SAFETY DIAGNOSIS OF VEHICLE-BICYCLE INTERACTIONS USING COMPUTER VISION SYSTEMS: A CASE STUDY IN VANCOUVER, B.C.

by

Federico Martin Puscar

Lic. in Civil Engineering, University of Costa Rica, 2013

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE

in

The Faculty of Graduate and Postdoctoral Studies

(Civil Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

April 2017

Abstract

Active road users such as cyclists are usually subject to an elevated risk of collision. Therefore, there is a need for efficient techniques for evaluating the safety of active road users. Traditional road safety analysis has often been conducted using historical collision records. However, limitations associated with collision data have motivated the development of complementary proactive techniques for road safety analysis. Recently, there has been significant interest in using traffic conflicts to analyze safety which has been strengthened by the availability of automated traffic conflict analysis tools. This thesis demonstrates two applications of automated road safety analysis techniques using traffic conflicts.

The first application is a safety diagnosis of a major intersection in Vancouver, British Columbia, with bicycle and pedestrian safety issues. Automated video-based computer vision techniques are used to extract and analyze data from the video footage. Traffic conflict indicators, such as time to collision and post-encroachment time, are used to assess conflicts along the intersection to identify safety problems based on the frequency and severity of conflicts. Different spatial and temporal non-conforming behavior patterns are also analyzed. The diagnosis revealed that the Burrard Bridge's access and exit ramps are the main sources of conflicts at the intersection and their design encouraged many non-conforming behavior patterns. It can be expected that removing both ramps will address a significant amount of safety problems.

The second application covers detailed analysis of cyclist yielding behavior at the same intersection. Cyclist yielding behavior is evaluated by analyzing vehicle and bicycle yielding rates in two bicycle crossings with different rules of priority. Compliance with traffic regulations is also studied by looking at how intersections actually operate in contrast to the formal traffic rules. Results showed that bicycle yielding rates can change significantly depending on the crossing's configuration and legal right-of-way.

Low bicycle yielding rates in combination with consistent but relatively low vehicle yielding rates can present a safety problem: understanding cyclist yielding behavior can enable engineers to design and build safer intersections which are consistent with road users' expectations, and to develop more realistic models of traffic behavior, safety, and operations.

Preface

Portions of chapters 1, 2, 3, and 5 were presented in the technical report *Intersection Safety Diagnosis Using Automated Video Analysis: Application for the Intersection of Burrard St. and Pacific St. – Vancouver, British Columbia, Canada* (Puscar, Sayed, Bigazzi, and Zaki, 2016), delivered to the representatives of the City of Vancouver in November, 2016. Moreover, these portions are to be used in a journal article to be submitted for publication. The expected title for the article is *Assessment of Bicycle Safety Improvements with Automated Traffic Conflict Analysis* (Puscar, Sayed, Bigazzi, and Zaki, 2017). I was responsible for the manual observation analysis, the results' interpretation and discussion, and wrote most of the manuscript.

Portions of Chapter 4 are to be used in a journal article to be submitted for publication. The expected title for the article is *Analysis of Cyclist Yielding Behavior at Intersections* (Puscar, Sayed, Bigazzi, and Zaki, 2017). I was responsible for developing the methodology to conduct the analysis, the results' interpretation and discussion, and wrote most of the manuscript.

The methodology in Section 3.2 is taken from previous work done by the Transportation Research Group at the University of British Columbia (Sayed, Zaki, and Autey, 2013, Essa, 2015, Reyad, 2016, and Zaki and Sayed, 2016b). The steps necessary to conduct an automated road safety diagnosis, presented in sections from 3.2.1 to 3.2.5, as well as the software programming to conduct the counting and speed validations from sections 3.3.1 and 3.3.6, respectively, were done by Dr. Mohamed H. Zaki. Reviewers of the written manuscript were Dr. Tarek Sayed, Dr. Alexander Bigazzi. Video footage was provided by the Engineering Services Department of the City of Vancouver, represented by Liliana Quintero.

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Acknowledgments

I will be forever grateful to my professors, Dr. Tarek Sayed and Dr. Alexander Bigazzi, for giving me the opportunity to pursue my graduate studies at the University of British Columbia. Their support and guidance throughout the program were remarkable. Their wisdom and teachings, combined with the professional mentorship of Dr. Jonathan Aguero, Dr. Luis Guillermo Loria, Erick Acosta, and Manuel Martinez, are the reason why I am here today. I would also like to thank the wonderful people at the Transportation Research Group of the University of British Columbia for their collaboration and support during the time I spent as a Graduate Research Assistant. A special mention to Dr. Mohamed H. Zaki, who worked side-by-side with me since the very beginning of the research and proved to be an excellent mentor.

I could not have done it without the support from the people I care most about in the world. My beloved wife, Kris, who from the very first day believed in me and supported me in this new adventure. I will never be able to repay her enough for all she has done for me. She was, is, and will be my motivation to give my best. My dear family: Fabio, Estela, Julian, and Candela, as well as the rest of my family back in Argentina, who encouraged me to follow my dreams and never give up. They have always given me the strength I needed to succeed in each and every one of my goals. Last but not least, to my close friends in Argentina, Costa Rica, and Canada, particularly the ones who helped me get through my studies at UBC. Friends are the family you choose. Thank you for always making me feel at home.

Dedication

In loving memory of my grandfather, David Puscar.

1. INTRODUCTION

1.1 Challenges of road safety

Mobility and accessibility are demanded by a society which generally underestimates the safety problems associated with modern transportation. According to the World Health Organization (2015), road collisions are the world's leading cause of preventable death. Over 1.25 million people die every year on the roads because of traffic collisions, and traffic injuries have become the number one cause of death among people aged between 15 and 19 years old. The World Health Organization further states that traffic collisions represent an economic burden, as road traffic casualties in low- and middle-income countries are estimated to generate costs equivalent to up to 5% of the nation's GDP, and 3% of the GDP worldwide. In Canada, is calculated by willingness-to-pay that each traffic-related fatality costs over $CAN 5.2 million, while a major injury costs $CAN 1.2 million (de Leur, Thue, and Ladd, 2010).

Non-motorized modes of transportation are subject to higher safety risks, as cyclists and pedestrians are more vulnerable road users than drivers because of they lack sufficient protection in case of collision with a motor vehicle. According to Transport Canada (2011b), pedestrians and cyclists accounted for 15% of road fatalities between 2004 and 2008. Similar numbers are shown in studies conducted in the United States (U.S. Department of Transportation, 2010), stating that pedestrian and cyclists accounted for 14% of road fatalities in 2008.

As a response to road safety issues, different agencies started to get involved in promoting road safety. Global campaigns such as the *Decade of Action for Road Safety 2011-2020* (UN, 2010) and *Vision Zero* (Whitelegg and Haq, 2006), as well as Canadian initiatives such as the *Road Safety Strategy 2025* (CCMTA, 2016), are examples of current multidisciplinary efforts in road safety, setting directions and targets for future research and developments to reduce traffic collisions.

In Canada, traffic-related fatalities and injuries have decreased over the last 20 years. From 1995 to 2014, road-related fatalities went down by 45% while serious injuries went down by 52%, as illustrated in Figure 1-1 and Figure 1-2, respectively (Transport Canada, 2016). Despite these reductions, there is still potential to further decrease the number of collisions by developing solutions in areas such as road safety management, safer roads, vehicles, and facilities, and improving post-collision response and hospital care (UN, 2010).

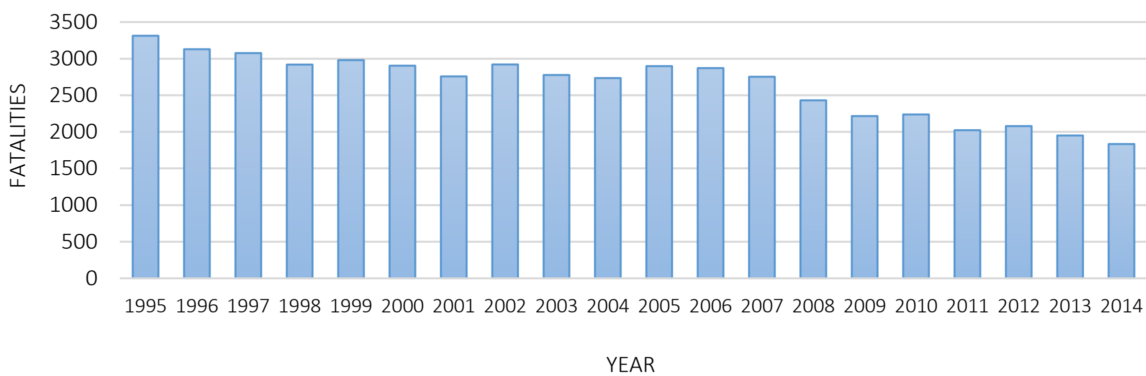

Figure 1-1 Fatalities (include all those who died as a result of a reported traffic collision within 30 days of its occurrence) per year in Canada. Source: Transport Canada, 2016.

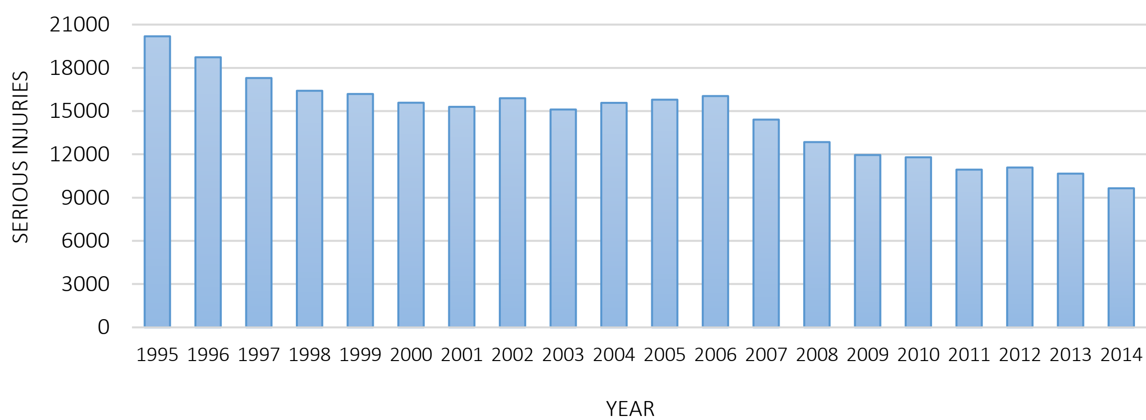

Figure 1-2 Serious injuries (include persons admitted to hospital for treatment or observation) per year in Canada. Source: Transport Canada, 2016.

1.2 Improving cycling safety in urban areas

As a transportation mode, cycling provides benefits for both its users and society, such as increases in physical activity and decreases in environmental pollution (Buekers, Dons, Elen, and Int Panis, 2015). There has been an increase in bicycle mode share in urban areas (Transport Canada, 2011a), while mid- and long-term targets are being set to shift the mode share even further towards active transportation (City of Vancouver, 2015a). However, encouraging cycling mode share has its challenges. Traditionally, streets are designed for motorized vehicles and sidewalks are designed for pedestrians. In contrast, bicycle-exclusive facilities are a responsibility that not all cities can provide. Cyclists often face the need to ride on the street due to the lack of bicycle-exclusive facilities. A study by Pulugurtha and Thakur (2015) concluded that cyclists are three to four times at higher risk when riding on streets without bicycle lanes than on streets with bicycle lanes, because of an increase in cyclist exposure to motor vehicle traffic in the later scenario.

Increasing cycling mode share in urban communities needs to be complemented by the development of bicycle-friendly facilities that can provide safe, efficient, and comfortable cycling. A report by Vijayakumar and Burda (2015) analyzed cycling statistics in urban areas of major Canadian cities (Toronto, Montreal, Vancouver, Ottawa, and Calgary), concluding that Vancouver has the highest cycling mode share with 4% while having the lowest bicycle collision rate (less than 1 bicycle collision per 100,000 bicycle trips). In contrast, cities like Montreal and Toronto have as much as 6 and 5 bicycle collisions per 100,000 bicycle trips, respectively. Is important to notice that collision data involving bicycles might be less accurate than collision data involving motor vehicles, as bicycle collisions may go underreported in police reports (Schramm, Rakotonirainy, and Haworth, 2010).

The implementation of the plan Transportation 2040 (City of Vancouver, 2015a) provides a local example of improving cycling safety in urban areas. The plan sets a mode share target that at least twothirds of all the trips in the city are to be done by waliking, cycling, or transit by 2040. To achive this target, the City of Vancouver is focusing on building cycling infrastructure that meets the needs of mobility, accessibility, and safety. Several upgrades are to be made to the cycling network in Downtown Vancouver. The northeast end of the Burrard Bridge (Burrard St. and Pacific St. intersection), which accounted for 1.4 million bicycle trips in 2015 (City of Vancouver, 2015a), will be one of the first locations to be interveined. Thus, a road safety diagnosis is required to assess the effectiveness of the developed safety upgrades.

1.3 Yielding behavior in vehicle-bicycle intersections

By understanding yielding behavior of drivers and cyclists, it is possible to design and build safer intersections and to develop more realistic models of traffic behavior, safety, and operations. At unsignalized vehicle-bicycle intersections governed by priority rules, the interactions between drivers and cyclists are often based on expectations and assumptions (Silvano, Ma, and Koutsopoulos, 2015). However, these expectations and assumptions can be sometimes wrong (Bjorklund and Aberg, 2005), as road users can fail to detect other road users in proximity, resulting in a failure to give the right-of-way.

One challenge of studying yielding behavior is the lack of a well-established definition of yielding. Definitions and recommendations can be found in driver and cyclist handbooks, in which transportation agencies (City of Vancouver, 2004, City of Toronto, 2014, and Ministere des Transports du Quebec, 2014) use a legal approach to define who has the right-of-way under different circumstances, without clearly defining what yielding the right-of-way is.

Legal right-of-way does not necessary define yielding behavior. According to Bjorklund and Aberg (2005), if formal traffic rules (i.e. signage) are unclear or counterproductive, road users may use informal traffic rules to address who has the right-of-way. Bjorklund and Aberg also concluded that informal rules may vary depending on the road design and road user's behavior. Thus, a separation between who has the legal right-of-way and who is yielding is required. Although research on driver yielding behavior at vehicle-pedestrian and vehicle-bicycle intersections has taken its first steps (Salamati, Schroeder, and Geruschat, 2013, Svensson and Pauna-Gren, 2015, and Silvano, Koutsopoulos, and Ma, 2016), cylist yielding behavior is yet to be studied.

1.4 Traffic conflict techniques

In the field of transportation engineering, road safety often refers to the number of collisions, by type and severity, at a particular location during a specific period of time. Road safety studies focus on understanding safety-related issues by analyzing collision reports and geometric and functional characteristics of a transportation facility, with the objective of identifying collision-prone locations and proposing effective countermeasures.

