THE DEVELOPMENT OF BEHAVIOR-BASED TRAFFIC CONFLICT INDICATORS
THROUGH AUTOMATED TRAFFIC SAFETY ANALYSIS

by

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Abstract

Traffic collisions are a severe epidemic that causes the loss of 1.25 million lives worldwide every year, the majority of which are in developing and emerging countries. Traditionally, road safety analysis has been conducted by relying on collision records as the primary source of data. This reactive approach has several shortcomings such as the poor quality of collision data, the long observation periods, the subjectivity of evaluation, and the difficulty in understanding the mechanisms that lead to collisions. These limitations have led to the growing interest in using surrogate safety measures, such as traffic conflicts (i.e., near misses), as a proactive approach to analyzing safety from a broader perspective than collision data alone. The analysis of traffic conflicts is typically performed using a number of conflict severity measures such as Time-To-Collision and Post-Encroachment-Time. These measures rely on road-users getting within specific spatial and temporal proximity from each other and, therefore, assume that proximity is the indicator of conflict severity. However, this assumption may not be valid in all driving cultures where road-users are less organized and traffic rules are weakly enforced. In these environments, close interactions between road-users are very common and sudden evasive actions are the primary collision-avoidance mechanism. The objective of this research is to investigate the applicability of existing time-proximity measures in less-organized traffic environments and to propose evasive action-based conflict indicators as complementary measures of conflict severity. The mechanisms by which road-users perform evasive actions are studied and used to recommend new behavior-based conflict indicators. Time-proximity and evasive action conflict indicators are then compared to evaluate conflict severity at locations from five major cities with different traffic environments; Shanghai, New Delhi, New York, Doha, and Vancouver. Ordered-response models were utilized to relate both indicators to conflict severity, taking into account the unobserved heterogeneity in
conflicts. The findings reveal that evasive action-based indicators are most effective in less-organized traffic environments such as Shanghai and New Delhi, with less potential in more structured environments such as Vancouver, where time-proximity measures are more effective. The results emphasize the need to select the proper conflict indicators depending on the studied traffic environment.
Lay Summary

Traffic collisions cause approximately 1,900 fatalities and 165,000 injuries on Canadian roads every year. Presenting an ethical dilemma, current reactive road safety practices rely on fatalities and injuries to accrue in order to remedy unsafe locations. Therefore, there is significant interest in using proactive surrogate safety measures such as traffic conflicts or near-misses to address safety from a broader perspective than collision statistics alone. Traffic conflicts are typically detected depending on road-users getting within a specific proximity to each other. However, in less organized driving cultures, road-users tend to accept close proximities to each other and, instead, do sudden evasive actions to avoid collisions. This research studies the mechanism by which road-users perform evasive actions in unsafe situations. Accordingly, new evasive action-based conflict indicators are introduced to evaluate traffic conflicts. Evasive action and proximity-based measures are compared in different traffic environments; Shanghai, New Delhi, New York, Doha, and Vancouver.
Preface

Articles published in refereed journals:

1- Parts of the introductory Chapter 1, parts of the literature review Chapter 2, parts of the methodology Chapter 3, and Chapter 4 are included in the published paper:

2- Parts of the introductory Chapter 1, parts of the literature review Chapter 2, parts of the methodology Chapter 3, and Chapter 5 are included in the published paper:

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<td>Akaike’s Information Criteria</td>
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<tr>
<td>ANOVA</td>
<td>Analysis of Variance test</td>
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<tr>
<td>BA</td>
<td>Before-After</td>
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<tr>
<td>BGR</td>
<td>Brooks Gelman Rubin</td>
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<tr>
<td>CS</td>
<td>Conflicting Speed</td>
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<tr>
<td>DIC</td>
<td>Deviance Information Criteria</td>
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<tr>
<td>DST</td>
<td>Deceleration to Safety Time</td>
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<td>GT</td>
<td>Gap Time</td>
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<tr>
<td>LCS</td>
<td>Least Common Sub-Sequence</td>
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<td>LPET</td>
<td>Lane-Based Post Encroachment Time</td>
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<tr>
<td>MCMC</td>
<td>Markov Chain Monte Carlo</td>
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<td>MSL</td>
<td>Minimum Step Length</td>
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<td>MSSF</td>
<td>Maximum Slope in Step Frequency</td>
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<td>MWR</td>
<td>Minimum Walk Ratio</td>
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<td>PE</td>
<td>Permutation Entropy</td>
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<td>PET</td>
<td>Post Encroachment Time</td>
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<td>PSD</td>
<td>Power Spectral Density</td>
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<td>TA</td>
<td>Time-to-Accident</td>
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<td>TCT</td>
<td>Traffic Conflicts Technique</td>
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Dedication

To my family...
Chapter 1: Introduction

1.1 Background

The world is facing a growing epidemic of fatalities and injuries resulting from road collisions. Road traffic collisions have become the eighth most leading cause of death globally and the leading cause of death among young people (15-29 years old) according to the World Health Organization (WHO, 2013). Every year, about 1.25 million person lose their lives around the world as a result of road collisions, and another 20 to 50 million sustain injuries and may be disabled because of traffic collisions. Additionally, traffic collisions are the cause of tremendous social and economic losses, estimated at US $518 billion per year globally (WHO, 2004). In Canada, traffic collisions result in approximately 1,900 fatalities and 165,000 injuries each year. It is predicted that road collisions will rise to become the fifth leading cause of death worldwide by the year 2030 unless urgent actions are taken. In 2010, the United Nations General Assembly adopted the resolution 64/255, which proclaimed the decade 2011–2020 as the Decade of Action for Road Safety. The goal of which is to stabilize and reduce the rising trends in road collisions, saving the lives of an estimated 5 million people all over the world by the year 2020. The main reason that has driven the global rise in road fatalities and injuries is the rapid increase of road collisions in low- and middle-income countries. More than 90% of the worldwide road collision fatalities occur in these countries, many of which are witnessing a rapid rate of motorization (WHO, 2015). Therefore, the need to reduce the social and economic costs of road collisions in these countries cannot be overstated.

Road collisions also represent a challenge for reaching the goals of sustainable transportation systems. Active modes of travel such as walking and cycling that improves the sustainability of
transportation systems suffer from the elevated risk of collisions. This is mainly due to the higher physical vulnerability of pedestrians and cyclists when involved in collisions. Road collisions involving such modes are usually highly injurious and physically damaging. However, until recently, research on vulnerable road users has received less attention in designing and planning road facilities. The issue is more pronounced in developing countries where the safety of vulnerable road users is not often prioritized that even renders the situation. A review of road collisions in many developing countries showed that the frequency of fatalities among vulnerable road users is always the highest (Downing, et al., 2000). In fact, half of the people dying from traffic collisions in the developing world are vulnerable road users (WHO, 2015). Nevertheless, there is now a heightened awareness among practitioners, researchers, and policymakers of the traffic threat towards vulnerable road users and the necessity to address the associated challenges.

The traditional approach to address road safety can be described as reactive that aims to mitigate safety problems based on the collected historical collision records. This reactive approach to address safety has several limitations regarding the quantity, quality, subjectivity, and attribution of the data since for collisions to be prevented they need to be observed first. Despite the fact that the number of collisions worldwide is unacceptably high, the collision frequencies for each location are rare. Therefore, an extended time for collection (e.g., three years) is needed to accumulate an adequate number of collisions in order to identify the safety problems before any action can be taken. As well, collision data is associated with random variations inherited in small numbers (Elvik, 1988). Therefore, drawing stable inferences from such data is typically challenging, which may lead to a paradoxical situation in which safety analysts, for the sake of methodological correctness, strive to observe more collision events that ought to be prevented (Sayed & Zein, 1999). The collision data, which are typically obtained through police reports and
insurance claims, usually suffer from completeness and quality issues. Police reports and interviews are often unevenly incomplete, lack sufficient data, and generally biased towards high-damaging incidents, as non-injurious collisions are sometimes not reported. This may not allow the right attribution of road collisions to a certain cause or a set of causes which makes it difficult to understand the failure mechanism that leads to collisions. The shortcomings of the reactive collision-based approach have motivated researchers to advocate a proactive safety approach that seeks to diagnose safety problems before they emerge (De Leur & Sayed, 2003).

Limitations of the collision-based approach led to a growing interest in traffic safety techniques that depend on surrogate safety (i.e., non-collision) measures in the quest to better understand, predict, and improve road safety. The use of surrogate safety measures has emerged as a subject of research where safety analysts would rely on data other than road collisions in evaluating safety. The Traffic Conflict Technique (TCT) was first proposed as a surrogate safety measure by Perkins & Harris (1968). They hypothesized that reducing near-miss traffic events will likely lead to reducing the frequency of road collisions since the same failure mechanism in the driving process leads to the occurrence of both traffic conflicts and collisions. Traffic conflicts can be viewed as precursors to road collisions according to the hierarchy of traffic events proposed by Hydén (1987), shown in Figure 1.1. This hierarchy establishes a severity dimension along which all traffic events can be arranged with uninterrupted passages at the bottom of the pyramid and traffic collisions at the top. The shape of the hierarchy was first postulated to be a pyramid, but later it was argued that the safety hierarchy shows the shape of a diamond considering only interactions where road users are on a collision course (Svensson, 1998).
Traffic conflicts are more frequent than collisions, can be clearly observed, have little, if any, social/economic cost, and can be collected in a much shorter period of time than collisions. Moreover, the observation and analysis of the road users involved in traffic conflicts provide an insight into the failure mechanisms that lead to collisions and the connection between behavior and safety (Sayed, et al., 1994). Therefore, the observation of traffic conflicts has been advocated as an alternative or complementary approach to analyzing traffic safety from a broader perspective than relying only on collision records.

![Hierarchy of traffic events severity pyramid](image)

**Figure 1.1 Hierarchy of traffic events severity pyramid (Hydén, 1987)**

The traffic conflict technique is based primarily on the evaluation of unsafe driving maneuvers between road users. Several researchers have shown that reducing traffic conflicts leads to the reduction of traffic collisions (Sayed & Zein, 1999) (Songchitruksa & Tarko, 2006) (Sacchi, et al., 2013). In the beginning, the traffic conflict technique involved observing, recording, and evaluating the frequency and severity of traffic conflicts at a location by trained observers (Parker, Jr. & Zegeer, 1989). A widely accepted conceptual definition of a traffic conflict is “an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged” (Amundsen & Hydén, 1977).
According to this definition, several traditional objective conflict indicators were proposed in the literature to measure the severity of traffic conflicts such as Time-to-Collision (TTC), Post Encroachment Time (PET), among others. These traditional indicators measure the proximity of conflicting road users in space and time in anticipation of a possible point of collision. The TTC, which is the most commonly used indicator, measures the expected time remaining between two road users to collide if a collision will occur between them when they continue on the same path at their current speeds (Hayward, 1972). The second commonly used traffic conflict indicator is the PET which is the actual time difference between the passages of two road users (Cooper, 1984). These conflict indicators measure road-users spatial and temporal proximity and, therefore, assume that proximity is the surrogate measure of conflict severity. However, this assumption may not be valid for all traffic environments.

1.2 Problem Statement

Culture plays a significant role in the behavior of road users and their collision-avoidance mechanism (Nordfjærn, et al., 2014). Studies comparing road user behavior across different countries showed different risk-taking behavior depending on the cultural norms in the society (Rundmo, et al., 2012) (Lund & Rundmo, 2009) (Nordfjærn, et al., 2014). The cultural differences between traffic environments are manifested in the variation of compliance with traffic regulations and collision-avoidance mechanisms. Road users in some traffic cultures tend to keep close proximities between each other. In some environments, such as Asian cities, a variety of unconventional traffic modes such as mopeds, scooters, and tricycles share the same road space with vehicles and tend to keep close proximity with other road users (Kadali & Vedagiri, 2016). Such different cultural norms, in addition to the public apathy towards traffic rules in general in
many environments, influence road users behavior and the occurrence of traffic conflicts (Atchley, et al., 2014).

In literature, time-proximity indicators have been largely validated as the main measure of traffic conflicts in organized traffic environments such as in Sweden (Grayson, et al., 1984) (Hydén, 1987), Canada (Cooper, 1984) (Sayed & Zein, 1999), Japan (Alhajyaseen, 2015), and the United States (Songchitruksa & Tarko, 2006) (Peesapati, et al., 2013). However, studies conducted to validate the traffic conflicts technique using time proximity measures in less organized traffic environments, such as in New Delhi, India, showed negative results with little correlation between conflicts and collisions collected from different intersections around the city (Tiwari, et al., 1998). This finding can be attributed to the difference in road user behavior in New Delhi compared to more organized traffic environments. Generally, in less organized driving environments, when road users are involved in an interaction, they may not stop or take any actions to avoid a collision. Instead, a road user will dynamically adjust his/her speed while in close proximity to the other road user and then decide whether a more pronounced evasive action is needed. Therefore, time proximity indicators may not be an efficient way to evaluate conflict severity in such environments. Since time-proximity conflict indicators have been commonly used in many organized traffic environments, its validity in less organized traffic environments is still questionable as to whether these indicators will be able to capture the true severity of traffic conflicts in these environments.

In some driving environments, where road users are in continuous interactions with other road users, the presence of evasive action can be an important indicator of the occurrence of a traffic conflict. A traffic conflict usually involves a chain of events in which at least one of the involved
road users performs some sort of evasive action to avoid potential collision (Parker, Jr. & Zegeer, 1989). If the strength of the evasive action is not sufficient to avoid physical contact, the involved road users will eventually collide. Therefore, in near-miss situations when road users were just about to miss each other by a very short time margin, their evasive behavior was found similar as if they were on a collision course (Svensson, 1998). In the literature, there is increasing evidence that time-proximity conflict indicators lack several aspects related to the definition of an evasive action (Archer, 2004). Consequently, they may not be suited for all traffic environments where evasive actions are the common collision-avoidance mechanism. Evidence in the literature also shows that time proximity measures have several other limitations in measuring the severity of conflicts (Chin & Quek, 1997). The basic definition of many time proximity measures depends on simplistic extrapolation of road users future movements assuming fixed directions and constant velocity (Hayward, 1972). These assumptions have been shown to be problematic and lead to missing many conflicts because the definition initially constricts that road users have to be on a collision course. Another issue arises from reporting equal time proximity measures for different road users. The same time proximity measures were extensively used in the literature for the analysis of vehicle-vehicle conflicts and vehicle-pedestrian conflicts. However, vulnerable road users such as pedestrians, cyclists, or motorcyclists are subject to a higher risk of injury than protected commuters inside a vehicle when involved in the same collision. This is because proximity measures generally quantify the risk of a collision rather than the consequence of the collision and do not take into account the type of road user involved (Laureshyn, et al., 2010). All these limitations show that time proximity measures provide only a partial image of the actual severity of traffic events and, as such, they can still miss many cues for the evaluation of the true conflict severity.
Several researchers acknowledging the limitations of time proximity measures have attempted to improve the calculation methods of the TTC and PET, or combine them into one index (Ismail, et al., 2011) (Gang, et al., 2012) (Nadimi, et al., 2016). Other researchers combined proximity measures with manual subjective observation scores to reflect the evasive action of road users (Sayed & Zein, 1999) (Kaparias, et al., 2010). However, the quantification of road-users evasive actions into an objective measure has never been attempted to assess missing cues in time proximity measures in evaluating conflict severity. Conflicts and collisions are generally of similar nature and they differ mainly in the degree of success of the evasive action to avoid physical contact. Therefore, the evasive action of road-users in traffic conflicts can provide an assessment of the interactions severity since it includes road-users perception of the risk of collision and the possible consequence of the collision.

The study of road-users behavior in different traffic environments can provide valuable information on their collision-avoidance mechanism. Although many studies have demonstrated the use of traffic conflicts in safety analysis, few studies have focused on understanding road user behavior in conflict situations. In the past, it was challenging to explicate the behavior of road users as the tools and techniques that could capture the microscopic behavior of road users were not readily available (Cottrell & Pal, 2003). Now with the advancement of computer vision techniques for traffic video monitoring, microscopic analysis of the explicit road users behavior can be undertaken at a much higher spatial and temporal accuracy (Hoogendoorn, et al., 2003) (Sayed, et al., 2012). The microscopic analysis provides an in-depth understanding of the evasive action mechanisms of road users in different situations. This refined understanding can enable the derivation of novel behavior-based conflict indicators that better reflect the severity of traffic conflicts. Using evasive action-based indicators can help improve the evaluation of conflict
severity especially in less organized traffic environments and create a stronger link with collision events which involve unsuccessful evasive actions.

In summary, there is a growing interest in using surrogate safety measures such as traffic conflicts to evaluate traffic safety. Traffic conflict evaluations have mainly relied on time-proximity indicators to identify conflicts and measure their severity. However, these indicators may not be good measures of the severity of traffic conflicts in all traffic environments, as they have several limitations that do not account for different characteristics of road-users behavior. Therefore, the detailed analysis of road-users behavior in traffic conflicts can help identify a set of evasive action-based measures as potential traffic conflict indicators. It is essential to test and validate these behavior-based measures for every road user towards a defined severity benchmark to emphasize its relevance for conflict severity and also compare them with time-proximity measures in different traffic environments.

1.3 Research Objectives

The main goal of this research is to develop and evaluate behavior-based traffic conflict measures that better reflect road-users behavior and overcome some limitations of existing traditional time proximity measures. The indicators are developed within an automated video-based traffic conflict technique to facilitate the objective assessment of traffic conflicts in a less organized traffic environment. The following specific objectives are considered in this thesis:

1- Investigating the applicability of existing time-proximity conflict indicators in less organized traffic environments. The selected locations in the thesis include less-organized traffic environments (e.g. Shanghai, China) which are considerably different from where traffic conflict measures were initially validated.
2- Understanding the evasive action of road users in less organized traffic environments. Specifically, the behavior of vulnerable road users (motorcyclists, cyclists, and pedestrians) are studied. The study is conducted by investigating the evasive action mechanisms of these road users in conflict situations.

3- Developing a set of evasive action-based indicators that consider road users behavior in traffic conflict situations and provide measures of conflict severity including the automated detection of traffic conflicts with evasive actions in a less organized environment.

4- Investigating the applicability of the developed evasive action-based conflict indicators in evaluating conflict severity in various traffic environments and comparing their use with time proximity measures. Five locations are considered in different cities namely Shanghai, New Delhi, New York, Doha, and Vancouver.

5- Developing ordered response models to test the efficiency of using the combination of time proximity and evasive action-based indicators in different traffic environments.

1.4 Thesis Structure

The thesis contains eight chapters organized as follows: The first chapter presents an introduction to the thesis with the background information related to the research, the research problem statement, and the main objectives. Chapter 2 documents a comprehensive review of the literature related to the topics addressed in the thesis. The review covers the existing traffic conflict techniques and the methodologies taken in addressing their limitations. Chapter 3 provides the information necessary for developing the thesis methodology; mainly the use of computer vision in traffic conflict detection and assessment. The approach used in investigating conflict severity measures are also included in this chapter. Chapter 4 covers the investigation of pedestrian traffic conflicts at a location in Shanghai, China. The applicability of using traditional time-proximity
Conflict indicators are tested on pedestrian conflicts, and the study of pedestrian evasive action behavior is conducted to develop evasive action-based conflict indicators. In Chapter 5, two-wheelers evasive action behavior is analyzed and several evasive action-based measures are evaluated in the studied environment. Chapter 6 focuses on the automated detection of evasive actions in traffic conflicts. A novel approach was investigated to detect pedestrian conflicts with evasive actions. Chapter 7 investigates the use of evasive action-based indicators and time proximity-based conflict indicators in different traffic conflict environments. Statistical models that relate both types of conflict indicators to conflict severity are developed. Finally, the summary of the research results, conclusions, and limitations are presented in Chapter 8. The chapter also provides the direction for future research inspired by the research findings.
Chapter 2: Literature Review

This chapter provides the background literature for the research covered in the following chapters. The literature review focuses on key studies that have a significant impact on the development of the traffic conflicts technique and other surrogate safety measures. The chapter also presents a critical review of previous studies that deal with developing conflict measures. The literature review conducted in this chapter covers seven main topics. First, the chapter review summarizes a number of studies that are considered a milestone in the development of traffic conflict techniques in sections 2.1 and 2.2. Second, a review is provided on the tools and methods that have been previously used to evaluate traffic conflicts, including time proximity measures in sections 2.3 and 2.4. Third, the review discusses the limitations of traditional traffic conflict measures in section 2.5. The fourth topic covers a detailed review of studies in the literature that accounted for these limitations and introduced improved methods for conflict measurements in section 2.6. The review also discusses the need for developing new conflict measures based on road-users evasive actions. Finally, the chapter discusses computer vision techniques and their use in evaluating traffic conflicts. Computer vision played a vital role throughout this research. The technology used to extract traffic conflicts from video data and to conduct a microscopic analysis of road-user behavior would not be possible without computer vision. As such, the last section of this chapter (section 2.7) is dedicated to present the state-of-the-art research related to the use of computer vision in traffic conflict applications.

2.1 Definition of Traffic Conflicts

The concept of traffic conflicts (or near misses) was first introduced by Perkins & Harris (1968). Their work was originally conducted to compare General Motors vehicles against other
manufacturers in terms of involvement in unsafe traffic situations. They defined a traffic conflict as any event involving two or more vehicles in which the action of one causes another to make an evasive maneuver to avoid a collision. According to this definition, a traffic conflict is identified by the presence of evasive actions such as hard braking or sudden change of direction. The definition stands for the fact that conflicts and collisions are of similar nature except for the degree of success of the evasive action to avoid physical contact. The approach by Perkins & Harris (1968) was to observe and count the instances in which a driver took an evasive action to avoid being involved in collisions. Their work is regarded as a milestone in the course of development of Traffic Conflict Techniques (TCT), as many conflict studies followed a similar approach.

Since that time, TCT has seen considerable interest from researchers, with many countries funding studies covering various aspects of the TCT. In a key step for formalizing the traffic conflict techniques, the conceptual definition of a traffic conflict was defined as “a situation in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged” (Amundsen & Hydén, 1977). According to this definition, an observed situation is determined as a traffic conflict by the proximity of road users in time and space. A severity hierarchy of traffic events was later introduced (Hydén, 1987). The hierarchy establishes a severity dimension along which all traffic events can be arranged in a safety pyramid. As shown in Figure 1.1, at the bottom of this hierarchy are the frequently-occurring uninterrupted passages. Fatal, injury, property damage only collisions, and traffic conflicts are at the top of this severity dimension. Traffic collisions which lie at the top of the pyramid are the least frequent events occurring on the road. As the frequency increases, the severity decreases to reach the other extremity where undisturbed passages lie at the base of the pyramid. Later, it was argued that, for a particular selection of severity measurements, the severity exhibits the shape of
a diamond considering only interactions where road users are on a collision course (Svensson, 1998) but the traffic conflicts were still viewed as precursors to road collisions. Therefore, it is theoretically possible to reduce the frequency of the very severe but infrequent events (i.e. traffic collisions) by reducing the frequency of the less severe yet more frequent events (i.e. traffic conflicts) (Svensson & Hydén, 2006).

