APPLICATION OF COMPUTER VISION TECHNIQUES IN SAFETY DIAGNOSIS
AND EVALUATION OF SAFETY TREATMENTS

by

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Abstract

Traditional road safety analysis is usually conducted using historical collision records. This reactive approach to road safety has been shown to have several shortcomings. Recently, there has been significant interest in using surrogate measures such as traffic conflicts to analyze safety. This interest has been strengthened by the availability of tools to automate the traffic conflict analysis from video data. Using automated computer vision techniques, road users can be tracked, classified, and their interactions determined accurately and reliably. This thesis demonstrates two applications of automated road safety analysis techniques using traffic conflicts.

The first application is related to the diagnosis of road safety issues. A case study of safety at a school zone in Edmonton, Alberta is used. 240 video-hours of traffic data were recorded in two different seasons. The data was analyzed to evaluate the current safety performance of the school zone to identify factors that may be contributing to safety concerns and to propose potential safety improvements. The analysis included the automated analysis of traffic conflicts, violations, and traffic speed. Several recommendations were presented that would potentially improve the safety for all road users without affecting the mobility along the intersections.

The second application included an evaluation of the safety effectiveness of improving the signal head visibility at two signalized intersections located in the City of Edmonton, Alberta, by conducting an automated before-and-after safety analysis using traffic conflicts. The use of automated conflict analysis in before/after safety evaluation can significantly reduce the time needed to reach conclusions about the effectiveness of safety countermeasures. More than 300 video-hours of traffic data were recorded at the two treated intersections before and after applying the treatment. In addition, traffic data was collected at two other intersections with similar characteristics to be used as comparison sites. A before/after road safety evaluation was performed using the Empirical Bayes method that accounts for the effects of the regression to the mean confounding factor. The methodology employs the use of a calibrated conflict-based safety performance function (SPF). The results showed a statistically-significant reduction (24.5%) in the average hourly conflict due to the improved signal heads.
Preface

Part of the analysis conducted in Section 5.4 by Sacchi and Sayed, 2015. "Conflict-Based Safety Performance Functions to Predict Traffic Collisions by Type." [In Transportation Research Board 95th Annual Meeting, no. 16-1605. 2016].

Part of the analysis in Chapter 4 is based on work conducted in the transportation group at UBC with the help of Dr. Mohamed Zaki. I was responsible for conducting most of the analysis and writing most of the text.

Part of the analysis in Chapter 5 is based on work conducted in the transportation group at UBC with the help of Dr. Emanuele Sacchi. I was responsible for conducting most of the analysis and writing most of the text.
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<td>AHC</td>
<td>Average Hourly Conflict</td>
</tr>
<tr>
<td>ATSC</td>
<td>Adaptive Traffic Signal Control</td>
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<tr>
<td>BA</td>
<td>Before and After</td>
</tr>
<tr>
<td>CF</td>
<td>Calibration Factor</td>
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<tr>
<td>CV</td>
<td>Computer Vision</td>
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<tr>
<td>DST</td>
<td>Deceleration-to-Safety Time</td>
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<tr>
<td>EB</td>
<td>Empirical Bayes</td>
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<tr>
<td>FHWA</td>
<td>Federal Highways Administration</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
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<tr>
<td>GLM</td>
<td>Generalized Linear Modelling</td>
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<tr>
<td>HTV</td>
<td>Hourly Traffic Volume</td>
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<tr>
<td>LCSS</td>
<td>Longest Common Sub Sequence</td>
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<tr>
<td>MUTCD</td>
<td>Manual on Uniform Traffic Control Devices</td>
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<tr>
<td>NB</td>
<td>Negative Binomial</td>
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<tr>
<td>NW</td>
<td>North West</td>
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<tr>
<td>OR</td>
<td>Odds Ratio</td>
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<tr>
<td>PDO</td>
<td>Property Damage Only</td>
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<tr>
<td>PET</td>
<td>Post-Encroachment Time</td>
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<tr>
<td>RTM</td>
<td>Regression to the Mean</td>
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<tr>
<td>SE</td>
<td>Standard Error</td>
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<tr>
<td>SMD</td>
<td>Speed Monitoring Displays</td>
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<tr>
<td>SPF</td>
<td>Safety Performance Functions</td>
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<tr>
<td>SRTS</td>
<td>Safe Routes to Schools</td>
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<tr>
<td>TCT</td>
<td>Traffic Conflict Technique</td>
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<tr>
<td>TE</td>
<td>Treatment Effect</td>
</tr>
<tr>
<td>TTA</td>
<td>Time to Accident</td>
</tr>
<tr>
<td>TTC</td>
<td>Time to Collision</td>
</tr>
<tr>
<td>UBC</td>
<td>University of British Columbia</td>
</tr>
<tr>
<td>WHO</td>
<td>World Health Organization</td>
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<tr>
<td>ZOSS</td>
<td>Time-Dependent Speed Control Zone</td>
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Dedication

To My Parents
Chapter 1: Introduction

This chapter consists of five sections, the first section describes some challenges associated with road safety analysis using collision data. The second section discusses the traffic conflict technique in safety analysis. The third section introduces the use of computer vision techniques in traffic safety analysis (identification, diagnosis, remedy, and before/after evaluation). The fourth section describes the research objectives, and the last section briefly describes the thesis structure.

1.1 Challenges

Road collisions are considered a global epidemic that causes 1.3 million fatalities worldwide every year. According to the World Health Organization (WHO), road traffic incidents caused approximately 1.25 million deaths worldwide in the year 2010. The World Health Organization (WHO) predicts that by 2030, traffic incidents will be the fifth leading cause of death worldwide. Given this magnitude, road authorities and safety advocacy groups around the world are working hard to improve road safety in an effort to reduce the economic and societal costs associated with traffic collisions.

Almost half of traffic deaths occur among vulnerable road users, pedestrians, and cyclists; 23% of traffic fatalities are motorcyclists, 22% pedestrians, and 5% cyclists. The rate of deaths due to road collisions is significantly higher in developing countries compared to the developed world, as only 7% of the world’s population have laws that could handle all the five main risk sources (wearing helmets, speeding, drinking and driving, seat belts, and child suppression). Therefore, there is an increasing need for efficient traffic safety analysis techniques. Safety diagnosis analysis is an important part of safety evaluations to evaluate the existing safety performance of road locations to identify factors that may contribute to safety
concerns and to propose potential safety improvements. Traffic safety analysis can also include conducting before-and-after safety evaluation to investigate the effectiveness of countermeasures applied to improve traffic safety of road locations.

Conventionally, traffic safety analysis has always been undertaken using historical collision records. This is a reactive approach that has many shortcomings (Sayed and Zein, 1999). First, there are quality and quantity problems associated with collision data. In almost all road jurisdictions, the quality and availability of collision data has been degrading. Second, reliance on collision data requires long observation periods, as collisions are rare events. Finally, reliance on collision data does not offer a good understanding of collision-contributing factors and how safety measures work. For these reasons, many researchers have advocated the use of surrogate measures, such as traffic conflicts, to evaluate safety from a broader perspective than collision data alone (Sayed et al., 1994, Ismail et al., 2011).

1.2 Traffic Conflict Technique

Because of the shortcomings associated with using collision records in safety analysis, there has been a growing interest in using traffic conflicts in safety analysis. The Traffic Conflict Technique (TCT) involves observing, recording, and evaluating the frequency and severity of traffic conflicts at a specific location by a team of trained observers. The technique, therefore, provides a means for the safety analysts to immediately observe and evaluate unsafe driving maneuvers at road locations and to investigate the relationship between such maneuvers and the road characteristics (Sayed and Zein, 1999).

The technique was also shown to be useful in conducting various safety analysis applications. However, incomplete conceptualizations and the cost of training observers who collect conflict data are factors inhibiting extensive application of this technique (Sayed et al.,
1994). Therefore, successful automation of extracting conflicts can have considerable benefits for traffic safety studies.

1.3 Computer Vision Techniques for Traffic Safety Analysis

Recently, with the growing interest in road safety, some advances have been made in road safety analysis and engineering. These advances included the development of improved techniques to identify and diagnose accident-prone locations, improved methodology to conduct effective road safety reviews and audits, and the introduction of sophisticated evaluation tools such as simulation models and expert systems aimed at the evaluation of road safety.

All these developments are creating a movement towards the explicit consideration of safety issues in road planning and design (de Leur and Sayed, 2003). However, associated with these advances are a series of obstacles that are inhibiting or complicating the future direction of road safety. First, the traditional supply of analytical road safety tools, such as statistical associations and reliance on aggregate historical collision data, is becoming depleted in the quest to better understand, predict, and improve road safety. Second, current field-based methods for collecting traffic conflicts data are labor-intensive, suffering from reliability issues, time consuming, and costly. Given the aforementioned issues, there is a significant need to explore and develop methods to enhance and automate the safety diagnosis.

Video sensors have become popular for recording different events for offline analysis, solving many of the above-mentioned issues. Vision-based analysis uses video footage captured at the location of interest as the main data source. Video data provides a permanent, verifiable account of road-user behavior which can improve the safety diagnosis process. A challenging task is how to interpret the traffic scene. In particular, the recognition of the road-user types is
necessary to learn traffic scenarios and understand behavior patterns within each road-user class (Saunier and Sayed, 2007)

Computer vision (CV) can provide an automated-based interpretation of the video scenes. Video data can be supported with practical computer vision applications to aid in the analysis of traffic scenes. CV techniques are not new to the transportation field. CV-based safety analysis lends itself to diagnostic studies both for ease of data collection and efficient analysis. The development of computer vision techniques for the purpose of automated detection and tracking of road users has been the subject of extensive work. Several studies noted the benefits of the video monitoring of collision events in providing insight into the factors contributing to collisions. In general, the application of computer vision technology aims at creating a bottom-up understanding of the scene; starting from microscopic road-user positions and ending with qualitative or aggregate-level quantitative inferences. Computer vision applications are typically composed of two layers:

- A video processing module for road user detection, tracking, and classification.
- Interpretation modules for traffic-related issues such as conflicts, violations, and data collection.

1.4 Research Objectives

There is past and ongoing research in the Transportation Engineering Group at the Civil Engineering Department of UBC that aims at developing an automated road safety analysis system based on video sensors (Saunier, Nicolas, and Sayed, 2007; Saunier et al, 2007). This video analysis system uses existing state-of-the-art computer vision algorithms. The current system developed at UBC was tested and applied successfully for automated safety diagnosis in many countries. Despite the potential benefits of automated traffic safety analysis based on video
sensors, limited computer vision research has been directly applied to road safety and even less so to the detection of traffic conflicts.

This thesis uses recent CV developments for safety evaluation and data collection at different locations. The analysis relies on automated conflict analysis encompassing various road users, generally vehicles and pedestrians. Traffic data collection, conflict analysis, and violation detection methods are applied to the collected video data. This study can be added to a group of recent studies that have utilized automated safety analysis and data collection (Sayed et al., 2012; Autey et al., 2012; Saunier, Sayed, and Ismail, 2010; Sayed, Zaki, and Autey 2013; Zaki et al., 2012). This shows that the technology is reaching a maturity level adequate to be deployed and utilized by practitioners.

The main objective of this thesis is to demonstrate two applications of automated video-based computer vision techniques in road safety diagnosis and analysis, as well as in before-and-after road safety evaluation to estimate the effectiveness of certain countermeasures applied to improve traffic safety. Two different case studies from the city of Edmonton, Alberta, Canada were presented and analyzed. Improving road safety and the development of sustainable transportation initiatives have been identified by the City of Edmonton as top priorities.

The first case study is to apply an automated traffic safety diagnosis and to demonstrate automated data collection techniques in the vicinity of the Dr. Donald Massey School. Concerns about the traffic and safety hazards were increasingly reported during the “drop off” and “pick up” times. Safety concerns were related to driving violations, illegal parking, as well as jaywalking. Concerns were also related to potential pedestrian-vehicle and vehicle-vehicle conflicts at the two main intersections in the school area, especially at the morning and afternoon peak hours. More than 120 hours of video data were collected in the fall season as well as 120
hours in the wintertime to investigate the effect of some severe winter conditions on vehicles’ and pedestrian’s behavior and interactions.

The second case study is to apply automated video-based computer vision techniques to investigate the safety effectiveness of improving the signal head visibility at two signalized intersections by conducting a before-and-after safety evaluation. As part of efforts made to systematically improve the safety performance at signalized intersections, the city of Edmonton, led by the Office of Traffic Safety, installed retroreflective tapes around the borders of traffic signal backplates on a number of signalized intersection approaches. A signal head equipped with a backplate and retroreflective border is expected to be more visible and conspicuous in both the nighttime and daytime conditions. The objective of the case study is to confirm whether traffic signal head improvements have, overall, decreased the number of conflicts at both intersections analyzed.

In summary, the main objectives of this thesis can be summarized as follows:

1. To demonstrate the ability of computer video-based analysis techniques in tracking vehicles and pedestrians, estimating different types of traffic conflicts, detecting violations performed by different road users, and evaluating road safety at different locations.

2. To present a practical case study of road safety diagnosis in school zones using a considerable amount of video data collected in different seasons and automatically analyzed using computer vision techniques.

3. To present the use of the TCT based on automated conflict analysis in school zones to diagnose safety, analyze conflict occurrence, and identify the most suitable countermeasures that could potentially improve the road safety.
4. To present a practical case study of a before-and-after road safety evaluation conducted to verify the effectiveness of a safety countermeasure (i.e. improving the visibility of signal heads) using computer vision and traffic conflict technique.

5. To model traffic conflict data, in a similar manner to collision data, by adopting and transferring the statistical methodologies used in collision analysis to conflict-based analysis.

1.5 Thesis Structure

This thesis is comprised of six chapters. Chapter one provides an introduction to the thesis by discussing the challenges to current traffic safety analysis techniques, the use of automated traffic conflict analysis, and the main objectives of the thesis. Chapter two provides a detailed literature review of the topics covered in this thesis. Chapter three provides details of the automated video-based road safety analysis process. Chapter four presents the first case study: a safety diagnosis of the school zone of the Dr. Donald Massey Elementary-Junior School in the city of Edmonton. Chapter five presents the second case study: an automated before-and-after safety evaluation of traffic signal visibility improvements in the city of Edmonton. Chapter six contains the research summary, conclusion, discussions, and potential future research.
Chapter 2: Literature Review

This chapter presents an overview of previous work related to the research topics presented in this thesis. The main objective of this chapter is to provide the current state-of-the-art computer vision algorithms for the thesis topics.

2.1 Traditional Techniques of Road Safety Analysis

The conventional approach to safety analysis relies mainly on collision data. Given that collisions are generally rare events, in order to draw statistically-stable conclusions, collisions are typically observed for long periods (1 to 3 years). Despite the extensive development of collision-based safety analysis, the reliance on collision data for safety analysis has several shortcomings (Saunier, 2007a; Saunier, 2007b; Sayed, 1999; Ismail, 2010; Songchitraksa, 2006). These shortcomings can be summarized as follows:

- **Attribution**: The information obtained by police reports and interviews often does not allow the attribution of road collisions to a single cause. It is sometimes difficult to pinpoint the failure mechanism that lead to a road collision.

- **Data Volume**: Despite the enormous social burden of road collisions, the frequency of road collision data is especially low. Drawing statistically stable and significant inferences from such data is not easy.

- **Data Quality**: Collision records are often incomplete and lack details. The quality of road collision reporting has been deteriorating in many jurisdictions. Reporting is also biased toward highly damaging collisions, while non-injurious collisions can go unreported.

- **Ethical Concerns**: While the object of road safety analysis is the reduction of road collisions, the analysis is typically based on the road collision as the main
data unit. That is, collisions have to occur and be recorded over an adequately long period in order to conduct safety diagnosis.

2.2 The Traffic Conflict Technique

The traffic conflict technique was introduced as an alternative or complementary approach to traffic collisions to overcome drawbacks of relying solely on collision data. The traffic conflict techniques are based on the analysis of the frequency and severity of traffic conflicts at a road segment or an intersection (Ismail, 2010). A traffic conflict is defined as “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 remained unchanged” (Amundsen and Hydén, 1977). Traffic conflicts are more frequent than road collisions and are of marginal social cost. Traffic conflicts provide insight into the failure mechanism that leads to road collisions. BA studies based on traffic conflicts can be conducted over shorter periods.

The relationship between conflicts and collisions was investigated for both signalized and unsignalized intersections (Sayed et al., 1999). The results showed that there is a strong relationship between collisions and average hourly conflicts for signalized intersections, while unsignalized intersection models showed a very weak relationship between conflicts and collisions. Sacchi and Sayed (2013) compared the results of a collision-based evaluation of a right-turn treatment to the results of a similar evaluation using automated traffic conflict techniques. The similarities overall and the location specific reductions in conflicts and collisions was remarkable, which provides strong support for using traffic conflicts in BA studies.

2.2.1 Traffic Conflict Hierarchy

A theoretical framework used in this study ranks all traffic interactions by their severity in a hierarchy, with collisions at the top, undisturbed passages at the bottom, and traffic conflicts
the middle. For this concept to be operational, the safety hierarchy is transferred into measurable parameters based on certain assumptions Figure 2.1. For each traffic event in the hierarchy, an associated severity can be estimated, thus representing its location in the hierarchy. An example of a mapping from road users’ positions to a severity measure is the use of conflict indicators.

![Safety Pyramid](image)

**Figure 2.1 The safety pyramid (Source: Hydén, 1987)**

### 2.2.2 Traffic Conflict Indicators

The main elements that constitute the severity are the distance in space and time between the drivers involved and their evasive action(s). Various conflict indicators have been developed to measure the severity of an interaction by quantifying the spatial and temporal proximity of two or more road users. A comprehensive summary of the different indicators is provided in the following studies (Brown, 1994; Tarko et al., 2009). Many severity indicators have been developed, such as the time-to-collision (TTC) (Hayward, 1968), which is defined as two road users on a collision course as the extrapolated time for the collision to occur. Traffic conflict indicators were discussed in many studies (Autey et al., 2012; Ismail, 2009; Essa, 2015).