However, collisions are "rare and random events" (AASHTO, 2010). Since collision frequencies are variables of stochastic nature, the observed collision frequency throughout a period of time should be considered as only one realization (Sacchi, Sayed, and de Leur, 2013). Thus, the collision frequency alone is not a reliable measure of road safety. Sayed and Zein (1999) explained that the use of collision records for road safety studies constitutes a reactive approach because it requires for a significant amount of collisions to be recorded before the analysis can be conducted. Moreover, the lack of detailed and accurate collision data is a recurrent limitation in collision-based studies (Sayed, Ismail, Zaki, and Autey, 2012).

As alternative approaches to evaluate road safety become available, researchers are given the opportunity to analyze road safety from a broader perspective than collision statistics alone (Sayed and

Zein, 1999), enhancing the accuracy and reliability of safety diagnosis. Traffic conflict techniques or TCTs (Perkins and Harris, 1968) are based on observing, recording, and evaluating traffic conflicts at a location, which combined with automatization, can provide considerable benefits for safety studies over traditional collision-based methods.

While collision data tend to cover more severe and rare events, the use of conflict data enables the analyst to capture a wider spectrum of interactions that otherwise would be omitted (Chin and Quek, 1997). Moreover, traffic conflict indicators can be used to assess conflicts in an objective and accurate manner. Time to collision (TTC) (Hayward, 1968) and post-encroachment time (PET) (Cooper, 1983), among other conflict indicators, are often used to determine the severity of a conflict. It was demonstrated that automating the extraction of traffic conflicts from video footage can provide additional benefits for traffic conflict analysis, and overcome many of the shortcomings of manual traffic conflict techniques (Sacchi, Sayed, and de Leur, 2013).

1.5 Computer vision-based safety evaluations

Video footage can provide valuable data for road safety evaluations, with the advantage of being relatively cheap and permanently available for future use. By recording movement patterns at points of interest (e.g. intersections, roundabouts, crosswalks, etc.), safety evaluations can be conducted. Computer vision systems allow for the automated extraction of road user information (i.e. position and speed) as it moves through the field of view of video cameras (Ismail, 2010). By automating the process to detect, track, and classify road users, traffic conflict analysis using computer vision systems can be more accurate, objective, and cost-efficient than traditional manual-based traffic conflict techniques (Sayed, Ismail, Zaki, and Autey, 2012). Moreover, computer vision can be used to assess non-conforming behavior (i.e. traffic violations), by identifying movement patterns that disobey or ignore traffic regulations (Zaki and Sayed, 2014).

The Transportation Research Group of the University of British Columbia is working continuously to improve its computer vision system based on video sensors and MATLAB-based software (Ismail, 2010, and Essa, 2015). The objective of this system is to enable analysts to assess traffic conflicts and violations of vehicles, bicycles, and pedestrians. Computer vision techniques have proved their accuracy and feasibility over manual field and video observation techniques to conduct road safety studies (Sayed, Ismail, Zaki, and Autey, 2012, and Sacchi, Sayed, and de Leur, 2013).

1.6 Research objectives

The first objective of this research is to demonstrate the capabilities of automated road safety analysis techniques using traffic conflicts by conducting a safety diagnosis for the Burrard St. and Pacific St. intersection, in Vancouver, British Columbia. Through a conflict-based safety evaluation, safety risks will be identified: traffic conflicts and violations will be assessed for vehicles, bicycles, and pedestrians. Since the City of Vancouver will develop several improvements for normalizing the intersection, the results of the diagnosis are to be compared to the planned improvements, providing qualitative expectations for the upgrades' effectiveness. The safety diagnosis is to be used as the *before* analysis of a before-and-after study. The results of the *before* analysis will provide a benchmark upon which the conflict frequency and severity found in the *after* analysis can be compared.

The second objective is to study cyclist yielding behavior in vehicle-bicycle interactions, by analyzing vehicle and bicycle yielding rates and cyclist compliance with traffic regulations. The video footage obtained from Burrard St. and Pacific St. intersection presents a good opportunity to study cyclist behavior under different rules of priority. A who-yields-to-whom analysis is to be conducted to provide a better understanding of the dynamics of vehicle-bicycle interactions, including cyclist probability to yield, conflict severity as result of bicycle-yielding, cyclist compliance to stop signs, cyclist use of hand gestures, and cyclist swerving maneuvers when facing a blocked intersection.

1.7 Thesis structure

The thesis is composed of five chapters. Chapter 1 includes the introduction to the different topics studied along the research, the research objectives, and the thesis structure.

Chapter 2 is a literature review covering traffic conflict techniques, computer vision systems, and cyclist behavior at intersections.

Chapter 3 describes the study location, methodology, and results of the safety diagnosis conducted at the Burrard St. and Pacific St. intersection.

Chapter 4 describes the methodology developed to classify vehicle-bicycle yielding interactions and the resulting yielding rates. A model is proposed to estimate cyclist probability to yield at the intersection. Conflict severity is evaluated as result of vehicle and bicycle yielding. Additional cyclist behavior elements, such as stop sign compliance, use of hand gestures, and swerving maneuvers, are also studied.

Chapter 5 closes the thesis by summarizing the conclusions of the thesis and introducing the limitations of the study, recommendations, and potential for future work.

2. LITERATURE REVIEW

2.1 Traffic conflict techniques

2.1.1 Moving from collision-based to traffic conflict-based safety studies

Traffic conflicts or near-misses are a complementary proactive approach to traditional collision-based road safety evaluations (Sayed and Zein, 1999). The concept was first introduced by Perkins and Harris (1968), as a method to identify evasive maneuvers and evaluate vehicle design flaws. A traffic conflict definition is given in Amundsen and Hyden (1978), 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*."

Using traffic conflicts as a surrogate for traffic collisions helps to overcome some challenges in collision-based safety evaluations, such as statistical problems arising from the lack of precision in the collision database, infrequent collision occurrence, and small size of collision sample statistics (Brown, 1994). Furthermore, the study of traffic conflicts can provide detailed data about recurrent actions and patterns that contribute to a collision occurrence (Ismail, 2010).

Despite the improvements made in state-of-the-art statistical techniques to conduct collision-based safety studies (Aguero-Valverde and Jovanis, 2009, and El-Basyouny and Sayed, 2009), the use of traffic conflict techniques can provide similar results without the limitations associated with collision-based studies. A study by Sacchi, Sayed, and de Leur (2013) supported the use of traffic conflict techniques by conducting a safety evaluation using two different approaches: a conflict-based before-and-after study and collision-based Full Bayes analysis. The authors concluded that there was a remarkable similarity between the overall results in conflicts and collisions.

2.1.2 Benefits of traffic conflict techniques

Higher event frequencies can be obtained by accounting for a more diverse variety of traffic interactions than by limiting the study exclusively to collision events. Since more events are included in the analysis, periods of observation required to gather sufficient data for the analysis can be shortened. These accountable events or traffic interactions are explained in the work of Chin and Quek (1997). The authors based their work on a previous study by Hyden (1987) to develop a hierarchy system to classify traffic interactions, presented in Figure 2-1. Chin and Quek explained that traffic interactions can be ranked by their frequency and severity in a hierarchy (i.e. pyramid) system, and it is assumed that every event can be classified in a particular level of the pyramid. The frequency of events in the pyramid increases from the top to the bottom, while the severity of the events increases from the bottom to the top. Even though fatalities, injuries, and damage-only events can be identified in a relatively straightforward manner, classifying the severity of events into the other levels may require the use of additional information, such as traffic conflict indicators.

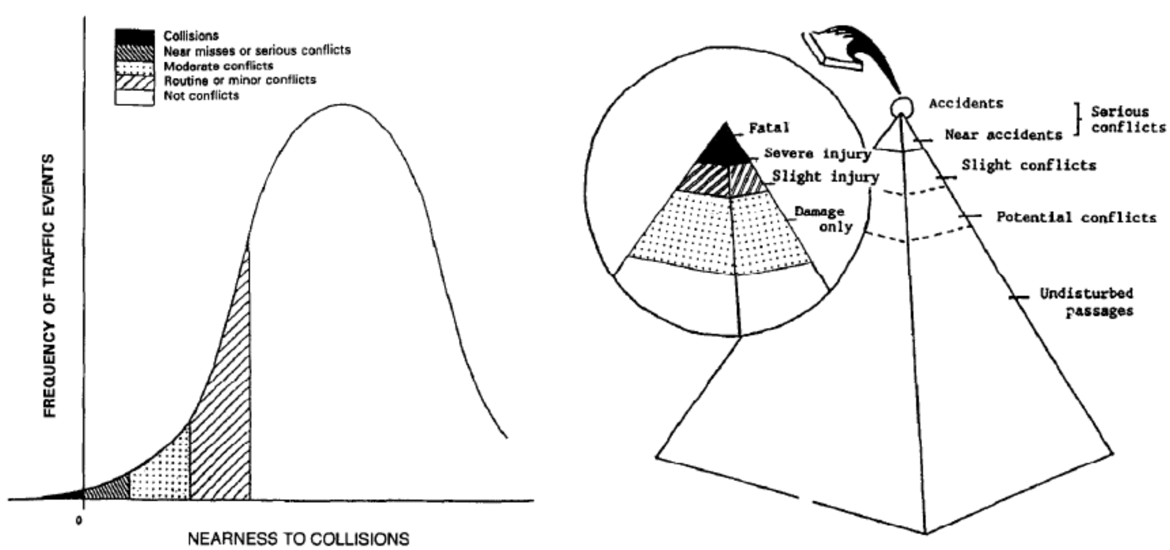

Figure 2-1: Frequency of traffic events (left) and the road safety pyramid – hierarchy of traffic events (right). Source: Chin and Quek, 1997.

Traffic conflicts can provide detailed information about the dynamics of road user interactions as it allows the analyst to observe the series of events that lead to the collision, allowing for a more comprehensive analysis than when using collision data alone. A study by Brown (1994) stated the convenience of using traffic conflict techniques over traditional collision-based studies, including: better control of the sample size, randomness, and information content by survey design.

2.1.3 Challenges of traffic conflict techniques

The usability, reliability, and validity of traditional manual traffic conflict techniques have been challenged and are a source of concern among researchers (Shinar, 1984, Chin and Quek, 1997, and Archer, 2001). Despite many decades of progress in the field, there is no universal operational definition of a traffic conflict, the validity of conflict techniques is judged by the adequacy in the correlation between conflict counts and accident records, and the subjectivity among observers challenges the reliability of conflict assessments (Ismail, 2010). In addition, conducting field observations and training observers can be expensive. The feasibility of traditional methods to collect traffic conflict data is addressed in the work of Sayed, Ismail, Zaki, and Autey (2012).

2.1.4 Use of traffic conflict indicators

Traffic conflict indicators are quantitative measures of the "*closeness of a conflicting pair of road users*" (Ismail, 2010) or the "*nearness to collision*" (Chin and Quek, 1997). By providing an objective measurement of a conflict's severity, conflict indicators can help to overcome the subjectivity limitations of traditional manual traffic conflict techniques. Despite their usefulness, conflict indicators are not exempted of challenges, as many of them rely on extrapolation of road user positions (Saunier and Sayed, 2008) or fail to differentiate the severity depending on the type of the involved road users (Ismail, 2010).

Many conflict indicators have been developed in the last 50 years, including: *time to accident* (Hyden, 1987), *time to collision* (Hayward, 1968), *extended time to collision* (Minderhoud and Bovy, 2001), *time to zebra* (Varhelyi, 1996), *post-encroachment time* (Allen, Shin, and Cooper, 1978), *gap time* (Archer, 2004), and *deceleration to safety time* (Topp, 1998). From these indicators, time to collision and post-encroachment time are often used to conduct traffic conflict analysis, as seen in previous road safety evaluations (Sayed, Zaki, and Autey, 2013, Hussein, Popescu, Sayed, and Kim, 2015, and Zaki and Sayed, 2016b). A comprehensive summary of the different indicators is provided in the work of Brown (1994) and Tarko, Saunier, Sayed, Davis, and Washington (2009).

The time to collision (TTC) (Hayward, 1968) conflict indicator is defined as "*the time until a collision will occur if the two conflicting vehicles continued on the same path at their current speed*" (Zaki and Sayed, 2016b). The drawbacks of the TTC indicator are given in the work of Ismail (2010), including that TTC requires road users to be on a collision course (i.e. projected collision course) and does not account for the speed of the impact nor the length of the interaction. The post-encroachment time (PET) (Cooper, 1983) conflict indicator is defined as "*the time difference between the moment an offending road user passes out of the area of possible collision and the moment a conflicted road user arrives at the area of possible collision*" (Zaki and Sayed, 2016b). The drawbacks of the PET indicator are given in Ismail (2010), including that PET does not account for continuous speed and distance measurement, lacks a clear definition of the right-of-way infringement, and has limited ability to comprehend the severity of interactions between motor vehicles and vulnerable road users.

2.1.5 Traffic violations as complement of traffic conflict techniques

The frequency of non-conforming behavior (i.e. traffic violations) is an important indicator of road safety. A study by Zhang, Yau, and Chen (2013) evaluated human, vehicle, and environmental risk factors to study the relationship between traffic violations and collisions frequency and severity, concluding that a decrease in traffic violations will have a positive impact in road safety. Traffic violations occur when road users disobey traffic regulations (Ismail, 2010), which may happen consciously by seeking an increase in mobility or unconsciously by ignorance of traffic regulations. Traffic violations can be used as surrogates measures of road safety in cases where collisions and conflicts are assumed to be attributable to non-conforming behavior. According to Zaki and Sayed (2014), detecting and understanding non-conforming behavior can be beneficial in identifying movement patterns or flawed design elements that may be causing safety deficiencies.

Two types of violations are considered in conflict-based safety evaluations: spatial violations and temporal violations. A spatial violation occurs when a road user is detected outside its designated area (e.g. pedestrians crossing a street outside of the crosswalk) and a temporal violation occurs when a road user is detected inside its designated area but during an improper moment in time (e.g. pedestrians crossing on the crosswalk during red light) (Zaki and Sayed, 2014). In addition, compliance with traffic signage and rules of priority (e.g. failure to stop at a stop sign or failure to give the right-of-way at a yield sign) may also be studied in a non-conforming behavior analysis (Fraboni, Puchades, De Angelis, Prati, and Pietrantoni, 2016).

2.2 Computer vision systems

2.2.1 Computer vision systems for data collection

Computer vision systems can be used for automated data collection and to support traffic conflict studies. A definition of computer vision is given in the work of Ballard and Brown (1982), as "… *the enterprise of automating and integrating a wide range of processes and representations used for vision perception … such as image processing, statistical pattern classification, geometric modeling, and cognitive processing*."

Traffic data collection can be conducted using manual field observations, manual video observations, and automated or semi-automated computer vision techniques, among other approaches (Zaki and Sayed, 2016b). Manual field observations, which are used for traffic counts and measurements, is expensive and time-consuming. Diogenes, Greene-Roesel, and Arnold (2007) concluded that manual field counts tend to underestimate road user volumes, depending on the observer's level of attention, motivation, and characteristics. The same authors also indicated that video data should be used mostly in situations in which the accuracy of the measurements is of primary importance.