2.2 Validity of the Traffic Conflict Technique

The validity of the traffic conflict technique has been an issue since the beginning of the development of the approach. The main concern was whether the occurrence of traffic conflicts could be a reliable predictor of road collisions. Many research studies have attempted to validate the traffic conflict technique. The validation, however, has always been judged by the relation between traffic conflicts and their respective collision records which stems from the long practice of relying on collision data in safety evaluation. The first attempt to validate traffic conflicts was performed by Baker (1972) to find an association between traffic collisions and traffic conflicts collected using the conflict observation method of Perkins & Harris (1968). This experiment showed positive correlation coefficients between conflicts and collisions from different signalized and non-signalized intersections. Later, Grayson et al. (1984) in the calibration of the Swedish traffic conflict technique, showed that conflicts collected by human observers and collision data from different sites were ranked in the same order by collisions and conflicts. Migletz et al. (1985) established relationships between collisions and conflicts and showed that the correlation between them increased with their disaggregation into specific characteristics, such as the type of maneuver, and level of severity. Afterward, Hauer & Gårder (1986) showed that establishing a solid relationship between traffic conflicts and road collisions is a persisting problem. Therefore, the validity of the traffic conflict techniques can be shown as a matter of degree measured by the
variance of a statistical estimator of road collisions in terms of the frequency of traffic conflicts. Similarly, Hydén, (1987) showed the validity of a set of conversion factors that establishes the relationship between the number of collisions and the number of serious conflicts. The first attempt to demonstrate the validity of pedestrian traffic conflicts was done by Lord (1996), using a flow-based safety performance function. The research showed that pedestrian conflicts collected using human assessment of evasive actions provided high correlation with collision data. Further evidence on the validity of traffic conflict techniques was found in the study by Sayed & Zein (1999), showing a statistically significant correlation between the frequency of traffic conflicts and collisions collected from several signalized intersections in British Columbia. Later, the model proposed by Songchituksa & Tarko, (2006) showed high correlations between the safety estimates of traffic conflicts and historical collision data. The model represented collisions as extreme realizations of the temporal proximities of road users. Another recent study by Sacchi et al. (2013) presented evidence supporting the validity of the traffic conflict technique by comparing the results of a collision-based and conflict-based before/after safety evaluation. The results showed a considerable similarity between the overall and the location-specific reductions in conflicts and collisions. El-Basyouny & Sayed (2013) also showed the existence of a consistent relationship between conflicts and collisions using a two-phase model of conflicts that yields collisions. In the first phase, a lognormal model was employed to predict conflicts using volume and some geometric-related variables, then, a conflict-based negative-binomial function was employed to predict collisions for several intersections.

Not all studies conducted to find a relationship between conflicts and collisions produced positive results. Some researchers failed to show a relationship between conflicts and collisions such as Williams (1981). Other researchers argued that the main problem for evaluating the validity of
traffic conflicts in this manner lies in the known inconsistencies of collision data provided (Chin & Quek, 1997). Tiwari et al. (1998) also showed a lack of correlation between traffic conflicts and collisions collected across different intersections in New Delhi, India. The work was the first attempt to try to validate the traffic conflicts in environments other than in Europe and North America where the traffic conflicts were originally validated. The lack of relationship between conflicts and collisions was likely because of the vast difference in the traffic environment in New Delhi. In general, the validity of traffic conflict techniques that are often defined in terms of its ability to predict road collisions has sometimes shown problems. Therefore, many researchers use the traffic conflict technique as a diagnostic and evaluative tool rather than a predictive one (Chin & Quek, 1997). It is believed that reducing traffic conflicts, which gives inference on the risk of collision, can help in achieving the ultimate goal – reducing collisions.

2.3 Traffic Conflicts Observation and Measurement

Initially, the traffic conflict technique involved observing, recording, and evaluating the frequency and severity of traffic conflicts at a location by trained observers (Glauz & Migletz, 1980). At each study location, typically two trained observers are stationed at the studied location for specific hours of observation. They were to register traffic conflicts if one of the possible evasive actions associated with a traffic event can be specified (Asmussen, 1984). Several countries have developed traffic conflict collection procedures to collect traffic conflict data such as the United States (Parker, Jr. & Zegeer, 1989), France (Muhlrad, 1982), Finland (Kulmala, 1982), and the United Kingdom (Baguley, 1984). In these manuals, the measurement of traffic conflict severity is determined using a score that measures the severity of the traffic conflict which depends on the evasive action of the road users and the perceived control they have over the situation. These
methods were not only limited to vehicle conflicts but also expanded to different road-users interactions such as pedestrian conflicts (Cynecki, 1980).

However, these earlier traffic conflict observation methods were criticized because of their subjectivity and the need for considerable judgment by the observers. The grading of evasive action severity can vary from one observer to another, which affects the collection of accurate conflict data (Hauer & Gårder, 1986). The human observer severity rating of traffic conflicts suffers from inter- and intra-observer variability. The first variability, inter-rater, is the variation in interpretation and recording of a given situation between different observers. The second variability, intra-rater, rises from lack of consistency of an observer in the recording because of the repeatability (Asmussen, 1984). The subjectivity of the results of human observers has often made the comparison of traffic conflict studies difficult. In an attempt to make the process less subjective, the procedure included many rules for field observers to follow. These details sometimes imposed a heavy burden on field observers, especially in situations associated with complicated encounters. In some situations, the field observer would be overwhelmed with the detection and rating rules. Thus, it increases the chance of mistakes in conflict registration, especially when a quick assessment is needed. Therefore, observer training was an essential step which added to the already high cost of conducting manual traffic conflict surveys. To overcome on-site problems, in-office analysis of traffic video observations has facilitated repeated viewing of conflicts. However, the limitations of human judgments inspired researchers to formalize the traffic conflict collection through the introduction of objective measures that overcome these subjectivity concerns.
2.4 Time Proximity Objective Measures

Objective conflict indicators are quantitative measures of the severity of the conflict situation. The key advantages of these conflict indicators are:

1- The indicators overcome the subjectivity limitations of traditional observer-based conflict scores
2- They measure quantitative severity aspects of traffic conflicts
3- Traffic events that contain calculable conflict indicators have been shown to be more frequent than collisions
4- They enable validation and cross-comparisons of traffic conflict studies.

Several objective conflict measures have been adopted in numerous studies in the literature. The most popular measures are the ones based on temporal proximity, and there are also some measures based solely on spatial proximity. A list of primary time proximity measures and their definitions are included in Table 2.1. They are also known as proximal safety indicators or proximity measures. These indicators measure the severity of an interaction involving a conflicting pair of road users by quantifying their closeness in space and time in anticipation of a possible collision point. Therefore, they include an ordinal time-proximity dimension on the severity scale.

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<tr>
<th>Time Proximity Measures</th>
<th>Reference</th>
<th>Definition</th>
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<tbody>
<tr>
<td>Time-To-Collision (TTC)</td>
<td>(Hayward, 1972)</td>
<td>Expected time remaining for two road users to collide if they continue on the same path with their speeds</td>
</tr>
<tr>
<td>Post Encroachment Time (PET)</td>
<td>(Allen, et al., 1978)</td>
<td>Actual time difference between road users passing their crossing point which is their potential collision point</td>
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</table>
The most commonly used measure is the Time-to-Collision (TTC) or Time-to-Accident (TA) introduced by Hayward (1972) is defined as "the time remaining until a collision would have happened between two vehicles if they were to continue at their present speed and the same path" (Hayward, 1972). The TTC is a measure that varies throughout the interaction process. The TTC profile usually takes a declining pattern until the involved road users are no longer on a collision course. Commonly, the minimal TTC was used as an estimator of the severity of the traffic conflict (Kraay, 1985). The lower the value of the minimum TTC of a conflict the higher the severity. The TTC is widely used as a measure of traffic conflict severity because of its practicality and positive validity in several case studies (Saunier, et al., 2010) (Autey, et al., 2012). The second commonly used time proximity measure is the Post Encroachment Time (PET) introduced by Allen, et al. 1978). It is defined as the time difference between the moment an "offending" road user passing out of the area of the potential collision and the moment of arrival of the "conflicted" road user possessing the right-of-way to that potential collision point. Therefore, the PET indicates the extent to which the road users miss each other. The PET was found effective for right-angle conflicts, such as crossing pedestrian conflicts (Cooper, 1984). This indicator, unlike TTC, does not require any speed or distance assumption and has only one value in an interaction. Several researchers have used PET in the case of crossing conflicts, such as pedestrian-vehicle conflicts (Alhajyaseen, et al., 2012) (Peesapati, et al., 2013). Although included in the validation of the Swedish traffic conflict technique, it was found that observers related more to TTC than to PET (Grayson, et al.,

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<th>Time Proximity Measures</th>
<th>Reference</th>
<th>Definition</th>
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<tr>
<td>Gap Time (GT)</td>
<td>(Glauz &amp; Migletz, 1980)</td>
<td>Expected time difference between two road users if no collision would happen in the TTC definition</td>
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</table>
However, no consensus has been reached on which measures should be used (Guido, et al., 2011). A few researchers employed the Gap Time (GT) as a measure of severity of conflicts which was initially described in Allen, et al. (1978). The gap time is the time difference between the passages of two road users if no collision is expected to happen between them at their point of crossing (Glauz & Migletz, 1980). In other words, the GT is the time difference between the two road users if no collision would happen in the TTC definition. Gap time was shown useful in the case of right-turn merging vehicles (Huang, et al., 2013).

The use of quantitative proximity measures has been significantly increasing in traffic conflict studies, especially with the development of advanced computer technologies in traffic conflict analysis which have made the use of these measures more appealing because manual data calculation of these measures is rather time-consuming and labor intensive. In practice, traffic conflicts are identified once the values of the measure are less than a predetermined threshold. Several diagnostic and Before-After (BA) studies have benefited from the use of objective measurements of traffic conflicts (Brown, 1994) (Autey, et al., 2012). These measures have been shown very useful for conducting many safety studies. However, in literature, there are still shortcomings associated with these measures, as will be discussed in the next section.

2.5 Limitations of Time Proximity Measures

The limitations of the time proximity measures were acknowledged by several researchers starting from the time of the validation of the Swedish traffic conflict technique (Grayson, et al., 1984). During the validation, it was found that conflicts with low TTC values are considered severe conflicts, but not all conflicts rated by human observers as severe have low TTC values. A number of fundamental problems in use and the definition of conflict indicators have been identified in the
literature (Chin & Quek, 1997) which, in some cases, affect the evaluation of conflict severity and their validity. These limitations include the sole dependency on proximity, extrapolation assumptions, and lack of accounting to the expected outcome of the event.

The first issue arises from the sole dependency on proximity as a measure of conflict severity. In some traffic environments, when road users behavior is less organized and not necessarily conforming to traffic regulations (following lane discipline, crossing marking,…etc.), road users commonly accept smaller distances between each other in their regular interactions (Nordfjærn, et al., 2014) (Kadali & Vedagiri, 2016). Since the estimation of severity using time proximity measures relies on road users getting within specific temporal and spatial proximity from each other. Road users might be in a very close encounter with each other in some cases and, yet, would be considered normal, as they resort to swift evasive actions to avoid potential collisions (Atchley, et al., 2014). Time proximity measures have been shown to be a viable measure for conflict severity in more organized traffic environments where road users are more conforming to traffic regulations so are already less likely to be on a collision course. However, further evidence in literature shows that time proximity measures are inconsistent in the definition of an evasive action (Ismail, 2010). In the work by Tiwari et al. (1998), the lack of relationship between traffic conflicts and collisions in New Delhi, India was attributed to this difference in the road-users behaviors.

The second limitation in the definition of the time proximity measures is the dependency on a fixed assumption for the expected movement of road-users trajectories. Many problems arise from assuming that road users would follow the same path with their same speed. Additionally, many practices depend on rather simplistic linear extrapolation of road user positions assuming a constant speed (Saunier & Sayed, 2008). While this extrapolation may be close to reality in some
cases, such as a vehicle continuing to move in the same lane, it is not the case for many road users conflicts (Archer, 2004). The problem is more pronounced in environments with frequent violations and where road-users movements are difficult to predict. This problem is reflected in studies where traffic conflicts are missed because road users need to be on a collision course to be identified in the TTC definition (Ismail, et al., 2009). Problems have also been identified in the misrepresentation of some events such as a PET in which a motorist, for example, decelerated strongly to stop as to avoid a collision with a crossing pedestrian. The PET value, in that case, might not reflect the actual severity of that event. Therefore, traffic events with non-calculable or misrepresented time proximity indicators have proven to be significant in some investigations (Zaki, et al., 2014). The simple assumptions of an unchanged direction extrapolation can be problematic in cases of complex road user behavior such as vulnerable road users (pedestrians, cyclists, or motorcyclists), which have frequent direction changes.

The third limitation is that time proximity measures are limited to estimating the collision risk without accounting for the possibility of a potential collision (Laureshyn, et al., 2010) (Bagdadi, 2013). In an early validation study of the traffic conflict technique, it was found that observers incorporate other aspects to the severity of the situation apart from the TTC or PET, such as the minimum distance between the road users, types of road users, and type of maneuver (Grayson, et al., 1984). The evaluation of conflict severity using TTC or PET by definition are conducted at a particular point in time along the course of the interaction. This quantification does not allow accounting of any information before or after that point. Conflict severity indicators should allow for a continuous evaluation, not only at a specific moment. The TTC profile, for example, usually takes a declining pattern until the starting point of the evasive action where the road users are no longer on a collision course. Human observers would typically measure the severity of this evasive
action, which is not quantified in the TTC definition. Previous researchers show that the consequence of the potential collision of a traffic conflict event is not reflected in the TTC definition. Kruysse (1991) showed that time proximity measures do not account for the expected impact of the collision in severity quantification, the factor which is typically reflected in a human evaluation.

The same limitation results in reporting identical severity measurements for different road users. Vulnerable road users (pedestrians, cyclists, and motorcyclists) are likely to suffer more severe injuries than protected road users that are traveling in a vehicle. The way traffic conflicts are analyzed using time proximity measures does not take into account the vulnerability of the road users involved (Laureshyn, et al., 2010). Time proximity measures estimate the risk of the road-users involvement in a collision without accounting for the possible consequence of the collision.

Considering the case of two conflicts with the same TTC values, one involves a pedestrian-vehicle interaction and the second is between two vehicles, a human observer will intuitively rate the first traffic conflict at a higher severity level than the second because of the expected consequence of the collision that might occur and the road users involved.

Limitations, in the definition and use of time proximity measures, indicate that they provide a partial image of the true severity of traffic events missing some clues of the real conflict severity. Despite these limitations, time proximity measures have been widely used to evaluate traffic conflicts in many developed countries including Sweden (Grayson, et al., 1984) (Hydén, 1987), Canada (Cooper, 1984) (Lord, 1996) (Sayed & Zein, 1999), Japan (Alhajyaseen, 2015), and the United States (Songchitruksa & Tarko, 2006) (Peesapati, et al., 2013). Researchers acknowledging these drawbacks mainly used one of three approaches to improve conflict measures.
(1) Improvement in the calculation of time proximity measures;

(2) A combination of different time proximity indicators

(3) Introducing non-time proximity measures.

2.6 Improvements in Traffic Conflict Measures

2.6.1 Improvements of Time Proximity Measures

Several researchers introduced modified measures derived from the TTC, PET, and GT that can address some of the drawbacks of time proximity measures. A comprehensive list of these improved indicators and their definitions is listed in Table 2.2. Van der Horst (1990a) introduced the Time-to-Intersection (TTI) for vehicles approaching an intersection which is the time expected for a vehicle to enter the intersection at a speed just at the onset of braking. This measure was shown successful in measuring the severity of crossing vehicle-vehicle interactions at non-signalized intersections. In another application, van der Horst (1990b) presented the Time-to-Stop line (TTS), which measures how far the driver approaching a signalized intersection is away from the stop line at the onset of the yellow signal. Várhelyi (1998) showed that the Time to Zebra (TTZ) is a significant indicator for vehicle-pedestrian conflicts at midblock crossings. The measure quantifies the time remaining for vehicles to reach the zebra crossing at the moment the pedestrian arrives at the curb. Van Winsum et al. (2000) introduced the Time to Lane Crossing (TLC) to measure the driver unintended lane departures which is defined as the time remaining for a vehicle to reach the border of their traffic lane based on the lateral movement of the vehicle. Zhang, et al. (2012) showed that the Time-Difference-to Collision (TDTC) is a useful measure of pedestrian-vehicle conflicts at crosswalks. The definition of TDTC is derived from the GT definition as the positive or negative GT, considering the order by which pedestrians or vehicles cross first. Almodfer et al. (2016) showed a lane-based PET (LPET) as a better measurement for pedestrian-
crossing conflicts. The LPET measures the PET considering the lane width as a potential conflict area instead of a point conflict as in the PET definition. Overall, the above-listed measures have shown potential in identifying conflict severity as they quantify the encountered hazard of drivers for certain types of conflicts. The methodologies are based mainly on road user violation maneuvers which are deemed hazardous traffic situations. However, these measures are still less practical than TTC, PET, or GT because they are situation-based measures for specific maneuvers and cannot be generalized to other settings or utilized for other road users.

Other researchers introduced measures derived from the typical profile of the TTC, PET, and GT. Chin et al. (1992) used the reciprocal of TTC as a better measure of traffic conflict severity. Later, Keifer et al., (2005) showed similarly that the inverse of TTC is the key element of the underlying process where drivers decide to do hard braking versus a normal braking because of the inverse relationship between severity and TTC. Minderhoud & Bovy, (2001) introduced two indicators derived from the typical TTC profile. The first is Time Exposed to TTC (TET), which covers the time duration at which the vehicle is exposed to a critical TTC value under a certain threshold, and the second is Time-integrated TTC (TIT), which is the integral of the TTC profile under a certain threshold in sec². Both measures showed different aspects of severity covered in the TTC profile. Laureshyn et al. (2010) showed the Time Advantage (Tadv) as a direct improvement to the PET calculation, which expresses the predicted PET value considering the size of the road users involved and T2, which calculates the predicted PET of the second road user until the first road user leaves the conflict point, also considering the size of both road users. Although all these measures seem to have potential in better estimating the severity of traffic conflicts, there is still no evidence that quantifies any improvements or that the modified measures do not hold the same time proximity drawbacks.
<table>
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<tr>
<th><strong>Indicator</strong></th>
<th><strong>Reference</strong></th>
<th><strong>Definition</strong></th>
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<tr>
<td>Time-to-Intersection (TTI)</td>
<td>(van der Horst, 1990a)</td>
<td>Time expected for a vehicle to enter a non-signalized intersection at the speed just at the onset of braking for another vehicle approaching the intersection</td>
</tr>
<tr>
<td>Time-to-Stop line (TTS)</td>
<td>(van der Horst, 1990b)</td>
<td>Time remaining to the stop line at the onset of the yellow signal for the driver approaching a signalized intersection</td>
</tr>
<tr>
<td>Time to Zebra (TTZ)</td>
<td>(Várhelyi, 1998)</td>
<td>Time remaining for vehicles to reach the zebra crossing of a mid-block crossing at the moment the pedestrian arrives at the curb</td>
</tr>
<tr>
<td>Time to Lane Crossing (TLC)</td>
<td>(van Winsum, <em>et al.</em>, 2000)</td>
<td>Time remaining for a vehicle to reach the border of the traffic lane based on the lateral movement of the vehicle</td>
</tr>
<tr>
<td>Time Difference to Collision (TDTC)</td>
<td>(Zhang, <em>et al.</em>, 2012)</td>
<td>GT considering the order by which a pedestrian and a vehicle arrive at their predicted point of collision.</td>
</tr>
<tr>
<td>Lane-based Post Encroachment Time (LPET)</td>
<td>(Almodfer, <em>et al.</em>, 2016)</td>
<td>PET value considering the lane width as the potential conflict area at pedestrian crosswalks</td>
</tr>
<tr>
<td>Inverse of TTC</td>
<td>(Chin, <em>et al.</em>, 1992) (Kiefer, <em>et al.</em>, 2005)</td>
<td>The reciprocal of TTC better reflects the underlying process where drivers decide to do hard brake versus normal brake</td>
</tr>
<tr>
<td>Time Exposed to TTC (TET)</td>
<td>(Minderhoud &amp; Bovy, 2001)</td>
<td>Time duration at which the vehicle is exposed to critical TTC value under a certain threshold</td>
</tr>
<tr>
<td>Time Integrated TTC (TIT)</td>
<td>(Minderhoud &amp; Bovy, 2001)</td>
<td>Integral of the TTC profile under a certain threshold in sec²</td>
</tr>
<tr>
<td>Time Advantage (Tadv)</td>
<td>(Laureshyn, <em>et al.</em>, 2010)</td>
<td>Predicted PET value considering the size of the road users involved</td>
</tr>
<tr>
<td>Indicator</td>
<td>Reference</td>
<td>Definition</td>
</tr>
<tr>
<td>-----------</td>
<td>-----------</td>
<td>------------</td>
</tr>
<tr>
<td>$T_2$</td>
<td>(Lareshyn, <em>et al.</em>, 2010)</td>
<td>Predicted PET of one road user until the other road user leaves the conflict point considering the size of the road users involved</td>
</tr>
</tbody>
</table>

A few researchers have considered probabilistic approaches for calculating time proximity measures such as the TTC and PET. Saunier and Sayed (2008) predicted road users positions based on the observation of the movement patterns of previous road users moving through the same location. The extrapolation hypothesis was represented by a probability calculated based on the frequency of observing a specific motion pattern (Saunier & Sayed, 2008). This probabilistic representation of TTC was shown to better reflect severity, especially for the uncertain course of road-users actions over the deterministic approach. In the study by Berthelot, *et al.* (2012), the TTC is calculated based on an updating algorithm that calculates a probability distribution of the TTC. The probability distribution, which is updated based on the vehicle dynamics, was found useful especially in handling arbitrary situations. In general, probabilistic methods to handle TTC and other time proximity measures have been shown useful in many situations and, therefore, were adopted in the thesis.

### 2.6.2 Combination of Indicators

Based on the fact that existing time proximity measures provide different clues for the underlying level of safety of a conflict situation. Some researchers suggested combining different measures to cover the missing aspects of addressing traffic conflicts. Ismail *et al.* (2011) suggested a method for aggregating various time proximity measures into a safety index. Also, Gang *et al.* (2012) aggregated conflicts by clustering the different time proximity measures in one measure to better capture the severity aspect of each conflict. Similarly, Nadimi *et al.* (2016) combined TTC and
PET in a mixed index using fuzzy inference to assess the severity of rear-end conflicts. These studies combined conflict indicators using different methodologies. However, one shortcoming of these approaches is not including other aspects beyond time proximity that can affect conflict severity, such as the potential consequence of the conflict situation and the severity of the road user evasive action.

Other papers suggested a combination of time proximity measures with other observational risk scores to address the evasive action of the road users involved (Salamati, et al., 2011) (Kaparias, et al., 2010). The combination of TTC with the subjective risk of collision score was shown successful in evaluating the severity of traffic conflicts at several intersections (Sayed & Zein, 1999). One major drawback for these efforts, however, is that the observational scores need human assessment for every conflict which is subjective, time-consuming, costly, and can be impractical in the case of conducting a large conflict assessment of a traffic location or several locations. Therefore, a reliable quantification of the evasive action of the road users could lead to better evaluation of conflict severity.

2.6.3 Non-Time Proximity Measures

Apart from time proximity measures, researchers have proposed several surrogate safety measures that are not proximity-based and does not quantify time. The spot speed, approach speed, and speed reduction at certain locations were applied by Thompson & Perkins (1983) and (Perkins & Bowman (1986) to study the relative effect of speed as a surrogate safety measure. Therefore, the use of conflicting speed (CS) was combined with TTC in the Swedish traffic conflict technique, as it was assumed that it would account for the road users evasive actions (Hydén, 1987) (Svensson, 1998). In that case, the conflicting speed represents the speed of the road user taking
evasive action at the moment just before the start of the evasive action, for which the TTC is estimated. They showed that conflicting speed combined with TTC was related to the severity of collisions. Other research studies have cited indicators depending directly on speed as a major contributing factor to collisions such as approaching speed (Kloeden, *et al.*, 1997), maximum speed (Gettman & Head, 2003), difference in speed (delta V) (Shelby, 2011), and accumulated speed variations (Moreno & García, 2013). However, the use of road user speeds as a surrogate safety measure has always been controversial in representing traffic conflict risk. The problem is the lack of complete understanding of the actual relationship between speeding and collisions because converting the change in speed to the change in collision frequencies is difficult. Therefore, speeding may not be a reliable predictor of a collision (Tarko, *et al.*, 2009). Moreover, studies on the severity of collisions showed that the consequence of a collision is dependent, not only on the speed, but also on the nature of the involved road users and the angle of the collision (Hutchinson, 1977) (Evans, 2001). Therefore, considering of speed as a sole indicator is not adequate. Although, speed is an essential component of any surrogate event definition, the reliability of speed itself as a standalone surrogate is doubtful due to the complexity of the speed-safety relationship (Bagdadi, 2013). This complicated relationship is based on the fact that speed quantification of severity assumes that the consequence of the conflict situation will be the same regardless of the involved road users or their evasive actions (Laureshyn, *et al.*, 2010).