#### 2.2.2.1 Time-to-Collision

The time-to-collision (TTC), or some modified versions based on the same concept of (TTC), is the most widely used traffic conflict indicator. Collision courses are expected to occur between
road users using a method of predicting their future positions. The time expected until a hypothesized collision will occur is estimated using simple kinematics. There are many methods used for extrapolating the future positions of road users, which vary with different implementations of TTC.

This primary TTC indicator was originally suggested by Hayward (1972) who defined it as “the time required for two vehicles to collide if they continue at their present speeds and on the same path” (Hayward, 1972). Another definition was introduced later by Amundsen and Hydén (1977) as “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 remained unchanged”.

Some previous studies tried to use modified versions of TTC. A different definition was proposed (Svensson, 1998), defining TTC as a value calculated for each pair of conflicting road users at the moment one of the two road users initiates evasive action, which is referred to time-to-accident (TTA). This method assumes the two road users continue at the same speed. The Swedish TCT developed at the Lund Institute of Technology derives a measure of severity by dividing the TTA by the closing speed which is the instantaneous velocity of the vehicle taking evasive action at the time this action is commenced (Svensson, 1998; Autey et al., 2012).

A probabilistic approach has been used in several previous studies to estimate TTC in order to define expected future trajectories of pairs of conflicting road users (Autey et al., 2012; Essa, 2015; Saunier and Sayed, 2008). In the probabilistic approach, a technique based on common motion patterns is used to predict a road user’s expected future position. An instantaneous speed of a road user is used to extrapolate its position along the assigned motion trajectory (Autey, 2012).
A minimum TTC threshold was established by many previous studies (Brown, 1994; Hayward, 1972; van der Horst and Brown, 1989; van der Horst and Hogema, 1993) to be used in estimating the number of critical conflicts in field studies, to identify a conflict, and also to distinguish between near-misses and undisturbed passages. Van der Horst (1990) found that the value that can be used to distinguish between normal and severe events is 1.5 seconds. This value was investigated as a result of an experiment involving the application of a driver simulator to a closed course road (van der Horst, 1990; van der Horst and Hogema, 1993).

There are two main issues that limit the use of TTC as an accurate measure of safety levels. The first issue is that many combinations of speed and distance of road users may result in the same TTC measure, while these combinations may be of different severities. Second, measurements of TTC require accurate details of vehicle trajectories to be presented in time and space, which is difficult to accomplish. Some techniques, such as computer vision video analysis, can solve the second problem (Saunier, 2007).

2.2.2.2 Post-encroachment Time

Another commonly-used conflict indicator is the post-encroachment time (PET). PET is defined as a time difference between two road users occupying the same area of potential collision. PET is less complex than TTC as it does not require a future projection of a road user’s position or speed. Its value can be estimated discretely and directly through the observation of vehicle trajectories (Autey, 2012).

An essential drawback of PET measurement is that it is difficult to confirm the willingness of the driver to accept the risk (Chin and Quek, 1997); it also does not require speed and distance measurements, which makes it difficult to investigate the severity of the event (Archer, 2004). PET also poses another shortcoming, where vehicles follow common courses as
in rear-end and merging conflicts (Archer, 2004), that makes it difficult to judge the situation as a collision possibility, even if the PET was calculated, because PET can be calculated if the following vehicle has a lower or equal speed to the lead vehicle, while no conflict exists (Autey et al., 2012).

### 2.2.2.3 Gap Time

Gap time (GT) is another conflict indicator defined as the difference between the time one road user on the main traffic stream reaches the conflict zone and the time required for the yielding road user to clear the conflict area. The arrival time of the main traffic stream road user calculated using distance and speed relative to the instant at which the other road user starts the maneuver. This can also be identified as the expected PET should road-users’ trajectories and velocities remain constant (Cunto, 2008; Autey et al., 2012).

### 2.2.2.4 Deceleration-to-safety Time

Deceleration-to-safety time (DST) was proposed by Hupfer (1997), who defines it as the deceleration required for a road-user to attain a non-negative gap time in relation to another road user. In other words, it is the deceleration that one vehicle must undertake to arrive immediately following the other road user for a pair of road users with a calculable gap time, (Autey, 2012). The previously-mentioned indicator has several applications. The primary application of this indicator is the vehicle-pedestrian conflicts where a vehicle must decelerate to avoid colliding with a pedestrian (Cafiso et al., 2010; Essa, 2015).

### 2.2.3 Challenges to Traffic Conflict Technique

Several shortcomings of the traffic conflict technique have been investigated by many studies, despite the obvious benefits of this technique. Basically, most of the problems associated with the TCT stem from three essential issues listed in the following subsections (Chin, 1997).
2.2.3.1 Consistency in Conflict Definition

Conflicts are usually defined as evasive actions taken by drivers, but not all these evasive actions are considered as a conflict or an action to avoid collision, but can be part of a normal driver’s behavior. Regarding conflicts as evasive actions have resulted in several ways of defining and interpreting the conflict event, which could lead to errors in conflict registration (Chin, 1997; Perkins, 1967).

2.2.3.2 Validity of TCT

Validity of the TCT is often defined as the ability of traffic conflicts to predict collisions; in other words, there should be a statistically-significant correlation between conflicts and collisions (Chin, 1997). Part of this issue is due to the inaccuracy and unreliable accident reports. Several studies investigated the correlation between conflicts and collisions (Sayed, 1999) and a significant correlation was found especially for signalized intersections. While others were skeptical to this new approach (Williams, 1981).

2.2.3.3 Reliability in Conflict Measurements

The reliability of conflict measurements depends mainly on the method of conflict measurement. Subjective measurement of conflicts may lead to the possibility of unreliable results. There are two types of uncertainties: the first one arises from inconsistency in recording conflict made by an observer, while the second type is due to the variability in interpretation of a certain event between different observers (Chin, 1997). Also, other human factors such as fatigue, lack of training, and lack of experience may affect conflict observation accuracy and lead to misleading results (Chin, 1997).
2.3 Automated Video-based Road Safety and Data Collection Techniques

Recently, video-based automated computer vision techniques were shown to be useful for automated traffic conflict detection and in conducting various safety analysis applications such as before-and-after safety evaluations and studying road-user behavior (Autey et al., 2012; Sayed et al., 2012; Sayed et al., 2013). The video-based computer vision approach can have many advantages. First, automated video-based analysis overcomes the shortcomings associated with the manual collection of conflict data in terms of the cost and data reliability. Second, automated analysis of field conflicts depends on tracking road-user trajectories and, therefore, can have more accuracy in terms of determining conflict severity (e.g. TTC) and conflict location. Third, video cameras have the ability of collecting rich and detailed traffic data. Fourth, the installation of video cameras is easier than the installation of the other sensors such as the magnetic loop detectors, which requires the road surface to be excavated (Saunier and Sayed, 2006).

2.3.1 Road-users Data Collection

One of the main challenges in conducting detailed analysis on road-user behavior is the lack of reliable data. This can have a significant impact on several transportation engineering and planning aspects. Two important areas of road-users data collection are volume counts and average speed measurement. Data collection is important, as it provides the necessary exposure measures and conveys essential information of the traffic patterns along the road segments of interest. For example, pedestrian crossing speed at signalized intersections is an important engineering design parameter as it determines the time required for safe pedestrian crossing at the intersection. Collecting reliable data is often labor-intensive and time consuming, as it is usually collected by manual counts or measurements.
Data collection methods for counting or measuring road-users’ speeds can be categorized into manual field observations, manual video observations, and automatic techniques. The manual methods currently used in practice for the collection of pedestrian data lack the ability to capture microscopic changes in position and speed (Shi et al., 2007). Automated video analysis is becoming more popular as it overcomes the shortcomings present in manual methods that are widely used. For automatic tracking of pedestrians, moving road users must be detected and tracked frame-by-frame and classified into pedestrians and non-pedestrians (Ismail et al., 2009). Common problems in this challenging task include global illumination variations, shadow handling, and multiple objects tracking (Forsyth et al., 2005).

The initial costs associated with automated data collection are likely higher than manual techniques due to initial equipment, implementation, and preparation costs. However, the labor costs and effort associated with data collection using automatic methods is much lower, especially when large sample sizes are desired. Many methods, such as infrared laser counters, have been used for that purpose (Schneider et al., 2005; NBPD, 2009).

2.3.2 Automated Road Safety Analysis at UBC

Research has been conducted for more than seven years now at the University of British Columbia to develop a system for automated road safety analysis using video sensors. The system can be used in two ways, either as a straight safety evaluation tool, of which results are validated and ready for use by safety practitioners, or as a complete exploratory tool assisting the user to identify relevant events in large amounts of video data and study them along various dimensions, in particular spatial and temporal.

The current system can detect and track road users in complex traffic environments such as urban intersections. It has also been shown that it can detect and measure the severity of traffic
conflicts. A new probabilistic framework has been presented to analyze road users' interactions by computing their probability of collision at each instant and was demonstrated on real data using the same system (Saunier and Sayed, 2008).

This video analysis system is based on existing state-of-the-art computer vision algorithms and has incorporated some adaptations for the study of other road users (pedestrian and cyclists). Despite the potential benefits of automated traffic safety analysis based on video sensors, limited computer vision research has been directly applied to road safety, and even less so to the detection of traffic conflicts. Maurin et al. (2005) stated that “despite significant advances in traffic sensors and algorithms, modern monitoring systems cannot effectively handle busy intersections”. Such a system requires a high-level understanding of the scene and is traditionally composed of two levels of modules:

1) A video processing module for road-user detection and tracking, and

2) Interpretation modules for traffic conflict detection

2.3.3 Tracking of Road Users

For road safety applications, the UBC approach relies on the building of two databases: a trajectory database, where the results of the video processing module are stored, and an interaction database, where all interactions between road users within a given distance are considered, and for which various indicators, including collision probability and other severity indicators, can be automatically computed. Identifying traffic conflicts and measuring other traffic parameters can be achieved through mining these databases.

The road-user detection and tracking module relies on a feature-based tracking method (Saunier and Sayed, 2006). Feature-based tracking is preferred because it can handle partial occlusion. The tracking of features is done through the well-known Kanade-Lucas-Tomasi
feature tracker. Stationary features and features with unrealistic motion are filtered out and new features are generated to track objects entering the field of view. Since a moving object can have multiple features, the next step is to group the features, i.e., decide what set of features belongs to the same object by using cues like spatial proximity and common motion. A graph connecting features is constructed over time. A detailed description of the tracking algorithm is presented by Saunier and Sayed (2006). The tracking accuracy for motor vehicles has been measured between 90% and 94.4% on three different sets of sequences. This accuracy is considered reliable, especially under heavy traffic flow conditions, and should have little impact on the accuracy of the calculation of conflict indicators. This means that most trajectories are detected by the system and the calculated conflict indicators are considered reliable. There are four main types in the literature of road-users tracking: 1) 3D model-based tracking, 2) region-based tracking, 3) contour-based tracking, and 4) feature-based tracking (Saunier, 2006; Cavallaro, 2005).

2.3.3.1 3D Model-Based Tracking

The 3D model-based tracking identifies vehicles by matching a projected model to the image data and uses prior knowledge of traffic objects in a given scene. This helps in recovering trajectories and models with high accuracy for only a small number of vehicles and to solve the problem of occlusion. The most dramatic drawback is the reliance on detailed geometric object models; it is impractical to have all the detailed models of all vehicles in the studied location before using the algorithm (Cavallaro, 2005; Saunier and Sayed, 2006; Dahlkamp, 2006).

2.3.3.2 Region-Based Tracking

The idea of this type of tracking is to identify connected regions of the image (blobs) related to each vehicle. Regions are identified through background subtraction and then tracked over time using the information of the identified region (color, texture, shape, and size). This approach is
computationally practical and works very well in free-flow traffic environments, while it becomes very difficult to separate individual vehicles, as vehicles occlude one another, these vehicles are grouped together as one large blob in the background image (Saunier, 2006; Magee, 2004; Maurin et al., 2005).

### 2.3.3.3 Contour-Based Tracking

Contour-based tracking is very similar to the idea of the region-based tracking technique, the contour of any moving object is represented by a ‘snake’ and updated according to the movement of this object. These contour lines rely mainly on the boundaries of the moving road user, which is why it is efficient to track a pedestrian by selecting the contour lines of its head. In contour-based tracking, the description of objects is more accurate and efficient than in region-based tracking, in addition to lower computational complexity, however, the occlusion problem still exists (Autey et al., 2012; Saunier and Sayed, 2006).

### 2.3.3.4 Feature-Based Tracking

The idea of feature-based tracking relies mainly on tracking the distinguished features of a moving object instead of tracking the whole object. This algorithm overcomes the problem of partial occlusion because, in this condition, some of the features of the moving object remain visible. Feature-based tracking can track features efficiently in daylight, twilight, and nighttime, as well as under any traffic condition, because it chooses the most outstanding points of a moving object. Tracking features is done using two developed methods: Kalman filtering and the Kanade-Lucas-Tomasi feature tracker. After tracking the most salient points of an object, grouping these points becomes a second priority. In order to decide that some points belong to the same object, spatial proximity and common motion are the two mainly-used cues (Saunier and Sayed, 2006; Autey, 2012).
2.3.4 Road-users Conformity to Traffic Regulations

Traffic violations occur when road users seek an increased mobility by disregarding existing traffic laws and regulations. This behavior can come at the expense of accepting additional collision risk. The detection and the understanding of non-conforming behaviors (violations) can therefore be beneficial for a sound safety diagnosis as well as for developing safety countermeasures. This practical benefit of observing violations as surrogates to traffic conflicts and, consequently, road collisions, is especially realized when observational periods are limited. In situations where it is likely that road collisions are attributable to violation actions, traffic violations can provide a reliable and timely surrogate road safety measure. Several studies argue on conceptual and empirical grounds that traffic violations are valid indicators of road safety. Road-user behavior and decisions leading to violations can be contributing factors to the occurrence of a possible traffic conflict prompting a collision. Accordingly, traffic violations may be viewed as a set of traffic events which encompasses both traffic conflicts and collisions. Recent work has already conjectured that traffic violations can be placed in the same severity hierarchy, albeit at a lower level, along with traffic conflicts and collisions. Similar to other data collection procedures, detecting violations is expensive and can be subject to several of the inconsistencies mentioned earlier. It is advocated that the automated observation and analysis of road-user violations may help improve our understanding of pedestrian safety issues. Moreover, such automation can enable the processing of extended observational periods while consuming limited time and staff resources.

Automated traffic violations detection using computer vision was the subject of a number of researches in recent years. In this study (Lim and Choi, 2002), a system was developed to detect different classes of violations including red-light, speed, and lane violations. To detect
violations, the scene was divided into finite regions. A tracked road user is considered in violation if it moves between different regions and any transition between those regions is specified as violation. In another study (Vijverberg, 2007), a geometric-based classifier of road user was used to distinguish violations such as reserved bus lane violations. Such a method is limited to few types of violations and relies heavily on the accuracy of the classification. In (Zhang et al., 2009), lane crossing detection implementation is provided. The main drawback of this method is possibility of wrong lane identification against the background.

Pedestrian crossing behavior is important for the design of urban intersections and signalized crossings. For example, the results in this study (Karkee et al., 2009) suggested a relation between pedestrian-crossing conformance and traffic conflicts, e.g., non-conforming pedestrian is more likely to be trapped in the middle of the street. This leads to an increase in collision exposure. The main factors that affect pedestrian behavior at intersections were studied (Yanfeng et al., 2010). Several parameters, such as waiting time, crossing time, and arrival rate were suggested as key variables for describing pedestrian characteristics and improving crossing design and signal timing plan (Yanfeng et al., 2010). Malinovskiy et al. (2008) presented a computer-vision based approach for collecting pedestrian arrival rate and headway information. Road users, including pedestrians, are identified via background extraction and are subsequently tracked. A waiting zone is selected at the beginning of the analysis and is used for pedestrian tracking initialization as well as a starting point for recording the arrival rate as well as the headway. A pedestrian and vehicle violation adopted in this research is based on travel pattern recognition proposed earlier (Ismail et al., 2011; Sayed et al., 2013; Zaki et al., 2012).
2.4 School Zone Safety: An Overview

School zone safety is an important problem that concerned parents, safety engineers, and law enforcement agencies are facing with many issues about the safety of children on their way to and from school. These concerns are raised mainly because of the severe expected consequences of an incident that might happen to any child, especially if he/she is a pedestrian or a cyclist. Several studies have been conducted at different school environments to investigate the level of safety and to propose some countermeasures to make school zones safer.

2.4.1 Identification of Collision-Prone School Locations

Identification of collision-prone locations is an active area of research in traffic safety. Identifying collision-prone school zones based on crash data was demonstrated by Abdel-Aty et al. (2007) using five-year crash data in Orange County, Florida. In this study, collisions involving school children and the conditions associated with these collisions were defined. The study also investigated the effect of different characteristics of driver, pedestrian/bicyclist, traffic, vehicle, and the road geometry on crash occurrences using geo-spatial and log-linear analysis of the crashes. Warsh et al. (2009) analyzed factors related to the school location and motor vehicles that affect child pedestrian collisions using GIS to estimate the distance between the school and collision locations. The results show that the highest number of collisions that occurred in school zones are more likely to occur among 5-9 year old children.

A research done in Berkeley found that the total number of young pedestrian injuries would be higher in areas with higher youth population density, unemployment, fewer high-income families, and higher traffic flow. Data analysis was done by a geographical information system GIS (LaScala, 2003). In Baltimore, Maryland, a study was conducted to investigate the relationship between pedestrian–vehicular crashes and the physical and social attributes in the
vicinity of schools. Collision data analysis showed that the presence of a driveway or turning bay at the school entrance helps in both crash occurrence and injury severity reduction (Clifton, 2007).