The introduction of manual video observations, which is supported by the use of video cameras, helped to increase the feasibility and reliability of collecting data, and enabled the creation of a video database for future analyses (Ismail, Sayed, and Saunier, 2013). Video methods are more important as data collection becomes a more complex task (Greene-Roesel, Diogenes, Ragland, and Lindau, 2008). However, manual video observation methods are not able to address some of the shortcomings of manual field observation methods, as they can be labor-intensive and time-consuming (Zaki, Sayed, and Cheung, 2013) and the scope and accuracy of data collection still relies on human observers.

Computer vision systems enable automated and semi-automated methods of traffic data collection. The use of computer vision systems for data collection has gained acceptance and has become more frequent with the introduction of more advanced technologies, as it overcomes many of the shortcomings encountered in manual video observation processes (Zaki and Sayed, 2016b). The key in computer vision systems is the use of a frame-by-frame tracking system to identify and classify different road users, based on the road user's location, movements, and attributes (Zaki and Sayed, 2016a).

Computer vision-based semi-automated methods use image processing tools to support manual tracking of road users (Lam and Cheung, 2000, and AlGadhi and Herman, 2002). There are advantages of semi-automated methods over field and video manual observation methods, including: allowing a more accurate microscopic analysis of traffic flow characteristics, extracting more diverse complementary data, accounting for the road user’s position in a frame-by-frame manner, and decrease the resources required for the survey (Zaki and Sayed, 2016b). However, for large sample sizes, semi-automated methods can still be labour-intensive.

Computer vision-based automated methods give the analyst the opportunity to automate road user tracking and classification, providing a significant benefit over manual or semi-automated methods by reducing the resources required for long-term monitoring. Relying completely in automated methods is recommended for projects in which the accuracy of data collection is not critical (Zaki and Sayed, 2016b), as automated tracking-related issues such as over-segmentation, over-grouping, and miss-detection may limit the ability to properly detect road users continuously across the camera’s field of view. Feasibility of using computer vision-based automated methods is studied in the work of Sayed, Ismail, Zaki, and Autey (2012), supporting its use for before-and-after studies and demonstrating the capabilities of computer vision systems for traffic conflict analysis. Despite the realtively high costs associated with equipment acquisition, analyst trainging, and implementation, labor costs and efforts associated with data collection can be substantially reduced (Zaki and Sayed, 2016b).

Still, computer vision-based automated and semi-automated methods have their limitations. According to Ismail (2010), issues associated with the use of video cameras in automated and semi-automated methods for data collection are yet to be addressed. These issues include: visual occlusion caused by fixed objects or by other road users, varying user appearance (shapes, colors, and movement patterns), camera quality, camera location (e.g. height, direction, and angle in relation to the road user’s movement), illumination variation, shadow handling, distance to the recorded user, among others.

2.2.2 Computer vision systems for traffic conflict analysis

Besides the benefits for data collection, computer vision also offers the opportunity to conduct safety diagnostic studies in an efficient manner. The use of computer vision techniques for traffic conflict analysis has been the subject of extensive work in recent years (Autey, 2012, Battiato, Farinella, Giudice, Cafiso, and Di Graziano, 2013, Sayed, Zaki, and Autey, 2013, St-Aubin, Saunier, and Miranda-Moreno, 2015, and Reyad, 2016), showing the benefits of video monitoring of conflict events and providing insights into the factors contributing to collisions and overcome many of the shortcomings observed in manual traffic conflict techniques (Sacchi, Sayed, and de Leur, 2013). Computer vision techniques can be used to analyze accurate microscopic road user positions to infer macroscopic road safety deficiencies (Zaki and Sayed, 2016b). One of the benefits of using of computer vision techniques for traffic conflict analysis is the objective measurement of conflict indicators. With computer vision, TTC and PET values can be extracted from video data in an automated manner, minimizing the effects of observer's subjectivity.

Furthermore, computer vision can be used for the automated detection of traffic violations, complementing the traffic conflict analysis. To improve traffic enforcement cameras, a system for automated traffic violation detection was proposed to classify violations into four types: red light running, lane violation, stop line violation, and speed violation (Lim, Choi, and Jun, 2002). In Vijverberg, de Koning, Han, de With, and Cornelissen (2007), a region-based tracking system selectively updates the background to increase the accuracy of detections, especially when users stand still for extended periods of time (e.g. when there are traffic signal at intersections). In Zhang, Gao, and Liu (2009), a lane-crossing violation detection system was implemented through a mixture of Gaussian methods. Case studies of the use of computer vision techniques for automated detection of traffic violations can be seen in the work of Zaki and Sayed (2014), Hussein, Popescu, Sayed, and Kim (2015), and Zaki and Sayed (2016b).

2.3 Cyclist behavior studies for vehicle-bicycle interactions

2.3.1 Cyclist behavior at intersections

Traditionally, research on travel behavior analysis was focused mostly on motorized modes of transportation, such as private vehicles, public transit, and freight, as cyclist behavior was relatively understudied by most researchers (Algers, et al., 1997). The rapid increase in cycling mode share has served as motivation for researchers to start inquiring in cyclist behavior research. Understanding cyclist behavior at intersections is fundamental to increase cyclist comfort and safety on mixed traffic facilities (Mantuano, Bernardi, and Rupi, 2016).

Safety-related cyclist behavior studies often investigate crossing speeds, crossing gap/lag acceptance behavior, compliance with traffic regulations, group-riding or peloton behavior, influenced versus uninfluenced behavior, among others (Wood, Lacherez, Marszalek, and King, 2009, Gatersleben and Haddad, 2010, and Twaddle, Schendzielorz, and Fakler, 2014). A study by Ling and Wu (2004) concluded that crosswalks and pedestrians have a negative influence on cyclist compliance with traffic regulations, as cyclists feel safer in pedestrian facilities and are less likely to obey traffic signals. Fraboni, Puchades, De Angelis, Prati, and Pietrantoni (2016) found that 63% of the 1,381 observed cyclists in signalized intersections crossed despite having a red light indication, and stated that human factors and external environment play an important role in cyclist non-conforming behavior. Developing a better understanding of cyclist non-conforming behavior at intersections requires the analysis of interactions between bicycles and vehicles (Fruhen and Flin, 2015) and pedestrians (Hatfield and

Prabhakharan, 2016), as driver and pedestrian behavior towards cyclists can have a negative impact in bicycle safety and compliance with traffic regulations.

There is evidence suggesting that findings of driver behavior studies can not be adopted to cyclist behavior. Hiles (1996) stated that because cyclists lack the physical and social constraints that describe driver behavior, cyclist behavior should not be judged as "*appropriate or inappropriate*" by motor vehicle behavior standards. A similar conclusion was obtained in the work of Twaddle, Schendzielorz, and Fakler (2014), stating that it is not possible to directly adopt behavior models originally developed for motorized traffic to bicycles. However, conventional modeling methodologies and software still neglect important variables when addressing cyclist behavior at intersections (Huff and Liggett, 2015), and fail to provide the necessary tools to model bicycle capacity and safety across different types of bicycle and mixed traffic facilities.

The introduction of computer vision systems expanded the scope of cyclist behavior analysis. Bicycle tracks obtained from video data can provide useful contributions to the study of variables such as group size, travel path, lane position, and helmet use, and how these variables affect the mean speed of the bicycle (Zaki, Sayed, and Cheung, 2013). Furthermore, computer vision also provides an accurate analysis of cyclist behavior under high density conditions in comparison to manual field and video observation methods (Zaki and Sayed, 2016a).

2.3.2 Road safety in vehicle-bicycle interactions

Cyclists are subject to higher safety risks, as cyclists are more vulnerable road users than drivers because cyclists lack of sufficient protection in case of collision. According to the National Collision Database (Transport Canada, 2016), cyclists accounted for an average of 3% of road fatalities in Canada between 2010 and 2014. Studying vehicle-bicycle collisions can help to understand how drivers and cyclists behave in vehicle-bicycle interactions and to identify several behavior-related deficiencies that lead to collisions.

Schramm, Rakotonirainy, and Haworth (2010) studied 6,328 police-reported vehicle-bicycle collisions to identify different causes that lead to collisions. The authors found that drivers were at fault in 66% of vehicle-bicycle collisions, with traffic violations being the reason for 85% of diver-at-fault collisions. In contrast, cyclists were at fault in 28% of vehicle-bicycle collisions. However, the same authors acknowledged that these numbers may not be precise, as minor collisions involving cyclists usually go underreported. A study by Aldred (2016) involving 1,596 cyclists and 4,662 reported collisions concluded that cyclists show a "*general feeling of lack-of-control over incidents*". According to the surveyed cyclists, cyclists can avoid nearly 20% of vehicle-bicycle collisions by improving their behavior while cycling. Cyclist behavior factors contributing to vehicle-bicycle collisions can be found in Knowles, et al. (2009), including: not using hand gestures to announce intentions, not wearing proper clothing to ease cyclist detection at night, performing abrupt or sudden maneuvers in proximity of vehicles, failing to identify vehicles in the proximity, and poor judgement of vehicle speeds, trajectories, and intentions, among others. The introduction of more advanced technologies offers the opportunity to study road safety of vehicle-bicycle interactions from a proactive approach. Road safety diagnoses (Sayed, Zaki, and Autey, 2013, and Zaki and Sayed, 2016b) were conducted to assess cyclist road safety by analyzing vehicle-bicycle interactions using video data, obtaining measurements of cyclist exposure to traffic conflicts and information on driver and cyclist behavior that lead to collisions.

2.3.3 Vehicle-bicycle yielding interactions

Driver and cyclist behavior in yielding-required situations can have a significant impact on road safety. In intersections where yielding frequencies (i.e. yielding rates) are higher, the severity and frequency of collisions should be lower. Evidence of this is presented in the work of Svensson and Pauna-Gren

(2015). The authors found that at intersections with higher vehicle yielding rates, the conflict risk per crossing cyclist is lower (“*conflict risk per crossing cyclist”* refers to the number of detected conflicts divided by the number of crossing cyclists per hour). Furthermore, Bjorklund and Aberg (2005) studied yielding frequencies under different hypothetical scenarios by surveying drivers and concluded that driver yielding behavior varies depending the intersection’s design (e.g. three-way or four-way intersection, crossing vehicles approaching from the left or from the right, and the width of the road). Furthermore, Fraboni, Puchades, De Angelis, Prati, and Pietrantoni (2016) concluded that road user behavior at intersections is likely to change depending on the culture of the surveyed population (i.e. different cities, different countries), the characteristics of the facility, weather and traffic conditions, and time of the day.

The analysis of yielding interactions should not be limited to questions such as “who goes first” or “who has the legal right-of-way”, as yielding interactions can have different outcomes. Bjorklund and Aberg (2005) found that if formal traffic rules (i.e. signage) are unclear or counterproductive, road users may use informal traffic rules to address who has the right-of-way. Moreover, informal traffic rules can contradict the formal rules of priority, as road users often give importance to the other road user’s behavior. There is evidence that signage alone is not likely to determine the road safety of a bicycle crossing, but a combination of signage, type of location, bicycle flow, yielding behavior, and motor vehicle speed (Svensson and Pauna-Gren, 2015).

The probability of a vehicle to yield to bicycles has been modeled in previous research. A study by Silvano, Ma, and Koutsopoulos (2015) found that bicycle speed and proximity are positively correlated to a driver yielding probability. Silvano, Koutsopoulos, and Ma (2016) proposed a two-level probabilistic framework to model driver yielding decisions in vehicle-bicycle interactions. The study showed that the conflict probability depends on who arrives at the intersection first.

Because bicycles are a more flexible and vulnerable mode of transportation than motor vehicles, understanding why and how cyclists yield to vehicles at intersections becomes as important as understanding driver yielding behavior. Up to the author's knowledge, there is no published research addressing bicycle yielding rates, cyclist yielding probability in vehicle-bicycle interactions, nor changes in conflict severity as result of bicycle-yielding.

3. INTERSECTION SAFETY DIAGNOSIS USING AUTOMATED VIDEO ANALYSIS

In June 2015, significant transportation-related improvements were approved for the Burrard St. and Pacific St. intersection (Figure 3-1), among several other active transportation projects (City of Vancouver, 2015a). The improvements at the intersection are set to be completed by late 2017 and are part of the City's Transportation 2040 plan, which aims for a safe, convenient, comfortable, and accessible active transportation network. Before the upgrades in the Burrard St. and Pacific St. intersection are implemented, it is required to make a detailed safety evaluation to set a standard upon which the safety improvements can be assessed. The safety diagnosis includes vehicle-vehicle, vehicle-bicycle, bicycle-bicycle, and vehicle-pedestrian conflicts, as well as violations that may compromise road safety.

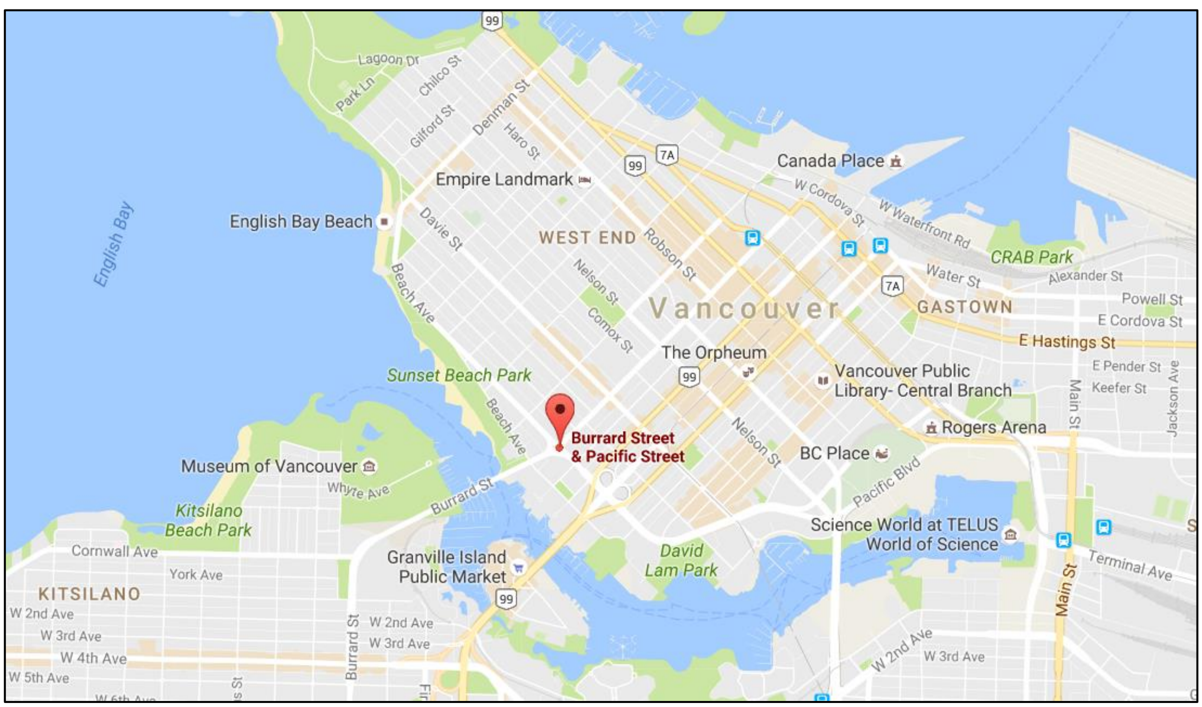

Figure 3-1: Location of the Burrard St. and Pacific St. intersection. Source: Google Maps, 2016.