Alternatively, some researchers suggested using acceleration as a behavioral surrogate to safety. The use of the deceleration rate to assess the severity of traffic conflicts (Gettman & Head, 2003) showed that the higher the deceleration of a vehicle the higher probability of collision. Hupfer, (1997) first introduced the deceleration to safety time (DST) as the minimum deceleration necessary for a driver to avoid the collision, i.e., to turn a collision course TTC situation into a
PET situation. Additionally, the deceleration value and maximum deceleration during the interaction were used in several conflict studies (FHWA, 2008) (Archer, 2004) (Malkhamah, et al., 2005). However, other researchers showed that it is difficult to validate the use of the deceleration information solely to identify conflicts (Várhelyi, 1998) (Wahlberg, 2000). They showed that deceleration should be combined with other measures to reflect severity. Therefore, Bagdadi, (2013) developed a measure incorporating the Time-to-Collision with speed, and deceleration to estimate the severity of traffic events in a homogenous way.

Other surrogates have been reported in (Gettman & Head, 2003) such as delay, travel time, percent stops, queue length, stop-bar encroachments, red light violations, and percent left turns. However, no attempt was made to relate the traffic conflicts obtained by these measures quantitatively to collisions. Aggressive lane merging and red-light violations were also tested as surrogates in (Kloeden, et al., 1997) (Porter & Berry, 2001). The main issue with these behavioral surrogates, however, is the fact that they are case-specific and they may not be able individually to capture the road-users behavioral severity aspect in full of any traffic conflict.

Overall, the evidence in literature shows no unique traffic conflict indicator that reflects all relevant aspects of conflict severity is existent. The intricacies that characterize traffic conflicts in different traffic environments represent a challenge towards adopting a single universal indicator to quantify severity for any traffic conflict. Some research studies have proposed useful indicators to address conflict severity, some of which can be appropriate in addressing time proximity indicator drawbacks. However, there is no consensus on which indicator should be used apart from the time proximity measures that were extensively studied. Previously, it was even difficult to explicate behavior of road users in traffic conflicts. Advanced tools for studying behavior using positional
analysis were not well developed. Issues with understanding road user collision-avoidance mechanisms and evasive actions were evident that it is sometimes challenging to explicate evasive actions from normal adaptations of the road-users movements while navigating in their environment. Now with the advancement of computer vision techniques, microscopic investigation of road-users behavior is now possible at a very high spatial and temporal accuracy. This microscopic analysis can provide a clear understanding of the evasive action mechanism of road users in different situations. It is believed that the change in the dynamic behavior of road users can determine unique characteristics of severity such as the effect of braking (Wahlberg, 2006) and the level of aggression (Johnson & Trivedi, 2011).

2.7 Development of Computer Vision Safety Applications

The methodology in the thesis is highly dependent on the analysis of traffic video data. Automated analysis of video data is now possible using techniques developed in the computer vision field. The idea of using computer vision techniques can be seen as an attempt to equip transportation systems with a “visual sense”. Computer Vision is defined by Ballard & Brown (1982) as “… the enterprise of automating and integrating a wide range of processes and representations used for visual perception … such as image processing, statistical pattern classification, geometric modeling and cognitive processing”. Numerous traffic applications benefit from using video sensors. The primary goal of adopting computer vision techniques in this thesis is the automated extraction of road-users trajectories as they navigate the field of view in the video. Extracting road user trajectories from video sequences enables positional analysis at a high spatial and temporal resolution than any of the current techniques available in practice, such as mobile positional techniques, GPS, etc.
Computer vision techniques have gained recent significant interest as a useful automated tool that can be used in many safety applications (Sayed, et al., 2012) (Autey, et al., 2012). As shown in the literature, there are several advantages to adopting computer vision in analyzing video data. Firstly, the informed application of computer vision techniques is a time- and resource-efficient way that overcomes the limitations of manual video data collection. Conducting manual analysis, such as volume or speed count, from traffic video data is always time, cost, and labor consuming. Secondly, recent advances in automated video-based data collection methods have facilitated more reliable traffic conflict assessment. The automation improves the accuracy of the calculated severity measures, as will be demonstrated in this thesis, and also reduces the labor burden. Thirdly, the use of computer vision enables a microscopic analysis of road-users behavior and interactions (Hussein & Sayed, 2015) which enables an in-depth understanding of road-users naturalistic actions, i.e., the evasive actions in conflict situations.

In the literature, there are different approaches for detecting and tracking road users from video data. The most famous methodologies are either model-based tracking, region-based tracking, or feature-based tracking. The model-based tracking approach applies supervised learning algorithms to develop models that can detect road users from video scenes. The method depends on prior knowledge of road users geometric models (Koller, et al., 1993) which induces a high accuracy in tracking. However, the drawbacks of this method rise from the fact that it needs an adequate database of geometric road users models collected from the traffic location analyzed in order to be able to track road users accurately. Consequently, it is unrealistic to be able to have a detailed model for all road users on the road (Coifman, et al., 1998). In region-based tracking, the video background image is subtracted from every incoming video image looking for pixels that are different in identifying connected regions (blobs) for each road user (Guido, et al., 2014). This
approach works reasonably well in free-flow traffic conditions. However, under congested traffic, it suffers from the over-grouping of objects. The over grouping occurs when multiple road users are grouped as one large moving object, which is a known problem in crowded video scenes. The feature-based tracking, which is used in this research, searches for distinguishable features on moving objects in the video scene. Then, features that share similar movement patterns regarding speed and movement direction and exist in close proximity are grouped to form coherent objects (Saunier & Sayed, 2006). Objects are then tracked over the video frames to extract the road user trajectories. The first advantage of this method is that it does not need a pre-set learning of the road-users geometric models in the video scene to be able to track them. The second advantage is that, even in the presence of partial occlusions such as crowded areas, some of the features remain visible and can be tracked on the moving objects. The advantages of using feature-based tracking make it more appealing than the other methods in the case of tracking road users from traffic video data.
Chapter 3: Methodology

This chapter describes the core methodology used to undertake the various components of the thesis research. The chapter is divided into five main sections. The first presents the process conducted to automatically extract road-users spatiotemporal information (i.e. trajectories) from traffic videos. The second covers the mechanism used to detect traffic conflicts from road-user trajectories and evaluate their severity using standard conflict measures. The third and fourth components cover supplementary techniques essential to process trajectories for applications such as noise reduction and violation analysis. The fifth component describes the approach adopted in the validation of the behavior-based conflict indicators. A detailed description of these steps is explained and examples are shown.

The research in the thesis relies primarily on the collection of traffic videos as the main source of data acquisition. Traffic videos provide the basis for traffic conflict detection and the road-users behavior investigation. Using traffic videos in data collection has several advantages:

1- Video data are rich in details as it covers a wide field of view; one camera placed at a vantage point can be sufficient to monitor an entire intersection.

2- Video cameras are now becoming relatively inexpensive and technically less challenging to use and install than many other data collection equipment such as radar sensors and inductive loop detectors.

3- Video cameras are often already installed and used in monitoring traffic intersections/roadways by many jurisdictions.

4- The record of the traffic data obtained can be permanently kept for archiving, future analysis, and human review.
5- Video sensors allow the automated collection of traffic data using computer vision techniques which are usually manually collected.

The video tracking in this thesis is performed using the computer vision system developed at the University of British Columbia. The system uses algorithms to automatically detect, track, and classify road users in video scenes. The amount of manual intervention needed to collect this data can be significantly reduced by deploying this system. The computer vision platform is mainly comprised of two modules:

1. A video processing module for road-user detection and tracking
2. An interpretation module for different applications; classification of road users, conflict analysis, violation detection, and the analysis of road-user behavior.

Several applications previously developed and applied have shown the capability of the system in extracting road-users positional data (Ismail, et al., 2009) (Sayed, et al., 2013) (Hediyeh, et al., 2014). In this thesis, the extracted road user tracks are obtained for two purposes. First, road user trajectories are used in the extraction of traffic conflicts and evaluating their severity, as presented in chapters 4 and 5. The second purpose is to perform a detailed analysis to understand road-users behavior in traffic conflict situations, presented in chapters 4, 5, and 6. The role of the computer vision system in the data collection and analysis is explained in the following sections.

3.1 Road User Tracking

To extract road-users positions from the video data, the analysis procedure is comprised of a series of steps, as shown in Figure 3.1. During traffic video recording, the three-dimensional real-world is captured on a two-dimensional image space. The translation of three-dimensional coordinates into two-dimensional coordinates is a transformation associated with the camera position, orientation, and its lens (Ismail, et al., 2013). The first step in video analysis is the camera
calibration to define the homography matrix associated with this transformation. Camera calibration is necessary for tracking road users and relating these tracks to the real world (Dubrofsky & Woodham, 2008). Camera calibration is adopted using a mixed-feature approach by annotating features in the camera image and an aerial, orthographic image of the intersection. Three types of annotations are used for the camera calibration optimization corresponding points, distances, and angles. The selected features must be on the horizontal plane of the road or at a specified height above the road plane to accurately relate to where the road users are moving. An optimization algorithm adjusts the camera calibration so that when these features are projected from the camera image to the orthographic image or vice versa, the corresponding points match (Ismail, et al., 2013). The calibration error is represented by the discrepancy between calculated and annotated segment lengths for the whole scene. In the end, a validation of the calibration accuracy is viewed through a displayed grid in both the real-world image and the camera image (Figure 3.1).

Knowing the translation of the video image to the road plane, the video tracking relies on algorithms to differentiate between features of road users and features that are part of the environment. Features are identified and tracked using an implementation of the Kanade-Lucas-Tomasi feature-tracker algorithm (Tomasi & Kanade, 1991) so that features that remain stationary are assumed to belong to the background (i.e., the environment) and are discarded. Features must be continually generated in order to identify moving features that may subsequently be tracked. Figure 3.1 shows the features as red points on the moving objects. Feature-tracking errors are dealt with by enforcing regularity motion checks to remove features with unreasonable acceleration or abrupt changes in direction so that features with motion properties that are not physically possible can safely be classified as tracking errors (Saunier & Sayed, 2006).
Road Users Detection and Tracking

Road users form relatively large objects with many distinguishable physical features and, as such, will generate multiple features in the feature-tracking step. The next step is to decide which set of features belongs to a unique road user, i.e., a moving object. Feature grouping is carried out using clues like spatial proximity and a common motion of features. Among a detailed set of criteria, the connection distance between features along with the similarity of the motion-vectors are the most important criteria in features grouping (Saunier, et al., 2006). For a feature to be connected to another feature in order to create or add to a group, it must be within a maximum connection...
distance. In the real world, features of a physical body of a road user such as a vehicle's side mirrors and bumpers have identical motion vectors. Computer-tracked features must exhibit the same motion characteristic to be associated with a common road-user. Features with motion vectors differing by more than a specified threshold are assumed to not belong to the same vehicle and are not grouped, regardless of their spatial proximity. Eventually, the continuous tracks of the resulting moving objects translated to the road plane represent the coordinates of the road users in time, as shown in Figure 3.2.

![Figure 3.2 Output of road users tracking in the video sequence as a set of tuples recorded over the video recording](image)

The output of the tracking in the real-world coordinates are the moving object trajectories \((R_j)\) recorded as a set of points along the video frames.

\[
R_j = \{(X_1, Y_1, V_{x1}, V_{y1}), \ldots, (X_i, Y_i, V_{xi}, V_{yi}), \ldots, (X_N, Y_N, V_{xN}, V_{yN})\}
\]

where, \(X_i, Y_i\) are the spatial coordinates of the moving object \(R\) at any frame \(i\) and \(V_{xi}, V_{yi}\) are the corresponding velocities.
Every point corresponds to the location of the road user on the road plane at every video frame. Traffic videos are usually between 25 and 30 frames per second. The velocity is calculated by the change of these positions in time. The speed profile can then be deducted as \( S = \text{norm} (V_x, V_y) \) describing the speed variations along the trajectory time series. The tracking accuracy has been previously validated on three different video datasets and the tracking accuracy was reported to be satisfactory between 84.7% and 94.4% (Saunier & Sayed, 2006). This accuracy is considered reliable, especially under heavy traffic conditions, and should have an insignificant impact on further calculations. However, some challenges remain in handling issues such as:

1- The variation of global illumination as the tracking quality at night is affected by the street illumination. Features might not get tracked as well as in the daytime because road users in the video at night can look similar to the road surface.

2- Occlusions affect the tracking accuracy. Road-users occlusion happens when a fixed object such as a pole/wire or another moving road user blocks seeing part of the movement. In this case, it leads to the discontinuity of the track and the start of a new tracked road user. However, partial occlusions can be handled in some cases so the track is not lost when continuous features exist on the non-occluded part of the road user. For example, the existence of wires or thin poles, for the most cases, does not affect the presented trajectories.

3- Shadows are sometimes tracked jointly with the road-users objects which can deviate the projected trajectory from the center of the movement. Although this error is present on sunny days, it has little impact on the results because typically, it has a slight deviation on the resulted positions of the road-user trajectory.
4- Distant objects in the scene are not tracked as accurately as they get closer to the camera field of view. The tracking accuracy is affected by the projection of the camera view to the world coordinates. At distant points in the scene, the discrepancy between the points translation can create an error different than that of close objects.

3.2 Traffic Conflicts Detection

Road user detection and tracking facilitate many traffic applications using the positional data of the road users. One of the main safety applications in the thesis is traffic conflict detection and evaluation. Several steps are performed in the analysis of traffic conflicts, shown in Figure 3.3, such as road-users classification and prototype matching to extract road-users events and evaluate their severity.

The first step is to classify the moving objects into their respective road user types. Object trajectories hold clues that reveal the nature of the road user characteristics. The ambulation of the walking steps governs a pedestrian movement pattern. Therefore, the pedestrian speed profile demonstrates periodic cyclic variations repeated continuously over time. Vehicle movement patterns are primarily composed of linear segments corresponding to different speeds throughout the trajectories. Therefore, the oscillatory behavior associated with a pedestrian and also existent in the cyclist pedal movement with lower frequency, while lacking in vehicles, is the main characteristic upon which classification is based. Other complimentary clues such as maximum speed and object size assist in the classification procedure. The accuracy of the road-users classification previously assessed was reported to be between 82.1% and 96.7% (Zaki & Sayed, 2013). In the end, the classification of the moving objects is based on their corresponding category namely pedestrian, bicycles, motorcycles, and vehicles (Zaki & Sayed, 2013) (Zaki, et al., 2015).
Traffic Conflicts Analysis

Figure 3.3 Layout of traffic conflict detection and evaluation module showing the four essential steps in the analysis of traffic conflicts

The next step is prototype generation which is a procedure carried out after tracking to extract traffic conflict events. The term “prototypes” refers to a group of movement patterns that define the common set of movements carried out by road users. The synthesized prototypes represent the expected road-users movement trajectories. A subset of the video data tracks that contain all common traffic movements is selected to represent the full data set. Trajectories for this subset is extracted automatically from the collected history of the road-users positional tracks. This set is reduced to a group of hundreds of prototypes by drawing synthetic prototypes representing their
typical movement patterns. In the end, prototypes for certain road users maneuver following similar trajectories (e.g., right-hand turns) may begin and end at different locations but still describe the same movement pattern.

The generation of interactions between road users depends on the trajectories and the prototypes obtained. First, the trajectory of an object is matched to every individual prototype from the full set of prototypes using the Least Common Subsequence (LCS) algorithm. The LCS algorithm is based on maximizing the matching distance that contains same tracking subsequences of an adequate length (Saunier & Sayed, 2008). Therefore, every trajectory is matched with more than one prototype with a probability weight determined from the LCS matching distance. Then, the matched prototypes are translated to the road user center and matched for its velocity. This provides a set of predicted future positions with associated probabilities of occurrence. Conflicts between road users can then be determined by evaluating if these future positions coincide both spatially and temporally with each other (Saunier, et al., 2010). This automated conflict analysis was previously demonstrated and applied to different conflicts such as pedestrian conflicts (Ismail, et al., 2010), bicycle conflicts (Sayed, et al., 2013) and vehicle conflicts (Autey, et al., 2012).

### 3.2.1 Time Proximity Measures

Conflict severity evaluation is typically performed by calculating time proximity measures such as TTC and PET, as discussed. The analysis of traffic conflicts is done on the level of every pair located in the scene within any overlapping time intervals. If a pair of road users is on a collision course at any time instant (i.e. time frame), the TTC is calculated by measuring the time remaining until a collision would have happened between the road users. The TTC profile usually has a declining pattern until the road users are no longer on a collision course. Figure 3.4 shows an
example of a conflict and the corresponding TTC profile. Since TTC varies throughout the interaction process, van der Horst has considered different points at which time-to-collision should be measured (van der Horst, 1990a). The minimum TTC was shown to reflect the differentiated critical or serious conflicts from normal encounters. Therefore, the minimum TTC value during the course of interaction is usually taken to represent severity. On the other hand, the PET is only one value indicator for every conflict. The PET requires no collision criterion and, therefore, makes no speed and direction assumptions. PET rather simply quantifies the time by which every conflicting road users missed each other. During conflicts analysis, PET is calculated by finding the time difference between intersecting trajectories that missed each other, as shown in Figure 3.5. The PET serves better in measuring the severity of crossing conflicts, such as pedestrian conflicts. However, when the angle between road users decreases, the PET does not perform as well. For example, in rear-end conflicts, typically PET will give values that might not reflect the severity of the interaction (Cooper, 1984).

![Image of pedestrian-vehicle conflict and TTC profile](image)

**Figure 3.4** An example of a pedestrian-vehicle conflict and the corresponding TTC profile. TTC is calculated at every time frame. Typically, the TTC profile shows a declining pattern until road users are no longer on a collision course
The severity evaluation starts by filtering events with TTC and/or PET. In the end, some events include TTC only or PET only or both measures. Conflicts are chosen when their minimum TTC and/or PET is less than a certain threshold, usually 3 seconds (Sayed & Zein, 1999). Conflicts could be further classified into rear-end, merging, right angle, side-swipe, head-on, etc. Further analysis of the obtained conflicts is performed through evaluating the frequency, severity, and location distributions.

Figure 3.5 PET of a pedestrian-vehicle conflict. PET is calculated by the time difference between the passage of one road user to a point and the passage of the other to the same point.

3.3 Violation Detection

Violation analysis identifies road users that are not conforming to traffic rules and regulations. Previous research shows a high association between locations with a high number of violations and the involvement in collisions (Parker, et al., 1995). Violations can be classified into spatial and temporal violations. A spatial violation is when road users occupy a non-designated space during their movement, such as pedestrian jaywalking. A temporal violation is when road users are traversing a location (e.g. intersection) during a non-designated time, i.e. violating their signal phase. The identification of violations is undertaken by comparing the spatial and temporal
information of each road user against the traffic signal cycles (Zaki & Sayed, 2014) and region-based boundaries drawn for designated areas in the intersection such as the pedestrian crossings, approaches, and sidewalks, as shown in Figure 3.6. The violation detection is then implemented in two consecutive steps. First, the time the trajectories of the road users crossing the boundaries of the regions of interest are identified. Second, the period of every trajectory is compared to the signal phase timings. For example, a temporal violation happens when a pedestrian leaves the sidewalk and enters the crosswalk at a red phase. A spatial violation happens when a pedestrian leaves the sidewalk or crosswalk and enter other areas. Similarly, the same method applies to other road users movements when leaving the approach.

Figure 3.6 Regions drawn for violation detection. Violation is registered from the time the road user trajectory crosses the region boundaries and contradicts with their signal phasing

3.4 Noise Reduction

The analysis in this thesis needs accurate trajectories to interpret road-users behavior and to estimate conflict measures correctly. During the computer vision analysis process, tracking noise
can sometimes affect the generated trajectories. Noise in the trajectories occurs because features that disappear from the tracking are sometimes not backed up by newly generated ones. Primary sources of noise are the feature quality, with variations in the selected features due to occlusions or shadows. With the noise affecting the accurate spatial information of the trajectories, high order operations on those trajectories (velocity and acceleration calculations) amplifies the noise. To alleviate this issue, smoothing filters are used. The second order degree, Savitzky–Golay filter, is used for the current application (Savitzky & Golay, 1964). The Savitzky–Golay filter is a simple, practical filtering and smoothing mechanism that reduces the undesirable effect of irrelevant information for data with limited discontinuities. The described filtering setup has been shown successful in similar applications (Wahlberg, 2000) (Zaki, et al., 2014). This filter is specifically suitable for time series profiles with fixed or uniform intervals. The smoothing technique eliminates the noise in the presented trajectories while keeping relevant information for further analysis. A visual inspection of the filtered profiles was performed to choose the best setup that suppresses most of the noise while preserving the trajectory shape. The produced trajectory profiles were smooth and close to the original profile. Figure 3.7 shows an example of a motorcycle trajectory speed profile and the corresponding filtered profile.
Figure 3.7 An example of a motorcycle trajectory speed profile and the corresponding filtered profile. Smoothing was performed using the Savitzky–Golay filter.

3.5 Validation of Conflict Severity Measures

In this thesis, evasive action measures are proposed for measuring the severity of traffic conflicts. The primary validation point of reference performed on those indicators is the severity evaluation of traffic safety experts. The validation is performed in two stages.

- First, potential indicators are compared to the expert ranking evaluations to identify their suitability.
- Second, the ability of those indicators to differentiate between conflicts at different severity levels is statistically tested.
3.5.1 The Need of Expert-Based Validation

Studies show that humans have an internal concept of the dangerousness of a near collision (Shinar, 1984). In 1984, Shinar showed that humans are consistent in their evaluation relative to the real severity of traffic events. The human assessment was shown previously to capture sophisticated aspects of traffic conflicts, as the human observer takes into account not only the probability of a conflict to become a collision but also the consequences of the potential collision that could transpire had no adequate action taken place. The assessment of the conflicts typically measures the seriousness of the observed conflict between the involved road users as shown in many types of research (Grayson, et al., 1984) (Kraay, 1985) (Kruysse, 1991) (Svensson, 1992). In the validation of the Swedish Traffic Conflict Technique, it was found that serious traffic conflicts rated as such by human assessments were in stronger correlation with collisions than serious conflicts rated by objective conflict indicators such as TTC (Svensson, 1992) (Grayson, et al., 1984). Human traffic conflict assessment reflects a wider picture of severity than the captured solely by time proximity measures (Shinar, 1984). These findings show that observers internally incorporate the evasive action severity of a situation, besides TTC or PET. One plausible explanation is that human observers consider both the collision risk and the consequence, while objective measures, such as TTC or PET, often reflect just one of the aspects (collision risk). Researchers such as Laureshyn et al. (2010) recommended using human observers to evaluate video data filtered through automated time proximity measures to complement the video data analysis (Laureshyn, et al., 2010).

3.5.2 Shortcomings of Expert-Based Validation

Despite the benefits of incorporating the human assessment of traffic conflicts, there are consistency issues to consider. Inconsistencies arise from the variations in the observers’
judgments themselves (Shinar, 1984). Two types of inconsistencies could occur in the evaluation. The first is the inter-observer inconsistency, which is the variation in the way different experts evaluate severity. The second is the intra-observer inconsistency, which likely happens because of the repeatability problem, where the individual reviewer evaluates in a way that changes through the evaluation process. In the studies by Grayson et al. (1984) and Malaterre & Muhlrad (1979) different observers were asked to rate conflict severity from a common dataset and some variations in the scores were suggested by them. The differences were mainly in the detection of incidents as conflicts rather than in the evaluations of severity, where the observers largely agreed on the levels of severity and the level of agreement. Their agreements were high for the most severe conflicts. Therefore, training observers was always a requirement in the manual conflict data collection on site. However, later studies even show that experts and lay-persons can be equally reliable to judge traffic conflicts based on their concept of danger (Kruysse & Wijlhuizen, 1988) (Kruysse, 1992).