The research presented by McDonalda (2015) assessed the risk and cost of different school travel modes by using collision and exposure data from North Carolina from 2005 to 2012. It was found that, on a per trip basis, school buses had an injury rate 20 times lower and a fatality rate 90 times lower than riding with a teen driver. Also, it was found that walking and cycling had a per-trip injury rate equal to that of school buses, but a fatality rate 15 times higher than school buses. An assessment of the risk associated with different travel modes for school commuting was performed in New Zealand. It was found that the highest injury risk per million trips is associated with cycling, followed by walking, then vehicle travel is the least source of risk. (Schofield, 2008). Early research on collision-prone locations near school zones was presented (Zegeer, 1980). The procedure using traffic conflicts was applied in school zones in the Rochester School District. A set of site improvements were selected based on each conflict type and the safety deficiencies associated with each site.

### 2.4.2 Effect of Countermeasures on Crash Reduction in School Zones

A study in Toronto (Roberts, 1995) investigated the influence of adult presence on the risk of pedestrian injury during school commuting. The results show that the company of an adult has the potential to significantly reduce child pedestrian injury rates. The effect of ten countermeasures commonly incorporated into school programs on the incidence of collisions involving child pedestrians and the behaviors known to result in these collisions were investigated. These countermeasures are divided into three categories; engineering (sidewalks, bicycle lanes, traffic calming measures, crosswalks, medians, and refuge islands), enforcement
active police enforcement, school zone flashers, and crossing guards), and education (child pedestrian education programs and motorist education programs). The results show that some of these changes have actual and significant safety benefits but the effect of others is unknown (Dumbaugh and Lawrence, 2007).

In this research (Sarkar et al., 2003), an image-based survey was performed to assess the capability of children in identifying safety hazards. The study concluded that older children have knowledge about the traffic better than that of younger ones and children who were driven to school perform worse than those who walked to and from school. Ragland et al. (2013) evaluated the safe routes to school program in California assessing the long-term impact of safety due to infrastructure improvements. The study was performed in a collision before-and-after framework, showing the effectiveness of the installed improvements. Another study done in New Zealand (Collins, 2001) evaluated the perceptive safety effect of the improvements in school zones by surveying children and their parents. To examine whether area-wide traffic calming caused reductions in child pedestrian injury rates or not, a study was done for two cities in the UK (Jones, 2005) to compare the total number of causalities before-and-after the installation of speed humps, road narrowing, and road closures. Results show that changes in injury rates are significantly inversely correlated with the number of features per km road length (density of traffic calming features).

To investigate the effectiveness of the Walk-Safe intervention program in the Miami-Dade County, sixteen elementary schools were chosen in a single high-risk district. All the selected schools implemented the school-based educational injury prevention (Walk-Safe) program to improve children’s behavior and pedestrian skills through training sessions. In addition, some engineering modifications were installed which included signage, school speed
zone flashers, and road striping. Traffic laws were also enforced among drivers traveling in and around school zones. All these interventions were found very effective in reducing the number of injuries (HOTZ, 2010). A study in New Zealand (Kingham, 2011) suggested that the overall traffic levels should be reduced in order to reduce the collisions related to school commuting instead of focusing only on safety improvements in the vicinity of the schools.

2.4.3 Effect of Countermeasures on Speed Reduction in School Zones

Hawkins et al. (2007) conducted a before-and-after study in Texas, USA to examine the effectiveness of rear-facing school beacons. Findings indicated that the speed was reduced after using these beacons by 10%. The effectiveness of speed-monitoring displays was examined by Lee et al. (2006) to assess the short and long-term effect on speed reduction in school zones, using both the average speed and the 85th percentile speed. It was found that the application of these displays had a positive impact on the drivers’ behaviors for a long period of time.

A before-and-after safety evaluation was conducted (King, 2001) to evaluate the effectiveness of two trials, which are the Flashing Lights at School Zones trial and the High Visibility Bus Strips trial. The study found that speed reduced significantly after one week and one month, while there were mixed results after six months. The second trial was performed in two areas for their effectiveness in raising awareness of the school bus and changing behavior around it by conducting a survey; the perception of drivers, teachers, parents, and pupils was different.

Kattan et al. (2011) investigated the speed limit in school zones and playground zones in the city of Calgary, Alberta focusing on the mean speed and the 85th percentile speed. The ratio of vehicles driven over and below the speed limit was estimated to examine the non-compliance of the speed limit in addition to other characteristics. They concluded that the mean and 85th
percentile speeds, as well as the violation rates, were higher in the off-peak times when there were no observed children in the study site. Hidayati et al. (2012) conducted an analysis to quantify the effect of roadside activities and a time-dependent speed control zone (ZoSS) on speed behavior in Indonesia. Results showed that the application of ZoSS was found not effective in reducing speeds.

Studies were performed in Australia to examine whether or not drivers were consciously responsible for their speeding behavior near school zones. It was found that a flashing reminder helped in reducing speed (Gregory, 2014). Saito et al. (2005) conducted a study in the state of Utah to evaluate the effectiveness of installing speed-monitoring displays (SMD) in four school zones in increasing the speed compliance. A public survey was also conducted to find out driver’s opinions and views about current traffic controls in school zones. Speed data was collected using time mark road tubes provided by the UDOT. Results showed that the signs proved to be very effective in reducing the speed. A research study was performed (SAIBEL et al., 1999) to examine the speed compliance in the school zones of Washington. Forty schools were selected and vehicle-speed data were evaluated using a pneumatic-tube speed device. The effectiveness of different types of school zone speed signs was compared. Yoo et al. (2009) investigated an approach to regulate the speed in school zones using sensors to measure and display the speed of the vehicles to the driver. The system proved useful with a high detection rate. This device was applied to 15 school zones in this study.

To measure the effectiveness of flashing beacons on school zone signs that were placed in the school zones of North Carolina, a laser gun was placed to measure the speed in on-school and off-school times. It was also measured in the morning and afternoon school periods. The process was conducted in flasher and non-flasher sites to compare the results. Findings of this
A study indicates that there was no difference in the speed compliance between the flasher and non-flash sites (Simpson, 2008). Another study was conducted in the state of Texas in order to set guidelines to control the speed in school zones. Twenty four school sites were chosen to measure the speed using laser guns and traffic counters in three periods. The results were used to develop guidelines for traffic control devices for school speed zones. The findings show that the school speed limit varies depending on many factors; the relative distance in the school zone, drivers’ behavior, time increments from the start or end of school, area type, number of lanes, and school driveway density (Fitzpatrick, 2010).

Tay et al. (2009) conducted a research study in Calgary, Alberta to investigate the driver behavior and compliance in school and playground zones and how this behavior differs between different types of zones. The study also investigated the effect of the road width and the presence of fencing on the speed and the level of compliance. Twenty samples of spot speed measurements were placed in the school and playground zones selected. It was found that the mean speed in playground zones was slightly higher than that of school zones, and the non-compliance rate was more common in playground zones. It was also found that the mean speed in a four-lane road was higher than that in a two-lane road.

2.4.4 Promoting Active Transportation in School Trips

Buliung et al. (2009) investigated the trends of children (11–13 years) and youth (14–15 years) in choosing active transportation for their school trips in the greater Toronto area. They found that there was a decline in the use of active modes for journeys to and from school. It was concluded that policies and programs to promote active transportation should be introduced. Another research was done by Yeung et al. (2008) using a questionnaire to investigate the mode used by children to go to school and the factors that influenced the parents’ decision in using
their children active transport modes to school in an area in which a ‘Walk-to-School’ program was about to be completed. The common reported factors were age of child, existence of safe sidewalks, adult supervision, fitness level of the child, and commuting distance.

The study (McMillan, 2007) measured the influence of the urban form on the children’s mode of travel to school using surveys. It was found that urban form had a significant effect on mode choice, but not the main factor; there are many other important factors such as traffic safety. Eyler et al. (2007) investigated different policies to promote active transportation in school zones (ATS). Nine elementary schools in seven different states were involved in this case study in addition to interviews for 69 stakeholders. These interviews were transcribed for the policies that already exist and how to make it successful. The results showed that ATS initiatives should take into account local policies and relevant state. As well, factors such as weather, infrastructure, and crossing guard/crosswalk status should be addressed proactively to ensure the success of the initiatives.

### 2.4.5 School Zones Safety Evaluation

Isebrands et al. (2007) conducted a study to evaluate the safety level in Iowa State’s school zones by using site visits to 16 elementary and 4 middle schools at both dropping off and picking up periods, as well as interviews with traffic engineers. The study observed many safety problems, on site problems, and on street problems, and suggested common solutions for them. Pinkerton et al. (2013) investigated the presence and quality of the safety features associated with active transportation modes: walking and cycling. The results suggest that there are good quality crosswalks and sidewalks in most Canadian school zones, but there is a lack of traffic-calming measures and bicycle lanes. A research in West Virginia was conducted to evaluate safety around schools using survey-polling county and district transportation officials to provide
insights into the problems facing school zones (Hamric, 2013). In addition to school zone collision data in order to figure out the common causes of crashes, the poll suggested improvements which included increased penalties for traffic violations within a school zone and traffic calming measures to reduce drivers’ speed (Hamric, 2013).

Medina et al. (2010) provided a framework to evaluate safety around school zones. The analysis was based on collision data and field and interview surveys. The analysis was conducted for 4 schools, using typical forms to assess each item and develop recommendations. The analysis highlighted the importance of relying on historical collision data in the safety assessment. Wooldridge et al. (2005) conducted observations at 14 selected school zones to investigate the required research to handle the transportation issues. It was found that the time spent at the morning drop-off was almost constant compared with the pick-up time that was significantly variable. Some of the schools were using separation for the different types of traffic using traffic cones and gates and/or other barriers; they also used staff for on-site traffic control. These schools have less traffic conflicts than those that do not use such practices. Mailer et al. (2001) prepared questionnaires to evaluate safety in the Austrian school zones and to draw a picture of the current state of zone safety. They concluded that planning should focus on the walking and cycling paths because 85% of the causalities are due to these two modes. In addition, it was found that crossing should be improved and traffic-calming measures should be installed, and that there is a need of separated cycling tracks.

The Colorado Department of Transportation Regional and Headquarters Traffic Engineering staff prepared a checklist consisting of five sections: School Population Characteristics, Transportation Issues, Physical Settings, Education Issues, and Law Enforcement to assess the current state of the school zones’ safety and to help install new control
measures that are necessary to provide safe movement of child pedestrians within the school zone (Colorado school zone traffic safety evaluation, 2005). McArthur et al. (2014) conducted a study in Michigan to develop safety performance functions to be used for the prioritization of candidate schools for funding from the Safe Routes to School Programs (SRTS), using 5-year crash data in areas around the school, in addition to socioeconomic and demographic data for each school district. These attributes were used to measure their effects on crash frequency in each school zone.

2.5 Before-and-After Safety Studies Using TCT

As mentioned earlier, one safety application that could significantly benefit from automated video-based safety analysis is the before-and-after (BA) evaluation of safety countermeasures. Several studies have demonstrated the use of automated video-based safety analysis in BA studies. Autey et al. (2012) conducted a BA safety analysis using automated video-based analysis to evaluate a new right-turn lane design, termed ‘smart channels’. The results suggested that the new design has resulted in a considerable decrease in the conflict frequency and severity. A study conducted by Ismail et al. (2009) to investigate the effectiveness of applying a scramble phase treatment to reduce pedestrian-vehicle conflicts was carried out using a video data from Chinatown, Oakland, California. In this study, two hours of video before applying the treatment and two hours of video after applying the treatment were analyzed. The automated analysis of video data showed a considerable reduction of the spatial density of conflicts as well as the conflict frequency.

Tageldin et al. (2013) conducted a before-and-after study for two intersections in the city of Surrey, BC, to evaluate the effectiveness of the Adaptive Traffic Signal Control (ATSC). The study was done using automated traffic conflict analysis for the two signalized intersections. The
findings showed a considerable increase in the severity and frequency of the total conflicts in the period following the implementation of the (ATSC) due to an increase in vehicle travel time.

A simple comparison between the number of conflicts or collisions is called “naïve before-after study”. In this method, all the changes are observed regardless of many confounding factors that could also affect the safety level after the treatment. Confounding factors are briefly discussed in this research (Sayed et al., 2004) and can be summarized in the following subsection.

2.5.1 Confounding Factors
The results of before/after studies can be influenced by factors that are not related to the treatment being evaluated. These factors include history, maturation, and regression artifacts (Sayed et al., 2004).

2.5.1.1 History
The history of a traffic facility refers to factors other than the countermeasure being investigated and considered as a factor affecting the number of collisions from before to after the implementation of the countermeasure. Examples of history are time of day and weather conditions. These factors could affect the number of conflicts or collisions, so its effect should be separated from the treatment effect (Elvik, 2002; Sayed et al., 2004; Autey et al., 2012).

2.5.1.2 Maturation
Maturation refers to the conflict or collision trends over a long period of time (years) in the location of the applied countermeasure, which is independent of any safety improvement. The number of conflicts or collisions may decline after the implementation of a certain countermeasure, but this reduction may be part of a continuing diminishing trend occurring over many years (Elvik, 2002; Sayed et al., 2004; Autey et al., 2012).
2.5.1.3 Regression to the mean

Regression artifact refers to the statistical phenomena ‘Regression to the mean’ which is defined as the tendency of extreme events to be followed by less extreme values, in other words, the highest tends to be lower and vice versa. The regression to the mean bias or the ‘random effect’ is considered as the most important source of error in the evaluation of road safety programs because treated locations are being chosen based on the recorded high number of conflicts or collisions, and this high number may regress to the mean in the after treatment period, regardless of the treatment itself and this, as a result, might lead to an overestimation of the treatment effect (Elvik, 2002; Sayed et al., 2004; Autey et al., 2012).

2.5.1.4 Exposure

The traffic volume of any road facility has a direct influence on the number of conflicts or collisions (Sayed and de Leur, 2008). In the after treatment period, a decrease of conflicts or collisions may be observed, independent of the treatment effect, it could be simply due to a decline in the number of facility users (Autey et al., 2012). Also, the number of collisions has been proved to have a non-linear relationship with traffic volume (Sayed and de Leur, 2008; Autey et al., 2012).

2.5.2 Overcoming Confounding Factors

The effect of history and maturation can be accounted for through the use of comparison groups. Comparison groups are sites considered somewhat similar to the treated locations and located in the geographic vicinity of the treated sites. By comparing the observed conflicts before and after the treatment of the treated sites to the comparison sites which haven’t been exposed to treatment measures, the treatment effect could be calculated based on what would have happened had no
treatment taken place (Sayed et al., 2004; Autey et al., 2012; Sayed and de Leur, 2008). This method is accomplished by calculating an odds ratio.

2.5.2.1 The Odds Ratio

The odds ratio is a relative statistical measure of the effect of an intervention by comparing the performance of treatment and comparison groups. This method is commonly used in many fields such as medical science and road safety for comparing the effect of a treatment to a comparison group. The odds ratio is defined as the change in the control site or group from pre- to post-treatment divided by the change in the treatment site as well as from before to after treatment (Autey et al., 2012; Sayed et al., 2004).

Where

\[ A_i = \text{Condition at control sites in the before period} \]
\[ C_i = \text{Condition at control sites in the after period} \]
\[ B_i = \text{Condition at treatment sites in the before period} \]
\[ D_i = \text{Condition at treatment sites in the after period} \]

2.5.2.2 The Empirical Bayes Method

To account for the regression to the mean bias, the Empirical Bayes technique is often employed. This method assumes that there are two types of clues for the safety performance of each location: its traffic and geometric characteristics and its collision history or claim data. The Empirical Bayes method combines those two clues to produce a more accurate and location-specific safety evaluation (Autey et al., 2012; Sayed et al., 2004). Hence, the methodology adopted in this thesis is based on the Empirical Bayes (EB) method that accounts for the regression to the mean effects. The methodology also uses before-and-after conflict and traffic
volume data for comparison groups to account for the history and maturation confounding factors.

2.6 Safety Impact of Improved Signal Visibility at Urban Signalized Intersections

Considerable research exists on traffic signal visibility. Most of these studies employed laboratory or controlled field testing to determine the effect of factors such as signal lens size, backplates, weather conditions, and driver characteristics on the visibility of traffic signals. Cole and Brown (1968) indicated that signal visibility was insensitive to the signal lens size and that only intensity affects visibility. This intensity can be obtained by using higher-intensity sources in 200mm lenses. However, in practice, larger signals are used to increase the light output of the signal so that it can be seen at a greater distance (Janoff, 1994).

The use of backplates was found to reduce the intensity required by about 25% to 40% at distances of about 100m and greater reductions were found at shorter distances (Cole and Brown, 1968; Hulscher, 1975). King (1981) found that signal visibility was relatively unaffected by the signal lens size and intensity for nighttime operation. However, it was indicated that signal type, a variable that combines both lens size and illumination intensity, has a significant effect on signal visibility for daytime operations. King (1981) also introduced color as the most dominant factor that influences signal visibility during daytime operation. Freedman (1985) supported King’s findings by stating that reduced signal luminance had no significant effect on the response of drivers from different age groups, which accordingly means that luminance does not influence signal visibility.

2.6.1 Before-and-After Safety Evaluation of Signal Visibility

Although the literature on signal visibility is extensive, few studies have been carried out on the potential safety benefits of improving signal visibility. In a simple before-and-after analysis
carried out by Kassan and Crowder (1969), improved signal visibility reduced right-angle collisions by 32% to 57% and rear-end collisions by 44% to 86%. However, the same study showed significant increases between 33% and 98% for other collision types.

Craven (1986) also used a simple before-and-after analysis to investigate the safety performance at 24 signalized intersections after a general signal upgrading was performed that included increasing the lens size from 200mm to 300mm and mounting the signal heads at the proper height and locations as stipulated in the MUTCD. The results showed a reduction of 10% to 40% in the total number of collisions per site and a 25% overall reduction at all sites. Wainwright (2004) found that using 300mm lenses has shown safety benefits in Michigan and North Carolina. However, the quantification of these safety benefits was not presented. Ogden (1996) presented potential collision reduction factors for various roadway treatments. He proposed that improving signal visibility could reduce rear-end collisions by 30% to 40%.