This chapter presents the study location, methodology, and results of the safety diagnosis at the Burrard St. and Pacific St. intersection. The diagnosis addresses conflict severity and frequency, traffic violations, and the expected changes in safety for the different issues encountered throughout the analysis.

3.1 Study location: Burrard St. and Pacific St. intersection

3.1.1 Site characteristics

The study location is the intersection between Burrard St. and Pacific St. in Vancouver, British Columbia. This intersection constitutes the north end of the Burrard Bridge and its access and exit ramps. The bridge serves as the main connection between Downtown Vancouver and the Kitsilano neighborhood, as seen Figure 3-1. As part of Vancouver's Cycling Network (City of Vancouver, 2015a), the Burrard Bridged accounted for a daily average of 4,700 cyclists during the data collection period (April 2016), and the daily average during 2016 was 3,933 cyclists (City of Vancouver, 2017).

A two-phase signal system controls this intersection. Mixed traffic (vehicles, bicycles, and pedestrians) converge on several zones of the intersection. Due to the presence of the ramps, two traffic islands are created. For analysis purposes, the access and exit ramps are named On-ramp and Off-ramp, respectively, while the traffic islands are named East and West traffic islands. The different approaches to the intersection are illustrated in Figure 3-2 and detailed as follows (EB, NB, WB, and SB stand for eastbound, northbound, westbound, and southbound, respectively):

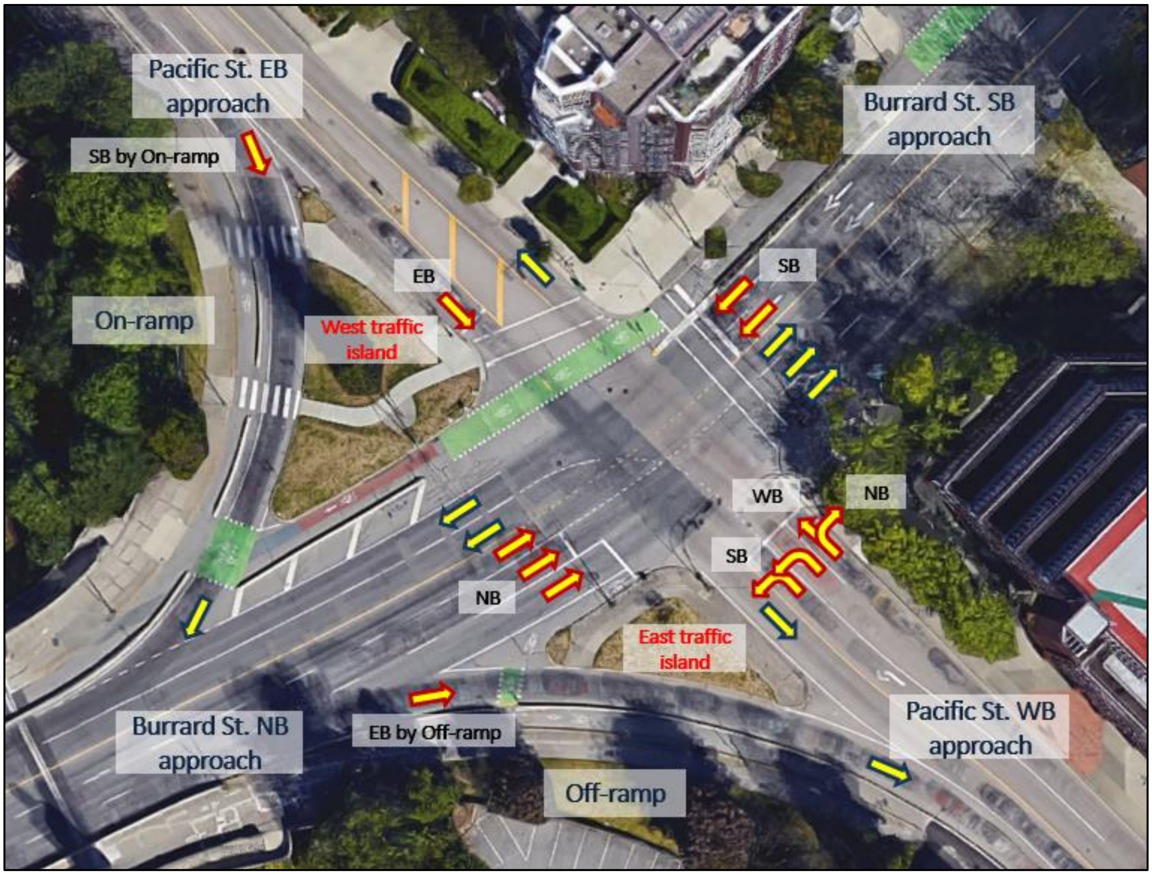

Figure 3-2: Satellite view of the approaches to the Burrard St. and Pacific St. intersection.

Burrard St. NB and Off-ramp

The Burrard St. NB approach comes from the Burrard Bridge into Downtown Vancouver. Consists in three lanes to cross straight through the intersection. Burrard St. keeps the three lanes after the intersection, so no lane-reduction is experienced. Left- and right-turns are not allowed at the intersection from this approach. In case a vehicle requires to make a right-turn after the bridge, it can use the right lane of the approach to access the Off-ramp and merge into the Pacific St. EB traffic flow. The Off-ramp has only one lane and has a bicycle crossing at the beginning of the ramp.

Pacific St. WB

The Pacific St. WB approach provides access to vehicles in south, west, and north directions. It has three lanes: two left-turn lanes, and one straight and right-turn lane. The left-turn movement is controlled by an exclusive left-turn traffic signal. Vehicles turning right should yield to pedestrians and bicycles traveling on the crossing through the Burrard St. SB approach. No lane reduction is experienced in any of the movements.

Burrard St. SB

The Burrard St. SB approach comes from Downtown Vancouver into the Burrard Bridge. Consists in two lanes to cross straight through the intersection. Burrard St. keeps the two lanes after the intersection, so no lane-reduction is experienced. Left- and right-turns are not permitted at the intersection from this approach.

Pacific St. EB and on-ramp

The Pacific St. EB approach consists of two lanes: one to cross straight through the intersection and one which transforms into the On-ramp. Left- and right-turns are not permitted at the intersection from this approach. In case a vehicle requires to make a right-turn into the bridge, it can use the On-ramp and merge into the Burrard St. SB traffic flow. The On-ramp has only one lane and has two crosswalks and one bicycle crossing distributed throughout the ramp.

Active transportation network

The Burrard St. and Pacific St. intersection also has cycling and walking networks. The networks for active transportation modes at the intersection are illustrated in Figure 3-3.

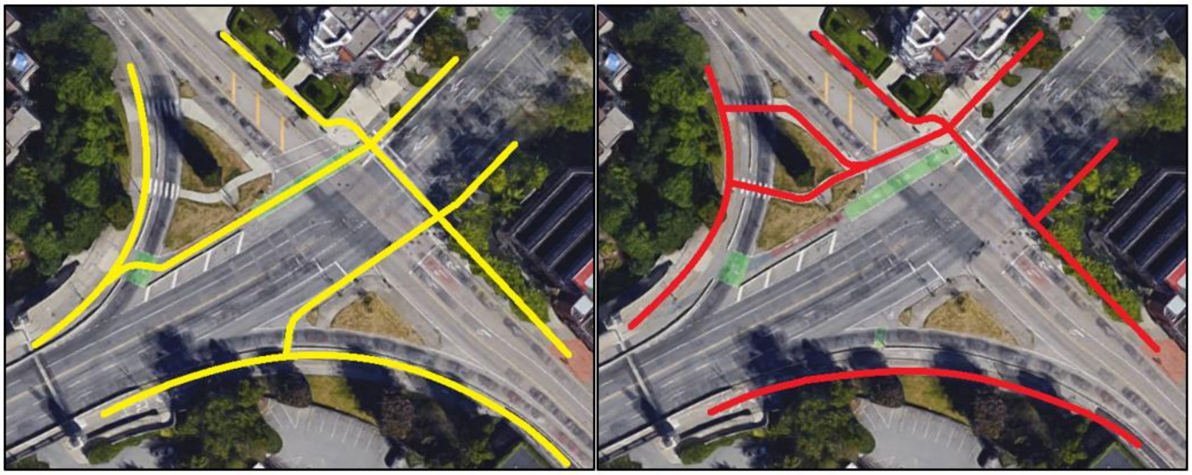

Figure 3-3: Cycling (left) and walking (right) networks in the Burrard St. and Pacific St. intersection.

Differences between the cycling and walking networks can be observed at the south side of Pacific St.:

1. The Off-ramp has a sidewalk and a protected bike lane with access to an exclusive northbound-only bicycle crossing, allowing bicycles to cross through the Off-ramp and the Pacific St. WB approach. Since pedestrians are not allowed to cross through the Pacific St. WB approach, the sidewalk at the East traffic island should remain unused. Pedestrians are expected to walk to the next intersection (Hornby St. and Pacific St.) to make the cross.

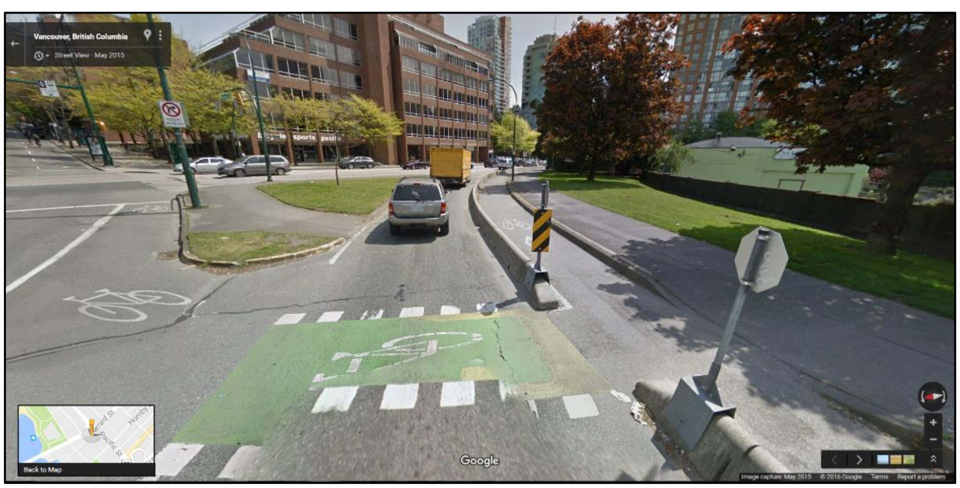

Figure 3-4: Driver's perspective of the Off-ramp. Source: Google Street View, 2015.

2. The On-ramp has a sidewalk and a protected bike lane. The On-ramp is crossed by two crosswalks (to be named North and South crosswalks for research purposes) and one bicycle crossing with the Burrard St. SB bike lane. The bicycle crossing is southbound-only, while the crosswalks allow pedestrians to cross in both directions. If bicycles are to cross northbound through the Pacific St. EB approach, cyclists are expected to dismount and walk through any of the crosswalks. Both crosswalks on the West traffic island merge into one when crossing through the Pacific St. EB approach.

Figure 3-5: Pedestrian's perspective of the West traffic island. Source: Google Street View, 2015.

3.1.2 Field survey: video data

To conduct an automated safety analysis, quality and quantity of video footage at the location of interest are fundamental. The City of Vancouver provided the video footage to the University of British Columbia. It was recorded between April 11th, 2016, and April 15th, 2016: dates are consistent with what is expected to be typical non-holiday weekdays during school session. The video footage was taken at the very beginning of the improvements' development. Thus, personnel from the City of

Vancouver is occasionally seen in the video footage implementing traffic control techniques that may limit the validity of the results.

Three cameras were used for data collection. Camera 1 was temporarily attached to a street light post in the East traffic island. Camera 2 was located on top of the traffic signal post in the Burrard St. SB approach. Camera 3 was located on top of the traffic signal post in the Pacific St. WB approach. The location of the cameras can be seen in Figure 3-6, Figure 3-7, and Figure 3-8.

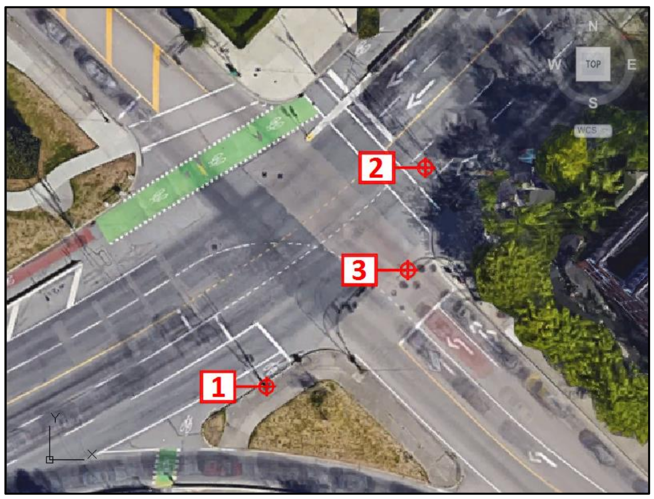

Figure 3-6: Location of the cameras 1, 2, and 3 at the intersection.

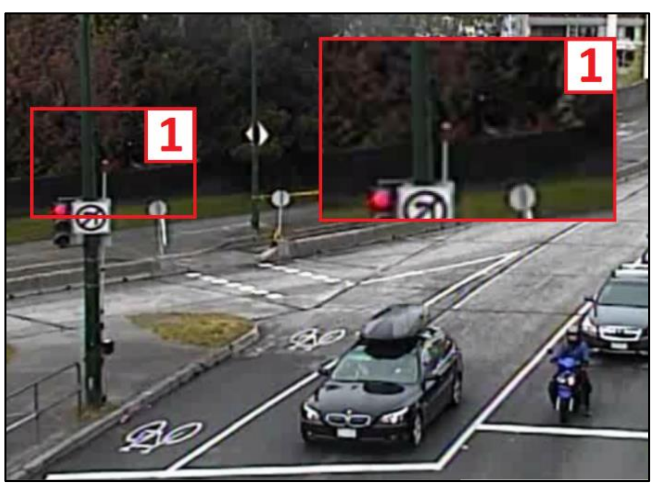

Figure 3-7: Location of Camera 1 (as seen from Camera 2).

