classification model.

Studies using kinematic video analysis approaches for evaluating gait have the benefit of being able to evaluate the entire body of the cow as she walks, encompassing multiple anatomically relevant locations and multiple aspects of gait (Nejati, 2021). Multiple studies have used kinematic motion tracking to analyze gait when studying factors that influence dairy cow locomotion, such as hoof pathologies (Blackie et al., 2013; Flower et al., 2005) and flooring (Flower et al., 2007; Franco-Gendron et al., 2016). Motion tracking software allow for measures of locomotion focusing on specific spatial or temporal aspects of gait and on specific parts of the body to be obtained. These measures often resemble the aspects of gait that are focused on in visual locomotion scoring systems; measures like stride length, tracking up, and range of motion that can be obtained through motion tracking software reflect common visually observed gait attributes such as gait symmetry, tracking up, and joint flexion. However, when these measures are obtained through motion tracking software, they have more data to explain in detail what is occurring with each aspect of gait as the cow walks. Kinematic data are also not prone to the reliability issues that coincide with the subjective nature of visual locomotion scoring. Finally, motion tracking software is able to obtain kinematic locomotion measures that could not be observed with the human eye alone, such the maximum height of specific joints on the limbs or lengths of specific regions of the spine during movement as recorded by Blackie et al. (2011). These more detailed types of measures would be especially useful for detecting minute or less-obvious changes in gait that would help identify the development of locomotor impairment earlier on. However, the previous studies using commercially available motion analysis software for dairy cow gait analysis have only used one camera, and therefore were limited to a 2D analysis of gait. Two-dimensional analysis has limitations such as parallax error, through which a measurement of length may appear inaccurate, when the body moves too far away from the camera's optical axis (Nejati, 2021). In 2D analysis, movement across the third dimension is not accounted for accurately.

Previous work conducted by Karoui et al. (2021) used similar kinematic data, obtained from a predecessor of our current kinematic system, to test the ability of a Convolutional Neural Network (CNN) to identify lame cows. Cows were designated as lame if they were assigned a score of 3 or higher according to a visual locomotion scoring system (the 5 pt. numeric rating system (NRS) developed by Flower and Weary (2006)). The CNN performed well with lame cow classification, yielding results with the performance metrics of accuracy, precision, recall, and F1-score above 90%. While automated identification of clinical lameness is useful, oftentimes smaller changes in gait or gait abnormalities which are less obvious than limping may develop before more severe, obvious cases of lameness appear. Gait which exhibits these more subtle abnormalities but where the cow's movement is not yet severely impaired would be represented by scores within the NRS that are between "perfect" and "severely lame". Identifying cows at this locomotor ability level will help allow for intervention and prevention of more severe cases of lameness. The objective of the current study was to validate an updated kinematic system used in conjunction with two types of artificial neural networks (ANNs) to predict specific NRS scores. In particular, we aimed for a model to be able to predict scores that represented cows with more subtle gait abnormalities (scores 2 and 2.5 on the 5 pt. scale) but which were not yet presenting clinical lameness (scores of 3+) with a high accuracy. The hypothesis of our study was that the 3D coordinates collected through the kinematic system would reflect what was visually observed by the individual conducting locomotion scoring to the extent that the model(s) could achieve a high accuracy.

3.3. MATERIALS AND METHODS

3.3.1. Ethics Statement

The use of animals in this study and the protocol followed were approved by the Animal Care Committee of McGill University (FACC protocol 2016-7794). All components of this study meet the standards set by the Canadian Council on Animal Care.

3.3.2. Selection of Animals

The study was conducted from Jan. 18 to Feb. 12, 2021 at the Macdonald Campus Dairy Unit of McGill University (Sainte-Anne-de-Bellevue, QC, Canada). Lactating Holstein cows housed in a tie-stall barn were screened for inclusion. Cows were required to have an absence of severe injuries and a generally cooperative demeanor while being led by halter to ensure handler safety and adequate acquisition of walked "passages" – a recording of the cow walking along the 7m walkway - for data collection. The aim was to include cow with a range of locomotor ability, encompassing cows with ideal or near perfect gait, cows with minor gait impairment or abnormalities, and cows with lameness (obvious limping). Ultimately, 12 cows were enrolled. Animal characteristics such as parity and lactation stage were not considered as inclusion criteria. While these cow characteristics may influence gait, they were not relevant, as the study considered passages individually to compare an NRS score predicted by the artificial neural networks (ANNs) to a score given by a human observer.

3.3.3. Technology

Data was collected in an area of barn designed specifically for recording kinematic video. Six high performance cameras (Basler Ace, Ahrensburg, Germany) were mounted on the walls of the room and positioned around the passageway on which cows walked to have their gait recorded (Figure 3.3.1). Cameras had a 4 mm lens, a 6.1 mm x 4.9 mm CMOs sensor, and were set to record at 60 frames per second. Cameras recorded synchronized video through the Vicon Motus Capture Engine within the motion analysis software, TEMPLO (CONTEMPLAS GmbH, Kempten, Germany). Videos recorded through TEMPLO were then transferred into Vicon Motus 3D video-based motion analysis software (CONTEMPLAS GmbH, Kempten, Germany) for digitization and processing. Vicon Motus uses a direct linear transformation process to establish a direct linear relationship between the digitized 2D coordinates recorded from multiple cameras and 3D space coordinates by using intersections of vectors from each camera view to determine a point location in space. Cameras were positioned to always overlap with at least one other camera throughout the passageway to allow for 3D analysis of the gait in the passage recording. Origin points for scaling during 3D analysis were achieved through use of a calibration device consisting of 24 markers with known coordinates in 3 dimensions (Figure 3.3.2.). After scaling, digitization, and processing in Vicon Motus, the 3D coordinates of each marker as the cow walked the passageway were acquired. The full process conducted between TEMPLO and Vicon Motus to overlay video recordings on “templates” for 3D gait analysis is described in Figure 3.3.3. The steps taken between the two software to export and process video recordings were conducted after all data collection (video recording) was completed.