Using an improved signal head design, Sayed et al. (1998) found that total collisions were reduced by about 24% and that both fatal and injury collisions were reduced by about 16% in 10 urban signalized intersections in British Columbia. The improved signal head design used in the study comprised a 300mm lens for green, amber, and red lights in addition to a reflective tape of 50mm on the outer edge of the backplate. The results of this study contributed to a new standard design in British Columbia, that is, the use of three 300mm lenses rather than the 300-200-200mm design previously used (Traffic Signal Displays for Aging and Color Deficient Drivers, 2001). Sayed et al. (2007) evaluated the impact of improved signal visibility on 139 urban signalized intersections in BC using the Empirical Bayes (EB) approach. The visibility improvements included one or a combination of the following upgrades: signal lens size, new backboards, reflective tapes added to existing backboards, and additional signal heads. Collision
reductions of 8.5%, 5.9%, 6.6%, and 7.3% for PDO, daytime, nighttime, and total collisions, respectively, were found.

2.7 Conflict-based Safety Performance Functions SPF

Traffic conflict data can be modeled from a statistical point of view as non-negative, discrete, and rare events (compared to the circulating traffic volume), similarly to crash data. In doing so, it is possible to adopt and transfer the statistical methodologies based on collision frequency and conflict-based analysis. For instance, the analytical tools (regression models) for predicting impact on road safety given traffic volume and site-specific characteristics of the location, i.e., safety performance functions (SPFs), have been successfully developed using traffic conflict observations (El-Basyouny and Sayed, 2013; Sacchi and Sayed, 2015). This new stream of research is considered promising in road safety research as conflict-based SPFs represent a useful tool that can be used in a variety of road safety problems, such as before-and-after evaluations.

El-Basyouny and Sayed (2013) investigated the relationship between conflicts and collisions using a two-phase model. The first model is a lognormal model used to predict conflicts based on traffic volume, area type (urban/suburban), and other geometric-related variables. The second model is a conflict-based negative binomial (NB) safety performance function (SPF) used to predict collisions. The data used in this model were 51 intersections in British Columbia. The results showed that there is a significant proportional relationship between conflicts and collisions. The goodness-of-fit of the NB model was examined using the scaled deviance and Pearson $\chi^2$. The model was found to be a good representative of the observed conflict data (El-Basyouny and Sayed, 2013).
Pin et al. (2015) used the automated conflict approach to conduct a before-and-after study to evaluate several pedestrian safety improvements in Surrey, BC. The treatments included geometric realignment of the crosswalks to ensure pedestrian travel perpendicular to the flow of traffic, a shift of the western crosswalk farther west to protect pedestrians from south-bound through vehicles, signal phase modifications, and pedestrian countdown timers. The results showed a significant decrease in both conflict frequency and severity.

The BA results from the research conducted by Autey et al. (2012) were compared to the results of a collision-based BA study done by Sacchi et al. (2013) for the same locations. The comparison suggested that there was a remarkable similarity between the total and location-specific reduction of the two studies (conflicts and collisions). These findings support the use of conflicts in the before-and-after safety evaluation.
Chapter 3: Automated Video-Based Computer Vision Techniques

This chapter details the tools, methods, and analysis protocols used in this research. The study is based on several techniques presented in past research studies. The following details how each tool works and how it fits into a traffic safety diagnosis protocol. Figure 3.1 outlines a summary sequence of the analysis methodology of the two case studies.

![Figure 3.1 Video Analysis Block Diagram]

3.1 Study Location and Data Collection

3.1.1 The First Case Study (Case Study A)

The first case study of this research is to conduct an automated traffic safety diagnosis and to demonstrate automated data collection techniques in the vicinity of Dr. Donald Massey School in Edmonton, Alberta. The school is situated in a residential neighborhood on a main road (162nd Avenue). The road intersects with a set of local roads (55th Street and 54b Street). Concerns
about traffic safety hazards were increasingly reported during the “drop off” and “pick up” times.

**Figure 3.2** shows the selected location (orthogonal satellite view).

![Figure 3.2 Dr. Donald Massey School Zone Location](image)

The automated safety analysis employed in this study requires adequate video footage of each segment of the intersection. The video cameras used for data collection were mounted in security camera housings designed for exterior conditions to allow for easy mounting and protection of the cameras from rain and wind. The video cameras were attached to signal heads with assistance from the City of Edmonton personnel, as shown in **Figure 3.3**. Use of these cameras is attractive since no additional time or cost is required for data collection.
Figure 3.3 The Mounting of Cameras on Lamp Posts and Traffic Signal Heads

**Figure 3.4** demonstrates the different approaches for the specified school zone. In order to properly capture the traffic in the school zone, six cameras were installed at different locations covering the study area (see Table 3.1). The location of the monitoring cameras is such that the entire intersection cannot be viewed in one shot. Multiple angles were required to ensure as many conflict types as possible could be recorded and analyzed. The selection of camera angles is not a trivial task; automated tracking quality is largely dependent upon the ability to see individual road users clearly. In order to properly capture the traffic at the locations, it was proposed to install six cameras, as shown in **Figure 3.5**.
Figure 3.4 School Zone with the Annotated Approaches

Figure 3.5 Camera Positions with Selected Views
Figure 3.6 Snapshots of all Views from the Installed Cameras

Figure 3.6 shows the positions of camera scenes based on the six different camera views covering the school zone. Camera 1 is pointed toward 55th street (approach A) to capture the movement of vehicles entering and exiting this street to merge with 162nd avenue. It also shows the vehicle-vehicle and pedestrian-vehicle interactions. Camera 2 (approach B) is quiet similar to camera 1 as it captures the vehicles coming from the school to 54b street and the vehicles leaving it to 162nd avenue. Camera 3 is positioned to show the movement of vehicles in the area between the two intersections (entering and coming from approach C). It is directed to the school exit intersection to capture the vehicle-vehicle conflicts as well as the pedestrian-vehicle interactions at the crosswalk area. Camera 4 is also fixed in the spacing between the two intersections (mid-block), focusing on the school entrance to show the interactions between vehicles and pedestrians in this area. Camera 5 is mounted at the beginning of approach D and directed at the school entrance and the crosswalk area. Similarly, Camera 6 is pointing towards approach C to
record traffic at the second intersection and the school exit. This camera captures the movement of vehicles as well as pedestrians at the second crosswalk.

Data is collected for the study on various days in September 2014 and January 2015 (See Table 3.1). The data are referred to as the fall data set and the winter data set throughout the chapter. Data collection dates are consistent with typical traffic data collection standards (typical weekdays). The collection times of the study are taken in a time of the year when schools are in operation. The specific times and hours of data are chosen to match traffic and weather conditions as closely as possible. A total of two days of data are used for each data set. Table 3.1 shows the recorded views as well as the time and duration of their recording.

Upon a first review of the videos by traffic experts, several traffic safety concerns were identified. The most prominent are the following:

1- Pedestrian crossing control and availability of safe crosswalks
2- Violations of pedestrian crossing
3- The location of bus stops causes conflicts and delays for other vehicles
4- Availability of parking and specific areas for drop-off and pick-up
5- Vehicle speed violations and lack of traffic calming measures
6- Impact of snow which affects available road width
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<th>End Time</th>
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(a) Fall 2014 Data Set Recording Information

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<td></td>
<td>Jan. 14th, 2015</td>
<td>6:38 AM</td>
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</tr>
</tbody>
</table>

(b) Winter 2015 Data Set Recording Information

Table 3.1 Recording Information for the Intersection

Figure 3.7 illustrates the possible conflicts of typical trajectories of vehicles and pedestrians in each camera scene. The prominent type of conflict in this school zone is the sideswipe conflict, especially in wintertime. This is likely because of the limited lane width. Additional issues seem to be of concern at this location. As an example, parking illegally on
162nd avenue and 55th street, which leads to a very limited road width, as well as the size of the school bus and public bus compared with the width of the street. Rear-end conflicts are observed in all the camera views. It is observed that vehicles are spending a long time waiting to enter or exit the school area because of limited parking space in the school vicinity. This is the main cause of rear-end conflict along with the sudden and frequent stoppage of the school bus and public bus. In addition, many conflict events between vehicles and pedestrians in and out of the crosswalk area are observed. The absence of clear stop signs, which force the cars to stop and give the priority to vulnerable road-users, is likely a main reason for such a potential safety issue. Conflicts outside the crosswalk are attributed to jaywalking and crossing outside the crosswalk area. Yet, it is noted that there is no clear marking at the crosswalk to provide proper crossing guidance, demand for pick-up and drop-off areas seems to exceed the available facilities, and snow in the wintertime impacts accessibility. This is considered a major concern given the nature of the area which is full of school children who may or may not be supervised by a caregiver.
Potential Conflicts (Camera 1 and Camera 2)

Potential Conflicts (Camera 3)

Potential Conflicts (Camera 4)
Figure 3.7 Possible Conflict Regions for Vehicle Interactions and Vehicle-Pedestrian Interactions in Each Camera View
The traffic count was also estimated from the videos for the four days of data. The traffic volume per one day is as follows: 1,252 vehicles in approach D, 728 vehicles in approach A, 104 in approach B, and 1,696 vehicles in approach C. Pedestrians who are crossing the first intersection (162nd avenue & 55th avenue) are 1,416 per day, and 524 in the second intersection (162nd avenue and 54b street). Details of the counts are illustrated in Figure 3.8. It shows the number of vehicles in each direction during the fall (average of two days) and the average of the two days during the wintertime as well. For the fall flow, the highest traffic volume was the through volume coming from approach C, the lowest is the through volume coming out of the school entrance to approach A. The number of pedestrians crossing the first crosswalk is almost double the crossing pedestrians in the second crosswalk. For the winter data counts, the highest traffic volume also comes from the same direction as in fall (the through volume from approach C), the lowest traffic count is also the vehicles directed to approach A from the school entrance. There is a significant drop in the number of crossing pedestrians in the two crosswalks during the wintertime, which clearly illustrates the effect of snow and weather conditions on mode choice. The morning peak hour counts of fall and the afternoon peak hour counts of the wintertime are also shown in Figure 3.9.
Fall (Average of the Two Days)

Winter (Average of the Two Days)

Figure 3.8 Road Users Count per Day
Figure 3.9 Road Users Count in the Peak Hours of Fall and Winter
3.1.2 The Second Case Study (Case Study B)

As part of efforts to systematically improve the safety performance at signalized intersections, the City of Edmonton, led by the Office of Traffic Safety, installed retroreflective tapes around the borders of traffic signal backplates on a number of signalized intersection approaches. Signal heads equipped with backplates and a retroreflective border are expected to be more visible and conspicuous in both nighttime and daytime conditions. Figure 3.10 shows the shape of the signal at the two treatment intersections.

![Traffic Signal Head](image)

**Figure 3.10 Treatment of the Traffic Signal Head**

Two treatment and two control (untreated) intersections were identified and studied during the ‘before’ and ‘after’ periods in order to evaluate the effectiveness of the improved signal visibility. The treatment and control intersections are shown in Figure 3.11.
For all the treatment and control intersections, one approach was selected and captured by two cameras. One camera was mounted in front of the approach and the second camera was
located further back on the approach. The first treatment site is the intersection of Whitemud drive and Gateway boulevard (WhG) and the second treatment intersection is 170th street and 100th avenue (170100). The first control site is the intersection of Gateway boulevard and 34th avenue (G34), which is very close to the first treatment site (WhG). Similarly, the second control intersection is between Stony Plain road and 170th street (S170), which is also located very close to (170100) and has very similar geometry. Gateway boulevard is a one-way major arterial road in south Edmonton. It is a major commuter route for communities south of Edmonton. Whitemud drive is the main east-west freeway in southern Edmonton. The 2014 average weekday traffic of the first treatment intersection (WhG) was 62,200 vehicles/day. The matched control intersection (G34) had a traffic volume of 60,600 vehicles/day. The average weekday traffic at the second treatment site (170100) and second control site (S170) were 31,400 and 27,000 vehicles/day, respectively. Schematics of the camera locations at each individual intersection are presented in the following sections.

**Whitemud Drive and Gateway Boulevard**

Whitemud Drive is the main east-west freeway in southern Edmonton, Alberta. It is a 28km-long freeway that intersects with many roads and has much controlled access and limited at-grade intersections with traffic signals. The traffic signal head at the intersection of Whitemud drive and Gateway boulevard was modified. This research seeks to investigate the effectiveness of this treatment (see **Figure 3.12**).
170\textsuperscript{th} Street and 100\textsuperscript{th} Avenue

100\textsuperscript{th} avenue is one of the roads that 170\textsuperscript{th} street crosses at a signalized intersection. 100\textsuperscript{th} avenue is 6.6km long and starts at Stony Plain road. This road intersects with 170\textsuperscript{th} street and Mayfield road at two major signalized intersections. The area of interest is also the approach prior to the signal zone. This intersection was modified with the treatment described in the previous section (Figure 3.13).
Gateway Boulevard and 34th Avenue

Gateway Boulevard has six lanes and intersects with 34th Avenue NW, which has four lanes, at a signalized intersection as shown in Figure 3.14. Gateway Boulevard is a 14.9km-long road, which crosses many roads until it terminates at Saskatchewan drive NW. This study focuses on the part of Gateway Boulevard upstream of 34th Avenue in order to study the behavior of vehicles in the intersection area. This intersection was not treated; it is a control site for the study.
Stony Plain Road and 170th Street

170th street is a 16.1km-long street, which terminates at Levasseur road NW. It consists of six lanes and crosses a five-lane-wide road (Stony Plain) at a signalized intersection. The study location is the approach ahead of the intersection area. This site was also defined as a control intersection in this study.
Video data was collected in Edmonton, Alberta before and after the improvement of the signal head visibility at the two treatment sites as well as at the untreated control sites. Data for the ‘before’ period was collected for the four intersections for April 21\textsuperscript{st} and April 22\textsuperscript{nd}, 2015. The before data was collected for twelve consecutive hours for each of the two days. The after data was also collected for the four intersections for two days, May 26\textsuperscript{th} and 27\textsuperscript{th}, 2015 for twelve hours each day. The after data was collected for two additional days, June 2\textsuperscript{nd} and 3\textsuperscript{rd}, 2015, for one control and one treatment intersection. The ‘after’ days were chosen to match the weather and traffic conditions of the ‘before’ period. The collected timespans during the days were matched as closely as possible from the ‘before’ and ‘after’ periods.
The video cameras used for data collection were mounted in security camera housings designed for exterior conditions to allow for easy mounting and protection of the cameras from rain and wind. The video cameras were attached to signal and lamp poles with assistance from the City of Edmonton personnel. The duration of video recordings are shown in Tables 3.2 and 3.3.

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</tr>
<tr>
<td>Whitemud Drive &amp; Gateway Blvd (Treatment 2)</td>
<td>1</td>
<td>Apr-21</td>
<td>12:47 PM</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Apr-21</td>
<td>12:52 PM</td>
</tr>
<tr>
<td>Gateway Blvd &amp; 34 Avenue (Control 1)</td>
<td>1</td>
<td>Apr-21</td>
<td>13:32 PM</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Apr-21</td>
<td>14:00 PM</td>
</tr>
<tr>
<td>Stony Plain Road &amp; 100 Avenue (Control 2)</td>
<td>1</td>
<td>Apr-21</td>
<td>10:52 AM</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Apr-21</td>
<td>11:17 AM</td>
</tr>
</tbody>
</table>

Table 3.2 ‘Before’ Video Data Gathering Hours
3.2 Automated Video-Based Computer Vision Techniques

The following subsections present in detail the steps of automated video-based computer vision techniques developed at UBC. The following steps were applied for both case studies A and B. Details of the automated video analysis process as well as its past application in safety analysis are presented in the following studies (Autey et al., 2012; Saunier and Sayed, 2006; Saunier and Sayed, 2008; Saunier, 2007).

3.2.1 Video Encoding

The first step in the video analysis is to conduct the video conversion of the recorded raw video footage to a format used in the analysis described later.

Table 3.3 ‘After’ Video Data Gathering Hours

<table>
<thead>
<tr>
<th>Intersection</th>
<th>Scene</th>
<th>Day1</th>
<th>Day2</th>
</tr>
</thead>
<tbody>
<tr>
<td>170 Street &amp; 100 Avenue (Treatment 1)</td>
<td>1</td>
<td>May-27</td>
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<td></td>
<td>2</td>
<td>May-27</td>
<td>12:00 PM</td>
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<tr>
<td>Whitemud Drive &amp; Gateway Blvd (Treatment 2)</td>
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<td>13:27 PM</td>
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<tr>
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<td>May-26</td>
<td>14:08 PM</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>May-26</td>
<td>14:22 PM</td>
</tr>
<tr>
<td>Stony Plain Road &amp; 100 Avenue (Control 2)</td>
<td>1</td>
<td>May-27</td>
<td>10:27 AM</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>May-27</td>
<td>11:02 AM</td>
</tr>
</tbody>
</table>
3.2.2 Camera Calibration

The positional analysis of road users requires an accurate estimation of the camera parameters. During video recording, the three-dimensional real-world is captured on a two-dimensional image space. This translation of three-dimensional coordinates into two-dimensional coordinates is a linear transformation that is associated with the properties of the camera and its lens. The linear transformation is defined by a matrix, called the homography matrix, which is related to the camera’s extrinsic parameters (camera position and orientation), as well as its intrinsic parameters (focal length, skew angle, and radial lens distortion). Camera calibration is the process of determining the homography matrix of a camera angle and is necessary for tracking vehicles in the camera image and relating these tracks to positions in the real world. Details of the adopted mixed-feature camera calibration approach are presented in previous work (Ismail et al., 2013).

Each calibration process begins with the user annotating features in the camera image and in an aerial, orthographic image of the intersection. Google satellite images were used in this study, as shown in Figure 3.16. Four types of annotations were used for camera calibration optimization:
(a) Geometrical Features in the Image Space
Camera 1 (Case Study A)

(b) Geometrical Features in the World Space
Camera 1 (Case Study A)

(a) Geometrical Features in the Image Space
Camera 3 (Case Study A)

(b) Geometrical Features in the World Space
Camera 3 (Case Study A)
Geometrical Features in the Image Space and in the World Space for Camera 1 (170th St. and 100th Ave.) (Case Study B)

Figure 3.16 Camera Calibration Process
3.2.2.1 Corresponding Points

Discrete objects or locations are identified and annotated in both the camera image and orthographic image. The selected points must be on the plane of the road or at a specified height above the road plane. The optimization algorithm adjusts the camera calibration so that when points are projected from the camera image to the orthographic image, or vice versa, the corresponding points match.