Figure 3-8: Location of cameras 2 and 3 (as seen from the West traffic island).

The location of the cameras is such that the entire intersection cannot be observed from one single image. Selection of camera angles is not a trivial task since tracking quality is dependent on the ability to see every road user in a clear manner (Zaki and Sayed, 2016b). To address this issue, the study uses five different scenes to cover most of the intersection: the Burrard Bridge's north end ramps, the Pacific St. WB and EB approaches, and part of the active transportation network. None of the scenes properly covers the Burrard St. NB nor SB approaches nor the crosswalks located on the On-ramp. Thus, the capacity for conflict detection in these facilities is limited.

The description of the five scenes is presented next, labeled as S2, S4, S5, S6, and S7. S1 was not used because of its irrelevant location for the research's objectives, while S3 was discarded due to its similarities with S2.

Scene 2 (S2)

Scene 2 was recorded from Camera 1 in southwest direction. It shows the beginning of the Off-ramp with its sidewalk, bike lane, and bicycle crossing, part of the East traffic island's sidewalk, and the

Burrard St. northbound bike lane. The expected conflict region to be captured in this scene is located at the bicycle crossing. Rear-end conflicts may be seen due to interrupted traffic flow in the Off-ramp.

Figure 3-9: Scene 2 and its expected movement patterns and conflict regions.

Scene 4 (S4)

Scene 4 was recorded from Camera 2 in southwest direction. It shows the three lanes of the Pacific St. WB approach, the Off-ramp, the unmarked bicycle crossing through the Pacific St. WB approach, and the Pacific St. EB lane. The expected conflict regions to be captured in this scene are located in the Off-ramp (rear-end conflicts), in the right-turn movement of the Pacific St. WB approach (rear-end conflicts), and in the left-turn lanes of the Pacific St. WB approach (rear-end and side-swipe conflicts).

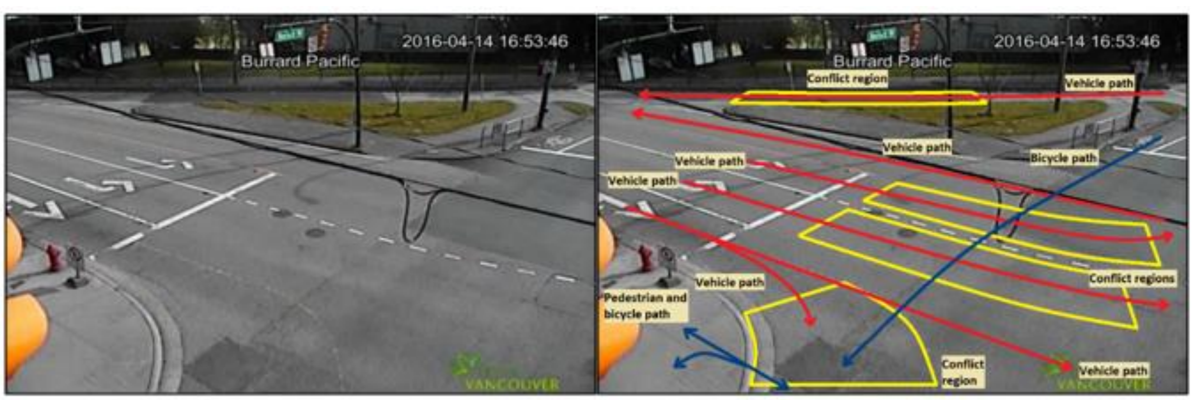

Figure 3-10: Scene 4 and its expected movement patterns and conflict regions.

Scene 5 (S5)

Scene 5 was recorded from Camera 3 in west direction. It shows the two Burrard St. SB lanes, the end of the On-ramp and its merger into Burrard St., and the bicycle crossing through the On-ramp. The expected conflict regions to be captured in this scene are related to the bicycle crossing and the On-ramp merger into Burrard St.

Figure 3-11: Scene 5 and its expected movement patterns and conflict regions.

Scene 6 (S6)

Scene 6 was recorded from Camera 3 in west direction. It shows the Burrard St. SB lanes, part of the On-ramp, the Burrard St. southbound bike lane, the bicycle crossing through the On-ramp, and the South crosswalk through the On-ramp. The expected conflict regions to be captured in this scene are related to the bicycle and pedestrian crossings through the On-ramp, as well as vehicle rear-end conflicts when tailgating along the On-ramp. The merger of the On-ramp into Burrard St. and the vehicles traveling before the crosswalk cannot be seen in this scene.

Figure 3-12: Scene 6 and its expected movement patterns and conflict regions.

Scene 7 (S7)

Scene 7 was recorded from Camera 3 in northwest direction. It shows the Pacific St. EB approach, part of the On-ramp, the Burrard St. southbound bike lane, the crosswalk through the Pacific St. EB approach, and the North crosswalk through the On-ramp. The expected conflict regions to be captured in this scene are located in the North crosswalk of the On-ramp since the traffic signal should help preventing vehicle-bicycle and vehicle-pedestrian conflicts in the Pacific St. EB approach.

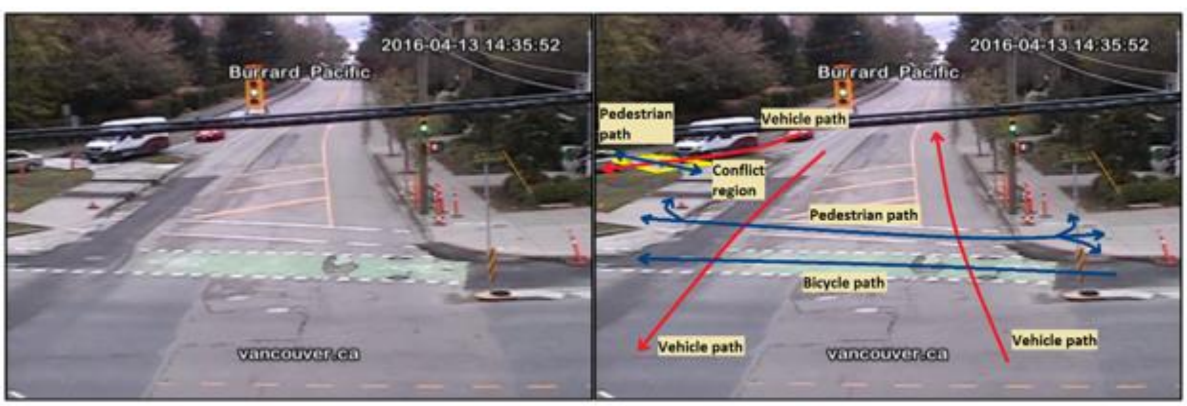

Figure 3-13: Scene 7 and its expected movement patterns and conflict regions.

Recording times and dates

Consistent recording times and dates are selected throughout the scenes. Video footage recorded between 7:00 am and 7:00 pm is used for the analysis to ensure both morning and afternoon peak hours are covered.

Table 3-1: Video recording information.

Scene	Date	Start time	Finish time
S2	April 13th, 2016	07:00	19:00
S4	April 13th, 2016	08:52	19:00
S5	April 15th, 2016	08:04	19:00
S6	April 11th, 2016	08:07	12:25
		14:06	19:00
S7	April 13th, 2016	07:52	19:00

The total combined recording time is 53 hours and 24 minutes. Video data were missing for a mid-day gap in Scene 6 as well as during part of the first two hours for scenes 4 to 7. The analysis is to be made correcting for the missing hours.

3.2 Automated road safety analysis

To conduct a computer vision-based traffic conflict analysis, this research follows the methodology presented in past studies developed by the Transportation Research Group at the University of British Columbia (Sayed, Zaki, and Autey, 2013, Essa, 2015, Reyad, 2016, and Zaki and Sayed, 2016b). In this section, the different steps of the methodology are briefly described.

3.2.1 Camera calibration

Once raw video footage has been converted to a useful format (i.e. video encoding), a proper estimation of the camera parameters is done to analyze road user positions in the camera image. When recording, the three-dimensional world is captured in a two-dimensional space. However, to conduct the road safety analysis, the tracks obtained from the two-dimensional video footage need to be converted to three-dimensional real world data using a linear transformation. This linear transformation is defined by the homography matrix, which is related to the camera's extrinsic parameters (camera position and orientation) and its intrinsic parameters (focal length, skew angle, and radial lens distortion) (Zaki and Sayed, 2016b). The camera calibration step consists in determining the homography matrix of a camera. Further details of the used mixed-feature camera calibration can be found in the work of Ismail, Sayed, and Saunier (2013).

The camera calibration step is done by annotating and cross-referencing different features in the video footage into an orthographic image of the area of interest. Images taken from Google Maps with good resolution are used as orthographic images. Four types of annotations are used for camera calibration optimization:

Corresponding points

This annotation uses the identification of discrete objects in both camera and orthographic images to calibrate the camera through an optimization algorithm, so that when points are projected from one image to the other, the corresponding points match. The selected objects must be on the plane of the road or at a specified height.

Distances

This annotation uses the known real-world distance between points positioned on the road surface to calibrate the camera, so that the projections of the points into the orthographic image are the correct distance apart.

Angles

This annotation uses the known angle between two lines in the camera image (e.g. parallel lines and lane markings), so that the projection of these lines into the orthographic image has the correct angle between them.

Global up directions

This annotation uses the poles mounted near the intersection and assumes that the poles are perpendicular to the road surface. By specifying the locations in the camera image of the tops and bottoms of poles, the calibration optimization algorithm can determine the tilt of the road surface.

Errors in camera calibration are seen as inconsistencies between measurements in the camera image and the orthographic image, and estimated as the difference between calculated and annotated segment length normalized by the length of each segment. Therefore, a step called "calibration verification" is done to ensure that the camera is properly calibrated. Calibration verification consists in a visual validation of the calibration accuracy by the use of displayed grids (known as "calibration grids") in both camera image and orthographic image.

Figure 3-14: Camera calibration illustration (S2 example).

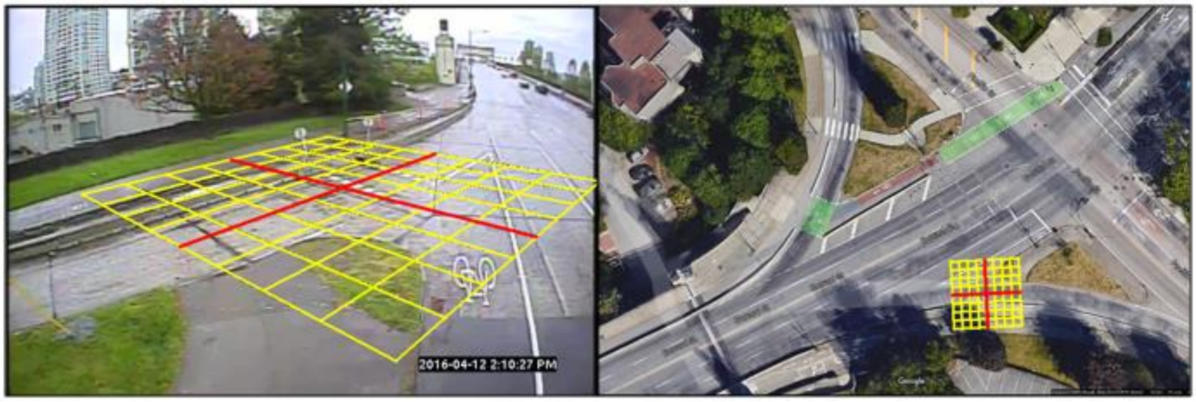

Figure 3-15: Camera calibration grid illustration (S2 example).

3.2.2 Feature tracking

The feature tracking step consists in the automated detection and tracking of features as road users navigate through the camera's field of view. To avoid tracking objects that are of no interest for the analysis, the Kanade-Lucas-Tomasi (Shi and Tomasi, 1994) feature-tracking algorithm is used to differentiate between features that belong to road users from those that belong to the environment. Fixed objects are filtered by removing those features that remain stationary and are assumed to be part of the environment (Saunier and Sayed, 2006). Two steps are done to optimize feature tracking. First, features are continually generated to identify moving objects and to filter fixed objects. Second, motion checks are done to help remove features that are displaying unreasonable motion properties.

Figure 3-16: Feature tracking illustration (S2 example).

3.2.3 Feature grouping

Road users, particularly motor vehicles, are large objects with many distinct physical features and, as such, will generate multiple features during the feature tracking step. Therefore, the feature grouping step is done to identify which set of features belongs to a unique road user and group those features so an object may be generated. For a feature (or group of features) to be added to another one, it must comply with two requirements. First, both features must be within a maximum distance apart specified by the analyst. Second, because of the physical rigidity of the object, it is expected for the features to have identical motion patters in terms of speed and direction. Features with motion vectors differing by more than a specified threshold are assumed to belong to different vehicles and are not grouped, regardless of their spatial proximity.

The work of Saunier and Sayed (2006) presents a detailed description of the tracking and grouping algorithms. Motor vehicles tracking accuracy has been measured between 84.7% and 94.4% on three different sets of sequences. This accuracy is considered reliable under heavy traffic flow conditions and should have a negligible impact on the accuracy of the calculation of conflict indicators (Zaki and Sayed, 2016b). Thus, it is considered that most trajectories are detected by the system and the calculated conflict indicators are reliable.

Figure 3-17: Feature grouping illustration (S2 example).

3.2.4 Road user classification

The classification step consists in classifying generated objects per road user type. The classification step is done based on the trajectories and speed profiles of the objects, as it is expected for these to differ depending on the type of road user. The trajectories hold cues that reveal the structure of the traffic scene which help to identify different characteristics of the road users. For pedestrians, the regular movement pattern is described by its walking gait (ambulation), with particular attributes such as walking speed, stride length, and frequency. For bicycles, the regular movement pattern is described by its pedaling process (cadence), as its speed profile will show periodic variations which are at lower frequencies than pedestrian walking frequencies. Motor vehicles speed profiles are composed of linear segments corresponding to different speeds throughout their trajectories.

The oscillatory behavior associated with pedestrians and cyclists, while lacking in vehicles, provides a classification basis through recognizing pedestrian and cyclist movement patterns. Other features like maximum speed and road user object size are used as complimentary cues to enhance the classification. Details of the classification are presented in the work of Zaki and Sayed (2013).

Figure 3-18: Road user classification illustration (S2 example).

3.2.5 Prototype generation and matching

Prototypes are groups of motion patterns that define the set of movements carried out by road users in the studied location. Prototypes can be synthesized from expected road user trajectories or can be extracted from a set of tracked road users. Prototype generation is a semi-automated process that, by using a subset of the video data with high traffic volumes to represent the full set of data, determines road user expected movements that resemble the common traffic movements. When feature tracking is carried out on the selected subset of the video data, the trajectories of a large number of features are recorded. This large set of trajectories is reduced to a more concise set of prototypes by using a clustering algorithm, called the Longest Common Sub-Sequence (LCSS) algorithm. The LCSS algorithm clusters features that contain matching subsequences of an adequate length, as feature tracks from a road user following similar trajectories may begin and end at different locations but still describe the same movement patterns. More information on the prototype generation and matching step can be found in the work of Saunier and Sayed (2008).