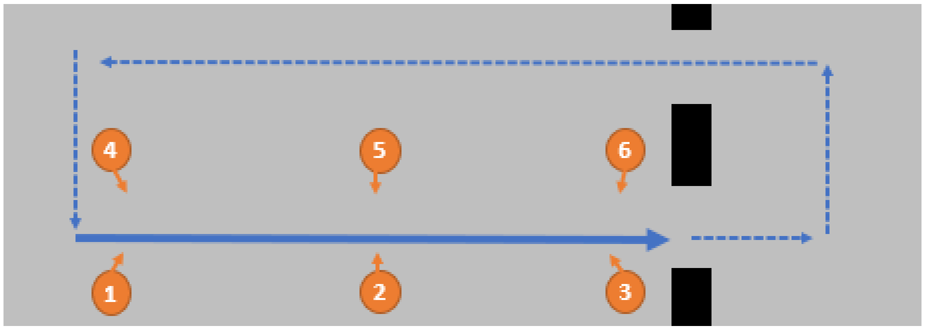

Figure 3.3.1. Diagram of Kinematic Room setup. The solid arrow represents the length of the passageway during which the cow's gait is recorded. The dotted areas represent the path where the cows are circled back to the "starting point" of the passageway. Numbered circles represent the individual camera placements (cameras attached to ceiling), and the black boxes represent the partial walls present in the room.

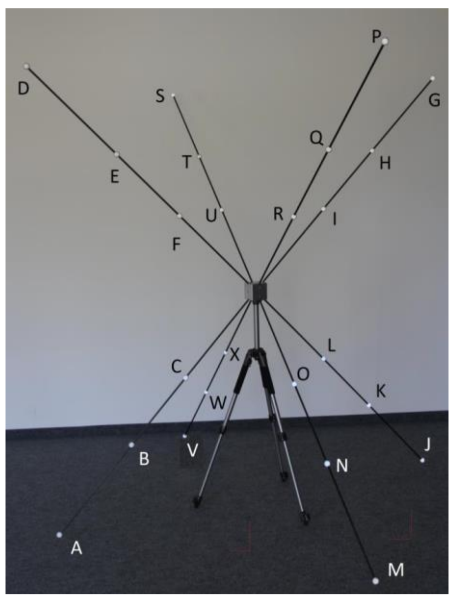

Figure 3.3.2. The calibration device used for the kinematic system. Each letter represents a “marker” on the calibration device that has known coordinates relative to the “origin” coordinates represented by marker A, allowing for calibration of a coordinate system in 3 dimensions.

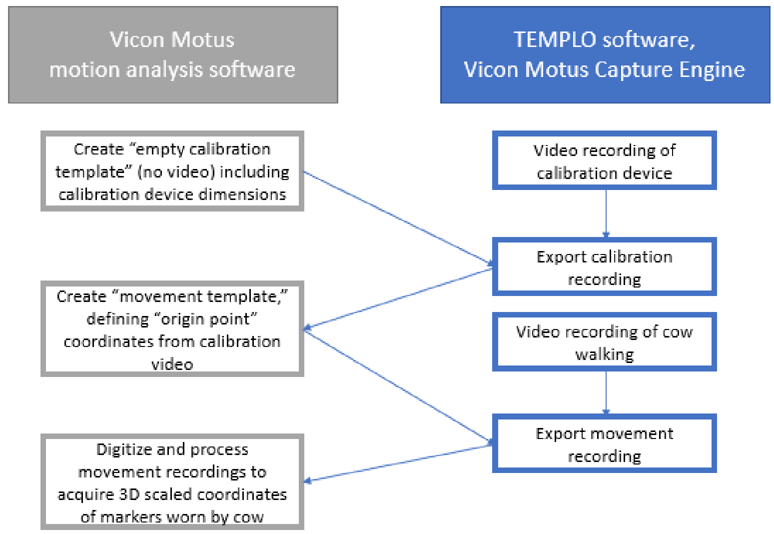

Figure 3.3.3. Steps to export and process video recordings between TEMPLO and Vicon Motus software to acquire 3D scaled coordinates of markers on cow.

3.3.4. Data Collection

Cows were brought to the kinematic recording room for marker placement and video recording. The kinematic room consisted of the six cameras centered around a 7m passageway, with 3 cameras each positioned to record the left and right side. Extra space to the side of the passageway allowed for cows to be circled back to the passageway "starting point" after completion of a passage (Figure 3.3.3). First, the cow would be led by halter to the room and tied in a pen for the duration of marker placement and attachment. Twenty-five mm, spherical reflective markers (B & L Engineering, Santa Ana, Ca) placed at specific anatomical locations adapted from Blackie et al. (2013). Markers were placed at 20 locations (Figure 3.3.4) on the cow: 4 on each leg and 4 on the back. Markers were placed at the coffin and fetlock joint of each leg, at the carpal and elbow joint of the front limbs, and at the hock and stifle joint of the hind limbs. The makers on the back were placed at the highest point of the spinous processes of the first few thoracic vertebrae (withers), the dorsal spinous process of the T13 vertebra (thoracic), the sacrolumbar joint (sacral vertebrae area between 2 tuber coxae), and the sacrococcygeal joint (tail head). To ensure marker placement consistency on individual cows across different days of data collection, a stencil (10 cm x 10 cm) was designed out of laminated paper. A trained individual would identify the anatomical location and draw an outline of the stencil, either with an ink marker or by shaving the hair of the cow. At the time of marker attachment during data collection, the stencil would then be lined up to the previously outlined area and the marker could be attached at its precise location.

The first step of the video recording process for data collection involved taking an approximately 1 second recording of the calibration device – a “calibration recording” - through the Vicon Capture engine within TEMPLO. One calibration recording was taken per day of data collection. The calibration device was then removed from the kinematic room and “movement recordings,” or video recordings of the cow walking used for gait analysis, could then be recorded.

To conduct kinematic video recordings, cows were led by halter down the passageway in the middle of the kinematic recording room. After completing a passage, the handler would circle the cow back to the starting point of the passageway using the additional space to the side of the room. Cameras continuously recorded, and an individual monitoring the recording system would note down the time of a recording when “good” passages occurred. A “good” passage was defined as a usable passage for kinematic analysis in which the cow did not stop, run, jump, frolic, or drastically change speed while walking along the passageway. It also required that the cow walked in a generally straight line along the passageway and that the handler was not having to pull at the area of the halter attached to the cow’s head to cause her to move. All markers had to be present for the duration of the passage without falling off, and at least two cameras always needed to view a marker at a given moment without obstruction to permit Vicon Motus to perform direct linear transformation and calculate the 3D coordinates of that marker. After data collection was completed for a day, videos were reviewed, and passages deemed usable were clipped and extracted out of the longer video recordings for kinematic analysis. If a usable passage was not obtained by after approximately 30 minutes of having the cow walk, the cow was returned to her stall and left to rest for the remainder of the day.