3.5.3 Validation of Experts Evaluation on Conflict Severity

The validation methodology is based on the long practice of on-site manual traffic conflicts collection and evaluation. The evaluation is performed according to the severity definition provided in Sayed & Zein (1999) where observer-based severity assessment of traffic conflicts was adopted. The experts decide on the severity level and rank of traffic conflicts based on their view of the perceived control the road users involved have over the situation. Typically, conflict studies conducted using human observers included two observers that were stationed on site to evaluate traffic conflicts (Asmussen, 1984) (Parker, Jr. & Zegeer, 1989). Similarly, the validation in this thesis is applied to a group of one hundred traffic conflicts of a specific conflict type that are randomly selected and presented to two safety experts to rank and categorize them. The experts are asked to categorize these conflicts in one of three groups based on severity level (Low
Severity/Intermediate Severity/High Severity) with at least 30 in each category. Afterwards, they are asked to rank the conflicts within the highest severity category. Since the use of human traffic conflict assessment is done in the validation process, the following procedures are adopted to reduce any potential inconsistencies that might happen.

1- The experts are carefully selected such that they have been involved in numerous traffic conflict studies before. They were traffic safety experts in North America and proved to have extensive experience in traffic safety studies.

2- Videos of individual conflicts, which are less than one minute in length, are given to the experts for repetitive viewing.

3- The group of traffic conflicts given to the experts is limited to 100 conflicts to reduce the potential intra-observer repeatability and inconsistency due to potential fatigue/boredom.

4- The evaluation was a controlled experiment in which experts would have to assign a minimum number of conflicts in every severity category. This would avoid potential discrepancies in the number of conflicts assigned to each category as a result of external factors not related to conflict severity.

5- A consistency test is performed on the expert results to check for inter-observer inconsistency and to ensure their consistency before further analysis on their results.

The following subsections explain the statistical techniques used for the validation of newly introduced indicators.

3.5.3.1 Consistency Test

The first step in the validation is to test the validity and consistency of the expert evaluations. The statistic Kappa (Fleiss, 1971) is employed to measure the agreement between the two experts.
Using the categorization of both experts, the agreements on the data is drawn, as shown in the example in Table 3.1.

**Table 3.1 Example of agreement results between expert results in three categories (Low Severity, Intermediate Severity, and High Severity)**

<table>
<thead>
<tr>
<th>Severity Category</th>
<th>Expert 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Expert 1 Low</td>
<td>24</td>
</tr>
<tr>
<td>Intermediate</td>
<td>9</td>
</tr>
<tr>
<td>High</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>34</td>
</tr>
</tbody>
</table>

From Table 3.1, the kappa statistic is calculated using equation 3.1 where $P$ is calculated by summing the number of observations in which the agreement exists by the total number of observations $P = \frac{64}{100} = 0.64$ and $P_c$ is calculated from the percentage of assignment of each expert to the three categories $P_c = \frac{34}{100} \times \frac{37}{100} + \frac{36}{100} \times \frac{33}{100} + \frac{30}{100} \times \frac{30}{100} = 0.335$.

$$
k = \frac{P - P_c}{1 - P_c} \tag{3.1}
$$

where $P =$ overall percentage agreement

$P_c =$ overall percentage agreement expected by chance.

A positive value for kappa indicates agreement between experts, a value of zero indicates an agreement that can be expected by chance, and a negative value indicates disagreement. The variance of kappa is calculated using equation 3.2. Under the hypothesis of no agreement beyond chance and using the central limit theorem, $k/\sqrt{\text{Var}(k)}$ is approximately distributed as a standard normal variant (Fleiss, 1971). Therefore, if $k/\sqrt{\text{Var}(k)}$ exceeds the critical Z value at 95%
significance level ($Z=1.96$), it indicates a statistically significant agreement between the two experts.

$$Var(k) = \frac{1}{N} \times \sum p_j^2 - \frac{(\sum p_j^2)^2}{(1 - \sum p_j^2)^2} \quad (3.2)$$

where $N = $ total number of cases

$j = 1 \ldots n = $ three categories of classification

$p_j = $ proportion of all assignments of the $j^{th}$ category.

### 3.5.3.2 Severity Trend

The second step is examining the validity of the proposed indicators towards severity. This test considers the trend of a traffic conflict indicator along with the severity categories assigned by the experts. The trend is an effective way to show the monotonicity in relation to severity and any conflict indicator. The mean of the different conflict indicators is first plotted among the three severity levels. The means that show a plausible trend for any indicator can potentially reflect the severity of the studied conflicts. For example, the TTC shows low values for the high severity conflicts and vice-versa. Therefore, it is expected that TTC profiles should show a declining pattern as the severity increase. The mean of the expert categories should show a logical pattern from the lowest severity to the highest severity for a potential measure to be further validated as a potential measure to reflect severity.

### 3.5.3.3 Severity Differentiation

The Analysis of Variance (ANOVA) test compares the difference between the means of each group of conflicts. In the thesis, the ANOVA test is used to provide a mean to identify the effectiveness of the proposed measures in reflecting expert evaluations. The ANOVA enables understanding the
significance of the difference between the expert group values. ANOVA is done by the hypothesis proposal of the mean of the equal groups as the null hypothesis \( H_0: \mu_1 = \mu_2 = \mu_3 \) and an alternative hypothesis of non-equal means as \( H_a: \mu_1 \neq \mu_2 \neq \mu_3 \). After calculating the t-statistic which shows the significance in the difference between the means from each other a p-value can be obtained. The p-value shows the ability to reflect the severity between the conflicts in the three categories. A significant p-value, at 95% confidence level, indicates a measure that can potentially differentiate between the categories of the three levels of the severity categories.

3.5.3.4 Ranking Correlation

The Spearman rank correlation coefficient is used to test the agreement between the expert ranking and the ranking based on proposed conflict indicators. The Spearman rank correlation coefficient is calculated using equation 3.3 (Spearman, 1904):

\[
 r_s = 1 - \left( \frac{6 \sum d^2}{n^3 - n} \right) \quad (3.3)
\]

where \( d \) = the difference between rankings by the measure and by experts, and

\[ n = \text{number of conflicts}. \]

In the end, the most important aspect in the validation is the closeness of the indicators in expressing the severity of conflicts. Many indicators can reflect changes that happen in road-users behavior as an explanatory feature of evasive action. However, successful conflict indicators should be yielded relevant to evaluate conflict severity.
Chapter 4: Pedestrian Evasive Action Behavior in Traffic Conflicts

A traffic conflict involves a chain of movements in which at least one of the involved road users perform some sort of evasive action to avoid potential collision (Parker, Jr. & Zegeer, 1989). If the strength of the evasive action is not adequate for avoiding physical contact of the interacting road users, the involved road users will eventually collide (Dingus, et al., 2006). As argued in the literature review, the investigation of the behavior of road users in traffic conflicts can aid in understanding the mechanism by which road users perform evasive actions. The in-depth analysis of road user behavior in traffic conflicts has always been a challenge due to the lack of tools and techniques required for the microscopic analysis of road-users movement tracks at such high precision. However, with the advancement of computer vision techniques, the explicit investigation of road-users behavior can be conducted at a high spatial and temporal accuracy. Using road-user trajectories in conflict situations enables the microscopic study of their evasive action behavior in much more detail than manually-performed analysis.

This chapter presents a comprehensive analysis of pedestrian behavior in traffic conflicts. The study is conducted on a dataset from a busy signalized intersection in Shanghai, China. The location is characterized by less organized traffic where many road-users violations, interactions, and non-conformance to traffic rules takes place. The traffic environment and the cultural norms differ significantly from traffic environments where conflicts techniques were initially validated and often used. The chapter presents the results of using traditional time proximity measures of traffic conflicts TTC and PET to identify pedestrian conflicts in less organized traffic environments and discusses their limitations. Several evasive action-based indicators are proposed as potential indicators of conflict severity.
The chapter is divided into five sections. The first section presents the data collection procedure and the characteristics of the studied location. The second section discusses the analysis of the pedestrian conflict using time proximity methods and the challenges facing such measures. The third section shows the investigation of pedestrian evasive actions in traffic conflicts. Changes in position, speed, and direction before and during studied interactions were examined to understand how they react to traffic interactions. This spatiotemporal information of pedestrians is further analyzed to relate their dynamic behavior to traffic conflicts. As such, profiles of each pedestrian during normal movement and interactions with other road-users were analyzed. In the fourth section, new conflict indications are introduced based on the understanding of pedestrian evasive actions in traffic conflicts. The fifth section shows the validation of these indicators to ensure its relevance in reflecting traffic conflict severity. During the validation, the proposed indicators are compared with time proximity measures.

4.1 Data Collection

The data was collected from a busy, congested intersection in the city of Shanghai, China. The intersection is near downtown Shanghai at the crossing of Wuning Road and Lanxi Road, shown in Figure 4.1. Wuning Road is a major corridor in Shanghai that connects the city center to Middle Ring Road. The intersection is located in the District of Putuo which is historically the heart of Shanghai’s cultural, residential, and commercial center. The neighborhood area has residential apartments, businesses, and universities. Therefore, the intersection is highly congested during the day with a large mix of different road users. The intersection is a signalized four-leg intersection. Wuning Road has three lanes per direction and Lanxi road has two lanes per direction. The speed limit on the approaching roads is 60kph. However, the high volume of traffic, especially on Wuning Road, makes the intersection busy and congested throughout the day.
Video data were recorded during the daytime using a high-resolution camera of 1920 × 1088 pixels. The video footage of the intersection was recorded, monitoring the middle of the intersection showing the four approaches and four crosswalks. The video generally shows unorganized road-user behavior as shown in Figure 4.1. Many safety issues can be spotted from the risky road user behavior and non-compliance with traffic regulations. The intersection has a considerable mix of different road users (vehicles, motorcycles, bicycles, and pedestrians) that share the same road space. Shanghai has a high volume of unconventional modes of transportation such as mopeds, e-bikes, and tricycles. Table 4.1 shows the average hourly volume of every road-user. Mopeds, e-bikes, and tricycles are classified under non-motorized bikes, according to
Chinese classification regulations (Weinert, et al., 2006). Traffic in the intersection shows many violations, constant interactions, and lack of compliance with traffic rules and regulations.

**Table 4.1 Average hourly volumes of the different road users in the intersection**

<table>
<thead>
<tr>
<th></th>
<th>Average Hourly Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicles</td>
<td>6264</td>
</tr>
<tr>
<td>Motorcycles</td>
<td>4928</td>
</tr>
<tr>
<td>Bicycles</td>
<td>1576</td>
</tr>
<tr>
<td>Pedestrians</td>
<td>1200</td>
</tr>
</tbody>
</table>

4.2 **Time-Proximity Conflict Indicators Analysis**

The analysis of the video footage is conducted using the computer vision system to obtain road users trajectories. Then the traffic conflicts module is applied on the trajectories to extract and evaluate pedestrian conflicts. Conflict analysis includes the calculation of TTC and PET to identify conflict frequency and severity. In the studied location, conflicts were detected using a threshold of 3 seconds for TTC (Sayed & Zein, 1999) (Hirst & Graham, 1997). The total number of pedestrian conflicts detected in the intersection in one hour is 2304. Table 4.2 shows a breakdown of the hourly number of pedestrian conflicts by type.

**Table 4.2 Volume of pedestrian conflicts per hour in the intersection**

<table>
<thead>
<tr>
<th>Conflict Type</th>
<th>Hourly Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pedestrian - Vehicle</td>
<td>489</td>
</tr>
<tr>
<td>Pedestrian - Motorcycle</td>
<td>1354</td>
</tr>
<tr>
<td>Pedestrian - Bicycle</td>
<td>461</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2304</strong></td>
</tr>
</tbody>
</table>
The frequency of pedestrian conflicts recorded at the intersection is considered very high because road users keep in close proximity to other road users. Pedestrians seem to be comfortable in keeping small proximities with other road users when in interactions and undertake sudden evasive actions to avoid collisions so that when pedestrians are involved in a conflict, they do not stop or take any actions. Instead, a pedestrian will adjust his/her speed to be in proximity to the other road-user and then dynamically decides whether a more pronounced evasive action is needed. In addition, each individual pedestrian encounters several conflicting situations along their moving path.

Figure 4.2 Pedestrian violations are a major contributor to many traffic conflicts

Pedestrian violations (spatial and temporal) were a major contributor to the high frequency of conflicts. Spatial pedestrian violations are very frequent such as jaywalking, walking in the road lane, and waiting on the crosswalk instead of the sidewalk which often blocks the turning movements causing congestion, as shown in Figure 4.2 Locations of the spatial distribution of
pedestrian conflict points in the intersection were determined. Figure 4.4 shows the spatial distribution at the intersection in conflicts/m². The distribution extends beyond the crosswalk boundary, as shown, because of the violation away from the crosswalk, such as jaywalking or walking in the road lane. Additionally, the highest conflict density is shown in the crosswalk corners where many pedestrians stop in the roadways instead of on the sidewalk.

![Figure 4.3 Spatial distribution of pedestrian conflicts. Intensity in conflicts per square meter approximated on the intersection layout](image)

Temporal violations were also frequent in the intersection where pedestrians cross at non-designated times. Many pedestrians temporally violate crossing the road when they have a clear headway in opposing traffic. Since the roadway is congested and large headways are rare, they accept close proximity to vehicles and undertake strong evasive actions, such as sudden running/stopping. Figure 4.4 shows the pedestrian conflicts distributed along a typical cycle interval for Wuning Road and Lanxi Road. The figure shows that the highest percentage of
pedestrian conflicts occur closer to the end of the red light on Lanxi Road because pedestrians do not wait until the end of the red signal time and rush into crossing, as shown in Figure 4.4a and b. Overall, 84% of pedestrian conflicts included violations (spatial and temporal). Risky maneuvers by pedestrians when in violation was a major contributor to many of the high conflict occurrences. The results are similar to the traffic conflict study conducted by Kadali and Vedagiri (2016) which showed that pedestrians keep less safety margin with two-wheelers and vehicles at a crosswalk in Mumbai, India.
Figure 4.4 Distribution of pedestrian conflicts across the typical cycle happening on each road.
4.2.1 Severity Distribution

Figure 4.5 and 4.6 show the distribution of pedestrian conflicts by type along the TTC and PET ranges. The figures show a considerable portion of pedestrian conflicts with low TTC and PET values, which is not typical at other, more organized traffic environments. The severity relation did not show a consistent trend between frequency and severity. Overall, the pedestrian conflict review shows that many pedestrian conflicts included evasive actions. Therefore, time proximity measures do not reflect the true severity of interactions in this traffic environment. Accordingly, the investigation of pedestrian evasive actions and their relation to traffic conflicts is important to understand the conflict severity in this environment.

Figure 4.5 Severity distribution of pedestrian conflicts across the TTC range for every type and for total conflicts
A review of the identified pedestrian conflicts show that the behavior of pedestrians is generally described as heterogeneous and less organized than vehicular traffic. They typically move freely and have less constraint on their speeds and turn movements. Pedestrian evasive actions can be classified into one or a combination of these maneuvers (sudden reduction in speed or stopping, sudden walking faster or running, or sudden change of direction) (Malkhamah, et al., 2005) (Hussein & Sayed, 2015). Overall, pedestrian evasive actions are manifested by changes in walking behavior, which can be reflected in the pedestrian speed, heading angle, and gait parameters (step frequency and/or step length) (Medina, et al., 2008).

Figure 4.6 Severity distribution of pedestrian conflicts across the PET range by types and total pedestrian conflicts
4.3 Gait Analysis

One important aspect of understanding pedestrian behavior in conflicts is the analysis of the spatiotemporal parameters of gait. Pedestrian movement (ambulation) is derived by the pedestrian control over their walking steps. Gait analysis is a microscopic-level investigation which allows the estimation of objective measures of a pedestrian walk pattern. Gait patterns contain information useful in understanding interactions with the walking environment, such as maneuvering a curb (Crowe, et al., 1996), physical obstacles (Lowrey, et al., 2007), and interaction with other pedestrians (Hussein & Sayed, 2015). Gait parameters (step frequency and step length) can be extracted from the speed profile to show the pedestrian dynamic behavior. Used in several applications, gait parameters can automatically classify pedestrians from other road users (Zaki & Sayed, 2013) and classify pedestrians according to age and gender (Hediyeh, et al., 2013).

Once the trajectories of pedestrians are extracted, the speed profile (S) describing the variation along the pedestrian movement is deducted from the change in trajectory coordinates in time where \( S = \text{norm} \ (V_x, V_y) \). Pedestrian speed profiles in the normal movement are typically not uniform with respect to time. Rather, a pedestrian speed shows cyclic fluctuations that are repeated continuously over time, as shown in Figure 4.7a. Each fluctuation corresponds to a step taken by the pedestrian while the stride frequency and length is highly correlated with the walking speed (Crowe, et al., 1996). This means that each cycle in the speed profile represents one forward step and the step frequency could be estimated from the reciprocal of the cycles (Saunier, et al., 2011). Therefore, the gait parameters can be determined along the movement cycles of the pedestrian.

First, the speed signal is smoothened and normalized (the mean speed is subtracted from the instantaneous speed). Identifying a step frequency profile requires detecting the dominant
periodicity in the signal for each pre-defined time segment. In the case presented, a two-second segment length was found adequate for step frequency calculations with an overlap of one and a half seconds between every two successive segments. The step frequency is then determined by evaluating the Power Spectral Density (PSD) of the speed profile, as described in Oppenheim & Schafer (1999). The detailed procedure of the automated extraction of pedestrian gait is described in Saunier, et al., (2011). The main advantage of using the automated application is that it can capture the natural movement of a pedestrian walking pattern at relatively high consistency and accuracy.

Once the dominant step frequency of each segment is determined, the average step length during that segment can be calculated from the fundamental linear relationship in equation 4.1:

$$\text{Walking Speed} = \text{Step Frequency} \times \text{Step Length}$$

where the walking speed is the average speed of the pedestrian during the time segment analyzed. The step frequency and step length profiles can be drawn as shown in Figure 4.7b and c. In normal walking conditions, pedestrians usually keep steady values of their step frequency and step length, as shown in the example in Figure 4.7. The error in the automated calculation of the step frequency and step length was shown previously on two datasets and was found to be around 0.17 step/sec and 6 cm, respectively (Saunier, et al., 2011). The study also considers another gait characteristic that can describe the temporal and spatial coordination of a pedestrian (i.e. stability), namely, the walk ratio. The walk ratio is a speed-independent measure that can reflect the balance in the walking pattern of a pedestrian. The walk ratio is defined as the step length to the step frequency ratio of a pedestrian. Figure 4.7 shows the profile of the walk ratio of a normal moving pedestrian. The walk ratio profile keeps steady values as the pedestrian continues to walk normally.
Figure 4.7 Typical speed profile of a pedestrian showing normal fluctuations because of walking steps, the extracted step frequency maintained, the derived step length and the calculated walk ratio.

4.4 Pedestrian Evasive Action Analysis

In pedestrian conflicts, the evasive actions involve a sudden change in the walking pattern reflected in the gait parameters. Figure 4.8 shows a pedestrian suddenly walking faster to avoid a vehicle conflict with the corresponding speed and gait parameters. The pedestrian motion shows changes by a sudden jump in the step frequency at the onset of the evasive action. The change in step frequency can be accompanied by a change in step length, as shown in Figure 4.8. The degree by which the evasive action is exerted differs from one conflict to another. Similarly, a pedestrian suddenly decelerating to avoid collision has a sudden drop in the step frequency and step length. Figure 4.9 shows the speed and gait profiles of a pedestrian in conflict decelerating to avoid a vehicle. During the interactions, the pedestrian speed might not show the change effectively. Therefore, the investigation of gait parameters shows changes as a result of their reactions to conflict situations.
Figure 4.8 Speed profile and the corresponding gait parameters (step frequency and step length profiles) for a pedestrian in conflict suddenly running to avoid a moving vehicle
Pedestrian conflict interactions with vehicles differ from other precautionary situations in the walking environment. Researchers that studied gait changes in pedestrians maneuvering a curb showed that they would adjust their step length specifically to successfully ascend or descend a curb (Crosbie & Ko, 2000). The action was found independent of speed but, rather, depends on the predicted foot position regarding the curb. Similarly, researchers showed that pedestrians avoiding other pedestrians in their walking environments were more likely to change their walking speed and step frequency as a reflection to the interaction (Hussein & Sayed, 2015), which is also a precautionary action to avoid fixed obstacles in the walking environment (Lowrey, et al., 2007). While pedestrians that engage in their environment in situations that make them change their speed or gait parameters, these movements are often precautionary and smoother in reaction than that of an erratic, evasive action due to a risky conflict situation.
Figure 4.9 Speed profile and the corresponding gait parameters (step frequency and step length profiles) for a pedestrian in conflict decelerating to avoid a moving vehicle
4.5 New Potential Pedestrian Conflict Indicators

Indicators describing the change in the pedestrian speed, gait parameters, and heading angle are investigated. The goal is to find potential indicators that can reflect the evasive action of pedestrians. The indicators investigated are summarized into 5 categories;

1- Maximum step frequency/step length/walking speed: the maximum value of these parameters can reflect the acceleration or running evasive action of pedestrians. Sudden running or acceleration usually has a high step frequency, step length, or walking speed.

2- Minimum step frequency/step length/walking speed/walk ratio: the minimum indicators reflect the deceleration or stopping evasive action of pedestrians. Road users that do suddenly decelerate or stop have low step frequency, step length, or walking speed.

3- Minimum walk ratio: The lower the walk ratio can signify either a lower step length (e.g., sudden decelerate) or a higher step frequency (e.g., sudden running).

4- The maximum slope-of-step frequency/step length/walking speed/walk ratio: Sudden maneuvers show a significant change in the steady pedestrian profile in a short time. The slope expresses the change in the maneuver, such that sudden running or stopping is reflected in a strong drop or rise in the profile.

5- The maximum slope of heading angle and the peak-to-peak ratio of heading angle: the change of the pedestrian heading angle reflects the change of the rotation of the pedestrian where swerving can be reflected.

Generally, mean values of the gait parameters (step frequency and step length) of a pedestrian are a characteristic of the individual age, gender, and group size (Hui, et al., 2007) (Hediyeh, et al., 2013). Therefore, comparing the maximum or minimum values of any characteristics between different pedestrians may not be useful. Instead, measures such as the ratio of the maximum or
minimum to the average gait parameters will be investigated. Table 4.3 shows a list of the tested indicators. These indicators are calculated for the pedestrians before the conflicting point at which the minimum distance between the vehicle and the pedestrian is reached during the conflict. Since the pedestrians can be involved in several conflicts along their path in the intersection, the search for the evasive action indicators is performed within 3 seconds before the conflict point.

Table 4.3 Proposed conflict indicators to reflect pedestrian’s evasive actions

<table>
<thead>
<tr>
<th>Pedestrian Conflict Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Maximum Step Frequency*</td>
</tr>
<tr>
<td>2 Minimum Step Frequency*</td>
</tr>
<tr>
<td>2 Maximum Slope-of-Step Frequency</td>
</tr>
<tr>
<td>3 Maximum Step Length*</td>
</tr>
<tr>
<td>3 Minimum Step Length*</td>
</tr>
<tr>
<td>4 Maximum Slope-of-Step Length</td>
</tr>
<tr>
<td>5 Maximum Walk Speed*</td>
</tr>
<tr>
<td>6 Minimum Walk Speed*</td>
</tr>
<tr>
<td>7 Maximum Slope of Walk Speed</td>
</tr>
<tr>
<td>8 Minimum Walk Ratio</td>
</tr>
<tr>
<td>9 Maximum Slope of Walk Ratio</td>
</tr>
<tr>
<td>10 Peak-to-peak Ratio of Heading angle</td>
</tr>
<tr>
<td>11 Maximum Slope of Heading Angle</td>
</tr>
</tbody>
</table>

* Indicator values divided by the average value along the history of the pedestrian

4.5.1 Validation of the Proposed Pedestrian Conflict Indicators

To test the ability of the proposed indicators in representing conflict severity, they were compared against the severity evaluation of safety experts, as explained in Chapter 3. The goal is to find the indicators that reflect the severity evaluations by the safety experts. A group of 100 of the extracted
pedestrian-vehicle conflicts was randomly selected and presented to two safety experts to rank and categorize them. The pedestrians were chosen, so their trajectory was not affected by the system tracking inaccuracies such as occlusions, shadows, etc. The agreement results between the expert results are shown in Table 4.4. The consistency test showed agreements between the experts in which the kappa was 0.356 and the variance of kappa was 0.005. The results indicate a moderate agreement between the two experts, statistically significant, at a 95% confidence interval.