Figure 3-19: Sample prototypes for road user movements: vehicles (left) and cyclists (right) (S2 example).

3.2.6 Traffic conflict analysis

Once the objects and trajectories are generated, the consequent step is to generate interactions between these objects to conduct the traffic conflict analysis. The trajectory of an object can be matched to individual prototypes using the LCSS algorithm with a maximum LCSS matching distance. The matched prototypes are moved to the object's center and corrected for the object's current speed. By matching the trajectory and speed of an object to a prototype, a set of predicted future positions can be determined with associated probabilities of occurrence.

As described in the work of Saunier, Sayed, and Ismail (2010), conflicts between road users can be determined by evaluating if any of their future positions coincide in space and time with other road users. Any given pair of road users that share temporal and spatial proximity (i.e. appear at the same time in the camera's field of view) are assumed to have the potential for a conflict, and potential conflicts between that pair of road users are calculated. Traffic conflict indicators are used to measure the severity of each detected conflict. The most severe value is used to represent the overall severity of the conflict.

The time to collision (TTC) values are calculated continuously between a pair of conflicting road users. Thus, a set of values is obtained for each conflict. The minimum TTC is extracted from this set of values to indicate the maximum severity of this interaction. In contrast, only one value is calculated for post-encroachment time (PET) is detected at the beginning of the interaction between two conflicting road users. Due to potential noise in road user tracks, different filtering strategies are used. Moreover, selected TTC and PET measured conflicts are manually reviewed to filter tracking errors. Not all conflicts are detected by both indicators, since the nature of the events and the limitations of computer vision techniques may hinder the capacity to detect both TTC and PET values for specific conflicts. Then, the total number of detected conflicts per conflict indicator is normalized by hour and traffic volume.

Furthermore, the minimum TTC value extracted for each conflict can be mapped into a severity index using the following equation based on the work of Saunier and Sayed (2008):

$$SI = e^{-\left(\frac{TTC^2}{2*PRT^2}\right)}$$

Where SI is the severity index and PRT is the perception and braking reaction time, which is assumed to be 1.5 seconds. The severity index is a unit-less measure of severity that ranges from 0 to 1, with 0 being uninterrupted passages and events with higher severity index corresponding to more severe events. Figure 3-20 shows how the severity index decreases as the minimum TTC value increases. It can be observed that the severity of conflicts with a minimum TTC higher than 4 seconds have a severity index lower than 0.1. Thus, this research only accounts for conflicts with TTC or PET values below the four-second threshold.

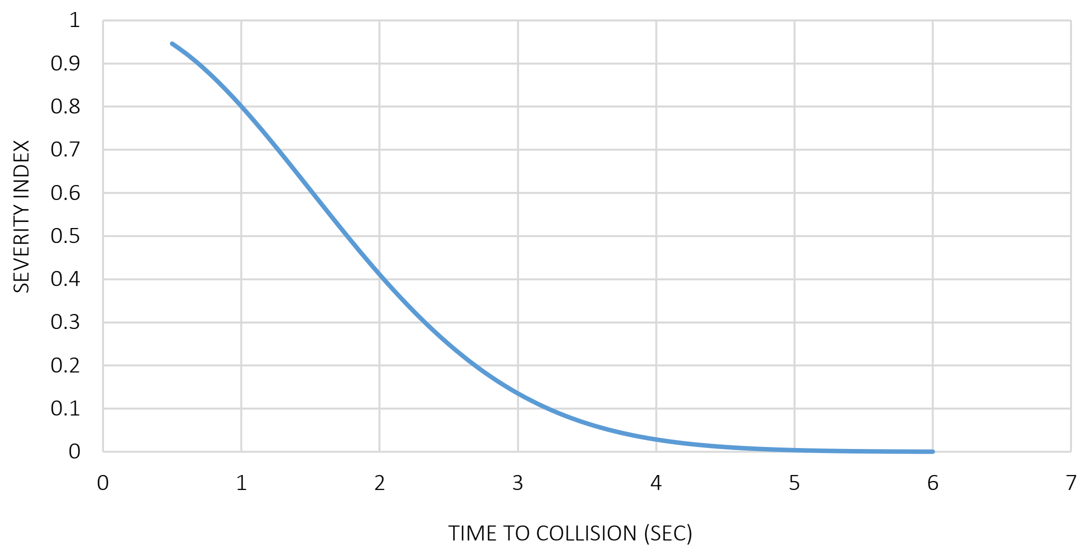

Figure 3-20: Mapping from time to collision to severity index.

Aggregation of the severity of all events is conducted. A normalization of the differences in observation periods and exposure is required, as video data are gathered throughout different periods of time and areas of the intersection. The exposure measure used is the theoretical maximum number of events, which is the product of the daily volumes for conflicting traffic streams.

$$SI\ Rate = \frac{SI}{Exposure}$$

Exposure is a normalized value applied to the conflict analysis' results. It serves as a way to correct for volume differences between the movements involved in a conflict and is used to account for expected variations in traffic volumes on a temporal basis. The following equation is used to calculate the exposure between two traffic volumes:

$$E_{i,j} = \sqrt{(V_i * V_j)}$$

Where $E_{i,j}$ is the exposure, V_i is the volume of road user movements *i*, and V_j is the volume of road user movements *j*.

3.2.7 Traffic violation analysis

The last step of computer vision-based traffic conflict analysis is the traffic violations analysis, which serves as an additional surrogate of road safety in those safety issues that are assumed to be caused by recurrent non-conforming behavior patterns. The traffic violation analysis is done by distinguishing between different road user behaviors and identifying possible non-conformance to the location's traffic regulations. In this research, vehicle, bicycle, and pedestrian temporal and spatial violations are identified by manual observation and automated detection.

The LCSS cluster algorithm can be adopted to detect traffic spatial violations. A spatial violation is detected by comparing the road user's trajectory against a given set of predetermined tracks (i.e. 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 committing a spatial violation. The computer vision system developed by the University of British Columbia has a built-in procedure to extract a set of normal tracks of road users (Saunier, Sayed, and Ismail, 2010) to be used in traffic violation detection. Temporal violations are performed by comparing the position of the road user during different signal times. In this research, motor vehicle not-yielding and bicycle speeding traffic violations are assessed using automated computer vision techniques, while the rest of traffic violations are assessed through manual video observation.

3.3 Summary of findings

The following section summarizes the results obtained from the automated safety analysis. Three components are demonstrated for the intersection: conflict analysis, violation analysis, and automated data collection. Conflict analysis includes identifying conflict frequency, severity, and location (i.e. conflict zones or regions). The conflicts observed at the intersection cover vehicle-vehicle interactions, both vehicle-pedestrians and vehicle-bicycle interactions, and bicycle-bicycle interactions. Violation analysis includes the identification of non-conforming behavior of vehicles, bicycles, and pedestrians. Automated data collection includes traffic counts and speed measurement of vehicles and bicycles.

3.3.1 Counting validation

The counting validation is performed by analyzing road user paths. Summary of the counts is shown in Figure 3-21, where red arrows represent vehicle counts and blue arrows represent active road user counts. Stated values are hourly averages throughout the day (between 7:00 am and 7:00 pm), correcting for counts taken from scenes which are not complete. In cases where one particular location is covered by more than one scene, averages between the different counts are used. Absolute road user counts are presented in Figure 3-22.

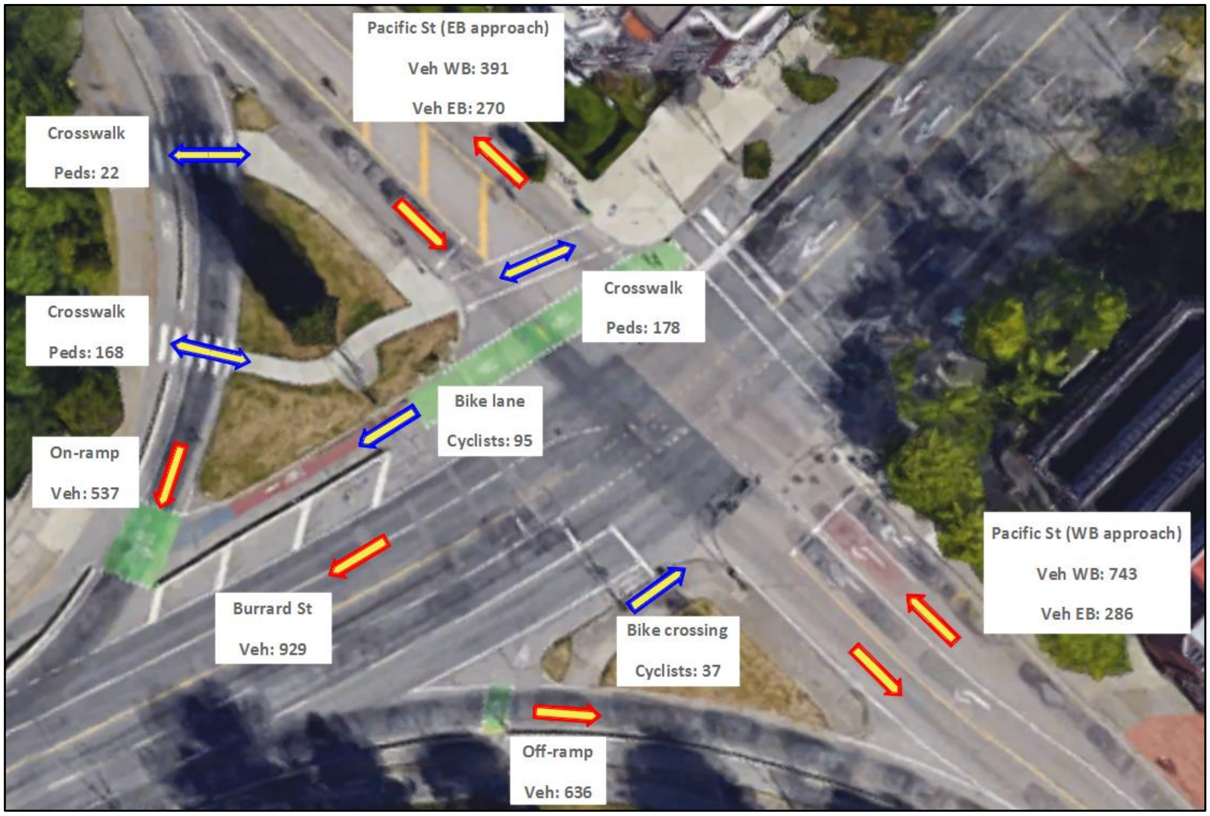

Figure 3-21: Summary of road user counts per day-time average hour.

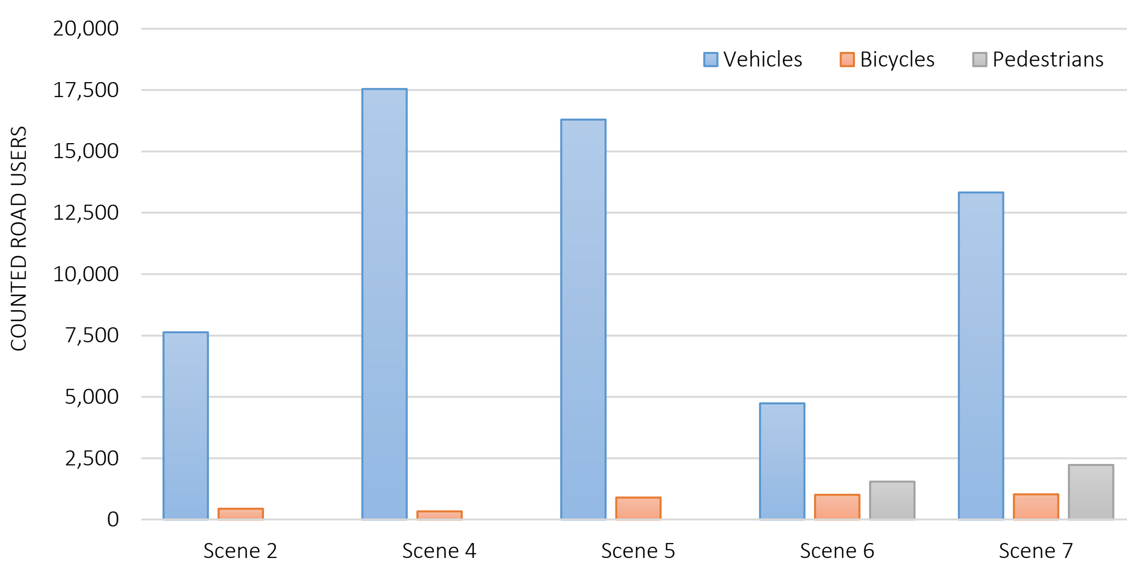

Figure 3-22: Road user counts distributed by type.

Automated counting is applied in some of the screens to validate the manual counts. Several screen lines are placed spanning midway across the travel regions. Illustrations presented in Figure 3-23 show the position of the screens for vehicles, bicycles, and pedestrians in different scenes. A procedure is devised to count the number of road users crossing these lines.

The validation results of road user counts are shown in Table 3-2. The validation is applied to four video components selected from different scenes. The difference in the count results can be caused by several factors. These factors can be defined as over-segmentation, over-grouping, and miss-detection (Ismail, Sayed, and Saunier, 2010):

Over-segmentation

It occurs when more than one tracking point is attributed to a single road user. In terms of counting, the effect of this is an inflation of counts (in the case that both tracking points pass through the screen line).

Over-grouping

It occurs when several road users are grouped together as a single object. Over-grouping may happen when road users are moving at a close distance and have similar speed. The effect of this is a deflation of actual counts.

Miss-detection

It occurs when a road user is not tracked. This is not similar to over-grouping (in over-grouping, the road user is tracked but grouped with others). Miss-detection implies the absence of tracked features and results in a deflation of road user counts.

Table 3-2: Count validation.

Scene	Screen	Manual counting	Automated counting	Accuracy
S2	Bicycle crossing	63	56	88.89%
S4	Pacific WB vehicles	947	904	95.46%
S5	Burrard SB vehicles	1,134	1,249	89.86%
S6	Bike lane	195	162	83.08%

Figure 3-23: Vehicle, bicycle, and pedestrian counters throughout the scenes.

3.3.2 Vehicle conflicts summary

The distribution of vehicle-vehicle conflicts by heat mapping is shown in Figure 3-24 (using PET indicator) and Figure 3-25 (using TTC indicator).