Data collection continued until all cows enrolled had at least 3 “good” passages, with the exception of one cow who only had 2. Generally, 3 days of recording were allotted for individual cows to reach the goal of 3 passages per cow, with additional days being added for specific cows as needed. In cases where cows could provide multiple “good” passages within a 30-minute period of recording, all passages that were deemed usable were kept for kinematic analysis.

There was no limit to the number of passages used per cow, as the goal was to obtain as many individual passages for analysis as possible overall regardless of animal. This resulted in some cows providing more usable kinematic passages than others.

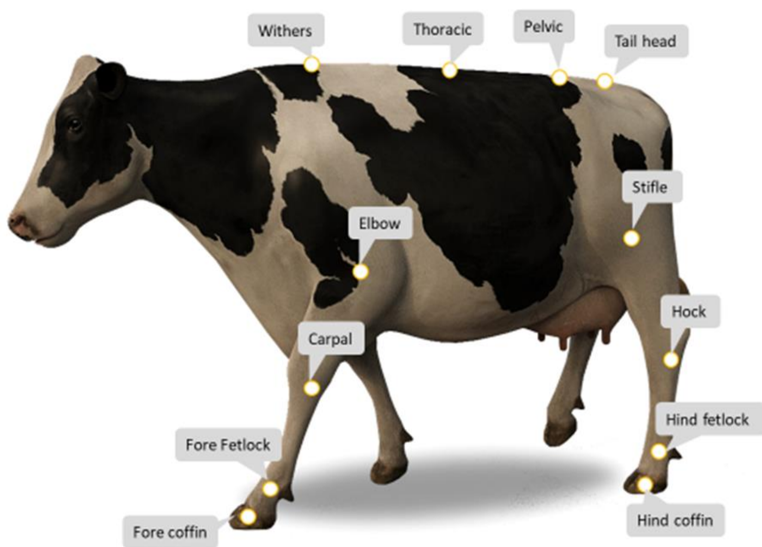

Figure 3.3.4. Anatomical locations of the 20 markers tracked for kinematic 3D gait analysis.

3.3.5. Gait Scoring

A trained observer conducted the gait scoring using the videos recorded by the kinematic video system from a side camera view. A 5-point NRS (numeric rating system) scale with 0.5 intervals was used based on Flower and Weary (2006), with 1 indicating the soundest score and 5 indicating severe lameness. Videos were randomized before scoring and the scorer was blinded to the name identity of the cow and date of the video. The observer underwent training with videos separate from the data collection for this study until an intra-observer reliability of a 90.9 extended percentage agreement for overall NRS scores was achieved. The extended percentage agreement (Gamer et al., 2019) was used for calculating agreement and reliability after observer training as it allowed for a tolerance level of 0.5, which reflects any scores differing by 0.5 were interpreted as "agreeing."

3.3.6. Data Analysis

3.3.6.1. Data Handling

Missing values were present in the final kinematic data sets obtained from Vicon Motus. Missing values occurred when a marker became physically blocked or was no longer visible in at least two cameras during the video recording process, when two markers overlapped with each other for a frame or a series of frames and could not be individually identified within the software, or when image quality was not sufficient in at least two cameras (typically due to blurriness because of quick movement or lighting issues) for marker identification and tracking in the software. In these cases, missing values were replaced with a value of 0.

Figure 3.3.5 shows the distribution of the locomotion scores assigned by the visual observer to each passage of recorded cows. There were few passages obtained for the scores 1.5 (1 passage) and 4 (2 passages), and no passages scored below 1.5 (score 1) or above 4 (scores 4.5 and 5). The passages with a score of 1.5 and 4 were removed from the data set before training since there were not enough samples to represent these classes, leaving 4 consecutive classes of gait in the middle of the range (scores 2.0 – 5.5) of the 9-classes NRS scores (Flower & Weary, 2006). Another disparity between passages acquired was the difference in the length of individual recordings, which varied due to different walking speeds of cows. To mitigate this as needed for the training of a models, the dimensions of each passage were fixed to guarantee a rectangular training matrix. A threshold for the number of rows was selected by finding the passage with the greatest number of rows and selecting this number as the default size for all passages. In the case of passages that had a lower number of rows, 0 was input for the “missing observations”.