<table>
<thead>
<tr>
<th>Severity Category</th>
<th>Expert 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Low</td>
<td>17</td>
</tr>
<tr>
<td>Intermediate</td>
<td>8</td>
</tr>
<tr>
<td>High</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>32</td>
</tr>
</tbody>
</table>

The first step in the investigation of the indicators validity toward severity is using the rank correlation coefficient to test the agreement of the expert ranking and ranking based on the indicators (time proximity measures and the evasive action measures). The Spearman rank correlation coefficient measures the strength of the ranking between the tested indicators and the expert rankings. Three evasive action-based indicators showed high correlation with expert rankings than the time proximity measures as shown in Table 4.5. The maximum Slope-of-Step frequency (MSSF), the minimum step length (MSL) and the minimum walk ratio (MWR). The MSSF has the highest correlation with the two expert rankings, statistically significant at 95% confidence interval. The higher the maximum change in the step frequency the higher the severity of the interaction. However, the TTC and PET did not correlate well with the experts’ ranking in
the studied environment. The results comply with the fact that pedestrians are more likely to change their step frequency than the step length when in interactions in their walking environment (Hussein & Sayed, 2015).

Table 4.5 Spearman rank correlation between experts rankings and the ranking using severity measures

<table>
<thead>
<tr>
<th>Pedestrian Conflict Indicators</th>
<th>Expert1</th>
<th>Expert2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Step Frequency</td>
<td>0.166</td>
<td>0.041</td>
</tr>
<tr>
<td>Minimum Step Frequency</td>
<td>0.006</td>
<td>0.037</td>
</tr>
<tr>
<td>Maximum Slope-of-Step Frequency</td>
<td>0.407*</td>
<td>0.374*</td>
</tr>
<tr>
<td>Maximum Step Length</td>
<td>0.027</td>
<td>0.032</td>
</tr>
<tr>
<td>Minimum Step Length</td>
<td>0.239</td>
<td>0.244</td>
</tr>
<tr>
<td>Maximum Slope-of-Step Length</td>
<td>0.163</td>
<td>0.138</td>
</tr>
<tr>
<td>Maximum Walk Speed</td>
<td>0.187</td>
<td>0.142</td>
</tr>
<tr>
<td>Minimum Walk Speed</td>
<td>0.127</td>
<td>0.129</td>
</tr>
<tr>
<td>Maximum Slope of Walk Speed</td>
<td>0.14</td>
<td>0.039</td>
</tr>
<tr>
<td>Minimum Walk Ratio</td>
<td>0.247</td>
<td>0.267</td>
</tr>
<tr>
<td>Maximum Slope of Walk Ratio</td>
<td>0.013</td>
<td>0.024</td>
</tr>
<tr>
<td>Peak-to-peak Ratio of Heading angle</td>
<td>0.117</td>
<td>0.015</td>
</tr>
<tr>
<td>Maximum Slope of Heading Angle</td>
<td>0.113</td>
<td>0.046</td>
</tr>
<tr>
<td>Time-to-Collision</td>
<td>0.220</td>
<td>0.208</td>
</tr>
<tr>
<td>Post Encroachment Time</td>
<td>0.087</td>
<td>0.149</td>
</tr>
</tbody>
</table>

* Statistically significant at 95% confidence interval

The next step is testing the trend of every specific indicator along the severity levels. The mean of the different conflict indicators in the three severity categories is shown in Figure 4.10. The means showed a logical pattern for three evasive action-based indicators: MSSF, MSL, and MWL. The two-time proximity measures TTC and PET were compared to these indicators. They showed little
variation between the three severity categories as in Figure 4.10. The trends show that the TTC and PET are not highly correlated with the conflict severity assigned by the experts as they do not reflect the actual severity of in the studied location.
The significance of the difference between the means of various indicators in the three severity groups is calculated by the Analysis of Variance (ANOVA) test. The hypothesis test possesses the mean of the equal groups as the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$ and the alternative hypothesis as unequal means $H_a: \mu_1 \neq \mu_2 \neq \mu_3$. The results in Table 4.6 show that all three evasive action-based indicators performed better in differentiating between conflicts in the three severity categories than time proximity measures. MSSF is statistically different at 95% confidence level between the three severity groups, indicating that it can differentiate between conflicts in the three severity categories.

**Table 4.6 Results of the p-value obtained from the ANOVA test on these means of the categories of different measures**

<table>
<thead>
<tr>
<th>p-value</th>
<th>Evasive Action Measures</th>
<th>Time Proximity Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSSF</td>
<td>MSL</td>
</tr>
<tr>
<td>Expert 1</td>
<td>0.002*</td>
<td>0.193</td>
</tr>
<tr>
<td>Expert 2</td>
<td>0.009*</td>
<td>0.282</td>
</tr>
</tbody>
</table>

* Statistically significant p-value at 95% confidence interval

**Figure 4.10 The mean value of the maximum slope-of-step-frequency, minimum step length, minimum walk ratio, TTC and PET in the severity level categories**

![Graph showing the mean value of the maximum slope-of-step-frequency, minimum step length, minimum walk ratio, TTC and PET in the severity level categories]
Overall, the results show that the measures extracted from gait parameters are useful in reflecting conflict severity of pedestrian conflicts in the studied environment. The MSSF showed a highly-significant effect in reflecting the severity of the traffic conflicts in this studied location. For a severity indicator to be placed in a continuum, it must be represented by a value describing the different severity levels located in one common severity hierarchy. The MSSF distribution showed less frequent values at the highest severity values and vice versa, as shown in Figure 4.11. The results can enable the MSSF to show the behavioral surrogate safety measure for pedestrian conflicts. Further investigation of MSSF is done in the following chapter to test the significance in identifying pedestrian conflicts and tested in different traffic environments.

![Figure 4.11 Distribution of MSSF of pedestrian conflicts in the studied location](image)

**4.6 Summary of Key Results**

The chapter presented a pedestrian-conflict analysis in a highly congested/less organized intersection in Shanghai, China. Using computer vision techniques, traffic conflicts were analyzed for this location then the pedestrian evasive action behavior in traffic conflicts was studied. The goal was to understand the mechanism by which pedestrians performed their evasive actions and
to recommend evasive action-based indicators that better reflect pedestrian conflict severity in the studied location. These are the summary of the findings:

1- Time proximity measures were shown to identify a high number of pedestrian conflicts that does not reflect the true severity of conflicts in the studied intersection in Shanghai, China.

2- Pedestrian behavior is a major contributor to the high number of conflicts where pedestrians keep in close proximity to other road users and perform pronounced evasive actions to avoid collisions.

3- The pedestrian evasive action is mainly reflected in the sudden change of gait parameters (i.e., step length and step frequency).

4- The maximum slope-of-step frequency (MSSF) showed a high correlation between safety expert severity evaluations and high ability to differentiate between different conflicts according to severity.

Overall, results showed that evasive action-based measures are better than time proximity measures in reflecting the severity of pedestrian conflicts in the location studied. Further investigation is done on other road users evasive actions and tested in different traffic environments.
Chapter 5: Two-Wheelers Evasive Action Behavior in Traffic Conflicts

Motorcycles and bicycles are one of the main modes of transportation in several Asian countries. China has one of the highest volumes of two-wheelers in the world, with about 98.3 million motorcycles on the roads (Yang, et al., 2008) in addition to a similarly high volume of bicycles (Wang, et al., 2012). However, the safety of two-wheelers is a major issue where traffic collisions involving motorcycles and bicycles constitute one of the highest causes of fatalities and injuries in China (Kong & Yang, 2009). The safety research covering two-wheelers in China and many other Asian countries still rely on collision data in addressing the safety of these road users (Mazharul Haque, et al., 2008) (Yao & Wu, 2012) (Ariannezhad, et al., 2014). However, there is considerable benefit from adopting the traffic conflicts technique in this environment given the current availability and reliability problems of collision data (Guo, et al., 2016).

Similar to the pedestrian behavior analysis conducted in Chapter 4, this chapter presents a comprehensive study of the behavior of two-wheelers in traffic conflicts conducted on the Shanghai dataset. The chapter presents a direct application of using existing time proximity measures to evaluate two-wheeler conflicts in a less organized traffic environment. Also, a detailed investigation of the behavior of motorcycles and bicycles is performed to understand the mechanism by which they perform evasive actions. Then evasive action-based conflict indicators are developed for two-wheelers. The study in this chapter is developed in four main steps. First, the analysis of conflict severity using current time proximity methods is presented and the challenges facing such methods to address conflict severity are shown. Second, the evasive action mechanism of two-wheelers in traffic conflicts is analyzed. Then potential conflict indications are introduced based on the understanding of evasive actions. Last, the validation of the indicators is
performed to ensure its relevance in reflecting conflict severity. In which the proposed indicators are also compared with time proximity measures in addressing conflict severity.

5.1 Time-Proximity Conflict Indicators Analysis

After video analysis is conducted using the computer vision system, motorcycle and bicycle traffic conflicts are extracted. Trajectories of two-wheelers involved in conflict interactions are analyzed in different conflict situations using TTC. Accordingly, the frequency, severity, and locations of traffic conflicts are identified. Table 5.1 shows a breakdown of the hourly volume of motorcycle and bicycle conflicts by type.

<table>
<thead>
<tr>
<th>Motorcycle Conflicts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conflict Type</td>
</tr>
<tr>
<td>Motorcycle - Vehicle</td>
</tr>
<tr>
<td>Motorcycle - Motorcycle</td>
</tr>
<tr>
<td>Motorcycle - Bicycle</td>
</tr>
<tr>
<td>Motorcycle - Pedestrian</td>
</tr>
<tr>
<td><strong>Total</strong></td>
</tr>
</tbody>
</table>

Table 5.1 Volume of motorcycle and bicycle conflicts in the intersection per hour

<table>
<thead>
<tr>
<th>Bicycle Conflicts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conflict Type</td>
</tr>
<tr>
<td>Bicycles - Vehicle</td>
</tr>
<tr>
<td>Bicycle - Motorcycle</td>
</tr>
<tr>
<td>Bicycle - Bicycle</td>
</tr>
<tr>
<td>Bicycle - Pedestrian</td>
</tr>
<tr>
<td><strong>Total</strong></td>
</tr>
</tbody>
</table>
Figure 5.1 Motorcycle and bicycle violations are a major contributor to many traffic conflicts

Results show a high level of conflict frequency recorded at the intersection. Motorcycle-involved conflicts are the most frequent among all road users, with a volume of 5954 conflicts in one hour. Bicycle conflicts are also high with 2090 conflicts per hour. The high volume of conflicts is a result of the behavior of the two-wheelers and which is highly disorganized and where they move in close spaces between vehicles. Motorcycles and bicycles encounter several conflicts along their path through the intersection and when involved in an interaction, they initially do not slow down or take any actions. Instead, they would adjust their speeds to be in proximity to the other road user and then dynamically decide whether a sudden evasive action is needed to avoid a collision.
a) Motorcycle conflicts

b) Bicycle conflicts

Figure 5.2 Spatial distribution of motorcycle and bicycle conflicts. Intensity is in conflicts per square meter approximated on the intersection layout

Violations are one of the contributing factors to the high frequency of conflicts. Automated violation analysis showed that approximately 75% of conflicts involve violations. Both
motorcycles and bicycles showed many violations such as running red lights, stopping on crosswalks, riding on sidewalks, driving in the wrong direction, and moving in between queuing vehicles to reach the front of the queue where slight distances between vehicles are available. Many two-wheelers violate by stopping over the crosswalk waiting for the signal, which blocks the turning movement causing congestion to the traffic stream, as shown in Figure 5.1. The behavior is shown to cause many conflicts with vehicles, as shown in the heat-maps of motorcycles and bicycle in Figure 5.2a and b. The high density of both motorcycle and bicycle conflicts generally covers the whole intersection while highly concentrated in the corners because of two-wheeler violations. Figure 5.3 shows the motorcycles/bicycles conflicts distributed along a typical cycle interval for Wuning Road and Lanxi Road. The figure shows that the highest percentage of conflicts occur closer to the end of the red light on Lanxi Road because two-wheelers do not wait until the end of the red signal time and rush into crossing the intersection.
5.1.1 Severity Distribution

Figure 5.3 shows the distribution of motorcycle and bicycle conflicts along the TTC ranges for different road users and total intersection conflicts. Although the number of conflicts in the intersection is high, there is no clear trend between the frequency and severity of conflicts. Because
of the lack of a consistent relationship between the severities of different conflicts using time proximity measures, it is shown that normal interactions may be misrepresented as conflicts in this location. The reason is that while motorcycles or bicycles involved in conflicts are already in close proximity, their sudden evasive actions are not reflected in the time proximity severity. The next step in the investigation of the evasive action behavior of two-wheelers in traffic conflicts is to understand the severity relation between proximity and evasive action.
5.2 Evasive Action Analysis

Motorcycle and bicycle movement can be described as unique because, in many encounters, they do not follow the same behavior as motorized vehicles. Two-wheelers are relatively smaller in size and physically occupy a small space within the lane, which makes their lateral movement more frequent (Nguyen, et al., 2014). Therefore, in traffic environments with weak lane discipline, their movement is often non-lane-based, essentially moving in spaces between vehicles, which makes their evasive actions more frequent because of their physical vulnerability (Choudhury & Mozahidul Islam, 2016). For each motorcycle and bicycle conflict identified, the occurrence of evasive actions is recorded by observing the video of every motorcycle and bicycle conflict independently. An evasive-action flag is assigned when a sudden action is seen such as hard braking, sudden running, abrupt swerving, etc. The dynamics of motorcyclist and cyclist...
movement is derived by the control over speeding, braking, and steering. In the studied location in Shanghai, the behavior of both the motorcycles and bicycles is similar in interactions and evasive actions. Their evasive actions can be classified into one or a combination of these maneuvers: powerful braking, powerful speeding, or sudden swerving (Nguyen, et al., 2014) (Choudhury & Mozahidul Islam, 2016).

5.3 Two-Wheelers Evasive Action-Based Conflict Indicators

The makeup of the two-wheelers evasive action is defined by a travel path (spatial) alteration through steering actions, and/or a headway change (temporal) through braking/speeding. The degree by which the evasive action is exerted differs from one conflict to another. Therefore, the travel spatiotemporal information of two-wheelers just before the conflict point is further analyzed to relate such behavior to traffic conflicts. Using positional trajectories enables the microscopic investigation of dynamic behavior changes and its relation to traffic conflicts severity. As such, the profiles of the speed and directions of the motorcycles and bicycles during interactions were analyzed to understand how they react to traffic interactions. In the case of motorcycles and bicycles that suddenly brake, their speed profile shows a sudden drop in speed at the onset of the evasive action. Figure 5.5 shows two examples of a motorcycle and bicycle suddenly braking to avoid colliding with a vehicle and the corresponding speed profile. Similar to the sudden braking evasive action, suddenly speeding to avoid collision shows a sudden jump in the speed profile. Figure 5.6 shows the speed profile for motorcycles in conflict suddenly speeding to avoid conflicting with moving vehicles. Three main parameters are considered to study the evasive action of two-wheelers: the acceleration, the jerk, and the yaw rate.
5.3.1 Acceleration/Deceleration Rate:

The acceleration/deceleration rate quantifies the magnitude of the change of the speed action of a road user. Acceleration plays a key role in studying the dynamics of the movements of two-wheelers. The deceleration rate is used in many conflict evaluations as a complementary measure to assess the severity of traffic conflicts since the higher the deceleration, the higher probability of collision (Gettman & Head, 2003). In normal situations, the acceleration profile usually has normal fluctuations because of the driver changes in speed. However, in conflicts, the acceleration profile for motorcyclists and cyclists performing evasive actions shows a sudden drop/rise in the acceleration profile, as shown in Figure 5.5 and Figure 5.6. A higher acceleration/deceleration rate in the interaction can suggest that there is less time to avoid a collision (i.e. a higher severity). Motorcycle and bicycle acceleration profiles were filtered to reduce additive noise and retain the changes of the profile using the Savitzky–Golay filter (Savitzky & Golay, 1964). Sudden deceleration or acceleration has a high positive or negative value usually higher than the fluctuations of normal speeding/braking movement. The maximum acceleration, minimum deceleration, and the absolute value of acceleration/deceleration before the conflict point is employed to reflect the sudden braking or speeding evasive action of motorcyclists and cyclists.
Figure 5.6 A speed, acceleration, and jerking profile of motorcycles in conflict suddenly speeding to avoid colliding with a moving vehicle showing a jump in the speed profile with the corresponding acceleration and jerking profile

5.3.2 Jerk Rate

Since the intensity of the braking action of road users varies as a reaction to the involved situation, the distinction between the different actions is further carried out in the temporal dynamics (variation over time) of the acceleration, which is called the jerk profile. Formally, jerk is the derivative of the acceleration. Jerk is used to study the comfort level of the vehicle dynamics as a result of sudden accelerations or decelerations (Punzo, et al., 2011). It is a key measure in showing the level of comfort/discomfort of passengers in motorized moving facilities. For example, in the design of trains and elevators, it is typically required to keep the value of jerk low for passenger comfort (Martinez & Canudas-de-Wit, 2007). The evasive action involving powerful braking is characterized by strong fluctuations in the jerk profile. The more abrupt the braking, the more powerful jerks are produced. The reaction is reflected in a high peak negative or positive value in the jerk profile. Sudden acceleration can be also be reflected in the jerk profile (Zaki, et al., 2014). Figure 5.5 and 5.6 show the example of the jerk profile of motorcycles and cyclists in conflicts with a vehicle suddenly braking or accelerating. The maximum values for jerk of the motorcycles before the conflicting point can reflect the severity of the braking action. Another measure that can reflect the change is the peak-to-peak value which is the difference in the jerk rate that happens before the conflict point. The peak-to-peak value was a significant factor in identifying critical situations on the road (Bagdadi & Várhelyi, 2013). The filtering mechanism used for the acceleration profile is also employed to remove noise from the jerk profile which removed signal
magnitudes that exceed unrealistic behavior. The analysis of the extreme values of jerk besides the peak-to-peak ratio are employed as potential conflict indicators.

5.3.3 Yaw Rate

The third indicator employed to cover the swerving behavior of two-wheelers is the yaw rate. The yaw rotation is the movement around the yaw axis of a body that changes direction to the left or right of its direction of motion. In other words, the yaw rate is the angular velocity of the rotation around the vertical axis (z-axis) or the rate of change of the heading angle. Typically, the yaw signal is measured using gyroscopes placed in moving vehicles. However, the yaw rate can be calculated from the produced trajectories using equation 5.1 which shows the calculation of the yaw rate \( r(t) \) as the change of the heading angle \( \psi \) of the motorcycle or bicycle in Figure 5.7 (Ayres, et al., 2004).

\[
yaw \ rate \ r(t) = \frac{d\psi}{dt} \tag{5.1}
\]

![Figure 5.7 Illustration of the heading angle for a moving road user (Ayres, et al., 2004).](image)
Figure 5.8 Yaw rate profile of motorcycles in conflict suddenly swerving to avoid colliding with a moving vehicle showing peak in the yaw profile

Drivers performing swerving maneuvers can be reflected in changes in the yaw rate profile. Strong swerving maneuvers show a peak (positive and/or negative) in the yaw rate profile happening in a short duration. Figure 5.8 illustrates an example of the yaw rate signal profile of two motorcycle conflicts that suddenly swerve to avoid colliding with a vehicle. The motion shows a peak in the yaw rate at the onset of the swerving action. Two parameters extracted from the yaw profile can reflect the extent of a sudden swerving maneuver, the slope of the yaw rate and the peak-to-peak ratio. The slope of the yaw rate expresses the angular acceleration of the two-wheelers. The peak-
to-peak ratio is the maximum change of yaw to the overall time change, as calculated in equation 5.2. A high value of this ratio indicates a high peak in a short period.

\[ \text{ratio} = \frac{\max (r(t)) - \min (r(t))}{t_{\text{start}} - t_{\text{end}}} \]  

(5.2)

Motorcyclists and cyclists can encounter several conflicts along their moving path. One challenge that remains is that the maximum value of an indicator might not reflect the value of the intended conflict. Although road-users trajectories from the video are limited to the camera field of view, the indicators are calculated before the conflicting point at which the minimum distance between the road users is reached during the conflict interaction to generally reflect conflict severity the time at which the evasive action should be recorded. Since two-wheelers can be involved in several conflicts along their path in the intersection, the evasive action indicators are performed within a 3-second threshold before the conflict point for the acceleration and jerk profiles. As for the swerving indicators, the yaw rate ratio was extended 2 seconds beyond the point of minimum distance between road users to include the full-swerving maneuver that extends beyond the conflict point to capture the change in the swerving behavior in a more accurate and precise manner. The indicators investigated are summarized in Table 5.2. The next step is to find the significant indicators that reflect the evasive action of motorcyclists and cyclists.

<table>
<thead>
<tr>
<th>Table 5.2 Proposed conflict indicators to reflect evasive actions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conflict Indicators</strong></td>
</tr>
<tr>
<td>1 Maximum acceleration</td>
</tr>
<tr>
<td>2 Minimum deceleration</td>
</tr>
<tr>
<td>3 Maximum absolute value of acceleration</td>
</tr>
<tr>
<td>4 Minimum negative value of jerk</td>
</tr>
<tr>
<td>5 Peak-to-Peak of jerk</td>
</tr>
</tbody>
</table>
Conflict Indicators

6 Maximum slope in yaw rate
7 Peak-to-Peak ratio of yaw rate

5.4 Validation of the Proposed Two-Wheelers Conflict Indicators

The validation of the conflict indicators in representing conflict severity is performed by the comparison against the severity evaluation of safety experts. The evaluation is done to find the indicators that can reflect the severity of conflicts. A group of 100 of the extracted motorcycle-vehicle conflicts and another group of 100 bicycle-vehicle conflicts were randomly selected and presented to the two safety experts to rank and categorize them. The conflicts were chosen so their trajectories were well tracked and not affected by the tracking system limitations, such as occlusions and shadows, etc. The results of the expert evaluation drawn for the two datasets are shown in Table 5.3. The consistency test performed between the expert’s evaluations showed a kappa of 0.428 for the motorcycle dataset and 0.414 for the bicycle dataset. The variance of kappa calculated for both was 0.005. The results indicate a moderate agreement between the two experts statistically significant, at a 95% confidence interval. The agreement is similar to the level of agreement in the results of Grayson, et al., (1984) between different traffic conflicts and human observers.

| Table 5.3 Agreement results between the two expert categorizations |
|--------------------------------|------|------|------|------|
| **Motorcycles conflicts**    | **Expert 2** |       |      |      |
|                             | Low  | Intermediate | High | Total |
| Expert 1                    |      |              |      |       |
| Low                         | 18   | 10            | 2    | 30    |
| Intermediate                | 9    | 20            | 7    | 36    |
| High                        | 3    | 7             | 24   | 34    |
| Total                       | 30   | 37            | 33   | 100   |
The first step in the validation of the indicators towards severity is using the Spearman rank correlation coefficient to test the agreement of the expert ranking and ranking based on the different proposed indicators. The rank correlation measures the strength of the ranking of the tested indicators and the experts ranking. Both the potential evasive action measures and time proximity measures were tested. Results of correlation on both motorcycle and bicycle datasets are presented in Table 5.4. For motorcycles, the peak-to-peak value of jerk and the peak-to-peak ratio of the yaw rate showed a relatively higher correlation with expert rankings than other indicators, including time proximity measures. The correlation with the two expert rankings was also significant at 95% confidence level. The results mean that the higher the values of these indicators, the higher the severity of the interaction. Results of bicycle data showed that only the peak-to-peak ratio of the yaw rate showed a relatively high correlation with expert rankings, statistically significant at 95% confidence level. The result means that the higher the peak-to-peak yaw rate ratio of a bicycle in a conflict reflecting the swerving behavior the higher the severity of the interaction. On the other hand, the TTC did not effectively correlate with the expert rankings of motorcycles and bicycles in the studied environment.
Table 5.4 Spearman rank correlation between experts rankings and the ranking using severity measures

<table>
<thead>
<tr>
<th>Conflict Indicators</th>
<th>Motorcycles</th>
<th></th>
<th>Bicycles</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expert 1</td>
<td>Expert 2</td>
<td>Expert 1</td>
<td>Expert 2</td>
</tr>
<tr>
<td>Maximum acceleration</td>
<td>0.061</td>
<td>0.192</td>
<td>0.019</td>
<td>0.231</td>
</tr>
<tr>
<td>Minimum deceleration</td>
<td>0.109</td>
<td>0.137</td>
<td>0.198</td>
<td>0.073</td>
</tr>
<tr>
<td>Maximum absolute value of acceleration</td>
<td>0.354</td>
<td>0.291</td>
<td>0.192</td>
<td>0.302</td>
</tr>
<tr>
<td>Minimum negative value of jerk</td>
<td>0.329</td>
<td>0.123</td>
<td>0.213</td>
<td>0.365</td>
</tr>
<tr>
<td>Peak-to-Peak of jerk rate</td>
<td>0.407*</td>
<td>0.443*</td>
<td>0.319</td>
<td>0.277</td>
</tr>
<tr>
<td>Maximum rate of change in yaw rate</td>
<td>0.069</td>
<td>0.192</td>
<td>0.253</td>
<td>0.259</td>
</tr>
<tr>
<td>Peak-to-Peak ratio of yaw rate</td>
<td>0.483*</td>
<td>0.412*</td>
<td>0.415*</td>
<td>0.443*</td>
</tr>
<tr>
<td>Time-to-Collision</td>
<td>0.258</td>
<td>0.195</td>
<td>0.203</td>
<td>0.153</td>
</tr>
</tbody>
</table>

* Statistically significant at 95% confidence interval

The next step is testing the trend of every specific indicator along the severity levels. The mean of the motorcycle conflict indicators in the three severity categories showed a logical pattern in the peak-to-peak jerk and peak-to-peak yaw rate ratio, as shown in Figure 5.9, while TTC showed a slight variation compared to the indicators between the three severity categories.
Figure 5.9 The mean value of the motorcycle indicators in the severity levels categories

For the bicycle conflicts, the mean of the conflict indicators showed a consistent pattern for the peak-to-peak yaw rate ratio in the three severity categories, as shown in Figure 5.10. The mean of the TTC showed a minor variation compared to the yaw rate ratio between the three severity categories.
The mean value of the bicycle indicators in the severity levels categories

Figure 5.10

The significance of the difference between the means of various indicators in the three severity groups was calculated by the Analysis of Variance (ANOVA) test. Results of the p-value are shown in Table 5.5. For motorcycles, the peak-to-peak jerk and yaw rate ratio are statistically different at 95% level between the three severity groups. This result indicates that peak-to-peak can differentiate between conflicts in the three severity categories better than TTC.