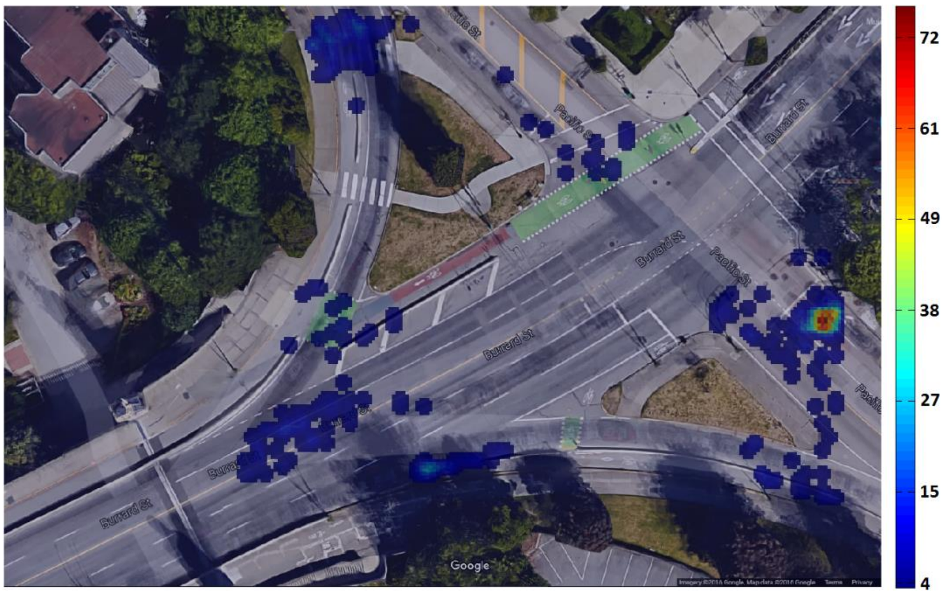

Figure 3-24: PET conflict frequency (conflicts/m^2) heat map.

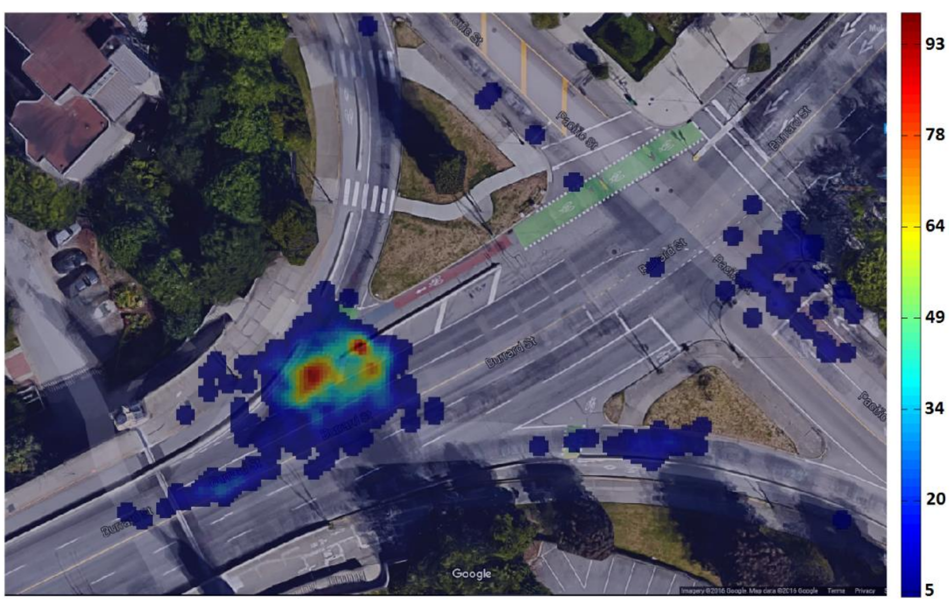

Figure 3-25: TTC conflict frequency (conflicts/m^2) heat map.

Vehicle-vehicle conflict examples are presented in Figure 3-26. The merging and rear-end conflicts between the On-ramp and the Burrard St. SB traffic flows seem to have the highest frequency of vehicle-vehicle conflicts per square meter (top-left and top-right). Other vehicle-vehicle conflict zones worth mentioning are the Pacific St. WB approach (mid-left and mid-right), the beginning of the On-ramp (bottom-left), and the end of the Off-ramp (bottom-right).

Figure 3-26: Vehicle-vehicle conflicts examples.

Figure 3-27 and Figure 3-28 show a breakdown of the number of conflicts using PET and TTC conflict indicators. The highest observed conflict frequency per exposure for PET-based conflict detection is at the beginning of the On-ramp, which shows a high amount of vehicle-vehicle rear-end conflicts. On the other hand, the highest observed conflict frequency per exposure for TTC-based conflict detection is at the merger between the Burrard St. SB and the On-ramp traffic flows, caused by the high speeds observed in many Burrard St. SB vehicles, as well as the On-ramp vehicles trying to get into the Burrard Bridge while avoiding blocking the bicycle crossing.

Figure 3-29 shows the conflict frequency per exposure from the severity index's perspective. Since there are more than 10 severe conflicts (SI over 0.95) per 1000 vehicles, the merger is not only conflict-prone but also experience a significant amount of severe conflicts. These results suggest that, from the vehicle-vehicle conflict analysis' perspective, the merger may require safety improvements to avoid potential collisions.

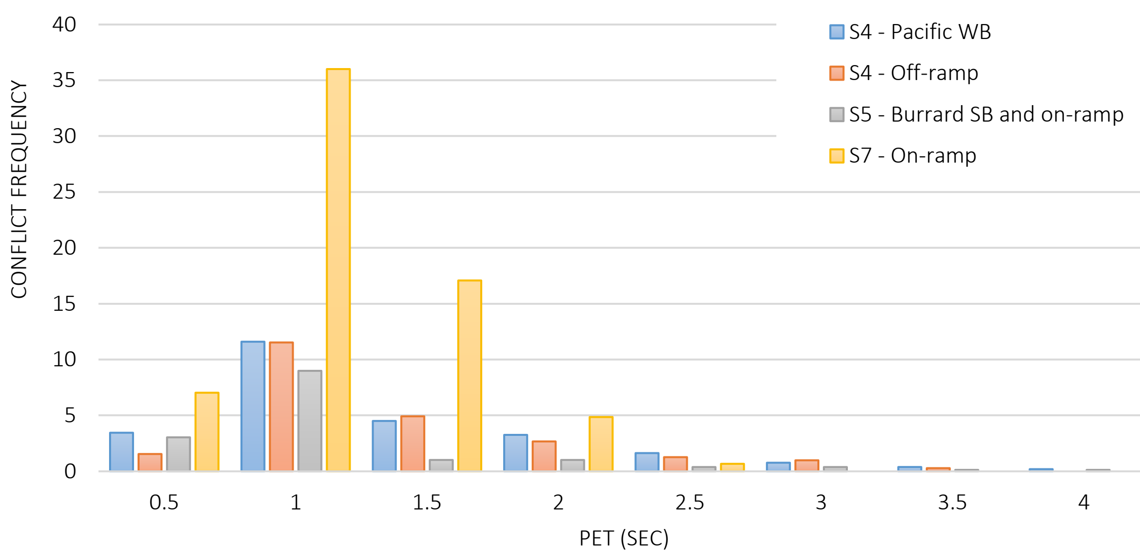

Figure 3-27: Conflict frequency per exposure (per 1000 vehicles) – PET-based conflict detection.

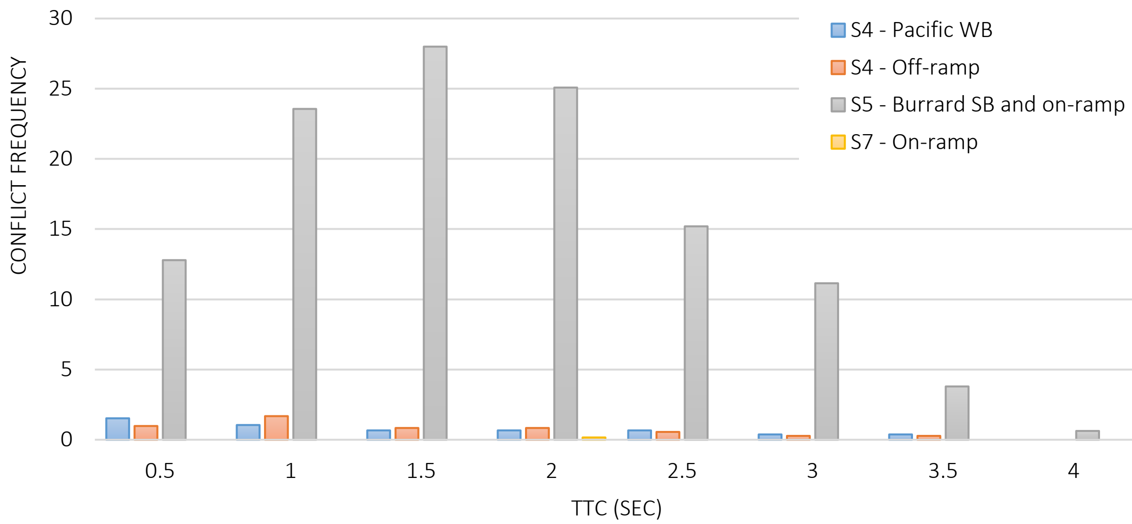

Figure 3-28: Conflict frequency per exposure (per 1000 vehicles) – TTC-based conflict detection.

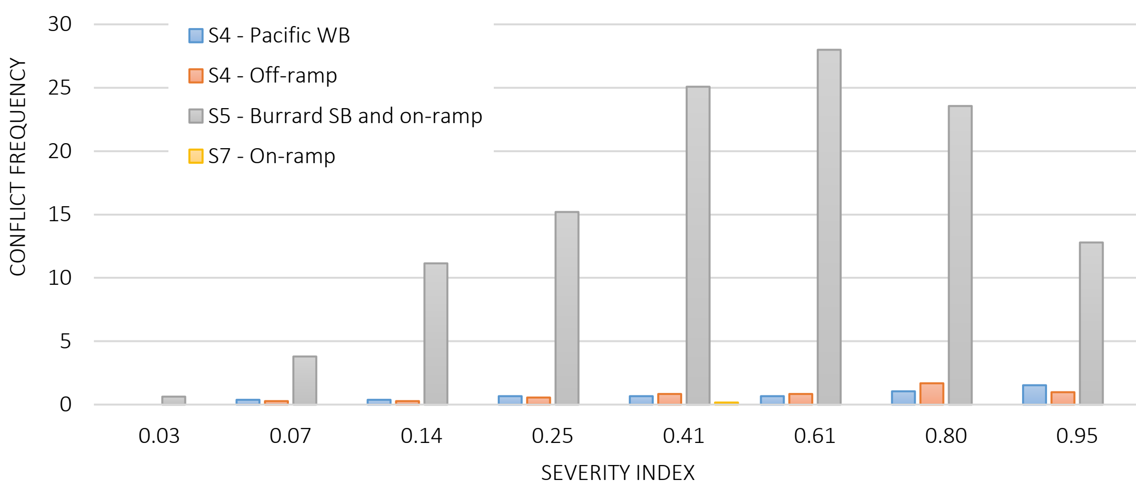

Figure 3-29: Conflict severity per exposure (per 1000 vehicles).

3.3.3 Vehicle, bicycle, and pedestrian conflict summary

The distribution of vehicle-pedestrian, vehicle-bicycle, and bicycle-bicycle conflicts by heat mapping is shown in Figure 3-30 (using PET indicator) and Figure 3-31 (using TTC indicator). Conflicts involving bicycles and pedestrians are combined in the same heat maps since the number of conflicts involving pedestrians is small compared with the number of conflicts involving bicycles. Summing all the different scenes throughout the analysis, 853 bicycle conflicts were detected (507 vehicle-bicycle and 346 bicycle-bicycle), contrasting 21 pedestrian conflicts. Vehicle-pedestrian conflicts on both crosswalks of the On-ramp are not properly detected due to limitations associated with camera parameters.

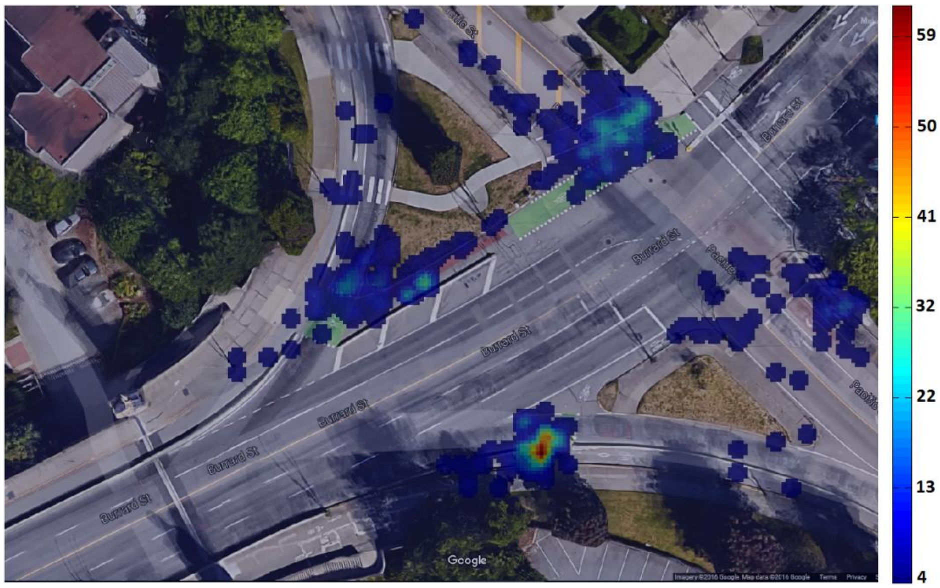

Figure 3-30: PET conflict frequency (conflicts/m^2) heat map.

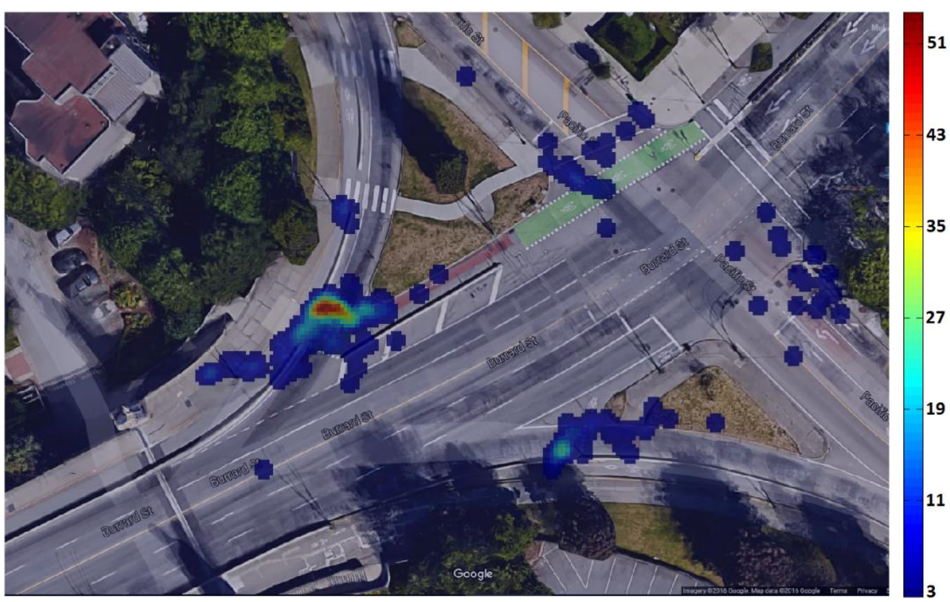

Figure 3-31: TTC conflict frequency (conflicts/m^2) heat map.