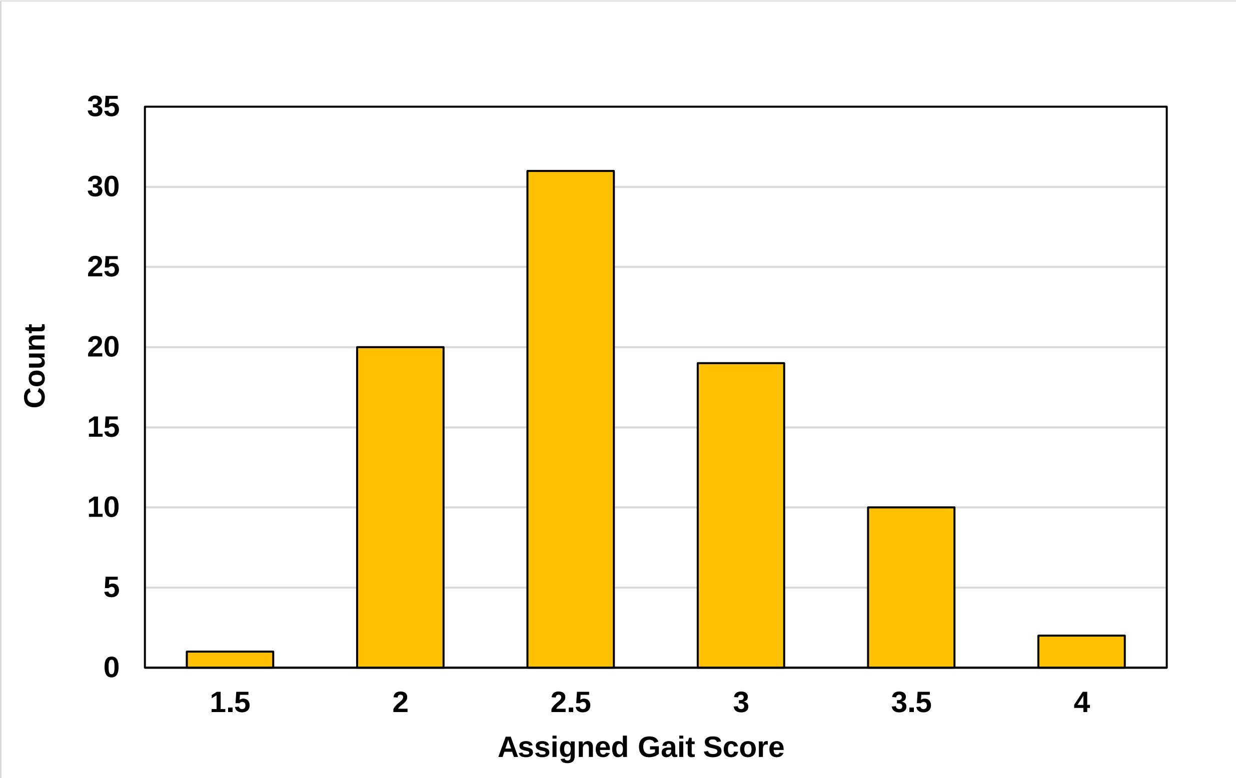

Figure 3.3.5. Distribution of NRS scores assigned by the visual observer in the kinematic data set (n= 74). The passages with a score of 1.5 and 4 were removed from the data set before analysis since there were not enough samples to represent these classes, leaving 4 consecutive classes of gait in the middle of the range of the 9-classes NRS scores (Flower & Weary, 2006).

3.3.6.2. Creating Working Data Set

To reduce overfitting of the model, a stratified cross-validation was applied by holding out a portion of the kinematics data set (n = 19) to create a validation set (25%) and the remaining (n = 55) as the training set (75%). The validation set was kept separate from the training procedure to continuously evaluate the performance of the model. With the stratified approach, the distribution of classes in the training and validation set remained identical.

Upon evaluation of data visualizations that had been created prior to model development, it was observed that no clusters of classes (locomotion scores) appeared. Some classes were also represented more than others, which could negatively influence the learning of the model. Based on this information and on the fact that a limited number of unique passages were available for model training (n = 55), a data augmentation strategy was deemed appropriate. The creation of artificial data helps to overcome the limitations of collecting data with this type of kinematic system, especially regarding the availability of animals and the time and labor involved in preparation of cows (movement to the kinematic room and marker attachment), data collection (acquiring "usable" video passages), and video processing and digitization. Artificially expanding datasets using label-preserving operations has also been identified as a useful strategy for combating overfitting and has been shown to improve performance in ML models (Shorten & Khoshgoftaar, 2019). To generate synthetic samples, we used an approach previously developed by Karoui et al. (2021) in a previous study which aimed to develop our ML framework for automatic lameness identification. Random noise was added to the motion trajectories from the training data set with varying magnitudes of 1% or 5% of the original value to stochastically determined rows. The number of artificially created passages varied for each NRS class to create two balanced final training datasets with 2,500 samples of each gait category, resulting in a total of 10,000 training passages with either 1% or 5% added random noise. Data augmentation was applied only to the training data and not the validation data to prevent overfitting and guarantee that the distribution of the validation set represented the "true" data set and not the modified one.

3.3.6.3. Modeling Methods

A convolutional neural network (CNN) and a long-short term memory (LSTM) network were the ANN methods used.

3.3.6.3.1. Convolutional Neural Network

Some researchers (Bai et al., 2018; Fawaz et al., 2019) have previously exploited the unique attribute of CNNs wherein a pooling step can be applied to reduce the dimensionality of a model and to reduce the influences of noise for use with temporal or sequential data. This approach was used in the development of the convolutional neural network (CNN) used by Karoui et al. (2021), whose methodology was used as a basis for the current study. The CNN employed was based on the *LeNet* architecture (Lecun et al., 1998), which was a 2-layer CNN originally developed for the classification of handwritten characters. The CNN architecture was constructed using two blocks, each composed of a convolution layer CONV (first = 6 filters, second = 16 filters) and an average pooling (POOL) layer. Following these blocks, two fully connected layers (ReLu activation function) and a decreasing number of neurons (first = 120, second = 84) were added. Finally, a prediction layer with four nodes (corresponding to the NRS prediction classes and softmax activation function) was added. The original network architecture is shown in Figure 3.3.6. Moreover, to each CONV and POOL layer, a dropout layer (dropout ratio = 50%) was added as a regularization measure to reduce overfitting of the model. The dropout layer could randomly "turn off" certain nodes in the layer, forcing the network to probabilistically determine which nodes take precedence over others. This regularization technique also helps to reduce the chances of errors from prior layers propagating throughout the network. The model was trained with 1 and 2 CONV/POOL/Dropout layers.

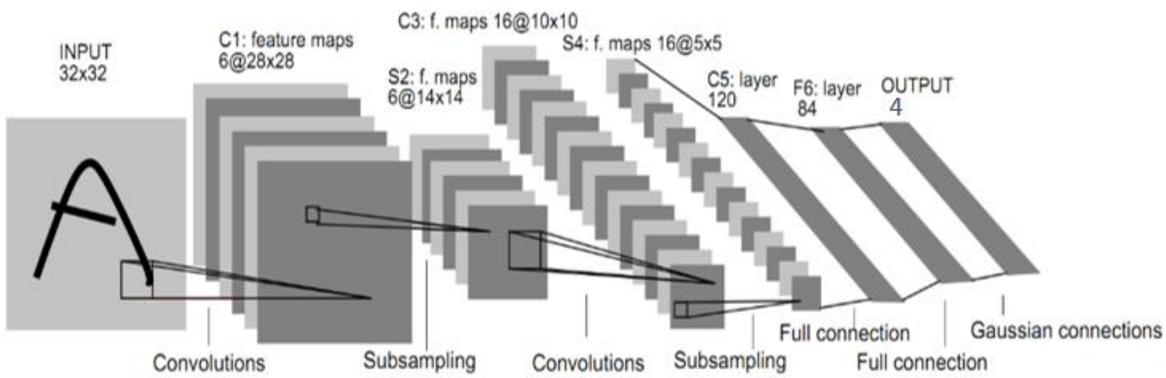

Figure 3.3.6. Illustration of the *LeNet* CNN architecture with output modified from Tra et al. (2017).