3.2.2.2 Distances

Distances between two points in the camera image, both situated on the road surface plane, can be annotated during calibration. The known, real-world distance between these points is specified and the optimization procedure adjusts the camera calibration so that the projections of the end points into the orthographic view are the correct distance apart.

3.2.2.3 Angles

If the angle between two lines in the camera image is known, this information can be used for camera calibration. Parallel lines of lane markings or the right angle lines at an intersection are often used for this purpose. During optimization, the calibration is adjusted so that the projection of these lines into the orthographic view achieves the specified angle.

3.2.2.4 Global Up Directions

The many poles mounted near intersections and road segments can provide information for retrieving three-dimensional coordinates from an image. It is assumed that poles are correctly mounted and are perpendicular to the road surface. By specifying the locations of the tops and bottoms of poles in the camera image, the calibration optimization algorithm can use this information to help determine the tilt of the road surface plane. Poles near the edge of the frame are especially useful for helping to determine the barreling effects of the camera’s lens.
3.2.3 Calibration Verification

The calibration error is represented by the discrepancy between calculated and annotated segment lengths normalized by the length of each segment. The accuracy of the final estimates was very good and no further error in conflict analysis was attributed to inaccurately estimated camera parameters. A visual validation of the calibration accuracy is possible through the use of a displayed grid in both the real-world image and the camera image, as illustrated in Figure 3.17.
Figure 3.17 Intersection Grid Illustration

(a) Camera 4 Grid Overlay in the Image Space
(Case Study A)

(b) Camera 4 Grid Overlay in the World Space
(Case Study A)

(a) Camera 1 Grid Overlay in the Image Space
(170th St. and 100th Ave.) (Case Study B)

(b) Camera 1 Grid Overlay in the World Space
(170th St. and 100th Ave.) (Case Study B)
3.2.4 Feature Tracking

The automated video analysis relies on computer 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 well-known Kanade-Lucas-Tomasi feature tracker algorithm. Tracked features are further refined through the addition of filters. First, features that remain stationary are assumed to belong to the environment and are discarded and not tracked (Saunier and Sayed, 2006). For this reason, features must be continually generated in order to identify moving features that may subsequently be tracked. Second, feature-tracker errors are dealt with by enforcing regularity motion checks to remove features demonstrating unreasonable acceleration or abrupt changes in direction. These features are displaying motion properties that are not physically possible for road users and can safely be classified as tracking errors. Figure 3.18 illustrates the vehicles tracking for different camera angles.
3.2.5 Feature Grouping (Object Creation)

Vehicles are large objects with many distinguishable physical features and, as such, will generate multiple features during the feature-tracking procedure. The next step is to decide which set of features belongs to a unique vehicle so an object may be generated. Feature grouping is carried out using cues like spatial proximity and a common motion of features. Among a detailed set of criteria, two important tests are the connection distance between features and the similarity of the motion-vectors features. For a feature to be added to another to create, or add to, a group, it must be within the maximum connection distance specified by the user. In the real world, features of a vehicle have identical motion vectors due to the physical rigidity of the vehicle.

Computer-tracked features must exhibit the same characteristic in order to be associated with a common vehicle. 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. **Figure 3.19** illustrates moving objects generated by the grouping of features. A detailed description of the tracking and grouping algorithm is presented in this research (Saunier and Sayed, 2006). The tracking accuracy for motor vehicles has been measured between 84.7% and 94.4% on three different sets of sequences. This accuracy is considered reliable especially under heavy traffic flow conditions and should have little impact on the accuracy of the calculation of conflict indicators. This means that most trajectories are detected by the system and the calculated conflict indicators are considered reliable. The subsequent step in the road-users analysis is the road-users classification. Road-users’ trajectories obtained through automated computer vision are rich in information. The trajectories hold features that reveal the structure of the traffic scene and provide important clues to the characteristics of the road users. For example, a regular movement pattern of a pedestrian is described by its walking gait (ambulation) with the main attributes being the walking velocity, stride length, and frequency.

The walking speed profile of a pedestrian typically fluctuates periodically at each stride. The ambulatory characteristics are manifested into sinusoidal segments dominated by the stride frequency of a moving subject. On the other hand, a cyclist’s movement patterns are governed by its pedaling process (cadence). In contrast, a vehicle’s movement patterns are primarily composed of linear segments corresponding to different speeds chosen throughout the trajectories. The oscillatory behavior associated with pedestrians, while lacking in vehicles, provides a classification basis through recognizing a pedestrians’ movement pattern. Other features such as maximum speed and road-user object size are used as complimentary queues to enhance the classification. Details of the classification are presented in this research (Zaki and Sayed, 2013a).
Feature Grouping Illustration for Camera 6
(Case Study A)

Feature Grouping Illustration for Camera 1
(Case Study A)

Feature Grouping Illustration for Camera 1
(Case Study B)

Feature Grouping Illustration for Camera 1
(Case Study B)

Figure 3.19 Grouping Illustrations
3.2.6 Prototype Generation

The term “prototypes” refers to a group of motion patterns that define the set of movements carried out by road users in the studied field of view. Prototype generation is a semi-automated procedure that must be carried out before the vehicle-tracking stage. The prototypes can be synthesized from expected the road-users’ movement trajectories or can be extracted automatically from a set of tracked road users.

Prototypes are generated from the expected movement that resembles the common traffic movements. Feature tracking is carried out on the video segment and the trajectories of a large number of features, usually several thousand, are recorded. This large set of trajectories is reduced to a set of several hundred prototypes through a clustering algorithm. The selected clustering algorithm is the Longest Common Subsequence (LCSS) method. Feature tracks from vehicles following similar trajectories (e.g., right-hand turns) may begin and end at different locations, but still describe the same movement pattern. As the name implies, the LCSS algorithm groups features that contain matching subsequences of an adequate length. In this manner, the initial set of trajectories is reduced to a concise set of prototypes (Saunier and Sayed, 2008). Figure 3.20 shows the vehicles’ trajectory prototypes synthesized for different camera angles.

3.2.7 Prototype Matching

The longest common subsequence algorithm (LCSS) is adopted for the road-users violation detection. More specifically, the comparison relies on an LCSS similarity measure between the movement prototypes and the trajectories to make a decision about the classification. The LCSS algorithm compares the tracks against a set of templates (prototypes) of expected road-user
behavior at the given intersection. The computer vision system described earlier has a built-in procedure to extract a set of common tracks of road users (Saunier et al., 2010). However, more often the set of generated prototypes does not provide adequate representation of the road-user tracks. This is primary depending on the footage length used in the prototype generation as well as the distinct tracks found in the footage. An iterative procedure may be implemented to ensure certain behavior coverage. An alternative procedure would be synthesize the prototypes to cover certain behavior that deemed it difficult to extract from the footage. An algorithm is developed to generate prototypes representing pedestrian behavior crossing at the designated crossing area.

Figure 3.20 shows an illustration of the synthetic trajectory prototypes.
3.2.8 Conflict Analysis

The generation of interactions between objects can be completed once features have been grouped into objects and the full trajectories of the objects have been obtained. The trajectory of an object is matched to individual prototypes from the full set of prototypes using the LCSS algorithm with a maximum LCSS matching distance. An object will therefore be matched with more than one prototype with a probability weighting determined from the LCSS matching distance. The matched prototypes are translated to the object’s center and corrected for the current velocity of the object. This provides a set of predicted future positions with associated probabilities of occurrence. Conflicts between vehicles can then be determined by evaluating if any of these future positions coincide spatially and temporally with other vehicles (Saunier et al., 2010).

Conflict data is then aggregated at the road-user level for this thesis. Every pair of road users that share temporal and spatial proximity has the potential for a conflict. Two vehicles that appear at the same time, both inside the field of view of the camera, are defined as having spatial and temporal proximity and potential conflicts between them are calculated. While most pairs of such vehicles show no conflicts, a small percentage will. A critical value of a conflict indicator must be drawn from each interaction. Typically, the most severe value is used to represent the overall severity of a traffic event.

The post-encroachment time (PET) is defined for two road users as the time difference between the moment an "offending" road user passes out of the area of potential collision and the moment of arrival at the potential collision point by another "conflicted" road user. A critical value of a conflict indicator must be drawn from each interaction. Typically, the most severe value is used to represent the overall severity of a traffic event. Due to potential noise in road-
user tracks, different filtering strategies have been tested. Furthermore, selected events were
visually reviewed to identify any tracking errors. In both A and B case studies, traffic events with
associated minimum PET of less than 3 seconds are considered for the safety evaluation.

The time-to-collision (TTC) conflict indicator is commonly implemented as a measure of
the severity of a conflict. The TTC is defined as the time until a collision will occur if the two
conflicting vehicles were to continue on the same path at their current speed. The TTC is
continually calculated between conflicting vehicles and, thus, a set of values is returned for each
discrete conflict. One representative value, in this case the minimum TTC, is extracted from this
set to indicate the maximum severity of this interaction. The aggregation method employed,
therefore, records the minimum TTC from all conflicting vehicles, and totals the number of
minimum TTCs that are less than three seconds. This value is then normalized by hours, traffic
volumes, or both. Due to potential noise in road-user tracks, different filtering strategies have
been tested. Furthermore, the first and last 10 frames of each track were discarded and selected
events were visually reviewed to identify any tracking errors. Figures 3.21 and 3.22 illustrate
common conflicting situations identified in the analysis.
Figure 3.21 Head-on Conflict Illustration (Case Study A)

Figure 3.22 Sideswipe Conflict Illustration (Case Study B)
3.2.9 Conflict Severity

The minimum time-to-collision (TTC) of each event can be mapped to a severity index using the transform (Saunier and Sayed, 2008):

\[ SI = e^{-\left(\frac{TTC^2}{2PRT^2}\right)} \]  \hspace{1cm} (3.1)

Where SI is the severity index and PRT is the perception and braking reaction time, which is assumed to be 1.5 seconds. Figure 3.23 shows a depiction of this severity mapping. The severity index is a unitless measure of severity that ranges from 0 to 1, with 0 being uninterrupted passages. Events with a higher severity index correspond to more severe events.

Figure 3.23 Mapping from Time-to-collision to Severity Index

Aggregation of the severity of all events is conducted. Normalization is required to account for differences in the observation period and exposure from “before” and “after”. The
exposure measure used is the maximum theoretical number of events, which is the product of the hourly volumes for conflicting traffic streams.

\[
SI \text{ Rate} = \frac{SI}{\text{Maximum Theoretical Exposure (millions)}}
\]  

(3.2)

3.2.10 Exposure

Exposure is a normalized value applied to the conflict results. It acts as a way to correct volume differences and is used to account for expected variation in volumes on a temporal basis. The procedure for including a measure of exposure is given in Equation 3.3 shown below, which is simply the square root of the product of conflicting vehicle and pedestrian volumes. The idea behind the controlling measure is to include volumes of both movements involved in a given conflict type. The resulting value itself provides no useful measure but it is a simple way to account for the density of each movement.

\[
E_{ij} = \sqrt{(V_i \times V_j)}
\]

(3.3)

Where:

\[E_{ij} = \text{Exposure Factor}\]

\[V_i = \text{Volume of Conflicting road-users Movements, } i\]

\[V_j = \text{Volume of Conflicting road-users Movements, } j\]

3.2.11 Violation Detection

A subsequent traffic analysis step is to distinguish between road-users’ behaviors and identify possible non-conformance to the location’s traffic regulations. In this thesis (Case study A), the spatial violations of pedestrians, bicycles, and vehicles are identified. Compared with vehicle
movements, pedestrians and cyclists movements are more complex. Vehicles usually move in predefined pathways and have a limited number of turning movements. On the other hand, pedestrians and cyclists move freely and do not have environment constraints on turn movements, reverse directions, and sudden stops. More important is the difficulty to predict a pedestrian/cyclist trip as the pedestrian/cyclist during the trip might combine multiple sub-trips that involve stops of an indeterminate length. A spatial violation detection for any road user is done by comparing the road-user trajectory against a given set of predetermined tracks (prototypes) representing standard movements. Any significant disagreement between both sequences of positions is interpreted as evidence that the given track represents the movement of a road user performing a traffic violation.

The longest common subsequence algorithm (LCSS) is adopted for the road-users violation detection. More specifically, the comparison relies on an LCSS similarity measure between the movement prototypes and the trajectories to make a decision about the classification. Temporal violations are performed by comparing the position of the road user during the different signal times. A validation procedure against ground truth (manual) classification was conducted to provide insight on the usefulness of the algorithm by analyzing the false positive and false negative rates of the results (Ismail et al., 2011) and (Zaki et al., 2012). Figures 3.24 and 3.25 illustrate two conflicts caused by violation actions; one because of jaywalking, and the other because of a vehicle that was parked illegally at a bus stop. In the first figure, the pedestrian was crossing outside the crosswalk area when the car approached her, a low TTC of less than 3 seconds was calculated, so it is considered as a conflict. The second figure shows a vehicle was parked at the bus stop when the bus came to stop, which is also considered as a conflict, as the TTC was less than 3 seconds.
Figure 3.24 Jaywalking Conflict

Figure 3.25 Illegal Parking Conflict
Chapter 4: Case Study (A): Safety Diagnosis for Dr. Donald Massey
Elementary-Junior School, Edmonton, Alberta

This chapter consists of six sections. The first section of this chapter describes the motivation, the challenges, and research contributions of this case study. Section two describes the objectives of this study. Section three presents the results of the analysis and discusses conflict contributing factors, causes, and associated road-user behavior. Section four presents recommendations that would potentially improve the safety along the study area. Finally, summary and conclusions are provided in the fifth section.

4.1 Motivation

Improving road safety and the development of sustainable transportation initiatives have been identified by the City of Edmonton as top priorities. The objective of this study is to conduct an automated traffic safety diagnosis and to demonstrate automated data collection techniques in the vicinity of Dr. Donald Massey School in Edmonton, Alberta. The school is situated in a residential neighborhood on a main road (162\textsuperscript{nd} Avenue). The road intersects with a set of local roads (55th Street and 54b Street). Concerns about the traffic and safety hazards were reported increasingly during the “drop off” and “pick up” times. Safety concerns were related to driving violations, illegal parking, as well as jaywalking. Concerns were also related to potential pedestrian-vehicle and vehicle-vehicle conflicts at the two main intersections in the school area, especially at the morning and the afternoon peak hours. As shown in Figure 4.1, the school entrance and exit are located on 162\textsuperscript{nd} avenue, cars are allowed to move in three directions; right, left, and through at the first intersection (162\textsuperscript{nd} avenue and 55\textsuperscript{th} street), but traffic directions are somehow restricted at the second intersection (162\textsuperscript{nd} avenue and 54b street) because of the
school exit. Pedestrians are allowed to cross 162\textsuperscript{nd} avenue from two crosswalks; one at the first intersection (school entrance) and the other at the second intersection (school exit). A detailed safety diagnosis analysis is therefore required to evaluate the current safety performance of the intersection, to identify factors that may be contributing to safety concerns, and to propose potential safety improvements.

![Figure 4.1 Selected Location in Google Map](image)

4.2 Objective

There is past and ongoing research in the Transportation Engineering Group at the Civil Engineering Department of UBC that aims at developing an automated road safety analysis system based on video sensors. This video analysis system uses existing state-of-the-art computer vision algorithms. Despite the potential benefits of automated traffic safety analysis based on video sensors, limited computer vision research has been directly applied to road safety
and even less so to the detection of traffic conflicts. The current system developed at UBC was tested and applied successfully for automated safety diagnosis in many countries.

This project uses recent CV developments for safety evaluation and data collection at the selected locations. The analysis relies on automated conflict analysis encompassing various road users, generally vehicles and pedestrians. Traffic data collection, conflict analysis, and violation detection methods are applied to the collected video data. The main components of this chapter include:

- Description of the Dr. Donald Massey School field survey
- Safety diagnosis and evaluation of the selected location using the UBC automated traffic safety analysis system
- Demonstration of the automated data collection capabilities of the system
- Recommendations and suggested treatments to improve the safety at the school location

This study can be added to a group of recent studies that have utilized automated safety analysis and data collection (Sayed et al., 2012; Autey et al., 2012; Sayed et al., 2012; Oppenheim and Schafer, 1999). This shows that the technology is reaching a maturity level adequate to be deployed and utilized by practitioners.

4.3 Summary of Findings

The following section summarizes the results obtained from the automated safety analysis (described in chapter 3). Three components are demonstrated for each intersection: conflict analysis, violation analysis, and automated data collection. Conflict analysis includes identifying conflict frequency, severity, and location (conflict points). The conflicts observed in the intersection cover vehicle-vehicle interactions and vehicle-pedestrian interactions. Violation
analysis includes the automated identification of non-conforming behavior of road users. Vehicle speed measurement and analysis is also provided. And the following trends were found:

- **Transportation mode**: More than 65% of conflicts are vehicle-vehicle interactions; about one-third are pedestrian-vehicle conflicts, and one-third are bus-related conflicts.

- **Severity**: The vehicle-vehicle conflicts are more severe than pedestrian-vehicle conflicts and bus-related conflicts. This trend was noted for both fall and winter data sets.

- **Seasonal trend**: Vehicle-vehicle conflicts are more frequent in the fall than in the winter. Conversely, pedestrian-vehicle conflicts are more frequent in winter, and bus conflicts are almost the same in the two seasons.

- **Hourly trend**: Most conflicts take place between 8 and 9 am, and from 3 to 4 pm for fall data, most winter conflicts also occur from 8 to 9 am and from 3 to 4 pm with two more peaks from 7 to 8 am and from 11 am to 12 pm.

- **Road surface**: The presence of snow in winter affects the severity of sideswipe/head-on conflicts, because the snow makes the road width very narrow.