Table 5.5 Results of the p-value obtained from the ANOVA test on these means of different measures in the severity categories

<table>
<thead>
<tr>
<th>p-value</th>
<th>Motorcycles</th>
<th>Bicycles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peak-to-Peak</td>
<td>Peak-to-Peak</td>
</tr>
<tr>
<td></td>
<td>Jerk rate</td>
<td>Yaw rate ratio</td>
</tr>
<tr>
<td></td>
<td>TTC</td>
<td>TTC</td>
</tr>
<tr>
<td>Expert 1</td>
<td>0.005</td>
<td>0.027</td>
</tr>
</tbody>
</table>
Overall, the results show that measures extracted from the jerk and yaw rate are useful for reflecting the severity of motorcycle conflicts in the studied environment. The acceleration/deceleration rate showed no significance in reflecting the severity of the traffic conflicts. The results that agree with Wahlberg, (2000) and Bagdadi, (2013) showed that it is difficult to identify traffic conflicts solely from the acceleration data. As bicycles have relatively low speeds, the jerk and acceleration values were not significant in reflecting the evasive action. Only the swerving behavior reflected in the yaw rate ratio was significant.

Figure 5.11 Distribution of peak-to-peak jerk value and yaw rate ratio of all motorcycle conflicts in the analyzed location

The indicator values for different conflicts showed a severity continuum. For an encounter to be placed in a continuum, it has to be represented by a value describing the different severity levels which make it possible to locate them in one common severity hierarchy. The severity distribution
of motorcycles indicators (peak-to-peak jerk and yaw rate ratio) were drawn for all motorcycle conflicts in the analyzed video in Figure 5.11. Similarly, the severity distribution of the bicycle yaw rate ratio was drawn for all bicycle conflicts in the analyzed video Figure 5.12. The distribution of both showed less frequency at high severity values and vice versa, which enable these indicators to show the behavioral surrogate safety measure in different conflicts.

![Yaw rate ratio distribution](image)

**Figure 5.12 Distribution of yaw rate ratio for bicycle conflicts in the analyzed location**

### 5.5 Application to Motorcycle-Pedestrian Conflicts with Evasive Action

The use of different evasive action-based measures can be integrated to reflect the severity of traffic events. The integration was tested on motorcycle-pedestrian conflicts as an example to detect traffic conflicts with evasive actions. Using the evasive action-based indicators and pedestrians, a threshold can be tested to identify motorcycle-pedestrian conflicts in the studied location. The 85th percentile of the peak-to-peak jerk value (0.08m/sec³) and the 85th percentile of the MSSF (0.7step/sec²) are tested as examples. Combining these thresholds motorcycle-pedestrian conflicts can be identified and compared with time proximity results. Figure 5.13 shows a comparison between the number and spatial distribution of pedestrian conflicts obtained using time proximity measures and evasive action-based indicators. The first heat map (Figure 9a) identifies motorcycle-pedestrian conflicts with TTC less than 3 seconds. Figure 9b shows the heat
map based on the TTC and PET thresholds of 3 seconds. Figure 5.13c shows the heat map using the 85th percentile thresholds of MSSF and peak-to-peak jerk. A significantly less number of conflicts are identified that show a better evaluation of the motorcycle-pedestrian conflicts that have evasive actions. However, a detailed comparison between conflicts identified by each measure should be further validated using actual motorcycle-pedestrian crashes to demonstrate the usefulness of the tested measures and thresholds.

(a) Time proximity measures: TTC (1354 conflict)

(b) Time proximity measures: TTC and PET (766 conflict)
Figure 5.13 Motorcycle-Pedestrian conflict heat maps detected by time proximity measures vs. evasive action-based measures

5.6 Summary of Key Results

This chapter presented the study of motorcycles and bicycle conflicts in a less organized intersection in Shanghai, China. Using computer vision techniques, traffic conflicts were analyzed and the mechanisms of the evasive action of motorcyclists and cyclists were investigated. Overall, results showed that evasive action-based measures are better in reflecting the severity of motorcycle and bicycle conflicts than time proximity measures. The main findings are summarized below:

1- Time proximity measures were shown to identify a high number of two-wheeler conflicts that did not reflect the true severity of their interactions in the studied location.

2- Two wheelers normally keep slight proximity to other road users and make pronounced evasive actions to avoid collisions, which is a major contributor to the high number of conflicts collected using time proximity measures.

3- The study of the behavior of motorcyclists and cyclists in conflicts showed that the evasive action is mainly reflected in sudden steering, braking, or speeding. Accordingly, indicators
that represent changes in the acceleration, jerk, and yaw rate were validated to reflect the evasive action.

4- For motorcycle conflicts, the peak-to-peak jerk value and peak-to-peak yaw rate ratio showed higher potential to reflect conflict severity than time proximity measures.

5- For bicycle conflicts, the peak-to-peak yaw rate ratio showed the highest potential to reflect the swerving evasive actions in bicycles.

Overall, results show that evasive action-based indicators are better in reflecting the severity of motorcycle and bicycle conflicts than time proximity measures. The evasive action-based indicators showed high relevance in similar severity trends and in segregating between different conflicts by severity level.
Chapter 6: Detection of Evasive Action in Traffic Conflicts

The differentiation of traffic conflicts from normal movements is a crucial step in the detection of traffic conflicts. Since traffic conflicts differ in the degree of severity, the challenge has always been to find a criterion that differentiates conflicts from normal adaptations. In the literature, the detection of traffic conflicts has always been determined through a fixed threshold where traffic conflicts are detected once the interaction TTC and/or PET is less than a pre-determined threshold. This approach has always been criticized by many researchers because the definition is inconsistent and sometimes shows normal movements as conflict situations (Peesapati, et al., 2013) (Zheng, et al., 2016). Additionally, thresholds were shown to significantly vary according to several road, traffic, and environment conditions (Zheng, et al., 2014). In practice, these thresholds practiced in many traffic conflict studies relied on user experience or expert judgment, which lead to further inconsistency in the traffic conflicts definition. Therefore, there is a need to develop a solid method to detect traffic conflicts coherently. The methodology should be robust to avoid the inconsistencies of using time proximity measures. This chapter presents a novel methodology to automatically detect traffic conflicts based on the detection of evasive actions. Pedestrian conflicts are used as a case study to show the detection of traffic conflicts with evasive actions.

As shown in Chapter 4, pedestrians with evasive actions have sudden jumps/drops in their speed profile. Given the complexity of the walking behavior and noise existence, the time at which the pedestrians start to perform the evasive action is not always apparent from the signal. This time is essential for detection of pedestrian conflicts with evasive action. The goal in this chapter is to find a proper abstraction of the pedestrian walking profile. Such abstraction prunes redundant
information in the signal and retains qualitative properties relevant to the evasive action occurrence. The automated detection of pedestrians with evasive actions is done using Permutation Entropy (PE). This chapter is divided into three main components. The first explains the concept of PE and the usefulness in the applied case. The second explains the automated application PE in the detection of pedestrian conflicts. The third section shows the validation methodology of using the variation in PE to detect pedestrians that perform evasive actions.

### 6.1 Permutation Entropy

In general, the term entropy refers to the measure of a system disorder. PE is an approach specifically used for time series profiles to detect qualitative changes. PE detects changes of the underlying dynamics in a time series signal. It is widely used in different fields with different applications, such as detecting an epileptic seizure from a patient brain wave (Cao, et al., 2004), recognizing voice sounds in a speech signal (Bandt & Pompe, 2002), and analyzing stock market profiles (Zanin, et al., 2012). In this thesis, it is tested to reveal the degree of abnormality in the walking pattern of a pedestrian by identifying the deviations from the normal free walking behavior. Approaches used in the literature for analyzing dynamic changes in a periodic time series depend either on learning techniques or prior knowledge of the signal profile, such as frequency counting, amplitude statistics, etc. However, PE is a quantitative measure based on the ordinal patterns of the neighboring segments in a signal. The method transforms time-series sinusoidal wave structure into an entropy domain space where variability in the dynamics is more pronounced and easier to detect compared to the time domain. PE is conceptually simple and computationally fast in detecting changes in a wave-shaped signal such as the pedestrian speed profile. The main advantages of using PE in discovering the dynamic changes in a pedestrian motion profile is that
6.2 Permutation Entropy Application

The PE approach captures the basic ordinal pattern information (i.e., increasing and decreasing transitions) of the time series and the frequency of their occurrence (i.e., distributions) which reveal the properties of the dynamics. A pedestrian trajectory with varying dynamics will have a varying complexity measured by Permutation Entropy (PE). The speed profile of a normal walking pedestrian essentially has a recurring ordinal pattern through the step motion (Figure 6.1) and a degree of abnormality at the start of the evasive action. PE can be used to detect when pedestrians perform the evasive action. The formal procedure of the permutation entropy detection and calculation is summarized below in these steps (Bandt & Pompe, 2002):

**Step 1: Embedding.** Given the time-series $T = \{x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+N}\}$ representing the pedestrian speed profile, an embedding is a reconstruction of a $d$-dimensional state space $X = [X_1, \ldots, X_i, \ldots, X_K]$, where $X_i$ is the $i^{th}$ state of $T$ with $X_i = [x_i, x_{i+\tau}, \ldots, x_{i+(d-1)\tau}]$, $i \in \{1, \ldots, K\}$ and $K=N-(d-1)\tau$, where $d$ and $\tau$ stand for the embedding dimension and delay time, respectively.

If the time series has a length $N=100$ with $d = 3$ patterns and $\tau = 2$, then there are $K=96$ possible states to analyze. The embedding dimension $d$ determines how much information is contained in each vector. The delay time $\tau$ allows the analysis of the dynamics at different temporal resolutions if $\tau \geq 2$.

**Step 2: Ordinal Mapping.** Given the $d$ elements of $X_i$ arranged in an increasing order is $[x_i+(r_2-1)\tau \leq x_i+(r_2-1)\tau \leq \ldots \leq x_i+(rd-1)\tau]$, then $X_i$ can be uniquely mapped onto the rank pattern $r_i = (r_1, r_2, \ldots, r_d)$. The ranks of this pattern sequence are indices organized in an ascending order.
representing the order index. The elements in state \( X_i \) with rank \( r_i \) is one of the \( d! \) permutations of the distinct symbols 1…d. For example, the pattern of the selected state with values (6, 11, 9) is 132. As such, the reconstructed \( T \) in the \( d \)-dimensional space is represented by a sequence of ordered patterns as each \( X_i \) is mapped onto one of the \( d! \) permutations.

Step 3: **Permutation Entropy.** Let \( \Delta \) be one set of state of \( X_i \) having ordinal \( d \)-pattern. The occurrence count of \( \Delta \) in \( T \) is denoted as \( \#_\Delta \). Therefore, the probability distribution \( P_\Delta \) is defined as \( P_\Delta = \frac{\#_\Delta}{N - (d-1)\tau} \). Now, the probability distribution for each pattern \( \Delta_i \) is \( P_j \), where \( j \leq d! \). The permutation entropy (PE) for the time series \( T \) is defined for the \( j \) distinct patterns of \( \Delta \) as in equation \( 6.1 \)

\[
H(d) = - \sum_{j=1}^{d!} P_j \log(P_j)
\]

\( H(d) \) attains the upper bound (maximum value) for a very uniform time series with a constant sequence of increasing/decreasing state values, where all possible permutations appear with the same probability. The lower bound is usually attained for a very random time series, where all permutations appear with different probabilities.

Let’s say the analyzed time series have these values \( T = (5, 8, 10, 9, 4, 7, 11, 12, 6) \) using the embedding dimension \( d = 3 \) and delay time \( \tau = 2 \) and given \( N = 9 \). Five sets of neighbors, \((5, 10, 4)\), \((8, 9, 7)\), \((10, 4, 11)\), \((9, 7, 12)\), and \((4, 11, 6)\) can be organized according to their relative values. The found states have two sets \((5, 10, 4)\) and \((8, 9, 7)\) for which \( x_{i+2} < x_i < x_{i+1} \) represented by the permutation 231. Two sets \((10, 4, 11)\) and \((9, 7, 12)\) for which \( x_{i+1} < x_i < x_{i+2} \) represented by the permutation 213. One set \((4, 11, 6)\) for which \( x_i < x_{i+2} < x_{i+1} \) represented by permutation 132. The
permutation entropy of order $d = 3$ and $\tau = 2$ is the measure of the probabilities of the permutations 231, 213 and 132. So the PE is $H(3) = -(2/5)\log(2/5) - (2/5)\log(2/5) - (1/5)\log(1/5)$.

**Figure 6.1** Speed profile of a normal walking pedestrian showing the ordered patterns through the steps motion

To reflect the variations in the dynamic complexity of pedestrian motion, the PE is computed in a sliding window fashion, as shown in Figure 6.1. The size of the window is defined by the number of ordinal patterns in the window (Keller, et al., 2007). A large window size can overlook the small, but critical changes in the pedestrian behavior as in the case of a sudden change of walking pattern, while a small window size can be more susceptible to noise. The choice of the sliding window is determined relative to the average gait step of the pedestrians (half a second). In the analyzed pedestrian signal, the embedding dimension and delay time was determined by the recommended values ($d=5$, $\tau=2$) shown in Cao, et al., (2004).

Figure 6.2 provides the speed and PE profile of a pedestrian walking normally and then start to run as a response to being in a conflict with a turning vehicle. This pedestrian speed profile shows the change because of the evasive action reflected in the PE profile with a drop. It is shown that changes in the walking pattern of a pedestrian lead to changes in the PE of the corresponding time-series of the speed profile. The non-uniform change of the signal yields a changeable PE value at
the time the pedestrian performs the evasive action. On the other hand, a steady moving pedestrian maintaining the same walking step pattern is shown in Figure 6.2. In this case, the cyclic signal of speed maintains a constant pattern and no change is shown in the PE profile. The PE drop with the pedestrian doing a sudden evasive action reflects the time at which the pedestrian performs the evasive action. The values of PE are at a higher level during normal walking states in comparison to the evasive action states, as the PE should be essentially constant during the normal walking. Therefore, sudden changes in the PE profile can detect the evasive action exerted by a pedestrian in conflict.

Figure 6.2 Two examples of pedestrians in conflicts and the corresponding speed and PE profile using $d = 5$ and $\tau = 2$ (a) Pedestrian in a conflict suddenly running to avoid a moving vehicle (b) Pedestrian moving normally
6.3 Variation in PE

The calculation of the maximum PE drop obtained from different pedestrian conflicts shows the evasive action behavior of the pedestrian. The next step is to analyze the PE drop obtained from different conflicts toward evasive actions exerted by the pedestrian. The maximum PE drop in the pedestrian profile is compared with an evasive action/no evasive action groups. The main objective is to examine and validate the possibility of using PE profiles to identify pedestrian evasive actions compared to traditional measures of traffic conflicts (i.e. TTC and PET). In the validation process, a group of randomly-chosen pedestrian conflicts is manually annotated by two traffic safety experts using the definition given in the US Federal Highway Administration (FHWA) of the traffic conflicts observer’s guide (Parker, Jr. & Zegeer, 1989). The experts were asked to classify these conflicts into two groups based on the existence of a pedestrian evasive action (Evasive Action/ No-Evasive Action). The agreement results between the experts are shown in Table 6.1. The consistency test showed agreements between the experts in which the kappa was 0.498 and the variance of kappa was 0.017. The result indicates a moderate agreement between the two experts statistically significant at 95% confidence interval.

<table>
<thead>
<tr>
<th>Severity Category</th>
<th>Expert 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Evasive Action</td>
</tr>
<tr>
<td>No Evasive Action</td>
<td>39</td>
</tr>
<tr>
<td>Expert 1</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>46</td>
</tr>
</tbody>
</table>

Table 6.1 Agreement results between the two expert categorizations
The pedestrian conflicts in the evasive action groups are compared in terms of severity for both experts. The evasive action group showed a higher severity of conflicts than the no-evasive action group for both experts as shown in Figure 6.3. The most severe conflicts showed evasive actions in the pedestrian movement. On the other hand, experts assigned over 60% of the no evasive action conflicts as low severity conflicts. This result shows the importance of detecting evasive actions in the evaluation of the severity of pedestrian conflicts.

![Figure 6.3 Conflict severity breakdown in the evasive action/no-evasive action groups assigned by the experts](image)

Table 6.2 shows the mean of the PE drop, TTC, and PET for the two conflict groups (Evasive Action/No Evasive Action). The mean of the PE drop is significantly higher for the evasive action group. This result is affirmed by the statistical significance (p-value) calculated using the ANOVA test on the difference between these means, shown in Table 6.2. The difference in the PE drop case
is highly significant at 95% confidence. The results affirm the usefulness of using the PE drop in differentiating conflicts involving evasive action and the no evasive action conflicts. The findings also show that the PE method is better than the traditional TTC and PET threshold method in identifying pedestrian conflicts with evasive actions.

Table 6.2 Mean and standard deviation of the maximum PE drop value for evasive action and no evasive action conflicts

<table>
<thead>
<tr>
<th></th>
<th>Expert 1</th>
<th></th>
<th>Expert 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Evasive Action</td>
<td>Evasive Action</td>
<td>No Evasive Action</td>
<td>Evasive Action</td>
</tr>
<tr>
<td>PE drop Mean</td>
<td>0.139</td>
<td>0.476</td>
<td>0.127</td>
<td>0.539</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>0.226</td>
<td>0.355</td>
<td>0.2103</td>
<td>0.349</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000*</td>
<td></td>
<td>0.000*</td>
<td></td>
</tr>
<tr>
<td>TTC Mean</td>
<td>1.316</td>
<td>1.294</td>
<td>1.368</td>
<td>1.227</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>1.378</td>
<td>1.274</td>
<td>1.445</td>
<td>1.156</td>
</tr>
<tr>
<td>p-value</td>
<td>0.95</td>
<td></td>
<td>0.64</td>
<td></td>
</tr>
<tr>
<td>PET Mean</td>
<td>0.818</td>
<td>1.027</td>
<td>0.771</td>
<td>1.116</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>1.096</td>
<td>1.637</td>
<td>1.034</td>
<td>1.752</td>
</tr>
<tr>
<td>p-value</td>
<td>0.683</td>
<td></td>
<td>0.433</td>
<td></td>
</tr>
</tbody>
</table>

* Statistically significant p-value at 95% confidence interval.

Results showed the benefit of using PE in the detection of pedestrian conflicts with evasive action. The amount of manual intervention needed to collect data on pedestrians in safety-hazardous situations can be significantly reduced by deploying the PE. PE can assist in identifying the conflicts with evasive action which help separate true traffic conflict events from other non-conflict events. The PE method is utilized in the next chapter to cover pedestrian conflict severity in different environments. However, there are some limitations in the calculation of PE:
1- The PE is applied only on pedestrians in conflict situations. Since traffic conflicts involve two road users and the evasive action can be exerted by either one of the conflicting road users, it is important to investigate the evasive action of vehicle drivers.

2- The PE was shown to be sensitive to the accuracy of the trajectories obtained. Since the trajectory quality is sometimes affected by the tracking nature inaccuracies such as occlusions, shadows, etc., it is important to check for any of these inaccuracies before calculating the PE from the pedestrian speed profile.

### 6.4 Summary of Key Results

This chapter presented an automated-detection method of pedestrian conflicts with evasive actions. The analysis was performed on a case study of the dataset in Shanghai, China. Using computer vision techniques, the pedestrian-evasive actions in traffic conflicts were identified using Permutation Entropy (PE) as a method to detect the anomaly in the normal-ordered patterns of pedestrian speed profiles. These are the summary of the findings

1- Sudden evasive actions in the walking behavior of a pedestrian lead to changes in the PE profile.

2- Results showed that the PE could identify pedestrian conflicts that have sudden evasive actions better than TTC and PET.

3- The findings show that the maximum variation in the PE profile (PE drop) is an indication of the time of occurrence of pedestrian evasive actions in traffic conflicts.

Overall, the PE indicator is used a complementary approach for studying pedestrian conflicts with evasive actions which shows a more realistic representation of pedestrian reactions during near-miss conflict situations than traditional time proximity measures. Using the pedestrian evasive action-based measures happening at the point of the PE drop is utilized in the next chapter to cover
pedestrian conflicts in different environments. The amount of manual intervention needed to collect data on pedestrians in conflict situations can be significantly reduced by deploying the PE approach.
Chapter 7: Evasive Action-Based Measures vs. Time Proximity Measures across Different Traffic Environments

As presented in the previous chapters, the developed evasive action-based conflict indicators were shown useful in addressing conflicts in the studied location in Shanghai, China. The validation demonstrated the potential of the new indicators in reflecting conflicts severity in a less organized traffic environment. However, it is still important to investigate these indicators in different traffic environments with similar as well as different conditions. Since traffic environments around the world vary in organization and configuration, the behavior taken by road users differs according to the cultural norms in society (Nordfjærn, et al., 2014) (Lund & Rundmo, 2009). The differences affect the risk behavior taken by road users and traffic conflicts, as shown in the results of the high frequency of traffic conflicts in the Shanghai location. The fact that road users normally accept close proximities between each other and the public apathy towards traffic regulations, affects their behavior and conflicts results (Atchley, et al., 2014). Therefore, the evasive action-based indicator has shown high potential to study conflicts in this environment. However, in more structured traffic environments, conflicts may not involve evasive actions the same way as experienced in Shanghai. There is a need to test the various conflict indicators in different environments. In this chapter, the pedestrian evasive action-based indicator (MSSF) and the time proximity measure (TTC) is applied to pedestrian conflicts on different data-sets from different traffic locations around the world. Video data are collected from traffic locations in five cities to cover different traffic environments. These locations are major intersections in main urban cities in China, India, Qatar, United States, and Canada. The objective is to investigate the effect of the traffic environment on the usefulness of traffic conflict indicators in measuring conflict severity and to test the
combination of different measures to address conflict severity. In this chapter, the details of the comparison of using MSSF and TTC in different environments is presented. The indicators were compared regarding the effectiveness in reflecting conflict severity in every environment independently. Models are developed to combine these indicators in the different environments. The details of data collection, the comparisons procedure, and the model development are presented in this chapter.