3.3.6.3.2. Long Short-Term Memory Network

A Long Short-Term Memory (LSTM) network was also evaluated. The LSTM networks are a particular type of recurrent neural network which benefit from directed connections in the network architecture that form a directed graph along a temporal sequence (Hochreiter & Schmidhuber, 1997), making it a suitable option to analyze sequential data such as kinematics. An architecture with 2 LSTM layers (LSTM1 = 32 nodes, LSTM2 = 64 nodes) and a single LSTM layer (LSTM1 = 32 neurons) were tested. After each LSTM layer, a dropout (25%) and batch-normalization layer were added. The last LSTM layer in both models was followed by dense layer with 32 nodes and Relu activation and a prediction layer with 4 nodes and a softmax activation.

3.3.6.3.3. Model Training

The ANN models were trained on a Desktop computer with an Intel Core i5-4690 CPU (Intel, Santa Clara, California) with 8Gb of RAM and a GeForce RTX 2070 graphics card (Micro-Star International, New Taipei City, Taiwan). All models were built using the Python programming language (version 3.8.8) and the Keras (version 2.3.1), TensorFlow (2.1.0), and Scikit-Learn (0.24.2) libraries. The models were trained having the sparse categorical cross entropy as the loss function for 100 epochs and using the RMSprop optimizer with a learning rate = 0.001. Categorical cross-entropy was used as the loss function in this multi-class classification experiment. It was defined by the equation $L_{CE} = \sum_{i=1}^{n} t_i \log(P_i)$ where n is the number of classes, t_i is the truth label (taking a value of 0 or 1) and P_i is the $Softmax$ probability for the i^{th} class. Categorical cross-entropy is a form of logistic loss, meaning that a prediction far from the truth value will yield a high penalty. A model that predicts instances perfectly will yield a cross-entropy loss of 0. Once the validation loss was stabilized, the learning rate would decrease by a factor of 10. Early stopping was also applied, in which training stopped if there was no improvement on accuracy after 10 epochs.

3.3.6.3.4. Model Evaluation

A selection of performance metrics including accuracy, precision, recall, F1-Score, and categorical cross entropy were used to evaluate the performance of each classification algorithm. Accuracy represents the capacity of the models to correctly classify passages. Accuracy is defined as: $Accuracy = \frac{\Sigma \text{TP} + \Sigma \text{TN}}{\Sigma \text{TP} + \Sigma \text{FP} + \Sigma \text{TN} + \Sigma \text{FN}}$, where TP and TN are the number of true positive and true negative classifications, respectively; and FP and FN are the number of false positive and false negative classifications, respectively. While it is an indicator of overall performance, it is not enough alone to determine the strength of an algorithm and whether it has correctly learned the designated task when a dataset is imbalanced.

Precision was used to determine the capacity of the models to correctly identify positive cases with respect to all the cases the algorithm has classified as positive. It was an indicator of how reproducible and repeatable a measurement is under unchanged conditions and was used to evaluate the exactness of a model. Precision is defined as $Precision = \frac{\Sigma \text{TP}}{\Sigma \text{TP} + \Sigma \text{FP}}$.

Recall was used to determine the model's capacity to correctly identify positive cases with respect to all positive cases in the data. It is a measure of the classifier's completeness. Recall is defined as $Recall = \frac{\Sigma \text{ TP}}{\Sigma \text{ TP} + \Sigma \text{ FN}}$.

The F1-Score combines both precision and recall into a single encompassing metric. Mathematically, the F1 score is the weighted average of precision and recall. F1-Score is defined as $F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$. Accuracy, precision, recall, and F1-score range from 0-1, with values closer to 1 representing better performance.

3.4. RESULTS

All models performed well on the training data (not shown), but performed poorly on the validation data (Table 3.4.1). The LSTM (2 layer, 5% var) model performed best in regards to precision (0.378 ± 0.106) and F1-score (0.299 ± 0.067). The LSTM (2 layer, 5% var) and the LeNet (1 layer, 5% var) models had the best accuracy out of all models (0.403 ± 0.109 and 0.403 ± 0.031, respectively). The LeNet (1 layer, 5% var) model had the highest recall (0.327 ± 0.029) of all the models.

Table 3.4.1. Precision, recall, F1-score, and accuracy measured on the validation data set of the recurrent neural network (CNN) and long short-term memory (LSTM) artificial neural network models trained on augmented data with added either 1% (1% var) or 5% (5% var) random noise.

Model	Precision		Recall		F1-Score		Accuracy	
	Avg	**Std Dev**	**Avg**	**Std Dev**	**Avg**	**Std Dev**	**Avg**	**Std Dev**
CNN (1 layer, 1% var)	0.219	0.063	0.271	0.040	0.229	0.012	0.351	0.030
CNN (1 layer, 5% var)	0.282	0.002	**0.327**	**0.029**	0.296	0.006	**0.403**	**0.031**
CNN (2 layer, 1% var)	0.317	0.021	0.292	0.058	0.297	0.048	0.386	0.061
CNN (2 layer, 5% var)	0.243	0.036	0.286	0.039	0.249	0.045	0.333	0.030
LSTM (1 layer, 1% var)	0.213	0.093	0.283	0.079	0.236	0.084	0.351	0.132
LSTM (1 layer, 5% var)	0.337	0.127	0.298	0.064	0.285	0.053	0.386	0.061
LSTM (2 layer, 1% var)	0.192	0.071	0.265	0.126	0.215	0.094	0.351	0.160
LSTM (2 layer, 5% var)	**0.378**	**0.106**	0.315	0.079	**0.299**	**0.067**	**0.403**	**0.109**

For both types of models (CNN and LSTM), overfitting occurred early in the training process since training stopped around epoch 5. Decreasing model complexity by removing layers did not seem to improve prediction results in general. The LSTM (2 layer, with 5% variation in the augmented data) model performed the best out of all models, with the best results overall for most of the evaluation criteria (Table 3.4.1.). The NRS scores with the greatest number of true predictions were 2.0 and 2.5 for the CNN and LSTM models, respectively (Figure 3.4.1.).