- **Road-user violations**: The most common violations are jaywalking and failing to yield to the other. These problems result in many left turn-crossing conflicts and pedestrian-vehicle conflicts.

**Figure 4.2** illustrates the total number of conflicts investigated by the tool for the two days of fall; vehicle-vehicle conflicts are more than 120 events (69%) and bus-related conflicts and pedestrian conflicts are more than 20 events representing 16% and 15% of total conflicts, respectively.

**Figure 4.3** demonstrates the total number of detected conflicts in the two days of winter for each road user type. The vehicle-vehicle conflict is the prominent type as shown; more than
100 conflicts are of that type (58%), the second highest is the pedestrian-vehicle conflicts of more than 40 conflicts in the two days (23%), and the bus conflicts were almost 30, or about 19% of the total number of observed conflicts in wintertime.

**Figure 4.2 Conflict Frequency Summary during fall**

**Figure 4.3 Conflict Frequency Summary during winter**

**Figure 4.4** illustrates the total number and the ratio of each conflict type of the automatically-detected conflicts. For the fall data, the prominent type of conflict is the rear-end conflict with a ratio of 43% of all the conflicts detected for the two days of fall. The second highest type is the left turn-crossing conflict, which constitutes 30% of all the fall events, then the vehicle-pedestrian conflicts at 18%, followed by the sideswipe and head-on conflict with ratios of 6% and 3%, respectively.
For the winter data, the sideswipe conflict is the highest ratio, which is mainly because of the road dieting caused by the presence of snow during this time. The second highest type is the rear-end conflict of 27% of the total number, then pedestrian-vehicle conflict with a percentage of 23%. The last two types are head-on conflict and the left turn-crossing conflict with ratios 8% and 6%, respectively.

**Figure 4.4 Ratios of Different Types of Observed Conflicts**

### 4.3.1 Conflict Severity

*Figures 4.5 and 4.6* show the conflict distribution using the conflict indicators TTC, PET, and severity versus the conflict frequency for each type of road user involved in the conflict. For the fall dataset, the highest number of conflicts is the vehicle-vehicle conflicts followed by bus-related conflicts then pedestrian conflicts, as shown in *Figure 4.5*. Most conflicts of the three types have a TTC less than 0.5 seconds and those conflicts are considered severe conflicts. The majority of vehicle-vehicle conflicts and bus conflicts have a PET value between 2 and 2.5 seconds, while the PET value for most of the pedestrian vehicle conflicts is 0.5 and 1 second.

For the winter dataset (see *Figure 4.6*), the highest number of conflicts is the vehicle-vehicle conflicts followed by bus-related conflicts then pedestrian conflicts. Most conflicts of the
three road-user types have a TTC of less than 0.5 seconds and those conflicts are considered more severe. The majority of vehicle-vehicle conflicts and bus-related conflicts have a PET value of between 0.5 and 3 seconds, while the PET value for most of the pedestrian-vehicle conflicts is 0.5 seconds.
Figure 4.5 Conflicts Distribution (Based on Type) for the Two Days of Fall Data
4.3.2 Conflict Temporal Distribution

Figures 4.7 and 4.8 show the conflict frequency for each type of road user involved in the conflict throughout the day. As shown in Figure 4.7, for the fall dataset, the highest number of conflicts always occurs in the morning peak hour (drop-off time) from 8 to 9 am and in the afternoon peak hour 15 to 16 (pick-up time). For vehicle-vehicle conflicts, more than 50 events occurred in the morning and the same for the pick-up time, for the rest of the day, conflicts are very few. It is the same case for the bus conflicts, except the conflicts happen only four hours during the whole day, two in the morning and two in the afternoon. Pedestrian-vehicle conflicts, on the other hand, occur mostly during the afternoon peak hour.

Figure 4.8 illustrates the change in the number of conflicts throughout the hours of the two days of wintertime for each type of road user involved in the conflict. It is clear that the three types have almost the same trend, and there are a few bus conflicts and pedestrian conflicts in the two days of winter compared with vehicle-vehicle conflicts. As shown, the peak morning hour is from 8 to 9 am for all the types, and the peak afternoon hour is from 15 to 16. Those two hours
intervals are associated with drop-off and pick-up activities. Generally, in winter, the conflicts are distributed throughout the day, this could show the effect of snow and severe weather conditions on the frequency of conflicts.
Figure 4.7 Conflict Frequency Temporal Distribution (Fall Dataset)

Figure 4.8 Conflict Frequency Temporal Distribution (Winter Dataset)
4.3.3 Conflict Spatial Distribution

Figure 4.9 shows a breakdown of the number of conflicts per exposure using a TTC conflict indicator, and the severity of the conflicts in Figure 4.10 for each approach for the two days of fall data. The highest observed conflicts are rear-end conflicts between vehicles that usually wait to enter or exit the school, or between vehicles that suddenly stop after a bus stop. The second observed kind is the left turn-crossing conflict between vehicles exiting approach A to enter approach C and vehicles coming from approach C to enter approach D. There are other detected conflicts, such as sideswipe conflict, which happens between vehicles entering and exiting approaches C, D, and A, and head-on conflicts; the main reason for these two types is the illegally-parked vehicles in the 162nd Avenue and 55th Street. As shown in Figure 4.9, a lot of conflicts have a TTC value less than 0.5 second for all the approaches, and for approach (A), most conflicts are severe with a value of 1 in Figure 4.10.

Figure 4.11 shows a breakdown of the number of conflicts per exposure (1000 road-user) using a TTC conflict indicator, and the conflict severity in Figure 4.12 for each approach for the two days of winter data. The highest observed rate is in approach (A), as most of these conflicts
are sideswipes that happen between vehicles entering and exiting the approach and head-on conflicts; the main reason for these two types is the limited road width, the illegally parked vehicles on 55th street, as well as the snow that causes road dieting. Rear-end conflicts are the second common type, as it happens between vehicles that are waiting to enter or exit the school, or between vehicles waiting after a bus when it stops. Another observed type is the left turn-crossing conflict between left turn vehicles from approach A to enter approach C and the through vehicles entering approach D because of the difficulty of yielding between the two directions and the intersection geometry. As shown in Figure 4.11, a considerable number of conflicts have a TTC value less than 0.5 seconds for approaches A and D; and for approach A, most conflicts are severe with a value of 1, as in Figure 4.12, while the majority of conflicts in the other two approaches have a severity value of 0.9.

Figure 4.9 Conflict Rate (1000 Vehicles) (TTC Based Conflict Detection) for Fall Dataset
Figure 4.10 Conflict Severity per exposure (1000 Vehicles) (TTC Based Conflict Detection) for Fall Dataset

Figure 4.11 Conflict Rate (1000 Vehicles) (TTC Based Conflict Detection) for Winter Dataset
Figure 4.12 Conflict Severity per exposure (1000 Vehicles) (TTC Based Conflict Detection) for Winter Dataset

The distribution of the total conflicts by heat mapping is shown in Figure 4.13. It is clear that there are different types of conflicts for different reasons; most conflicts are sideswipe conflicts, rear-end conflicts due to bus stopping, crossing conflicts due to the absence of stop signs, and pedestrian-vehicle conflicts. The main cause of most conflicts is the very limited lane width and the violators who are parking on 162nd avenue, which makes the road tighter.
Figure 4.13 Conflicts Frequency (Conflicts/m2) Heat Maps for the Two Intersections

4.3.4 Violations

Table 4.1 shows the counts and percentages of the manually-observed conflicts and violations of the two days of fall data. 49% of the total violations were manually detected by watching the recorded videos of people who are crossing outside the crosswalk. This ratio indicates that jaywalking is a common trend in this area. Vehicles that make a U-turn in the intersection area
make up 20% of the observed violations. 30% of the observed violations are vehicles parking or idling to drop-off or pick-up a child in no parking spots. Only two vehicles were observed to be driving the wrong way (in the opposite direction).

<table>
<thead>
<tr>
<th>Violation Type</th>
<th>Count</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crossing Violation (Jaywalking)</td>
<td>125</td>
<td>49</td>
</tr>
<tr>
<td>Vehicle Making U-Turn</td>
<td>52</td>
<td>20</td>
</tr>
<tr>
<td>Parking or Idling Violation</td>
<td>75</td>
<td>30</td>
</tr>
<tr>
<td>Wrong Way Violation</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4.1 Rate of Manually-Detected Conflicts and Violations (Fall Dataset)

Table 4.2 illustrates the counts and ratios of the inappropriate negotiations in the two days of wintertime. 35% of the total number of violations is vehicles making a U-turn in the intersection area, which is invalid behavior. Parking in no parking spots and jaywalking constitute 30% and 26%, respectively. A few vehicles are observed to do the following: moving backwards (5 vehicles), driving in the wrong direction (3 vehicles), and blocking the intersection (repeated 3 times).

<table>
<thead>
<tr>
<th>Violation Type</th>
<th>Count</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crossing Violation (Jaywalking)</td>
<td>33</td>
<td>26</td>
</tr>
<tr>
<td>Vehicle Making U-Turn</td>
<td>45</td>
<td>35</td>
</tr>
<tr>
<td>Parking or Idling Violation</td>
<td>39</td>
<td>30</td>
</tr>
<tr>
<td>Wrong Way Violation</td>
<td>3</td>
<td>2.5</td>
</tr>
<tr>
<td>Vehicle Moving Backwards</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Blockage</td>
<td>3</td>
<td>2.5</td>
</tr>
</tbody>
</table>

Table 4.2 Most Relevant Inappropriate Negotiations Summary (Winter Data)
Table 4.3 shows the counts of the total manually-observed conflicts and violations of the four days of data (fall and winter) and the inappropriate negotiation rate (per 1000 road users). The highest number of violations is for pedestrians crossing outside the crosswalk area, compared to the total number of crossing pedestrians in the four days, the inappropriate negotiation rate is found to be 39 per 1000 road users. The inappropriate negotiation rate of the vehicles making a U-turn in the intersection area is 6.9; there are only 97 vehicles. The inappropriate negotiation rate of the vehicles which park in no parking spots to drop-off or pick-up a child is 7.9, the total count of these vehicles in four days is 114. Vehicles entering approach D and change lanes in the intersection come fourth at a 5.9 inappropriate negotiation rate and a total count of 17. The total number of vehicles that observed changing lanes or moving backwards, moving in the wrong direction, and causing an intersection blockage are 11, 5, and 3, respectively.

<table>
<thead>
<tr>
<th>Safety Concerns</th>
<th>Count</th>
<th>Inappropriate Negotiation Rate (per 1000 Road User)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pedestrians Violations (Jaywalking): Crossing Outside Crosswalk Area</td>
<td>161</td>
<td>39</td>
</tr>
<tr>
<td>Vehicles entering approach D change their lane in the intersection area</td>
<td>17</td>
<td>5.9</td>
</tr>
<tr>
<td>Parking or Idling violation (The vehicle does not park properly and occupies part of the roadway or the vehicle stops on the roadway for picking up)</td>
<td>114</td>
<td>7.9</td>
</tr>
<tr>
<td>Vehicles move backwards and driver change their mind</td>
<td>11</td>
<td>0.8</td>
</tr>
<tr>
<td>Vehicles make U-turn in the intersection area</td>
<td>97</td>
<td>6.9</td>
</tr>
<tr>
<td>Vehicles move in a wrong way (Wrong direction)</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>Approach blockage due to long queue of vehicles</td>
<td>3</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 4.3 Total Potential Violation (Combined Datasets)
4.3.5 Vehicle Speed Validation

To calculate the speed of each road user, two imaginary parallel lines (screens) are located across a selected section of each crosswalk leg of the intersection. Most tracks cross both screens and the speed of those tracks are calculated based on the amount of time each track remains between the two screens. The mean average speed is calculated by averaging the obtained speed for each road user. Two parallel screen lines were placed on the desired road segment with a known physical distance between them. The time it took for a track to cross both lines is recorded and divided by the distance in order to measure the average speed. The screens along with the distances between them are shown in Figure 4.14. The main sources of residual errors are the tracking accuracy noise and projection issues due to the low camera angle.

![Figure 4.14](image)

(a) Camera 3  
(b) Camera 4
Figure 4.14 Speed Screens
Figure 4.15 Automated Speed Cumulative Distribution
As shown in Figure 4.15 and Table 4.4, for the major road (162\textsuperscript{nd} Avenue) on fall and winter days, more than 60\% of vehicles travel by a speed more than the 30 km/hour speed limit. It is observed also that 85\% of drivers in the fall use a speed of 50 km/hour and 42 km/hour on winter days; only 15\% of drivers exceed those values. Similarly, in approach (A), 15\% of vehicles travel above 42 km/hour in the fall and 32 km/hour in the winter. In approach (B), 85\% of drivers travel 39 km/hour in the fall and 26 km/hour in the winter. From the previous results, it is clear that vehicles travel at a higher speed in the fall than that of winter; this may be because of the presence of snow that causes road dieting and traffic congestion.

<table>
<thead>
<tr>
<th></th>
<th>Major Road (162\textsuperscript{nd} Ave.)</th>
<th>Approach A (55 St NW)</th>
<th>Approach B (54b St NW)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dataset</strong></td>
<td>85th Percentile Speed</td>
<td>85th Percentile Speed</td>
<td>85th Percentile Speed</td>
</tr>
<tr>
<td><strong>Fall Dataset</strong></td>
<td>50</td>
<td>42</td>
<td>39</td>
</tr>
<tr>
<td><strong>Winter Dataset</strong></td>
<td>42</td>
<td>32</td>
<td>26</td>
</tr>
</tbody>
</table>

**Table 4.4 Automated Vehicle Speed Summary (km/hour)**

4.4 Recommendations for Potential Safety Improvement

Based on the previous analysis, several recommendations can be presented that would potentially improve the safety for all road users without affecting the mobility along the intersections. It should be noted that these recommendations are only based on the analysis of the video data. It is recommended that a more in-depth safety diagnosis, including a review of the collision data, capacity analysis, traffic signage and marking, and adherence to geometric design standards be conducted.

Generally, it is recommended that the area should be provided with some countermeasures to help improve the performance of the two intersections during the drop-off
and pick-up times and to decrease the frequency of many observed conflicts in the school area (Figure 4.16).

The most important countermeasures are summarized below:

A. Paint crosswalk markings & install rapid flashing beacons at crosswalks to mitigate:
   a. Pedestrian-vehicle conflicts
   b. Pedestrian violations (i.e., jaywalking)

B. Paint lane markings to mitigate:
   a. Sideswipe conflicts
   b. Head-on conflicts
   c. Crossing conflicts

C. Installation of stop lines & stop bars to mitigate:
   a. Crossing conflicts
   b. Vehicle-pedestrian conflicts

D. Installation of high-visibility school zone signs & retroreflective poles to:
   a. Mitigate speeds
   b. Increase awareness of school zones

E. Review bus routes & bus stop locations to mitigate:
   a. Rear-end conflicts
   b. Sideswipe and head-on conflicts

F. Replace parking signs with no stopping signs; change the “No Loading” signs & improve enforcement to mitigate:
   a. Rear-end conflicts
b. Sideswipe and head-on conflicts

G. Left turn ban during pick-up & drop-off times to mitigate:

a. Left turn conflicts

Figure 4.16 Potential Countermeasures

In this chapter, automated video-based computer vision techniques were applied for safety analysis, diagnosis of safety issues, and recommending a list of countermeasures to improve the safety performance. Improving road safety and the development of sustainable transportation initiatives have been identified by the City of Edmonton as top priorities. The vicinity of Dr. Donald Massey School in Edmonton, Alberta was analyzed using video data and some recommendations were proposed to improve the safety performance of that area. The school is situated in a residential neighborhood on a main road (162\textsuperscript{nd} Avenue). The road
intersects with a set of local roads (55th Street and 54b Street). Concerns about the traffic and safety hazards were increasingly reported during the “drop-off” and “pick-up” times. Safety concerns were related to driving violations, illegal parking, as well as jaywalking. Concerns were also related to potential pedestrian-vehicle and vehicle-vehicle conflicts at the two main intersections in the school area, especially at the morning and afternoon peak hours. More than 120 hours of video data were collected in the fall season as well as 120 hours in wintertime to investigate the effect of some severe winter conditions on vehicles’ and pedestrian’s behavior and interactions.

Multiple angles were required to ensure as many conflict types as possible could be recorded and analyzed. The selection of camera angles is not a trivial task; automated tracking quality is largely dependent upon the ability to see individual road users clearly. In order to properly capture the traffic at all locations, it was proposed to install six cameras. Data is collected for the study on various days in September 2014 and January 2015. Data collection dates are consistent with typical traffic data collection standards (typical weekdays). The collection times of the study are taken in a time of the year when schools are in operation. The specific times and hours of data are chosen to match traffic and weather conditions as closely as possible. A total of two days of data are used for each dataset.

Upon a first review of the videos by traffic experts, several traffic safety concerns were identified. The prominent type of conflict in this school zone is the sideswipe conflict, especially in wintertime. This is likely because of the limited lane width. Additional issues seem to be of concern at this location. As an example, parking illegally on 162nd Avenue and 55th Street, which leads to very limited road width, as well as the size of the school bus and the public bus compared with the width of the street. Also, rear-end conflicts are observed in all the camera
views. It is observed that vehicles are spending a long time waiting to enter or exit the school because of limited parking space in the school vicinity. This is the main cause of rear-end conflict along with the sudden and frequent stoppage of the school bus and public bus. In addition, many conflicts between vehicles and pedestrians in and out of the crosswalk area are observed. The absence of clear stop signs, which forces the cars to stop and give the priority to vulnerable road-users, is likely a main reason for such a potential safety issue. Conflicts outside the crosswalk are attributed to jaywalking and crossing outside the crosswalk area. Yet, it is noted that there is no clear marking at the crosswalk to provide proper crossing guidance, demand for pick-up and drop-off areas seems to exceed the available facilities, and snow in the wintertime impacts accessibility. This is considered a major concern given the nature of the area which is full of school children who may or may not be supervised by a caregiver.