7.1 Data Collection

The data collected were chosen to essentially cover locations from different traffic environments. The video data covers intersection crosswalks with high pedestrian activity and interactions with other road users. These locations are major intersections with considerable congestion in Shanghai, New Delhi, Doha, New York, and Vancouver. The locations are near central business areas of the cities which can reflect the typical road-users behavior in the urban environment. Data were collected between April 2014 and March 2016 using cameras fixed on light poles, traffic signals, or nearby buildings to these intersections. The first dataset, video data no. 1, is the Shanghai, China location originally utilized in Chapters 4, 5, and 6. The detailed description of the other locations is illustrated below.

2.1 Video Data no. 2: New Delhi, India

This dataset covers a highly-congested intersection in the city of New Delhi, India, shown in Figure 7.1. The intersection was chosen to cover a less organized traffic location yet from a different culture than the Shanghai location. The intersection is located in Paharganj, which is a neighborhood in the downtown of Delhi, at the crossing of two major roadways, DB Gupta Road and Chitragupta Road/Sardar Thana Road. The intersection is a four-leg signalized intersection
with three lanes in each direction on DB Gupta Road and two lanes in each direction on
Chitragupta Road/Sardar Thana Road. A high-resolution camera was mounted at the southeast corner of one of the nearby buildings. Video data were recorded during daytime monitoring the middle of the intersection. Vehicle and pedestrian volume at the intersection are 1662 per hour and 1968 per hour, respectively. The high volume of traffic on both roads creates busy and congested condition throughout most of the day.

Figure 7.1 Video dataset no. 2 from New Delhi, India at the crossing of DB Gupta Road and Chitragupta Road/Sardar Thana Road

The video shows many risky interactions involving pedestrians and other road users because of the frequent violations and general lack of conformance to traffic regulations. The intersection has four crosswalks but clearly lacks proper infrastructure, such as crosswalk pavement markings and a designated sidewalk/curb on one corner. A large mix of different road users passes the intersection with a high volume of rickshaws and mopeds sharing the road with other vehicles. Rickshaws are three-wheeler cycles or motorized carts (Yellow/Green colored 3-wheelers in
Figure 7.1) commonly used in India and many other developing countries. These unconventional modes of transportation frequently interact with pedestrians and vehicles at the intersection. The traffic conditions in the intersection show many violations, constant interactions, and lack of compliance with traffic rules and regulations.

2.3 Video Data no. 3: New York, United States

This dataset covers a busy intersection in New York City, United States. The intersection is located on Manhattan Island, the heart of New York City, at the crossing of two major roadways, 6th Avenue and Houston Street, shown in Figure 7.2. Houston Street is an East-West two-way street in Manhattan with three lanes in each direction and 6th Avenue is a major one-way four-lane roadway that connects downtown to uptown New York City. The intersection is a busy signalized intersection with significant pedestrian activity. A high-resolution camera was mounted on one of the intersection poles where three crosswalks are included in the view. The intersection is busy throughout the day, with a high vehicle volume of 2400 per hour and a pedestrian volume of 1012 per hour. Severe conflicts are commonly seen between pedestrians and turning vehicles. Pedestrian violations to the signal and waiting on the roadway off the curb seems to cause many conflicts, which lead to many interruptions to the traffic flow.
Figure 7.2 Video dataset no. 3 from New York City, United States at the intersection of Houston Street and 6th Avenue in Manhattan

2.4 Video Data no. 4: Doha, Qatar

This video dataset is collected from the city of Doha, the capital of Qatar. The video covers a pedestrian crosswalk in a midblock intersection of Al Corniche Street, shown in Figure 7.3. The location is in the west bay area, which is the central business district of Doha. The area is surrounded by skyscrapers, businesses, hotels, and shopping centers. Al Corniche Street is a six-lane major corridor in Doha passing along the sea-side where pedestrians frequently cross to reach the Al Corniche promenade. Traffic control for the pedestrian crossing is a push-button signal activated by the pedestrian. However, interactions can be observed because drivers and pedestrians are not conforming to the signal operation. The video footage was collected from the city camera mounted on the traffic light pole of the intersection. The street is generally busy throughout the day with a vehicle volume of 1394 per hour. In Doha, commuters highly depend on passenger cars, which is why the pedestrian volume on the crosswalk was low. The pedestrian volume was 239...
per hour. Therefore, video data was recorded over two days to capture enough pedestrians and their respective conflict data.

**Figure 7.3 Video dataset no. 4 from Doha, Qatar showing a crosswalk location on Al Corniche Street**

### 2.5 Video Data no. 5: Vancouver, Canada

The last intersection studied is in Metro Vancouver, British Columbia. The intersection is at 104 Avenue and 152 Street in the city of Surrey, which is part of Vancouver metropolitan area. The intersection is a 4-leg signalized intersection located near Surrey Central metro station and downtown area where major recreational, educational, business, and shopping facilities exist. Therefore, the intersection is very busy throughout the day with a vehicle volume of 3584 per hr and a pedestrian volume of 555 per hour. 104 Avenue is a major corridor that connects Surrey center to Highway1. Both 104 Avenue and 152 Street have two lanes in each direction. The video
data were collected from the city camera fixed at the traffic signal height. The camera field of view covered two crosswalks and the middle of the intersection, as shown in Figure 7.4, where pedestrians conflict with turning vehicles. The behavior of the drivers seen shows compliance with traffic regulations in yielding/stopping to pedestrian movement on the crosswalks. Although the traffic location in Vancouver and New York both cover a North American traffic location, they are different in road-users behavior and environment.

![Image of intersection](image)

**Figure 7.4 Video dataset no. 5 from Metro Vancouver, British Columbia at the intersection of 104 Avenue and 152 Street in Surrey**

### 7.2 Video Analysis

Automated video analysis was conducted for the four locations to obtain road users trajectories and identify conflicts and their corresponding severity measures. Both types of severity measures (MSSF and TTC) were calculated for pedestrian conflicts. The locations analyzed differ in their
traffic characteristics and geometric configurations. However, this is not intended to affect the results of the study, as the analysis is performed on the same number of pedestrian conflicts from each of the five locations that reflect similar interactions (pedestrian-vehicle interactions on crosswalks). Therefore, a group of 100 conflicts of the extracted pedestrian-vehicle conflicts was randomly selected from each location. The pedestrian conflicts were carefully chosen, so their trajectory is well-tracked and not affected by any of the tracking system limitations such as occlusions, shadows, global illumination, etc.

The first step in the analysis of these conflicts is the violation detection to identify the percentage of road users in conflicts not-conforming to traffic regulations. Pedestrian or vehicles violations such as jaywalking, non-compliance to signal operation, etc. were automatically detected for each location. The identification of violations is carried out by comparing the spatial and temporal information of each road user with occupied areas of the intersection and traffic signal cycles. The violation results showed a high variation from one location to the other. Shanghai and New Delhi had the highest percentage of violations, between 84% and 88% of the pedestrian conflicts showed violations by the road users. The New York and Doha locations showed less percentage between 39% and 45% while Vancouver had the lowest percentage of 6%.

<table>
<thead>
<tr>
<th>Percentage of Violations</th>
<th>Shanghai</th>
<th>New Delhi</th>
<th>New York</th>
<th>Doha</th>
<th>Vancouver</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>84%</td>
<td>88%</td>
<td>45%</td>
<td>39%</td>
<td>6%</td>
</tr>
</tbody>
</table>

Table 7.1 Violation results on the pedestrian conflicts in the five datasets

To test the usefulness of different indicators in representing severity the conflicts groups from each location were presented to two safety experts. Each group of conflicts was given to two experts to evaluate them separately at different times. The goal is to seek the indicators that best reflect the
expert severity evaluation. The experts were asked to categorize these conflicts and rank them as before. These conflicts are compared to the severity evaluation of the same traffic safety experts in the five locations. Similar to before, the experts were asked to categorize the pedestrian-vehicle conflicts into three categories (high, intermediate, and low) and to rank them based on severity. The experts were not told which city the data was collected from nor were they asked to take traffic context in their evaluation. Although violations are highly existent in some locations as shown in Table 7.1, it is not expected to affect the judgment results of the experts. In a similar previous experiment by Kruysse, 1992, it was shown that the relation between violations of traffic regulations in a location and judgments of situations dangerousness by humans is weak (Kruysse, 1992). However, consistency tests were carried out for the five locations to further check the consistency together.

### 7.3 Test of Consistency

The validity of the results obtained by the two experts is firstly examined through the consistency test. To proceed further with the analysis, the Kappa test was employed to measure the agreement of the two experts. Using the categorization of both experts, the agreements between them is calculated as shown in Table 7.2 for the five locations.

#### Table 7.2 Agreement results between the two expert categorizations

<table>
<thead>
<tr>
<th>Shanghai</th>
<th>Expert 1</th>
<th>Expert 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>17</td>
<td>12</td>
</tr>
<tr>
<td>Intermediate</td>
<td>8</td>
<td>18</td>
</tr>
<tr>
<td>High</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>Total</td>
<td>32</td>
<td>38</td>
</tr>
<tr>
<td>Location</td>
<td>Expert 1</td>
<td></td>
</tr>
<tr>
<td>------------</td>
<td>----------</td>
<td>------------------</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Intermediate</td>
</tr>
<tr>
<td>New Delhi</td>
<td>Low</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Intermediate</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>30</td>
</tr>
<tr>
<td>New York</td>
<td>Low</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Intermediate</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>31</td>
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<tr>
<td>Doha</td>
<td>Low</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>Intermediate</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>33</td>
</tr>
<tr>
<td>Vancouver</td>
<td>Low</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>Intermediate</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>High</td>
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</tr>
<tr>
<td></td>
<td>Total</td>
<td>34</td>
</tr>
</tbody>
</table>

As shown in Table 7.2, the kappa statistic (k) was calculated for every data group. The results of the kappa test for all locations showed a kappa between 0.312 and 0.458, which can be considered
a moderate agreement between the experts. The results of the consistency test are listed for every location in Table 7.3. The kappa values were statistically significant at 95% confidence interval.

Table 7.3 Results of the consistency test between experts for the five datasets

<table>
<thead>
<tr>
<th>Conflict Locations</th>
<th>Shanghai</th>
<th>New Delhi</th>
<th>New York</th>
<th>Doha</th>
<th>Vancouver</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.57</td>
<td>0.54</td>
<td>0.55</td>
<td>0.62</td>
<td>0.64</td>
</tr>
<tr>
<td>P&lt;sub&gt;c&lt;/sub&gt;</td>
<td>0.332</td>
<td>0.333</td>
<td>0.334</td>
<td>0.335</td>
<td>0.335</td>
</tr>
<tr>
<td>k</td>
<td>0.356</td>
<td>0.312</td>
<td>0.332</td>
<td>0.42</td>
<td>0.458</td>
</tr>
<tr>
<td>Var(k)</td>
<td>0.006</td>
<td>0.005</td>
<td>0.005</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td>k/√Var(k)</td>
<td>4.8</td>
<td>4.379</td>
<td>4.69</td>
<td>5.93</td>
<td>6.37</td>
</tr>
</tbody>
</table>

7.4 Ranking Correlation

The Spearman rank tests the correlation strength and direction between the monotonic relationship of the studied indicators and the expert rankings. The correlation value, in this case, can reflect the ability to use the studied indicators (TTC and MSSF) in ranking different conflicts according to severity. The results of the correlation are shown in Figure 7.5 and listed in Table 7.4. The higher the correlation, the higher the ability of the indicator in differentiating between the conflicts severity (higher agreement with expert rankings). Initial results showed that the TTC had the higher correlation with expert rankings for Vancouver. New Delhi and Shanghai showed the least correlation. On the other hand, the results also showed that the MSSF had a higher correlation with expert rankings for New Delhi and Shanghai, and the least in Vancouver.
The significant results of the correlation coefficient confirmed the importance of considering the evasive action indicators in evaluating severity in environments such as New Delhi and Shanghai. However, some correlation values obtained are relatively low for individual indicators to reflect the severity of pedestrian conflicts solely.
Table 7.4 Results of the ranking correlation between expert rankings and the TTC and MSSF ranking for the five datasets

<table>
<thead>
<tr>
<th></th>
<th>Shanghai</th>
<th>New Delhi</th>
<th>New York</th>
<th>Doha</th>
<th>Vancouver</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expert1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.220</td>
<td>0.219</td>
<td>0.304</td>
<td>0.354*</td>
<td>0.380*</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.407*</td>
<td>0.469*</td>
<td>0.324</td>
<td>0.311</td>
<td>0.162</td>
</tr>
<tr>
<td>Expert2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.208</td>
<td>0.289</td>
<td>0.339*</td>
<td>0.316</td>
<td>0.365*</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.374*</td>
<td>0.381*</td>
<td>0.289</td>
<td>0.272</td>
<td>0.130</td>
</tr>
</tbody>
</table>

*Significant coefficient at 95% confidence interval

7.5 Severity Relation

The trend among the categories assigned by the experts is shown by the mean value of each indicator in the three severity categories as shown in Figure 7.6 and Table 7.5 which shows the overall mean and standard deviation of each severity category for the five datasets. For the locations in Vancouver, Doha, and New York, the TTC had logical trends (lower TTC for the highest severity category and vice versa). However, for the locations in New Delhi and Shanghai, the TTC trends were nearly horizontal (no difference in the means of the three categories). On the other hand, the MSSF showed a logical trend between the conflicts severity for most locations except for Vancouver. The trend showed a nearly horizontal line.

The following step is to test the significance of the difference between the means in the three categories through the ANOVA test. The p-value shows the ability to reflect the severity of the three categories. In Vancouver, the TTC proved useful in differentiating between the conflicts severity in the three groups (statistically significant p-values). However, the MSSF was not significant in differentiating between the conflicts severity in the three groups (non-statistically significant p-values). For the locations in New Delhi and Shanghai, the TTC, which did not show
the difference in the means of the three categories, was non-significant in terms of the p-values. However, the MSSF had a significant p-value. The locations in New York and Doha both had significant p-values. Therefore, the TTC has more relevance in describing conflict severity in Vancouver and little relevance for the locations in New Delhi and Shanghai. The MSSF is more relevant for measuring conflict severity for locations in New Delhi and Shanghai and little relevance in Vancouver. Both types of indicators MSSF and TTC can be relevant for measuring conflict severity for the locations in New York and Doha.

Table 7.5 Results of the mean and standard deviation of the TTC and MSSF for both experts in the five datasets

<table>
<thead>
<tr>
<th>Location</th>
<th>TTC (sec) Low</th>
<th>Intermediate (sec)</th>
<th>High (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shanghai</td>
<td>0.915 (0.861)</td>
<td>1.248 (1.136)</td>
<td>0.909 (0.737)</td>
</tr>
<tr>
<td></td>
<td>0.535 (0.265)</td>
<td>0.825 (0.346)</td>
<td>1.938 (1.284)</td>
</tr>
<tr>
<td>New Delhi</td>
<td>0.885 (0.592)</td>
<td>0.602 (0.323)</td>
<td>0.786 (0.549)</td>
</tr>
<tr>
<td></td>
<td>0.598 (0.306)</td>
<td>0.887 (0.515)</td>
<td>1.627 (1.097)</td>
</tr>
<tr>
<td>New York</td>
<td>2.407 (0.629)</td>
<td>1.526 (0.885)</td>
<td>0.579 (0.497)</td>
</tr>
<tr>
<td></td>
<td>0.448 (0.291)</td>
<td>0.594 (0.363)</td>
<td>0.766 (0.555)</td>
</tr>
<tr>
<td>Doha</td>
<td>3.342 (0.518)</td>
<td>2.254 (0.948)</td>
<td>0.720 (0.660)</td>
</tr>
<tr>
<td></td>
<td>0.741 (0.594)</td>
<td>0.660 (0.540)</td>
<td>1.186 (1.058)</td>
</tr>
<tr>
<td>Vancouver</td>
<td>2.662 (0.268)</td>
<td>2.072 (0.293)</td>
<td>1.238 (0.576)</td>
</tr>
<tr>
<td></td>
<td>0.912 (0.434)</td>
<td>0.778 (0.472)</td>
<td>0.965 (0.477)</td>
</tr>
</tbody>
</table>

*Values between parentheses are the standard deviation.
### Expert 1: Time to Collision

<table>
<thead>
<tr>
<th>City</th>
<th>TTC</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vancouver</td>
<td>0.00</td>
<td>0.0006*</td>
</tr>
<tr>
<td>Doha</td>
<td>0.00</td>
<td>0.0056*</td>
</tr>
<tr>
<td>New York</td>
<td>0.00</td>
<td>0.0072*</td>
</tr>
<tr>
<td>New Delhi</td>
<td>0.00</td>
<td>0.0841</td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.00</td>
<td>0.5677</td>
</tr>
</tbody>
</table>

### Max Slope Step Frequency

<table>
<thead>
<tr>
<th>City</th>
<th>MSSF</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vancouver</td>
<td>0.20</td>
<td>0.2543</td>
</tr>
<tr>
<td>Doha</td>
<td>0.01</td>
<td>0.0089*</td>
</tr>
<tr>
<td>New York</td>
<td>0.01</td>
<td>0.0390*</td>
</tr>
<tr>
<td>New Delhi</td>
<td>0.00</td>
<td>0.0001*</td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.00</td>
<td>0.0020*</td>
</tr>
</tbody>
</table>

### Expert 2: Time to Collision

<table>
<thead>
<tr>
<th>City</th>
<th>TTC</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vancouver</td>
<td>0.00</td>
<td>0.0007*</td>
</tr>
<tr>
<td>Doha</td>
<td>0.00</td>
<td>0.0009*</td>
</tr>
<tr>
<td>New York</td>
<td>0.00</td>
<td>0.0050*</td>
</tr>
<tr>
<td>New Delhi</td>
<td>0.00</td>
<td>0.4303</td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.00</td>
<td>0.6120</td>
</tr>
</tbody>
</table>

### Max Slope Step Frequency

<table>
<thead>
<tr>
<th>City</th>
<th>MSSF</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vancouver</td>
<td>0.20</td>
<td>0.2066</td>
</tr>
<tr>
<td>Doha</td>
<td>0.01</td>
<td>0.0150*</td>
</tr>
<tr>
<td>New York</td>
<td>0.01</td>
<td>0.0014*</td>
</tr>
<tr>
<td>New Delhi</td>
<td>0.00</td>
<td>0.0005*</td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.00</td>
<td>0.0093*</td>
</tr>
</tbody>
</table>
7.6 Model Formulation

Initial results show the significance of TTC in some locations and the significance of MSSF in other locations. Therefore, testing the combination of both indicators together in different environments can help improve the understanding of the effectiveness of these measures in quantifying pedestrian conflicts severities. The indicators are tested in a modeling framework to reflect conflict severity. Previous work on modeling pedestrian conflicts has mainly focused on modeling severity levels as a function of geometric, traffic, or road-users characteristics (Liu & Tung, 2014). Zhang et al., (2015) showed pedestrian conflict on different signal-phasing strategies using a multinomial logit model. Kadali & Vedagiri, (2016) modeled the probability of the existence of a pedestrian conflict at different crosswalk using binary logit models as a function of behavioral and road characteristics. Alhajyaseen & Iryo-Asano (2017) showed the speed changes of the pedestrians in conflicts using a multinomial logit model as a function of crosswalk length and initial pedestrian speed. Although multinomial logit models are used for nominal variables, ordered logit models can be preferred in considering the ordinal nature of the severity levels. Similar to conflict models, pedestrian collision severity models in literature mainly used the logit model to model severity against different traffic, geometric, and the characteristics of road users (Sze & Wong, 2007) (Haleem, et al., 2015) (Verzosa & Miles, 2016). Abdul Aziz et al. (2013) examined the severity of pedestrian injuries as a function of traffic, pavement, land use, demographic and collision characteristics. Eluru, et al. (2008) modeled the injury severity of
pedestrian collisions using a mixed generalized model that recognizes the ordinal nature of the categories in which injury severity are recorded.

According to the hierarchy of traffic events by Hydén (1987), the continuation of all traffic events is explained by a pyramid with traffic collisions and conflicts fall in three levels of severity. Therefore, different severity levels of conflicts constitute proportional volumes of the truncated pyramid. In the thesis, the ordered response logit model is utilized to model the three levels of conflict severity as a function of the different conflict measures. The dependent variable, in this case, represents the ordered conflict severity levels obtained from the expert evaluations (1 = low severity, 2 = intermediate severity, 3 = high severity). The model assumes that the error term representing the unobserved component of the latent variable is logistic distributed with a mean of zero and a variance of $2\pi/3$. The first model estimated, $M_1$ is a random effect model where the dependent variable outcome, $y^*$, is defined by equation 7.1

$$y^* = \beta X + \epsilon + u_i$$

(7.1)

$$where \; u_i \sim N(0, \sigma^2)$$

where $X$ is the vector of explanatory variables (in this case TTC and MSSF), $\beta$ is the vector of model coefficients estimated, $\epsilon$ is the logistic distributed model error term, and $u_i$ is the random effect term which is normally distributed with a mean of 0 and variance of $\sigma^2$. The latent propensity $y^*$ is mapped to the conflict severity levels by thresholds $c_j$ in an ordered response fashion. These thresholds that demarcate the observed severity categories are estimated in the analysis. In this case, three conflict severity types are modeled, the probability (P) of each alternative is shown in equations 7.2-7.4.
\[ P (y = 1) = \frac{1}{1+\exp(y^*-c_1)} \quad \text{(low severity conflicts)} \quad (7.2) \]

\[ P (y = 2) = \frac{1}{1+\exp(y^*-c_2)} - \frac{1}{1+\exp(y^*-c_1)} \quad \text{(intermediate severity conflicts)} \quad (7.3) \]

\[ P (y = 3) = 1 - \frac{1}{1+\exp(y^*-c_2)} \quad \text{(high severity conflicts)} \quad (7.4) \]

In the same conflict condition, pedestrian A may behave with an evident evasive action but pedestrian B may proceed with less evasive action strength. Several unknown factors could contribute to different evasive action behavior of one pedestrian compared to another if they were subjected to the same conflict. Adding a random effect parameter accounts for the unobserved heterogeneity in the data since the evasive action is a behavioral element that varies from one pedestrian to another in each conflict. Testing the correlation between the variables TTC and MSSF for the datasets have shown weak correlations that are not statistically significant except for the New York dataset, as shown in Table 7.6. The result confirms that TTC and MSSF provide different and independent aspects of severity. Therefore, the random effects model is suitable for the analysis. This result confirms with the findings of Ismail et al. (2011) which generally found a weak correlation between different time proximity and behavioral measures. Although, the New York and Doha datasets had the highest correlation compared to other locations and the New York dataset was the only one to show correlated results, the correlation values are still relatively weak.