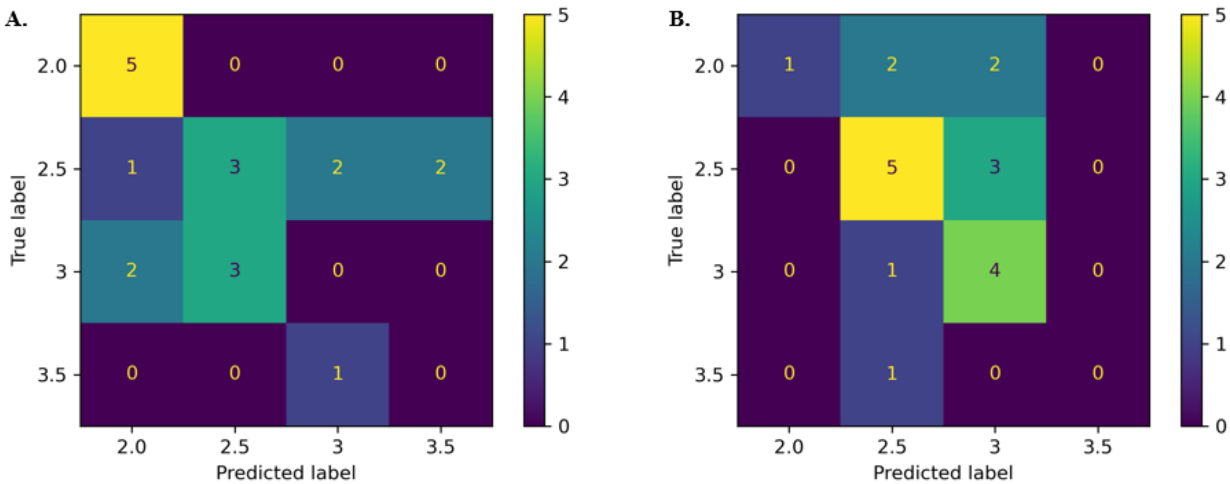

Figure 3.4.1 Confusion matrices showing the number of instances predicted for the best-performing model within each type of model. These were the convolutional neural network with 1 layer and 5% variation in the augmented dataset (**A**.) and the long short-term memory model with 2 layers and 5% variation in the augmented dataset (**B**.).

3.5. DISCUSSION

Our hypothesis that the 3D-scaled coordinates acquired through the kinematic system would reflect what was visually observed by the individual conducting locomotion scoring to the extent that the neural network models could achieve a high accuracy was not met. It is possible that this type of data acquired through the kinematic system does not have predictive potential for specific NRS scores. Karoui et al. (2021) were able to predict lame and non-lame cow passages with accuracy, precision, recall, and F1-score above 90% (as defined by an NRS score of 3 or higher) when this type of kinematic data in conjunction with a CNN. However, it is possible that the increased level of subjectivity involved when defining specific NRS scores (4 consecutive classes of gait), as opposed to a dichotomous classification of lame versus non-lame, is not reflected in the current dataset. Additionally, the differences in the data used for the present study due to the technological updates and advances made in the kinematic system may help explain the differing results of the CNNs used in these two studies. In the previous study, the arrangement of the room where kinematic recordings were conducted did not allow for both sides of the cow (left and right) to be viewed simultaneously by the cameras within the motion tracking software. This resulted in the data sets for the right and left side markers of the cow being processed and analyzed separately. The arrangement of the kinematic system used in the current study allowed for both sides of the cow to be recorded and analyzed simultaneously. This resulted in a dataset that had individual markers being tracked (having identified coordinates provided) at different starting and ending frames depending on when the body part where a given marker was attached crossed the designated starting and ending points of the passageway.

All models performed well on the training data (not shown), but poorly on the validation data. Both the CNN and LSTM models started to overfit early in the training process (around epoch 5). One possible reason for overfitting could be that a model that was more complex than necessary was used. However, this did not appear to be the case, as removing layers to decrease model complexity did not seem to help prediction results in general. It is possible that the data augmentation strategy used was unsuccessful, or that the problem at hand requires a simpler model. This is the first study using a 3D-video motion tracking approach in conjunction with an LSTM model architecture to evaluate movement of the cow's entire body as she walks. Previous studies using neural network approaches to specifically evaluate locomotion have primarily focused on one or a few specific parts of the body. Wu et al. (2020) used the YOLOv3 deep learning algorithm to identify legs of cows from video recorded from one camera and used the number of video frames taken for a cow to complete a step with a limb as a measure of stride length. Stride length as a characteristic vector was used to train an LSTM to predict lame vs. non-lame cows, with a resulting accuracy of 98.57% and a true positive rate of 0.97. This study, however, did not define how lame vs. non-lame cows were identified for model training and only used one camera, allowing for only a 2D analysis of motion. Abdul Jabbar et al. (2017) used a 3D-depth camera to acquire images of the backs of dairy cows with an overhead view to automatically track specific areas such as the hooks and spine. The height movements (variation symmetry) of these body regions were analyzed with a Hilbert transform and used as locomotion signals. A 1-5 scale locomotion scoring system (Sprecher et al., 1997) was used, with a score of 2 representing the threshold where a cow is considered lame. In using a linear Support Vector Machine (SVM) binary classification model, the threshold achieved an accuracy of 95.7% with a 100% sensitivity for detecting lame cows and 75% specificity for detecting non-lame cows. Both of these studies had success in focusing on regions or parts of the body to analyze gait, although they only focused on identifying cows as lame versus non-lame. Applying a similar approach wherein specific areas of the body (in this case specific joints on which markers are worn) are focused on with the kinematic system used in the current study could be a potential next step.

In an attempt to better understand which specific markers worn on the cow (i.e., which specific joints) show the most promise for reflecting abnormalities in gait that could be picked up by a trained model, methods for decomposing the input variables (the specific joints on the cow) or the development of PCA plots could be implemented and considered before development and testing of additional models. Future testing using the Random Forest feature importance function would highlight which specific markers, and even which dimensions (x, y, or z) for those markers, contribute the most to helping the model make its locomotion score prediction. Training a model with kinematic data generated only from these markers could be tested to evaluate if this method could improve the model's performance. Additionally, identifying anatomical locations (joints) which may be more "useful" for training a model could help reduce the time spent digitizing markers across the cow's entire body and could help reduce the time and memory costs of prediction models. On the other hand, an alternative model training approach that would not require the use of augmented data could also be tested as a next step. Instead of using a repeated k-fold cross-validation in combination with augmented data as was done in the current study, leave-one-out cross validation as was conducted by Zambelis et al. (2021) could be used instead.