The total number and the ratio of each conflict type of the automatically-detected conflicts were investigated. For the fall data, the most prominent type of conflict is the rear-end conflict with a ratio of 43% of all the conflicts detected for the two days in the fall. The second highest type is the left turn-crossing conflict which constitutes 30% of all the fall events, then the vehicle-pedestrian conflicts at 18%, followed by the sideswipe and head-on conflict with ratios of 6% and 3%, respectively. For the winter data, the sideswipe conflict is the highest ratio, which is mainly because of the road dieting caused by the presence of snow during this time. The second highest type is the rear-end conflict at 27%, then pedestrian-vehicle conflict with a percentage of 23%. The last two types are head-on conflict and the left turn-crossing conflict with ratios 8% and 6%, respectively.

One proposed area of potential research is the safety evaluation at the same school site after the implementation of the proposed countermeasures. Another proposed research is,
comparing the safety performance of the intersections located in the school vicinity before and after the installed improvements. Also, a safety performance function (SPF) can be developed using the before-and-after conflict data in order to predict the hourly conflict rate at different intersection approaches in the vicinity of other schools areas.
Chapter 5: Case Study (B): Before/After Analysis for Traffic Signal Treatments, Edmonton, Alberta

The first section of this chapter describes the motivation and the objectives for the research, as well as the challenges, research contributions, and the study location. The second section presents the results of the analysis and a comparison between before-and-after the signal improvement. Section three presents a before-and-after safety evaluation using the Empirical Bayes method as well as the development of a safety performance function (SPF). Finally, section four provides the case study summary, conclusions, and future research.

5.1 Motivation and Objectives

The purpose of this study is to investigate the safety effectiveness of improving the signal head visibility at two signalized intersections located in the City of Edmonton, Alberta, by conducting a before-and-after safety evaluation. As part of efforts to systematically improve the safety performance at signalized intersections, the City of Edmonton, led by the Office of Traffic Safety, installed retroreflective tapes around the borders of traffic signal backplates on a number of signalized intersection approaches. A signal head equipped with a backplate and a retroreflective border is expected to be more visible and conspicuous in both nighttime and daytime conditions. The improved visibility is intended to reduce potential contributing factors involving unintentional red-light running. Two treatment and two control (untreated) intersections were identified and studied during the ‘before’ and ‘after’ periods in order to evaluate the effectiveness of the improved signal visibility.
The source of data in this study is from video sensors. Video data is rich in detail and recording equipment is not costly. The analysis in this study is based on traffic conflict observations. The traffic conflict approach has been used as a surrogate safety evaluation technique to conventional methods based on collision records.

One safety application that could significantly benefit from automated conflict-based road safety analysis is the before-and-after (BA) evaluation of safety countermeasures. The main target of BA safety studies is to measure the effectiveness of a certain treatment to improve the safety performance of the road. The conventional approach to safety evaluation relies mainly on estimating the reduction in the frequency of collisions. In order to draw statistically-stable conclusions, collisions are typically observed for long periods (1 to 3 years) before and after the introduction of the treatment. Despite the extensive development of collision-based safety analysis, the reliance on collision data for BA analysis has several shortcomings:

- **Attribution.** The information obtained by police reports and interviews often does not allow the attribution of road collisions to a single cause. It is sometimes difficult to pinpoint the failure mechanism that lead to a road collision.

- **Data Volume.** Despite the enormous social burden of road collisions, the frequency of road collision data is especially low. Drawing statistically-stable and significant inferences from such data is not easy.

- **Data Quality.** Collision records are often incomplete and lack details. The quality of road collision reporting has been deteriorating in many jurisdictions. Reporting is also biased toward highly-damaging collisions, while non-injurious collisions can go unreported.
• **Ethical Concerns.** While the object of road safety analysis is the reduction of road collisions, the analysis is typically based on the road collision as the main data unit. That is, collisions have to occur and be recorded over an adequately-long period in order to conduct a safety diagnosis.

The objective of this study is to investigate the effectiveness of the signal visibility improvement by observing rear-end and sideswipe traffic conflicts before-and-after the improvement at the Whitemud Drive and Gateway Boulevard and 170th Street and 100th Avenue intersections. Automated traffic conflict analysis of video data collected for two days before and two days after the treatment for each treatment and control intersection is used in the study.

5.2 **Summary of Findings**

This section provides summary statistics of the identified traffic conflicts and the results of the before-and-after safety evaluation of conflict frequency and severity.

5.2.1 **Traffic Conflict Statistics**

The conflict frequency distribution at the two treated intersections is shown in **Figures 5.1** and 5.2 for before and after the signal visibility improvement. The conflict frequency is plotted over a range of TTC values from 0 to 4 seconds for both rear-end and total conflicts, where total conflicts is represented by the sum of rear-end and sideswipe conflicts.
Figure 5.1 Conflict Frequency Distribution Over the Range of TTC from 0 to 4 Seconds of the Intersection 170100 for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)

Figure 5.2 Conflict Frequency Distribution Over the Range of TTC from 0 to 4 Seconds of the Intersection WhG for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)
Figures 5.1 and 5.2 show a decrease in conflict frequency after the implementation of the signal visibility improvement at both intersections. Figure 5.3 shows the conflict frequency per hour at the two treated intersections before and after the signal visibility improvement. The figure shows clear reduction in the conflict frequency per hour at both intersections after the treatment. Figure 5.4 shows the number of conflicts per exposure (defined as vehicle hours) at the two treated intersections before and after the signal visibility improvement. The figure also shows clear reduction in the conflict frequency per exposure at both intersections after the treatment.

Figure 5.3 Average Hourly Conflicts Frequencies Before and After Treatments
Figure 5.4 Frequency of Conflict Events per Average Hourly Volume (AHV) Before and After Treatments

- Total Conflicts
- Severe Conflicts

Figure 5.5 Distribution of Conflicts per Hourly Volume along the Hours of the Day of the Two Intersections Combined for Total and Severe Conflicts

Figure 5.5 shows the total conflict frequency by exposure and the severe conflict frequency by exposure for the two treatment intersections over the hours of the day combined for the two intersections. Overall, the figure shows a considerable decrease in conflict frequency and
rate after the signal improvement where it is clear that the pattern for the ‘after’ period is less than that of the ‘before’ treatment period.

Figure 5.6 Conflicts Frequency (Conflicts/m2) Heat Maps for the Two Scenes of the Site

(170100) Before and After the Treatment
Figure 5.7 Conflicts Frequency (Conflicts/m2) Heat Maps for the Two Scenes Combined of the Site (170100) Before and After the Treatment
Figure 5.8 Conflicts Frequency (Conflicts/m²) Heat Maps for the Two Scenes of the Site (WhG) Before and After the Treatment
Figure 5.9 Conflicts Frequency (Conflicts/m2) Heat Maps for the Two Scenes Combined of the Site (WhG) Before and After the Treatment

The spatial distribution of total conflicts is shown in Figures 5.6, 5.7, 5.8, and 5.9, using spatial conflict density heat maps. It is clear that there is a considerable reduction in the number of conflicts in the two camera scenes from before to after the improvement. This suggests a clear safety improvement for the two treated intersections. Most conflicts are rear-end conflicts due to the sudden stoppage of the vehicles as well as a small number of sideswipe conflicts due to lane changes.

5.2.2 Before-and-After Analysis with the Comparison Group Approach

In this case study, there are two control sites. Gateway Boulevard and 34th Avenue (G34) is a control site for the Whitemud Drive and Gateway Boulevard (WhG) intersection. The other site is Stony Plain Road and 170th Street (S170), which is defined as a control site for the second treatment site, 170th Street and 100th Avenue (170100). Figures 5.10 and 5.11 show the before-and-after AHC distributions at the control sites.
Figure 5.10 Conflict Frequency Distribution Over the Range of TTC from 0 to 4 Seconds of the Intersection (G34) for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)

Figure 5.11 Conflict Frequency Distribution Over the Range of TTC from 0 to 4 Seconds of the Intersection S170 for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)
The before-after safety evaluation with the comparison group approach uses the odds ratio to calculate the effectiveness of the safety treatment. The odds ratio is a relative statistical measure of the effect of an intervention by comparing the performance of treatment and comparison groups. This method is commonly used in many fields, such as medical science and road safety, for comparing the effect of a treatment to a comparison group. The odds ratio is defined as the change in the control site or group from before-to-after then divided by the change in the treatment site also from before-to-after.

\[
OR_i = \frac{A_i/C_i}{B_i/D_i}
\]  

(5.1)

Where

\[ A = \text{Condition at control site in the before period} \]

\[ C = \text{Condition at control site in the after period} \]

\[ B = \text{Condition at treatment site in the before period} \]

\[ D = \text{Condition at treatment site in the after period} \]

The control sites are used to represent the changes in conditions from before -to-after the intervention that would have been observed had no treatment taken place. An odds ratio of one denotes that all changes observed at the treatment sites are similar to the observed changes at the control sites, meaning that 100% of the changes in the treatment sites are due to non-treatment related factors. The treatment effect (TE) is the change in the observed traffic conflicts after accounting for the unrelated effects as measured using control sites. The TE is calculated simply, as shown in Equation 5.2:
This value represents the change in conditions of the treatment sites after implementing the countermeasure, taking into account the time-trend effects measured at the matching control sites. The percent reduction in conflicts is $100\% \times (TE)$

To get the combined treatment effect, the two intersections need to be aggregated in a weighted average manner and the statistical significance estimated.

Odds ratios are always positive, as there cannot be a negative number of collisions, which leads to a common assumption that they follow a lognormal distribution. The log of the odds ratio is used for the combining and weighting procedures. The variance is calculated on the assumption that conflicts are rare and random events and, therefore, follow a Poisson distribution. The standard error of the individual intersection’s log odds ratio ($SE_i$) is approximated as:

$$SE_i = \sqrt{\frac{1}{A_i} + \frac{1}{B_i} + \frac{1}{C_i} + \frac{1}{D_i}}$$ (5.3)
So that asymptotically:

\[ Z_i = \frac{\ln(OR_i)}{SE_i} \]  \hspace{1cm} (5.4)

The total treatment effect is found through a weighted average of the individual intersection results. Weighting is done according to the inverse variance of each intersection. The weighting factor for intersection ‘i’ is calculated as:

\[ w_i = \left( \frac{1}{A_i} + \frac{1}{B_i} + \frac{1}{C_i} + \frac{1}{D_i} \right)^{-1} \]  \hspace{1cm} (5.5)

The total log odds ratio is therefore defined as:

\[ \ln(OR) = \frac{\sum_{i=1}^{n} w_i \cdot \ln(OR_i)}{\sum_{i=1}^{n} w_i} \]  \hspace{1cm} (5.6)

If the weightings are proportional to the inverse of asymptotic variance, a standard normal distribution can be attained using **Equation 5.7**

\[ z = \ln(OR) \sqrt{\sum_{i=1}^{n} w_i} \sim N(0,1) \]  \hspace{1cm} (5.7)
The null-hypothesis, or the hypothesis of no treatment effect ($H_0$=OR=1), is rejected whenever the approximate tail probability of the standard normal probability density function is smaller than the significance level. The significance of the combined odds ratios for rear-end and total collisions is presented in Table 5.3 using the T-statistics that can be calculated using the following formula:

$$T = \frac{\ln(OR)}{SE}$$

This value will be compared with the same Z-value of 1.96 for a two-tailed test.

<table>
<thead>
<tr>
<th>Conflict Type</th>
<th>Reduction</th>
<th>T-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rear-End</td>
<td>24%</td>
<td>-2.35</td>
</tr>
<tr>
<td>Total</td>
<td>14%</td>
<td>-1.41</td>
</tr>
</tbody>
</table>

Table 5.1 Treatment Effect (in Percent Reduction of AHC) for all Intersections Aggregated Together

5.2.3 Reductions in Conflict Severity

The minimum time-to-collision (TTC) of each event can be mapped to a severity index (Figure 5.12) using Equation 5.9:

$$SI = e^{-\frac{TTC^2}{2PRT^2}}$$

(5.9)
Where SI is the severity index and PRT is the perception and braking reaction time, which is assumed to be 2.5 seconds. The severity index is a unitless measure of severity that ranges from 0 to 1, with 0 being uninterrupted passages.

Figure 5.12 Mapping from TTC to a Severity Index (SI)

Aggregation of the severity of all events is then conducted. Normalization is required to account for differences in the observation period and exposure from ‘before’ and ‘after’. The exposure measure used is the maximum theoretical number of events, which is the square root of the product of the hourly volumes for conflicting traffic streams.

\[
SI \text{ Rate} = \frac{SI}{Maximum \text{ Theoretical Exposure} \ (\text{millions})} \quad (5.10)
\]

The rear-end conflict exposure is calculated as the square root of the approach volume squared, which simplifies the approach’s volume. The sideswipe conflict exposure, similarly, is
the same as the rear-end conflict exposure. The total conflict exposure is the sum of the two exposure volumes (rear-end and sideswipe).

5.2.3.1 Severity Distributions

Figures 5.13 and 5.14 show the severity distributions of conflicts at the treated intersections (170100 and WhG), both before and after the treatments. Rear-end and total conflicts are displayed separately; total conflicts is the sum of rear-end and sideswipe conflicts. The frequency of conflicts, normalized to exposure, is shown in Figures 5.15 and 5.16 over severity values from 0.2 to one.

![Graph showing conflict frequency distribution over severity](image)

**Figure 5.13 Conflict Frequency Distribution Over a Range of Severity 0.2 to 1 of the Intersection 100170 for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)**
Figure 5.14 Conflict Frequency Distribution, Over a Range of Severity 0.2 to 1 of the Intersection WhG for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)

Figure 5.15 Conflict Frequency Distribution, Normalized to Exposure, Over a Range of Severity 0.2 to 1 of the Intersection 100170 for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)
Rear-end Conflicts          Total Conflicts

Figure 5.16 Conflict Frequency Distribution, Normalized per Exposure, Over a Range of Severity 0.2 to 1 of the Intersection WhG for both Before and After the Treatment for Rear-End and Total Conflicts (Rear-End and Sideswipe Conflicts Combined)

Figure 5.17 and Table 5.2 show the results of the average hourly conflict values and the average value of severity indexes for the two treated intersections. Generally, there is a decrease in the average severity index in the ‘after’ period of rear-end and total conflicts of site 170100 and the average severity of rear-end conflicts of site WhG. On the other hand, an increase in the average severity value of total conflicts of site WhG was found.
This section aims to strengthen the analysis of the before-and-after safety evaluation by using statistically-rigorous methodologies for before-after studies. The objective is to confirm whether traffic signal head improvements have, overall, decreased the number of conflicts at both intersections analyzed. In the previous section, the evaluation was carried out simply by comparing the number of conflicts observed before and after the improvements. However, traffic conflict data can be modeled, in a similar manner to crash data, as non-negative, discrete, and rare events. In doing so, it is possible to adopt and transfer the statistical methodologies based on collision frequency to conflict-based analysis. For instance, the analytical tools (regression models) for predicting the impact on road safety given traffic volume and site-
specific characteristics of the location, i.e., safety performance functions (SPFs), have been successfully developed using traffic conflict observations (El-Basiouny and Sayed, 2013; Sacchi and Sayed, 2015). This new stream of research is considered promising in road safety research as conflict-based SPFs represent a useful tool that can be used in a variety of road safety problems, such as before-and-after evaluations.

The use of statistically-rigorous techniques for before-after studies is also essential in evaluating safety countermeasures, as simple cause-and-effect relationships are rare in road safety. Usually, several other factors operate simultaneously and may influence the road safety performance. Therefore, the effect of these other factors should be separated from the treatment effect. These confounding factors include history, maturation, and the regression to the mean. History refers to the possibility that factors other than the countermeasure being investigated caused all or part of the observed change in collisions. Maturation refers to the effect of collision trends over time. The regression to the mean refers to the tendency of extreme events to be followed by less extreme values, even if no change has occurred in the underlying mechanism, which generates the process.

Hence, the methodology adopted in this section is based on the well-known Empirical Bayes (EB) method that corrects the regression to the mean effects, which is an important consideration in road safety analysis. The methodology also uses before-and-after conflict and traffic volume data for comparison groups to correct the history and maturation confounding factors.

5.3.1 Empirical Bayes Technique

The evaluation methodology employs the use of conflict-based safety performance functions (SPFs). As introduced before, conflict-based SPFs are mathematical models that relate the
conflict frequency experienced by a road entity to various traffic and geometric characteristics of this entity. The mathematical form, which is similar to collision-based SPFs, should, in general, satisfy the following two conditions: first, it must yield logical results, (i.e., no negative value in predicting the number of conflicts) and second, prediction of zero conflicts for zero value of the exposure variable, such as the hourly traffic volume (HTV). Therefore, the foundation model (for road segments or single approaches at intersections) can be written as per the following equation:

\[ E(\Lambda_i) = a_o V^{a_1} e^{a_i X_i} \]  

(5.11)

Where:

\( E(\Lambda_i) \) = predicted number of conflicts (typically conflicts per hour) for location \( i \)

\( V \) = Road traffic volume expressed as hourly traffic volume (HTV)

\( X_i \) = additional covariates added to the model which can explain traffic conflict occurrence

\( a_o, a_1, a_i \) : Model parameters

Since conflict data is nonnegative, discrete, random, and conflicts themselves are sporadic events, the generalized linear modeling (GLM) through the maximum likelihood method can be used to estimate model coefficients, where the negative binomial (NB) error distribution models the number of observed conflicts. In doing so, the variance of the expected conflict frequency is given as:

\[ Var(\Lambda) = \frac{E(\Lambda)^2}{\kappa} \]  

(5.12)

Where: \( \kappa \) is the negative binomial parameter of the SPF
In before-after studies using the EB method, the model in Equation 5.11 is developed using the before data for the reference group sites, as will be described later.

The reduction in the number of conflicts at the treatment sites can be calculated using the Odds Ratio \((O.R.)\), according to Equation 5.13. The effect of the treatment is determined by subtracting one from the O.R., as shown below in Equation 5.14.

\[
\text{OR}_i = \frac{A_i/C_i}{B_i/D_i} \quad (5.13)
\]

\[
\text{TE}_i = \text{OR}_i - 1 \quad (5.14)
\]

Where: \(A_i\) = the sum of the number of conflicts in the comparison group in the before period;

\(B_i\) = the EB safety estimate at the treatment site(s) if no treatment occurred;

\(C_i\) = sum of the number of conflicts in the comparison group in the after period;

\(D_i\) = sum of the number of conflicts in the treatment group in the after period.