**Table 7.6 Correlation between variables MSSF and TTC in the five datasets**

<table>
<thead>
<tr>
<th>Correlation between TTC and MSSF</th>
<th>Vancouver</th>
<th>Doha</th>
<th>New York</th>
<th>New Delhi</th>
<th>Shanghai</th>
</tr>
</thead>
<tbody>
<tr>
<td>TTC and MSSF</td>
<td>-0.1748</td>
<td>-0.1926</td>
<td>-0.2502*</td>
<td>-0.0262</td>
<td>-0.0257</td>
</tr>
</tbody>
</table>

*Statistically significant correlation at 95% confidence interval

Model M_1 is estimated for each city location based on the results of both experts together. A summary of the statistics of the TTC and MSSF for each city is included in Table 7.7. Another
model $M_2$ is estimated by the same components as $M_1$ with random intercepts to incorporate the variability in each expert evaluation. The random intercept model adjusts the effect of every expert specific attributes. The models were estimated in a full Bayesian analysis platform using the WinBUGS statistical platform. Bayesian analysis allows for adding a random intercept to adjust for expert heterogeneity. To obtain the full Bayes estimates, it must specify prior distributions of the parameters. Prior distributions are commonly assumed to be diffused normal distributions (with zero mean and large variance) for the regression parameters and gamma distributed for $\sigma^2$. The priors used in the models have been successfully used in previous applications of road safety (El-Basyouny & Sayed, 2009). The posterior distributions in the full Bayes approach are obtained using Markov Chain Monte Carlo (MCMC) sampling, used to repeatedly sample from the joint posterior distribution. The technique chains with random points until the distributions converge to the target posterior distribution. At first, 10,000 iterations are used as a sub-sample to monitor convergence and then excluded as a burn-in sample. The next 10,000 iterations are used for parameter estimation, performance evaluation, and inference. To check convergence, two parallel chains with different starting values are tracked to ensure full coverage of the sample space. Convergence of multiple chains is assessed using the Brooks–Gelman–Rubin (BGR) statistic (Brooks & Gelman, 1998). A value under 1.2 of the BGR statistic indicates convergence. Convergence is also assessed by visual inspection of the MCMC chain plots for the model parameters and by monitoring the ratios of the Monte Carlo errors relative to the respective standard deviations, which should be less than 0.05 (El-Basyouny & Sayed, 2009).
Table 7.7 Summary statistics for TTC in seconds and MSSF in step/sec² for the 5 datasets

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Mean</th>
<th>Maximum</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shanghai</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.242</td>
<td>1.096</td>
<td>3.192</td>
<td>1.113</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.254</td>
<td>1.139</td>
<td>4.165</td>
<td>0.930</td>
</tr>
<tr>
<td>New Delhi</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.140</td>
<td>0.664</td>
<td>3.92</td>
<td>0.929</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.205</td>
<td>1.024</td>
<td>3.902</td>
<td>0.832</td>
</tr>
<tr>
<td>New York</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.233</td>
<td>1.518</td>
<td>3.731</td>
<td>1.014</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.000</td>
<td>0.600</td>
<td>3.027</td>
<td>0.435</td>
</tr>
<tr>
<td>Doha</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.342</td>
<td>2.413</td>
<td>3.948</td>
<td>1.288</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.000</td>
<td>0.850</td>
<td>3.801</td>
<td>0.788</td>
</tr>
<tr>
<td>Vancouver</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TTC</td>
<td>0.513</td>
<td>2.076</td>
<td>3.000</td>
<td>0.685</td>
</tr>
<tr>
<td>MSSF</td>
<td>0.014</td>
<td>0.875</td>
<td>2.588</td>
<td>0.470</td>
</tr>
</tbody>
</table>

The comparison between model M₁ and M₂ is conducted using the Deviance Information Criteria (DIC) (Spiegelhalter, et al., 2002), described in equation 7.5, which is a measure of model complexity and goodness of fit. The DIC is a Bayesian generalization of Akaike’s Information Criteria (AIC) that evaluates larger parameter models.

\[
DIC = \bar{D} + p_D ; \quad p_D = \bar{D} - \hat{D}
\]  

where D is the un-standardized deviance of the postulated model, \(\bar{D}\) is the posterior mean of D, \(\hat{D}\) is the point estimate obtained by substituting the posterior means of the model parameters in D, and \(p_D\) is a measure of model complexity estimating the effective number of parameters. The differences in a DIC of over 10 between two models might rule out the model with the higher DIC. Differences between 5 and 10 are substantial. If the difference in DIC is less than 5, and the models make very different inferences, then it could be misleading just to report the model with the lowest DIC (El-Basyouny & Sayed, 2009).
7.7 Model Results

Examination of the BGR statistics, ratios of the Monte Carlo errors relative to the standard deviations of the estimates and trace plots for all model parameters indicated convergence. Table 7.8 summarizes the parameter estimates and their 95% credible intervals for models M1 and M2 for each location. The table shows the parameter estimates that are significant as the 95% credible intervals were bounded away from zero, which shows that at 95% of the model trials the value of the parameter sign was not changeable. Model parameters were found significant except for the intercept in the Shanghai and New Delhi models. The results show that the MSSF was the only significant variable in the Shanghai and New Delhi locations, while on the other side, the TTC was the only significant factor in the Vancouver location. For New York and Doha, both TTC and MSSF were significant. Thus, the weight of the MSSF coefficient showed relatively higher values for the Shanghai and New Delhi location than the New York and Doha location. Incorporating the random effect in the model considering the heterogeneity of pedestrian behavior was shown to fit the data. However, the DIC statistics showed lower values in the M2 model compared to M1 for all locations. Therefore, incorporating a random intercept in the model considering the variation in each expert evaluation is shown to fit the data better.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model M1</th>
<th>Variable</th>
<th>Intercept Exp1</th>
<th>Intercept Exp2</th>
<th>MSSF</th>
<th>MSSF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.873 (-10.46, 14.02)</td>
<td>Intercept Exp1</td>
<td>1.739 (-10.69, 13.86)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSSF</td>
<td>10.01 (2.731, 17.64)</td>
<td>Intercept Exp2</td>
<td>2.04 (-10.32, 14.22)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shanghai</td>
<td>6.584 (1.156, 16.75)</td>
<td>MSSF</td>
<td>10.12 (2.779, 17.73)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c1</td>
<td>15.88 (3.696, 34.99)</td>
<td>c2</td>
<td>15.75 (3.551, 34.87)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c2</td>
<td>7.647 (1.234, 17.71)</td>
<td>σ</td>
<td>7.54 (1.098, 17.51)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>σ</td>
<td>328.05</td>
<td>DIC</td>
<td>321.56</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

136
<table>
<thead>
<tr>
<th>Variable</th>
<th>Model M₁</th>
<th>Variable</th>
<th>Model M₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.3553 (-12.31, 13.24)</td>
<td>Intercept Exp1</td>
<td>0.165 (-12.54, 13.03)</td>
</tr>
<tr>
<td>MSSF</td>
<td>9.48 (2.38, 17.38)</td>
<td>Intercept Exp2</td>
<td>0.6091 (-12.18, 13.48)</td>
</tr>
<tr>
<td><strong>New Delhi</strong></td>
<td>c₁</td>
<td>6.034 (0.1547, 19.05)</td>
<td>c₁</td>
</tr>
<tr>
<td></td>
<td>c₂</td>
<td>15.06 (3.184, 36.18)</td>
<td>c₂</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>8.196 (1.047, 20.44)</td>
<td>σ</td>
</tr>
<tr>
<td>DIC</td>
<td>299.68</td>
<td>DIC</td>
<td>294.11</td>
</tr>
<tr>
<td>Intercept</td>
<td>16.35 (4.86, 28.81)</td>
<td>Intercept Exp1</td>
<td>16.24 (4.733, 28.68)</td>
</tr>
<tr>
<td>TTC</td>
<td>-4.51 (-7.099, -1.941)</td>
<td>TTC</td>
<td>-4.413 (-6.98, -1.824)</td>
</tr>
<tr>
<td>MSSF</td>
<td>1.962 (0.2357, 4.637)</td>
<td>MSSF</td>
<td>1.935 (0.1602, 4.591)</td>
</tr>
<tr>
<td></td>
<td>c₁</td>
<td>7.694 (0.1659, 17.79)</td>
<td>c₁</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>3.584 (0.4103, 6.158)</td>
<td>σ</td>
</tr>
<tr>
<td>DIC</td>
<td>265.17</td>
<td>DIC</td>
<td>258.75</td>
</tr>
<tr>
<td>Intercept</td>
<td>24.96 (7.099, 50.67)</td>
<td>Intercept Exp1</td>
<td>25.08 (7.25, 50.89)</td>
</tr>
<tr>
<td>MSSF</td>
<td>1.472 (0.0057, 4.53)</td>
<td>MSSF</td>
<td>1.499 (0.0212, 4.521)</td>
</tr>
<tr>
<td></td>
<td>c₁</td>
<td>6.535 (0.325, 19.02)</td>
<td>c₁</td>
</tr>
<tr>
<td></td>
<td>c₂</td>
<td>17.39 (4.583, 36.64)</td>
<td>c₂</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>4.862 (0.310, 11.23)</td>
<td>σ</td>
</tr>
<tr>
<td>DIC</td>
<td>242.84</td>
<td>DIC</td>
<td>235.93</td>
</tr>
<tr>
<td>Intercept</td>
<td>29.87 (20.84, 36.44)</td>
<td>Intercept Exp1</td>
<td>29.78 (20.77, 36.32)</td>
</tr>
<tr>
<td></td>
<td>c₁</td>
<td>12.85 (0.8525, 19.7)</td>
<td>c₁</td>
</tr>
<tr>
<td></td>
<td>c₂</td>
<td>17.68 (6.828, 24.11)</td>
<td>c₂</td>
</tr>
<tr>
<td></td>
<td>σ</td>
<td>0.468 (0.044, 1.827)</td>
<td>σ</td>
</tr>
<tr>
<td>DIC</td>
<td>177.89</td>
<td>DIC</td>
<td>169.66</td>
</tr>
</tbody>
</table>
The effect of TTC and/or MSSF values on the severity can be drawn from model M2. Figure 7.7 shows the effect of the TTC and MSSF values on the probability (P) of conflict severity (High/Intermediate/Low) for the models of the Shanghai, New Delhi, and Vancouver locations. The three cities showed the relationship between the severity probability and TTC/MSSF as a 2D line for the three severity levels, in which the probability depends on one parameter of severity. On the other hand, Figure 7.8 and Figure 7.9 shows the effect of the TTC and MSSF combined with the severity probability reflected on a 3D surface for each severity level for the New York and Doha locations. The surfaces show, in both datasets, that the TTC has a greater effect than the MSSF on estimating the severity of a conflict. Therefore, the TTC can be deemed more important in identifying the severity of traffic conflicts than MSSF in both the Doha and New York locations.
Figure 7.7 Probability of conflict severity in each category versus TTC or MSSF in Shanghai, New Delhi, and Vancouver datasets
Figure 7.8 Probability of conflict severity in each category versus TTC and MSSF in New York dataset.
Figure 7.9 Probability of conflict severity in each category versus TTC and MSSF in Doha dataset
Results show that the time proximity indicator (TTC) have high relevance in describing conflict severity in Vancouver while little relevance for the locations in New Delhi and Shanghai. On the other hand, the evasive action-based indicator (MSSF) has most relevance for measuring conflict severity for the location in New Delhi and Shanghai and no relevance in Vancouver location. This result is attributed to the behavior in less organized environments such as Shanghai and New Delhi where road users keep small proximities between each other and do sudden evasive actions to avoid collisions. While this behavior is much less likely to be observed in more organized traffic environments such as Vancouver where drivers are more likely to yield/stop for pedestrians movements on the road. Their behavior is likely more precautionary and much smoother in reaction. The model results show that both indicators (TTC and MSSF) can be relevant for measuring conflict severity for the location in New York and Doha. The relationship is stronger when both are combined. However, the TTC is still the more significant in both locations. Overall, the difference in road-users behavior across traffic cultures was shown to influence the effectiveness of conflict measures. Road-users risk-taking behavior and reactions to traffic conflicts depend on the cultural norms of the society (Lund & Rundmo, 2009) (Nordfjørn, et al., 2014). Public apathy towards traffic rules and the frequent interactions in less organized traffic cultures leads to the acceptance of close proximity interactions that is less likely to occur in more structured environments. For example, many pedestrians in Shanghai and New Delhi temporally violate crossing the road when they have a clear headway in the opposing traffic. Since large headways are rare, pedestrians tend to keep close proximity to vehicles which forces them to undertake strong evasive actions when in close encounters such as sudden running/Stopping. Such behavior that causes interruptions and reductions of traffic speeds is less likely to be seen in New York and Doha and rarely in Vancouver. TTC calculations do not reflect these frequent evasive
actions in case of pedestrian conflicts. Therefore, the incorporation of evasive-action based indicators that can cover the evasive action aspect of road users is essential such as MSSF for pedestrian evasive actions. It is important to investigate on the other side vehicle drivers evasive actions and potentially to combine both which can also improve the models fitting.

7.8 Summary of Key Results

This chapter presented the use of different conflict measure approaches in measuring pedestrian conflicts severity in different traffic environments. The comparison of using the pedestrian evasive action-based (MSSF) and time proximity-based (TTC) is done regarding the effectiveness in reflecting conflicts severity in different locations (Shanghai, New Delhi, New York, Doha, and Vancouver). Furthermore, models were developed to combine the use of these indicators in the different environments. These results were found:

1- Time proximity indicator (TTC) has high relevance in describing conflict severity in Vancouver while little relevance for the locations in New Delhi and Shanghai where road users keep close proximities between each other by nature.

2- The evasive action-based indicator (MSSF) has most relevance for measuring pedestrian conflict severity for the location in New Delhi and Shanghai and no relevance in Vancouver location because pedestrians in these environments accept close proximity and sudden evasive actions to avoid collisions which are not reflected in the TTC measure.

3- The behavior in Shanghai and New Delhi is much less likely to be observed in organized traffic environments such as Vancouver where drivers are more likely to yield/stop for pedestrians movements on the road from a sufficient distance.
4- Model results show that both indicators (TTC and MSSF) can be relevant for measuring conflict severity for the location in New York and Doha. The relationship is stronger when both are combined. However, the TTC is the more significant measure in both locations. Overall, the findings show a significant variability in the effectiveness of traffic conflicts measures (time proximity-based and evasive action-based) across different environments. Therefore it is important to select relevant conflict severity indicators dependent on the studied traffic environments.
Chapter 8: Conclusions and Future Research

The growing epidemic of road collisions is causing tremendous social and economic losses worldwide. The importance of reducing road collisions cannot be overstated, especially for low and middle-income countries that suffer the most from this problem. This collision risk is not shared equally among various road users, as vulnerable road users such as pedestrians, cyclists, and motorcyclists suffer from an elevated risk of collisions. Traditionally, the approach used to address road safety has relied on historical traffic collision records. This reactive approach has several limitations in the quantity, quality, and attribution of collision data. Alternatively, several researchers have advocated the use of traffic conflicts as a surrogate safety measure. It is postulated that reducing traffic conflicts would result in the reduction of traffic collisions since the same failure mechanism in the driving process leads to the occurrence of both (Sayed & Zein, 1999) (Songchitruksa & Tarko, 2006).

Traffic conflict analysis is typically performed through the calculation of a number of time proximity measures that depend on road users being within a specific spatial and temporal proximity to each other. However, in some traffic environments, road users commonly accept close interactions between each other. In these less-organized traffic environments, road users typically keep close proximities between each other and when involved in a traffic conflict, they perform sudden evasive actions as a collision-avoidance mechanism. There is an increasing evidence in the literature that time-proximity conflict indicators may lack important aspects related to road-users evasive actions that can hinder their ability to evaluate the true conflict severity in less organized traffic environments.
In this thesis, a detailed analysis of road user behavior in traffic conflicts in a less organized traffic environment is studied. The road users interactions investigated are the most vulnerable on the road (pedestrians, cyclists, and motorcyclists). The methodology is applied to a highly congested intersection in Shanghai, China where road-users behavior is different from where time proximity conflict measures were initially validated and often used in the literature. The investigation helped in identifying a set of evasive action-based measures in an automated traffic conflict platform. The newly developed indicators are tested, validated, and compared to time proximity indicators in different traffic environments.

8.1 Summary and Conclusions

Existing time proximity measures were first tested in measuring the severity of traffic conflicts in a less organized traffic environment. Traffic conflicts were collected using an automated video-based traffic conflict extraction technique. The identification of pedestrian, bicycle, and motorcycle conflicts collected using time proximity measures resulted in a very high frequency of conflicts. The severity distribution of these conflicts did not show consistent patterns with frequency. Additionally, time proximity measures did not reflect the true severity of road-users interactions in the studied location. The road-users behavior in this environment was a significant contributor to the inadequacy of time proximity measures. Road users usually keep in close proximity to each other and make pronounced evasive actions to avoid collisions. Therefore, time proximity measures might not be the best measure to capture the true severity of traffic conflicts in this environment. The study of road-users behavior in traffic conflicts was conducted to understand the mechanism by which road users exert evasive actions. Accordingly, the extracted trajectories were used to calculate new indicators that reflect the evasive action behavior of road users and better reflect conflicts severity in less organized traffic environments. The developed
indicators were validated using a conflict data-set which was reviewed and ranked by traffic safety experts.

Pedestrian-evasive actions are mainly reflected in the walking gait parameters (i.e., step frequency). Several evasive action-based indicators were investigated for measuring the severity of pedestrian conflicts that represent changes in the spatiotemporal gait profile. The maximum slope-of-step frequency (MSSF) showed a high correlation with safety expert severity evaluations and showed a high ability to differentiate between the severities of different pedestrian conflicts.

Two-wheelers evasive actions are mainly revealed in the sudden steering, braking, or speeding actions. Several evasive action-based indicators were tested that represent changes in the acceleration, jerk, and yaw rate profiles of motorcycles and bicycles. Motorcycle-evasive actions were clearly shown to involve powerful braking and sudden swerving. Powerful braking or speeding shows a positive/negative peak value in the jerk profile. Therefore, evasive action is reflected in the peak-to-peak jerk value. Sudden swerving investigated in the yaw rate profile showed a sudden change in a short time. Therefore, the evasive action was reflected in the peak-to-peak yaw rate ratio. These two indicators showed the highest potential to reflect motorcycles conflict severity. On the other hand, bicycle-evasive action showed a similar behavior, although the evasive action was reflected in the swerving behavior only. Therefore, the peak-to-peak ratio of the yaw rate showed the highest efficiency to reflect bicycle conflict severity.

The automated detection of traffic conflicts with evasive actions has been demonstrated using a novel approach that avoids many drawbacks of the predetermined threshold approach used in time proximity evaluations. Permutation Entropy (PE) was introduced as a robust measure to identify pedestrian-evasive actions during interactions. The method was applied to pedestrian conflicts as
a case study to detect traffic conflicts with evasive actions. Sudden changes in the walking pattern of a pedestrian lead to changes in the PE profile. The PE drop can identify the time of occurrence of pedestrian-evasive actions. Therefore, PE can detect pedestrian conflicts that have sudden evasive actions better than TTC and PET. This measure is used as a complementary approach to automatically detect pedestrian conflicts with evasive actions.

The applicability of the proposed evasive action measures was tested in different traffic environments. A comparison of MSSF and TTC in pedestrian conflicts was done for intersections in cities with different traffic environments (Shanghai, New Delhi, New York, Doha, and Vancouver). Additionally, ordered response models were developed to test the efficiency of using the combination of these indicators. Random intercept models were also tested to consider the heterogeneity in expert evaluations. The time proximity indicator (TTC) has shown high relevance in describing conflict severity in the Vancouver location, while it had little relevance for the locations in New Delhi and Shanghai. The evasive action-based indicator (MSSF) has the most relevance for measuring pedestrian conflict severity for the location in New Delhi and Shanghai, yet no relevance in the Vancouver location because pedestrians in these environments keep small proximities to each other and make sudden evasive actions to avoid collisions. The behavior in Shanghai and New Delhi was much less likely to be observed in organized traffic environments such as Vancouver, where drivers were more likely to yield/stop for pedestrian movements on the road. Results show that both indicators, TTC and MSSF, can be relevant for measuring conflict severity in the New York and Doha locations, and the relationship is stronger when both are combined. However, the TTC had a higher in significance in both locations.
Overall, the findings confirm that the effectiveness of traditional time proximity measures varies with different environments. The intricacies which characterize the different aspects of traffic conflict severity represent a challenge towards adopting a universal indicator to quantify conflict severity in all traffic environments. The thesis presented objective measures for incorporating road-users evasive action behavior in the evaluation of traffic conflicts in less organized traffic environments. The applicability of these measures was shown in different traffic environments. Moreover, the research emphasizes the need to select different conflict measures, depending on the studied traffic environment.

8.2 Study Limitations

As with any research, the work described in this thesis has a number of limitations. The first is that the study was conducted at a limited number of locations. The datasets available for this study included five locations from different cities around the world. It is essential to test the applicability of the developed indicators using larger data-sets from different traffic environments. This will confirm the transferability of the results reported in this thesis to other traffic environments. Evaluating more locations can enable the definition of a solid criterion upon which the degree of organization of the traffic environments varies in terms of conflicts severity. The conditions used in the thesis to describe the degree of organization of traffic environments is dependent on the collected road user violations, interactions, and non-compliance with traffic regulations in the studied environment. However, it is still important to provide an objective method to define the differences in traffic environments upon which traffic conflicts severity measures vary.

The second limitation is that the study focused only on traffic conflicts involving vulnerable road users (pedestrians, cyclists, and motorcycles). Since traffic conflicts involve a pair of road-users,
it is important to investigate the behavior of vehicle drivers, including their evasive actions. This analysis can improve the understanding of the mechanism by which evasive actions are undertaken in conflicts. Also, it can improve the models developed in this thesis if driver evasive-action are considered. In the literature, some researchers have acknowledged that jerking can be useful in addressing traffic conflicts not detected by time-proximity conflict indicators (Zaki, et al., 2014) (Bagdadi & Várhelyi, 2011). However, it is important to investigate the explicit behavior of drivers in the quest to better reflect conflict severity in less organized traffic environments.

The third limitation is that the methodology described in this thesis depends on the quality of the tracking of road users in traffic video data. The algorithms used in the computer vision system depend on a feature-tracking method. The method outperforms many other tracking methodologies in terms of the quality of the output tracks from videos. However, the improvement of the quality of road-users trajectories is a fast developing field. Applying the latest computer vision algorithms can potentially improve the quality of road-users trajectories which can lead to better conflict detection and calculation of both time-proximity and behavior-based conflict indicators.

8.3 Future Work

The findings in the thesis stimulate several future research directions. One interesting direction is the study of the evasive action behavior of road users in actual collision data. Such research can be valuable in identifying the characteristics of evasive actions in conflicts and actual collisions in less organized traffic environments. However, it can be challenging to capture videos of collisions, given the scarcity of traffic collisions. The availability of such data can enable the evaluation and cross-validation of evasive action-based indicators as in El-Basyouny & Sayed (2013) and Sacchi et al. (2013). In these research, conflict-based studies were shown to give similar results as
collision-based studies at the same locations using time proximity measures. The investigation of collisions in less organized traffic environments can also enable the investigation of the explicit relationship between collisions and conflicts using evasive action indicators.

Another direction that can be inspired by this research is to investigate the factors affecting the evasive action of road users. Many unknown factors could contribute to different evasive action behavior if road users were subjected to the same conflict situation since the evasive action is a behavioral element that can vary among different road users. Therefore, it is important to investigate not only the factors upon which the evasive actions may vary, i.e. age, gender, experience, etc., but to seek the degree of variation of the executed evasive actions in similar traffic events. The study of these factors can potentially enable better evaluation of road-users evasive actions in traffic conflicts.

One important future direction that can benefit from the presented research is the use of the understanding of road-users evasive actions in connected vehicles technologies. In the future, vehicle technologies are expected to be connected via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. In these new technologies, data of road users navigating the vehicle surrounding will be available through real-time trajectories along with the other various traffic and infrastructure parameters. Accordingly, traffic conflicts evaluations are constantly conducted in real time to avoid any possible collisions. The incorporation of road-users evasive actions in these automated techniques can potentially improve the ability of these systems to react to real-time traffic conflict evaluations.
Bibliography


Berthelot, A., Tamke, A., Dang, T. & Breuel, G., 2012. A novel approach for the probabilistic computation of Time-To-Collision. s.l., Intelligent Vehicles Symposium (IV), IEEE.


Hupfer, C., 1997. *Deceleration to Safety Time (DST) - a Useful Figure to Evaluate Traffic Safety*. Lund, Sweden, Department of Traffic Planning and Engineering, Lund University.


Laureshyn, A., 2010. *Application of automated video analysis to road user behaviour*. Lund, Sweden: Traffic and Road, Department of Technology and Society, Faculty of Engineering, Lund University.