A logical next step following the aim of this validation study to have an ANN predict an overall NRS could be to use techniques such as permutation feature importance and partial dependence plots to see which patterns the model deemed "important" for its predictions of each class (locomotion score). It could then be determined if those patterns relate to or reflect any more specific aspects of gait, such as the additional gait attributes focused on in the NRS scale developed by Flower and Weary (2006). However, overall locomotion scores, such as the NRS used in this study, may not be ideal for the aim of this study to identify cows with subtle locomotor abnormalities or impairments who are not considered "perfect" regarding gait, but who are not yet clinically lame. In developed visualizations of the kinematic data used in this study, the classes (NRS scores) appeared ill-defined. Overall scores leave additional room for interpretation for the observer while conducting scoring and in some cases similar scores may be given when the gait issues across cows are not the same. For example, a score of 2.5

(representing "intermediate" gait where the cow exhibits some abnormality but is not yet considered clinically lame) may be assigned to one cow because of a limited range of motion in her limb joints, but assigned to another cow because of a prominent back arch and her back hooves not fully tracking up. To overcome this issue, future work could instead directly incorporate the scores of specific gait attributes for model training as opposed to an overall locomotion score. Gait attributes focusing on specific aspects of locomotion such as those outlined by Flower and Weary (2006) (swinging out of hind limbs, back arch, joint flexion, tracking up of hind limbs, gait asymmetry, and reluctance to bear weight on a limb) could be adopted. Specific descriptions provided for each gait attribute detailing how specifically to evaluate the attribute in questions (from a spatial perspective, temporal perspective, or both) that are provided by a locomotion scoring system could help to minimize the subjectivity that may occur with overall locomotion scores. This approach could also help to better learn the patterns associated with the specific gait attributes/abnormalities being exhibited within the kinematic data.

Limitations regarding the kinematic system and usable animal passages were present in the current study. Twelve cows (out of approximately 25 tested for kinematic recording ability) with whom "usable" passages could be obtained (i.e., no stopping, running, jumping, frolicking, or drastic change in walking speed present) were available for use in the analysis. A total of 74 total passages were used for data analysis, with scores for individual passages ranging from 2 to 3.5. These passages did encompass the type of "intermediate" gait we hoped to identify with the model, but because of these limited numbers, the test set used for model validation was small (19 samples). This meant that every time one sample was misclassified, the accuracy of the model decreased. These current limitations should be addressed through technological advancements of kinematic systems and motion tracking software in the future. This is especially expected as the use of markers may become no longer required and as kinematic systems become mobile, allowing for use on multiple types of farms with cows exhibiting a wider variety of gait quality and more differences in gait attributes affected. This will help redefine how locomotion is evaluated, and permit researchers and producers to move beyond the current limitations that exist with visual locomotion scoring.

There are multiple possible future directions of data collected through this type of kinematic system used in conjunction with ANN techniques. A similar way to use this data and an ANN as a tool could be to exchange the overall locomotion or gait attribute score for some type of factor that impacts gait, such as a specific hoof pathology. The overall goal of our research on automatic locomotion scoring is for an ANN to be applied to general kinematic data gathered from a herd to identify not only cows that are severely lame but also those who exhibit more subtle gait abnormalities. Going a step further, an appropriate ANN applied to the kinematic data could then allow for the specific causes of exhibited gait abnormalities (the specific hoof disorder or injury) to be identified for individual cows. This could be particularly useful for instances where early identification of a hoof pathology is key to preventing severe lameness. A model could also be trained based on environmental factors or aspects of management that may impact gait, such as housing type, flooring type, or exercise access. An ANN used with this type of kinematic data could have the potential to become a widely used approach for automated locomotion assessment and gait abnormality (or abnormality cause) identification for both on-farm and research purposes, as well as an approach for investigating a range of factors that may influence dairy cow locomotion. These types of approaches could help to improve detection of locomotion abnormalities at an earlier stage and to identify changes that could help minimize the occurrence of pathologies or injuries contributing to locomotor impairment, helping to reduce costs associated with lameness and improve the overall health and welfare of cows.

3.6. CONCLUSION

In this validation study, 3D kinematic data did not reflect what was visually observable by a trained individual conducting locomotion scoring to the extent that specific locomotion scores could be predicted with a high accuracy through use of a convolutional neural network (CNN) or a recurrent neural network with long short-term memory (LSTM) architecture. However, our previous work using similar kinematic data and a CNN to identify lame versus non-lame cows was able to do so with an accuracy of over 90%. More research is needed to determine a model that could be appropriate for use with this type of kinematic data. Next steps should involve investigation into the usefulness of specific anatomical locations (joints) compared to others and testing of scores for specific gait attributes for model training (as opposed to overall locomotion scoring). As technological advancements are made that would allow 3D-camera systems to be easily transported for mobile use and as motion tracking software no longer require the use of makers worn on the cow, this type of kinematic data used in conjunction with ANNs could have the potential to be used for multiple applications. An improved model framework could be used to identify cows that have impaired locomotion or changes in their locomotion while not yet clinically lame. Such a model could also be tested for uses such as automated early detection of lameness, identification of hoof pathologies or injuries, and investigation of environmental and management factors which influence dairy cow locomotion.

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CHAPTER 4 – GENERAL DISCUSSION

This thesis contained two studies. The first was the systematic literature review conducted according to PRSIMA guidelines to determine the measures that have been recorded through kinematic, kinetic, accelerometric, and other approaches in research evaluating environmental or cow-level factors that may influence locomotion. The second was a validation study of a kinematic system used in conjunction with an artificial neural network to predict locomotor ability of cows.

The literature review presented in Chapter 2 had 2 overall objectives. The first was to determine the measures recorded through kinematic, kinetic, accelerometric, and other approaches and to determine the relationships between the different types of measures and recording approaches used. A takeaway from objective 1 of the literature review was that it is difficult to compare these locomotion measures that have been recorded by kinematic, kinetic, and accelerometry technologies across studies. Use of these technologies for the purpose of assessing gait in dairy cows is relatively new and, therefore, a wide range of approaches, types of technologies, and arrangements of equipment, terminologies, and calculations for specific measure types have been used across studies. Different technologies can also be used to record the same types of measures (e.g., kinematic measures can be recorded through both kinematic technologies or PMS kinetic technologies). Although the measure definition may be the same, the technology used and approach to recording it must be taken into consideration.