It should be noted that all quantities in the odds ratio are observed quantities (with assumed Poisson distributions), with the exception of quantity \(B\), which is calculated. Therefore, the major work involved in evaluating the benefits of a certain treatment is determining the quantity \(B\). This quantity is calculated by using SPFs and the EB refinement procedure. The EB safety estimate and its variance for location ‘\(i\)’ are calculated using Equations 5.15 and 5.16 as follows:

\[
(EB_i)_b = \gamma_i \cdot E(\Lambda_i) + (1-\gamma_i) \cdot (y_i), \quad \text{VAR}(EB_i)_b = \gamma_i \cdot (1-\gamma_i) \cdot E(\Lambda_i) + (1-\gamma_i)^2 \cdot (y_i) \quad (5.15)
\]
\[ \gamma_i = \frac{E(\Lambda_i)}{E(\Lambda_i) + \text{VAR}(\Lambda_i)} = \frac{1}{1 + \frac{\text{VAR}(\Lambda_i)}{E(\Lambda_i)}} \]  

(5.16)

Where:

\( \gamma_i \) = A weight used to calculate the Empirical Bayes safety estimate for location \( i \);

\( y_i \) = The observed conflicts in the before period for location \( i \).

The value of \( B \) in the Odds Ratio, from **Equation 5.13**, is calculated by using **Equation 5.17** (Sayed et al., 2004) as follows:

\[ B = (EB_i)_a = (EB_i)_b \times \frac{E(\Lambda_i)_a}{E(\Lambda_i)_b} \]  

(5.17)

Where:

\( (EB_i)_a \) = The EB safety estimate of treated site \( i \) in the “after” period had no treatment taken place.

\( (EB_i)_b \) = The EB safety estimate of treated site \( i \) that occurred in the “before” period.

\( E(\Lambda_i)_a \) = The conflict frequency given by the SPF for treated site \( i \) using its traffic flows in the “after” period.

\( E(\Lambda_i)_b \) = The conflict frequency given by the SPF for treated site \( i \) using its traffic flows in the “before” period.

To get the expected value and variance of the odds ratio, the method of statistical differentials is used as follows:
By applying Equations 5.18 and 5.19 to the odds ratio as defined in Equation 5.13, the
following Equations 5.20 and 5.21 for the odds ratio can be obtained as follows:

\[
E\{Y\} = Y + \left[ \sum_{i}^{n} \left( \frac{\partial^2 Y}{\partial x_i^2} \right) \text{VAR} \{X_i\} \right] / 2 \tag{5.18}
\]

\[
E\{Y\} = Y + \left[ \sum_{i}^{n} \left( \frac{\partial^2 Y}{\partial x_i^2} \right) \text{VAR} \{X_i\} \right] / 2 \tag{5.19}
\]

5.3.2 Sample Data and Reference SPF

Data is required for three distinct groups of sites when completing a road safety evaluation with
the EB method:

- **Treatment Group Sites**: These are the two sites where the traffic signal head
  improvements took place (i.e., 170th Street & 100th Avenue, Whitemud Drive &
  Gateway Boulevard)

- **Comparison Group Sites**: This is the separate group of sites that have not been treated
  but are subjected to similar traffic and environmental conditions as the Treatment Group
  Sites (i.e., Gateway Boulevard & 34th Avenue, Stony Plain Road & 100th Avenue)
• **Reference Group Sites:** This is a large group of sites that are considered of similar character to the treatment sites and used to develop the collision prediction model used in the evaluation (only the before data is required for this group).

The details of the data required for the first two groups were provided in the previous sections. With regards to the third group, conflict-based SPFs developed from the reference group is used to correct the bias created by the regression to the mean and to determine the value of “B” in the odds ratio. However, no data from a reference population was available for this evaluation. Hence, a conflict-based SPF recently developed for signalized intersection approaches for Metro Vancouver was employed as a reference model (Sacchi and Sayed, 2015). Its functional form of the hourly conflict frequency is given by the following equation:

\[
E(\Lambda_i) = a_0 V^{a_1} e^{a_2 L} \tag{5.22}
\]

Where \(a_0\) is the intercept of the model, \(V\) is the hourly traffic volume, and \(L\) is the length of the area of the count of conflicts. The model was fitted using the negative binomial distribution and the resulting coefficients are given in **Table 5.3**.
Table 5.3 Parameter Estimates, Standard Deviations, and Percentiles for Reference SPF

(Sacchi & Sayed, 2015)

The model in Table 5.3 was based on rear-end conflicts only (mainly from braking, stopping events, or change of direction for multi-lane approaches), therefore, a recalibration of the SPF was carried out in order to apply it to the current dataset, which combines rear-end conflicts and a small portion of other conflict types. The more direct and easier alternative for a model’s calibration is suggested by the FHWA’s Highway Safety Manual (HSM, 2010). A calibration factor (CF) is multiplied by the original equation model to better suit local conditions, as per the following equation:

\[ E(\Lambda_r) = CF \ast \left( a_o V^{a_1} e^{a_2 L} \right) \]  \hspace{1cm} (5.23)

The CF was obtained as the total number of conflicts for the sample set (all conflicts in the ‘before’ period for treatment sites and all conflicts for the ‘before’ and ‘after’ periods for comparison sites) divided by the sum of the predicted conflicts for the sample, using the original model in Table 5.3. Thus, the value of the calibration factor is greater than 1 when there are more conflicts observed than are predicted by the predictive model. When there are fewer
conflicts observed than are predicted, the computed calibration factor will be less than 1. The results of the calibration process are shown in Table 5.4, where a CF equal to 0.43 was found.

<table>
<thead>
<tr>
<th>Number of conflicts/hour</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Observed</strong></td>
</tr>
<tr>
<td><strong>Predicted</strong></td>
</tr>
<tr>
<td><strong>CF</strong></td>
</tr>
</tbody>
</table>

Table 5.4 Calibration Factor Estimate

5.3.3 Odds Ratio Results

Table 5.5 shows the results of the EB safety evaluation. The results show a statistically-significant reduction of 24.5% in the average hourly conflict after the signal improvement.

<table>
<thead>
<tr>
<th>Conflict Type</th>
<th>Reduction</th>
<th>T-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
<td>24.50%</td>
<td>2.72</td>
</tr>
</tbody>
</table>

Table 5.5 Treatment Effect (in Percent Reduction of AHC), for the Two Treatment Intersections (EB Method)

5.4 Summary

In this chapter, another application of computer-vision safety analysis was introduced, a before-and-after safety evaluation was conducted to investigate the effectiveness of the installed retroreflective tapes around the borders of traffic signal backplates on a number of signalized intersection approaches. A signal head equipped with a backplate and a retroreflective border is expected to be more visible and more conspicuous in both nighttime and daytime conditions. The improved visibility is intended to reduce potential contributing factors involving unintentional
red light running followed too closely. Two treatment and two control (untreated) intersections were identified and studied during the ‘before’ and ‘after’ periods in order to evaluate the effectiveness of the improved signal visibility. As mentioned earlier, the source of data used in this chapter is from video sensors. Video data is rich in details and recording equipment is not costly. The analysis in this study is based on traffic conflict observations. The traffic conflict approach has been used as a surrogate safety evaluation technique to conventional methods based on collision records.

The first treatment site is the intersection of Whitemud Drive and Gateway Boulevard (WhG) and the second treatment intersection is 170\textsuperscript{th} Street and 100\textsuperscript{th} Avenue (170100). The first control site is the intersection of Gateway Boulevard and 34\textsuperscript{th} Avenue (G34); it is very close to the first treatment site (WhG). Similarly, the second control intersection is between Stony Plain Road and 170\textsuperscript{th} Street (S170), which is also located very close to (170100) and has very similar geometry. For all the treatment and control intersections, one intersection approach was selected and captured by two cameras. One camera was mounted in front of the approach and the second camera was located further back on the approach.

Results of a preliminary observation of the conflicts, before-and-after the signal implementation, represented by the heat maps, suggest that there is a considerable reduction in the number of conflicts in the two camera scenes from before to after the improvement. This suggests a clear safety improvement for the two treated intersections. Most conflicts are rear-end conflicts due to the sudden stoppage of the vehicles as well as a small number of sideswipe conflicts due to lane changes. By dividing conflict frequency per exposure of each type of conflict, results also show a considerable decrease in conflict frequency and rate after the signal
improvement, where it is clear that the pattern for the ‘after’ period is less than that of the ‘before’ treatment period.

The before-after safety evaluation with the comparison group approach uses the odds ratio to calculate the effectiveness of the safety treatment. Results show that the hourly average of the rear-end conflicts was reduced by 24% after the implementation of the improvements and the hourly average of the total conflicts (rear-end plus sideswipe) declined by 14%. For the conflict severity, generally, there is a decrease in the average severity index in the ‘after’ period of rear-end and total conflicts of site 170100 as well as in the rear-end conflicts of site WhG. On the other hand, an increase in the average severity value of total conflicts of site WhG was found.

The last section adopted a methodology based on the well-known Empirical Bayes (EB) method that corrects the regression to the mean effects, which is an important consideration in road safety analysis. The methodology also uses before-and-after conflict and traffic volume data for comparison groups to correct the history and maturation confounding factors. The evaluation methodology employs the use of conflict-based safety performance functions (SPFs). The results of this section show a statistically-significant reduction of 24.5% in the hourly average of the total conflicts (rear-end and sideswipe).
Chapter 6: Summary and Conclusions

6.1 Summary

The main objective of this thesis was to demonstrate different applications of automated video-based computer vision techniques in road safety diagnosis and to conduct before-and-after road safety evaluations. Two different case studies in the city of Edmonton, Alberta, Canada were presented and analyzed. In both case studies, the automated video analysis was applied to track moving objects (i.e. vehicles or pedestrians) and identify traffic conflicts using two time-based conflict indicators: the time-to-collision (TTC) and the post-encroachment-time (PET). The estimated conflicts were classified into different types (e.g. rear-end conflict, pedestrian-vehicle conflict). Subsequently, the frequency and the severity of different conflict types were determined. In addition, the conflict coordinates were shown using heat maps to identify hazard areas. Moreover, the automated video analysis was used in traffic counting and in identifying road-user violations.

The first case study covered in this thesis was to conduct an automated traffic safety diagnosis and to demonstrate automated data collection techniques in the vicinity of the Dr. Donald Massey School in Edmonton, Alberta. The school is situated in a residential neighborhood on a main road (162\textsuperscript{nd} Avenue) which intersects with a set of local roads. Concerns about the traffic and safety hazards were increasingly reported during the “drop off” and “pick up” times. Safety concerns were related to driving violations, illegal parking, as well as jaywalking. Concerns were also related to potential pedestrian-vehicle and vehicle-vehicle conflicts at the two main intersections in the school area, especially at the morning and afternoon peak hours.
In order to conduct safety diagnosis for the school zone, more than 240 video-hours of traffic data were recorded. The traffic data was collected in two different seasons, i.e., fall and winter, to investigate the effect of some severe winter conditions on vehicle and pedestrian behaviors and interactions. The collection times of the study were taken at a time of year when schools are in operation. The specific times and hours of data were chosen to match traffic and weather conditions as closely as possible. The video data was analyzed using automated video-based computer vision techniques to estimate traffic conflicts and violations. Based on the results of the analysis, several recommendations were presented that would potentially improve the safety along the study area.

The second case study was to investigate the safety effectiveness of improving the signal head visibility at two signalized intersections located in the City of Edmonton, Alberta, by conducting a before-and-after safety evaluation. As part of efforts to systematically improve the safety performance at signalized intersections, the City of Edmonton, led by the Office of Traffic Safety, installed retroreflective tapes around the borders of traffic signal backplates on a number of signalized intersection approaches. A signal head equipped with a backplate and retroreflective border is expected to be more visible and conspicuous in both nighttime and daytime conditions. The improved visibility is intended to reduce potential contributing factors involving unintentional red light running.

Two treatment and two control (untreated) intersections were identified and studied during the ‘before’ and ‘after’ periods in order to evaluate the effectiveness of the improved signal visibility. For all the treatment and control intersections, one intersection approach was selected and captured by two cameras. One camera was mounted in front of the approach and the second camera was located further back on the approach.
More than 300 hours of video data have been used for the two treated intersections, before and after the implementation of the signal improvements, in addition to 90 hours of video data of the two control sites before and more than 115 hours of the control sites after the signal improvement. Video data was analyzed using automated video-based computer vision techniques to estimate traffic conflicts before and after the treatment at all the treatment and control intersections. Heat maps of traffic conflicts, as well as the conflict frequency distribution, were developed. The before-after safety evaluation with the comparison group approach, which uses the odds ratio to calculate the effectiveness of the safety treatment, was conducted to account for the confounding factors such as history, maturation, and regression to the mean. In addition, the analysis included the adoption of a methodology based on the well-known Empirical Bayes (EB) method that corrects the regression to the mean effects. The applied EB methodology also uses before-and-after conflict and traffic volume data for comparison groups to correct the history and maturation confounding factors. The methodology employs the use of a calibrated conflict-based safety performance function (SPF).

6.2 Conclusions

In the first case study, several traffic safety concerns were identified. The prominent type of conflict in this school zone is the sideswipe conflict, especially in wintertime. This is likely because of the limited lane width. Additional issues seem to be of concern at this location. As an example, parking illegally in the 162nd avenue and 55th street, which leads to a very limited road width, as well as the size of the school bus and the public bus compared with the width of the street. Also, rear-end conflicts are observed in all the camera views. It is observed that vehicles are spending a long time waiting to enter or exit the school area because of limited parking space.
in the school vicinity. This is the main cause of rear-end conflict along with the sudden and frequent stoppage of the school bus and public bus.

In addition, many conflict events between vehicles and pedestrians in and out of the crosswalk area are observed. The absence of clear stop signs, which forces vehicles to stop and give priority to vulnerable road-users, is likely a main reason for such a potential safety issue. Conflicts outside the crosswalk are attributed to jaywalking and crossing outside the crosswalk area. Yet, it is noted that there is no clear marking at the crosswalk to provide proper crossing guidance, demand for pick-up and drop-off areas seems to exceed the available facilities, and snow in the wintertime impacts accessibility. This is considered a major concern given the nature of the area which is full of school children who may or may not be supervised by a caregiver.

The total number and the ratio of each conflict type of the automatically-detected conflicts were investigated. For the fall data, the prominent type of conflicts is the rear-end conflict, with a ratio of 43% of all the conflicts detected. The second highest type is the left turn-crossing conflict, which constitutes 30% of all the fall events, then the vehicle-pedestrian conflicts at 18%, followed by the sideswipe and head-on conflict with ratios of 6% and 3%, respectively. For the winter data, the sideswipe conflict is the highest ratio, which is mainly because of the road dieting caused by the presence of snow during this time. The second highest type is the rear-end conflict at 27% of the total number, then the pedestrian-vehicle conflict with a percentage of 23%. The last two types are head-on conflict and the left turn-crossing conflict with ratios of 8% and 6%, respectively.

In the second case study, results of a preliminary observation of the conflicts, before-and-after the signal implementation, represented by the heat maps, suggest that there is a considerable reduction in the number of conflicts from before to after the improvement. This suggests a clear
safety improvement for the two treated intersections. Most conflicts are rear-end conflicts due to the sudden stoppage of the vehicles as well as a small number of sideswipe conflicts due to lane changes. By dividing conflict frequency per exposure of each type of conflict, results also showed a considerable decrease in conflict frequency and rate after the signal improvement where it is clear that the pattern for the ‘after’ period is less than that of the ‘before’ treatment period.

The signal head improvement applied at the two treated intersections has resulted in a considerable reduction in rear-end and total conflicts. The combined reduction calculated by the treatment sites and control sites in an odds ratio for the two intersections was found to be approximately 14% and 24% for the average hourly of total conflicts and rear-end conflicts, respectively. The treatment effect estimated for the two treatment sites, normalized using the control sites, was found 24.5% for the hourly average of the total conflicts using the Empirical Bayes method. The results suggest the importance of using the EB method to refine the estimate of the treatment’s effectiveness.

Both case studies demonstrated the ability of computer vision techniques to automate the extraction of traffic conflicts from video data to overcome the shortcomings of the traditional manual conflict observation methods. The first case study illustrated the use of automated traffic conflicts to diagnose road safety at school zones. The second case study demonstrated the usefulness of using automated traffic conflicts in before-and-after safety evaluations. Traffic conflicts occur more frequently than collisions, allowing the desired sample size for analysis to be obtained in much shorter times. However, the linkage between traffic conflicts and traffic collisions needs to be clearly established before a wider application of the traffic conflicts technique is done.
6.3 Future Research

In the first case study, based on the previous analysis, several recommendations were presented that would potentially improve the safety for all road-users without affecting the mobility along the intersections. It should be noted that these recommendations are based only on the analysis of the video data. It is recommended that a more in-depth safety diagnosis, including a review of the collision data, capacity analysis, traffic signage and marking, and adherence to geometric design standards be conducted. After implementing the proposed recommendations, one proposed area of potential research is the safety evaluation of the school site by investigating the vehicle-vehicle and pedestrian-vehicle interactions. Another proposed research area is, comparing the safety performance of the intersections located in the school vicinity before-and-after the installed improvements. Comparison sites can also be combined in the before-and-after safety evaluation to account for the confounding factors. Also, an SPF can be developed using the before-and-after conflict data in order to predict the hourly conflict rate at different intersection approaches in other school areas.

Regarding the second case study, future work should focus on testing and validating the relationship between traffic conflicts and collisions. This will lead to a wider application of the traffic conflicts technique and a better understanding of the link between road safety, driver behavior, and dynamic traffic interactions. A comparison between the results of this study and a before-and-after evaluation using historical collision records should further strengthen the validity of the traffic conflict technique.
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