The second objective of the literature review was to evaluate the research contexts in which these locomotion measures had been recorded. The two main categories of research contexts were divided into the categories of environmental factors and cow-level factors. In the studies using kinematic, kinetic, and accelerometry technologies, environmental factors were more commonly examined. Flooring type was the most commonly studied environmental factor, followed by hoof-trimming. The presence of lameness or hoof disorders was the primary cow-level factor evaluated. Studies evaluating lameness and/or hoof disorders more often used alternative approaches to look at gait, specifically through the recording of indirect physiological measures associated with gait. Studies relying more heavily on the three technologies of primary interest to evaluate gait more often focused on the impacts of environmental factors.

Many of the studies included in the literature review recorded a visual locomotion score. These were sometimes used as an additional outcome measure of gait quality itself or were used to compare or validate against the more specific measures of locomotion recorded through the technologies. It should be acknowledged that using locomotion scores as a gold standard when developing or using these newer technologies can be problematic because of their relative subjectivity and sometimes low reliability (Schlageter-Tello et al., 2014). Visual locomotion scoring has been the most commonly used method of assessing gait for on-farm and research purposes. One could argue that it also focuses on kinematic-type measures, as it involves an observer often focusing on how the cow or specific parts of the body move through space and time. However, it is a more simplistic approach with relatively more subjectivity. Locomotion scoring systems may not always provide enough detail about which part of the body or which aspect (spatial or temporal) a gait attribute should be examined through to prevent observers from interpreting instructions differently. Kinematic technologies, or kinetic or accelerometry technologies which can extrapolate kinematic-types measures, are a more advanced way of looking at the visual (spatial and temporal) aspects of gait to gain insight into the potential underlying cause of a gait abnormality.

The objective of the validation study presented in Chapter 3 was to determine if kinematic data, recorded through a system consisting of 6 cameras and a motion tracking software, could be put into two different types of artificial neural networks (ANN; convolutional neural network and a long short-term memory model) along with the corresponding visually observed locomotion scores to predict locomotion score with a high accuracy. We aimed, in particular, for the model(s) to be able to identify cows that were not yet designated as clinically lame but which exhibited more subtle changes in locomotion or gait abnormalities. Our hypothesis that the 3D coordinates collected using the kinematic system would reflect what was visually observed by the individual conducting locomotion scoring to the extent that the model(s) could achieve a high accuracy was not met. All tested models performed poorly regarding the metrics of accuracy, precision, recall, and F1-score. It is possible that the scaled 3D-coordinates acquired through the kinematic system do not provide data with predictive potential for the NRS scores. It is also possible that there was not enough data with variability between NRS scores. Overall locomotion scores may not be an ideal approach for identifying cows with "intermediate" gait, where abnormalities are present but the cow is not yet clinically lame. Next steps should involve determining if particular anatomical locations (specific joints) have greater or more noticeable differences in their motion trajectories across different levels of locomotor ability, thus making them more useful for training of ANN models. This could help improve machine learning and reduce the amount of time spent on marker attachment and digitization of markers covering the cow's body within the motion tracking software. This would allow for more time to be spent on data collection, yielding a greater number of unique cow passages that could be used for model training or testing. Additionally, scored gait attributes (swinging out of hind limbs, back arch, tracking up of hind limbs, joint flexion, gait asymmetry, and reluctance to bear weight) should be tested for model training as an alternative to overall locomotion scores. Overall locomotion scores may be designated based on a number of abnormalities across these attributes, with the same scores sometimes being provided when the gait attributes affected are different between cows. Training a model with a specific gait attribute is expected to result in better machine learning and performance, as there is less subjectivity and fewer aspects of gait encompassed within an attribute score compared to an overall locomotion score.

Additional research to determine an improved model framework and technical advancements that allow for this type of kinematic system to become mobile are needed. Camera system mobility would allow for data collection to be conducted on multiple farms, likely encompassing a wider variety of locomotor ability and types of gait abnormalities than those available in this validation study. This will help push this type of technology used in conjunction with ANN techniques into a variety of uses. Locomotion score or gait attribute score as used with this type of model could be swapped out with some type of factor that impacts gait. For example, patterns of gait for cows with known injuries or hoof disorders could be evaluated. Cows with hoof pathologies or a specific hoof pathology at a known/scored level of severity could be studied. The pathology identification or severity could be entered into the model along with the kinematic data for training; if a high accuracy is achieved and consistent patterns can be detected for specific pathologies or severities, these patterns could be examined further and may represent how a pathology specifically causes a gait impairment or abnormality. The model could then be applied to general kinematic data gathered from a herd, and the specific causes or reasons behind locomotor impairment could be identified. This could be particularly useful for instances where early identification of a hoof pathology is key to preventing severe lameness.

Similarly, because we know that certain gait issues are associated with certain types of housing (like tie-stalls contributing to stiffness), the model could be trained based on housing types. If a high accuracy for predicting housing type was achieved, techniques could then be implemented to see which patterns were deemed important in the kinematic data for said prediction. The model could be used as a method to evaluate how, in much more detail and with much more specificity, a housing type affects gait. Additionally, overall locomotion score as used in the validation study could be substituted with other factors related to the cow's environment or management which may impact locomotion, such as exercise access, or exercise access frequency. As kinematic motion tracking software advance and no longer require marker attachment on cows and as cameras are developed for the use of providing 3D views in mobile, adaptable kinematic systems, this type of model could have the potential to become a widely used approach for automated locomotion assessment and gait abnormality (or abnormality cause) identification for both on-farm or research purposes.

Continued use of these kinematic, kinetic, and accelerometry technologies in research will provide more overlap between measures recorded. Technical advancements and the development of new approaches should also help to overcome their current limitations. Data acquired from these technologies could then be used with machine learning approaches as a tool, as demonstrated in Chapter 3, to evaluate factors that affect gait in a much greater detail than was previously possible with visual observer methods and scoring. This will help to improve detection of locomotion abnormalities at an earlier stage, identify changes that could help minimize the occurrence of pathologies or injuries contributing to locomotor impairment, and better address the overall health and welfare of cows.

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