There are four zones with high active road user conflict frequency: the bicycle crossing through the Off-ramp, the bike lane's crossing through the On-ramp, and both crossings through the Pacific St. WB and EB approaches. Other conflicts are scattered along Pacific St., as result of vehicle-bicycle conflicts caused by bicycles mixed in the motor vehicle flow. Not yielding to bicycles and pedestrians in both ramps seems to be a frequent behavior among many drivers, causing for conflicts in the ramps. However, active users crossing outside the Off-ramp bicycle crossing encourage drivers to start accelerating before the bicycle or pedestrian is completely out of the way. On the crossings of both Pacific St. WB and EB approaches, vehicles stopping beyond the crossing traffic lines or crossing under a red light are the cause for most vehicle-pedestrian and vehicle-bicycle conflicts. In Figure 3-32 and Figure 3-33, examples of conflicts in these four locations are presented.

Figure 3-32: Vehicle-pedestrian conflicts examples.

Figure 3-33: Vehicle-bicycle conflicts examples.

Figure 3-34 and Figure 3-35 show a breakdown of the number of conflicts using PET and TTC conflict indicators. The highest observed conflict frequency per exposure for PET-based conflict detection is at the Off-ramp bicycle crossing, which can be explained by the high amount of bicycles traveling very close to each other, constituting for bicycle-bicycle read-end conflicts. On the other hand, the highest observed conflict frequency per exposure for TTC-based conflict detection is at the On-ramp bicycle crossing, which can be related to the On-ramp geometric design: driver's attention is divided among two different crosswalks, a bicycle crossing, and the merging maneuver into the Burrard St. SB traffic flow (all in a 50-meters segment). Moreover, a tree in the West traffic island partially obstructs the driver's view of the bike lane. Current On-ramp design challenges driver's ability to notice bicycles with enough time to yield.

Figure 3-36 shows the conflict frequency per exposure from the severity index's perspective. Pacific St. WB approach's bicycle crossing, the Off-ramp bicycle crossing, and the bike lane through the On-ramp showed severe conflicts (SI over 0.95) per 1000 combined road users with similar frequencies. These results mean that, from the vehicle-pedestrian, vehicle-bicycle, and bicycle-bicycle conflict analysis' perspective, said locations may require safety improvements to avoid potential collisions.

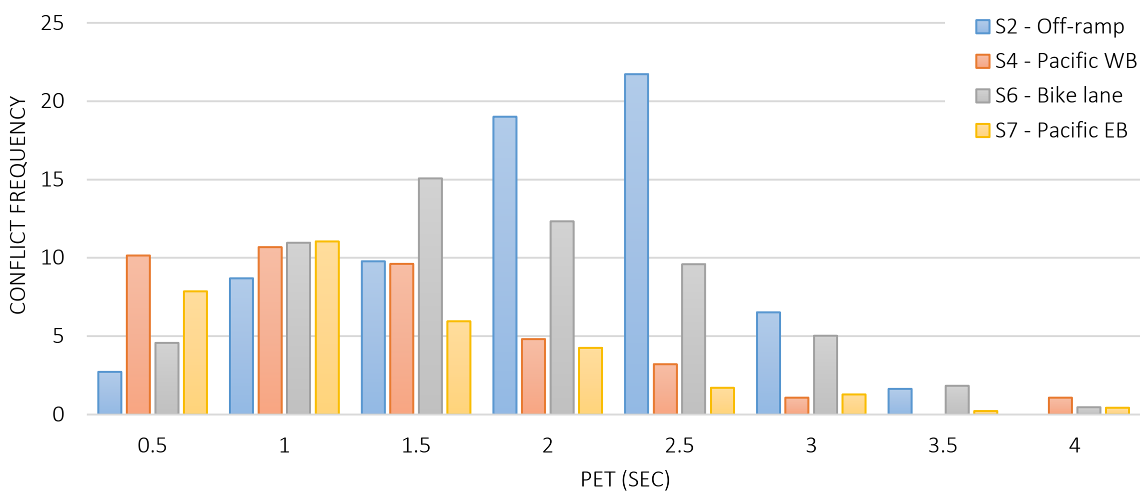

Figure 3-34: Conflict frequency per exposure (per 1000 road users) – PET-based conflict detection.

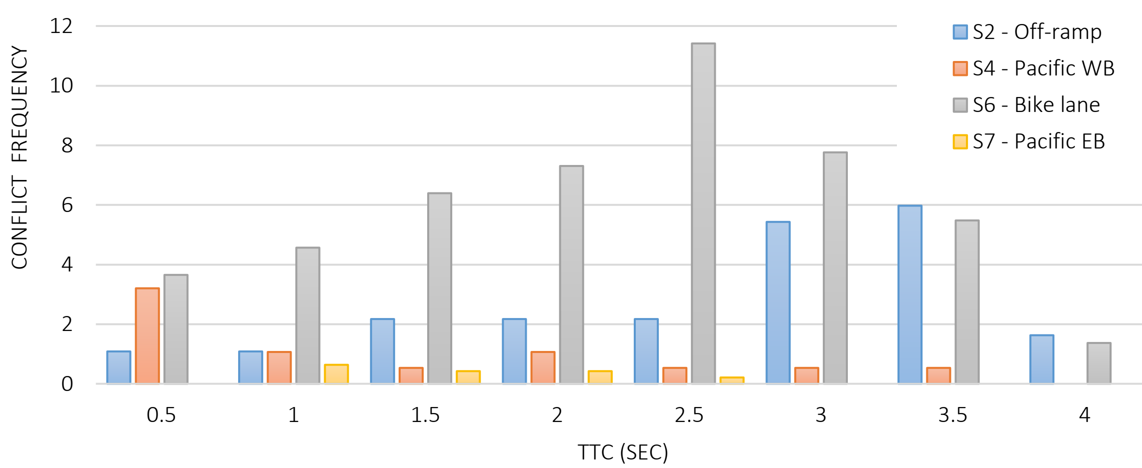

Figure 3-35: Conflict frequency per exposure (per 1000 road users) – TTC-based conflict detection.

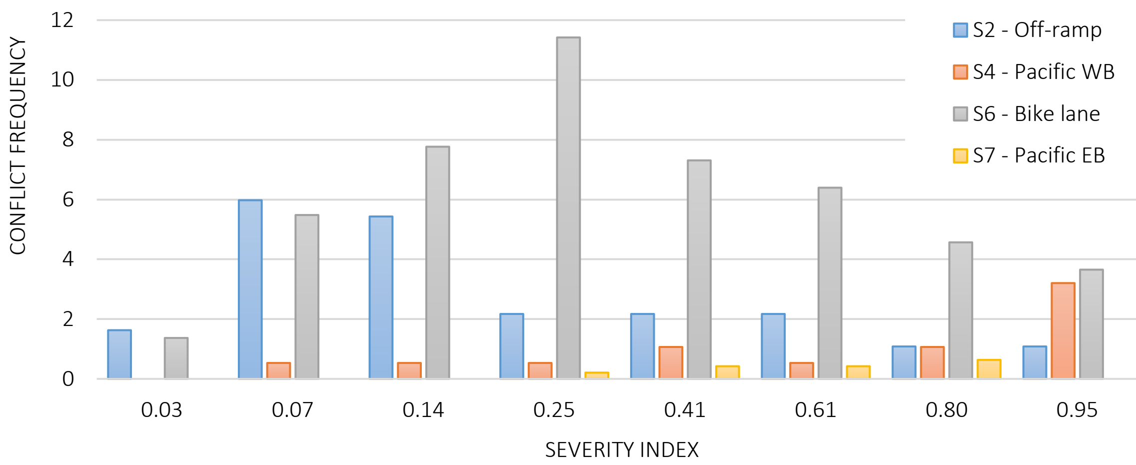

Figure 3-36: Conflict severity per exposure (per 1000 road users).

3.3.4 Intersection conflict zones: summary of conflicts

A summary of the detected-conflict distributions per scene is shown in Figure 3-37 and Figure 3-38, comparing the amount of vehicle-vehicle conflicts to the combined amount of different types of conflicts involving active transportation users (vehicle-pedestrian, vehicle-bicycle, and bicycle-bicycle). Vehicle-vehicle conflicts comprise the majority of detected conflicts. Once again, the contrast of PET and TTC based detections can be appreciated.

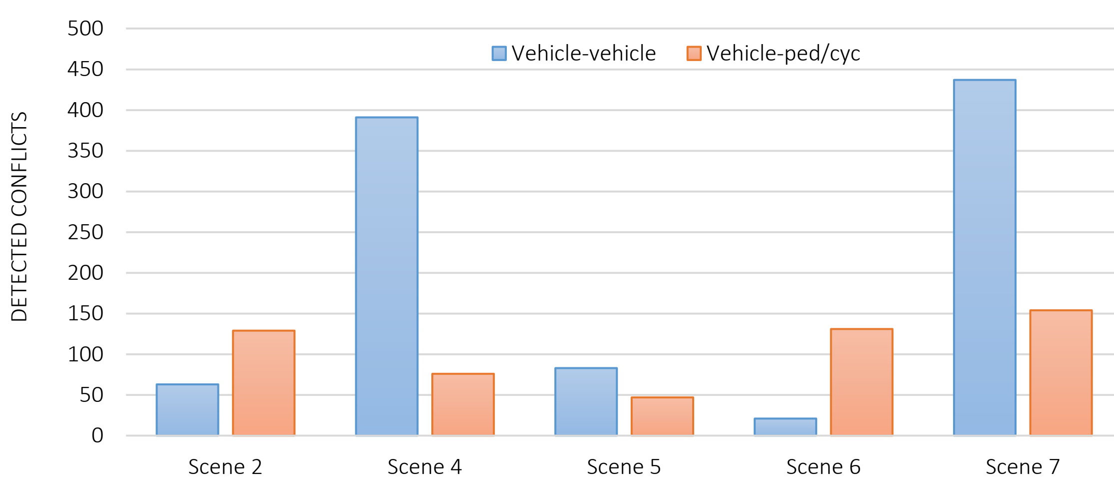

Figure 3-37: Total PET-based conflicts detected per scene.

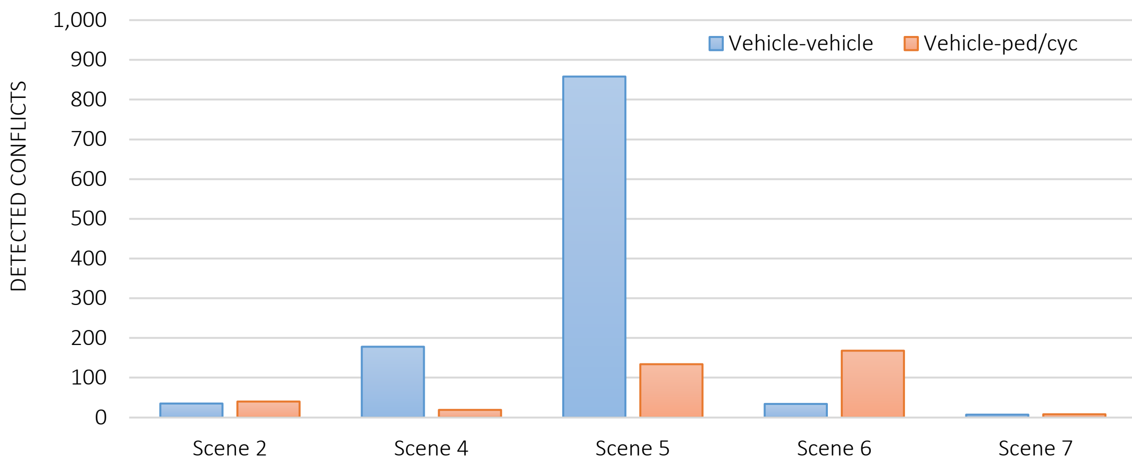

Figure 3-38: Total TTC-based conflicts detected per scene.

Figure 3-39 and Figure 3-40 show the temporal distribution of conflicts throughout day-time hours (between 7:00 am and 7:00 pm), combining PET- and TTC-based detected conflicts. These figures are for illustration purposes only, since the footage of each scene was not taken on the same day and not all the scenes have footage for the complete 12-hour temporal scope.

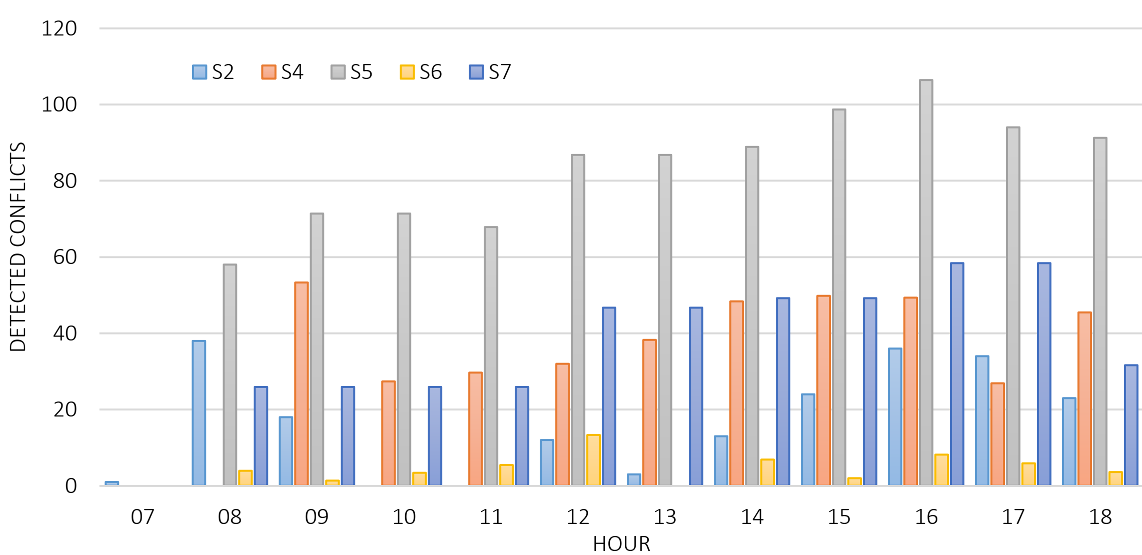

Figure 3-39: Vehicle-vehicle conflict distributions per scene throughout the day.

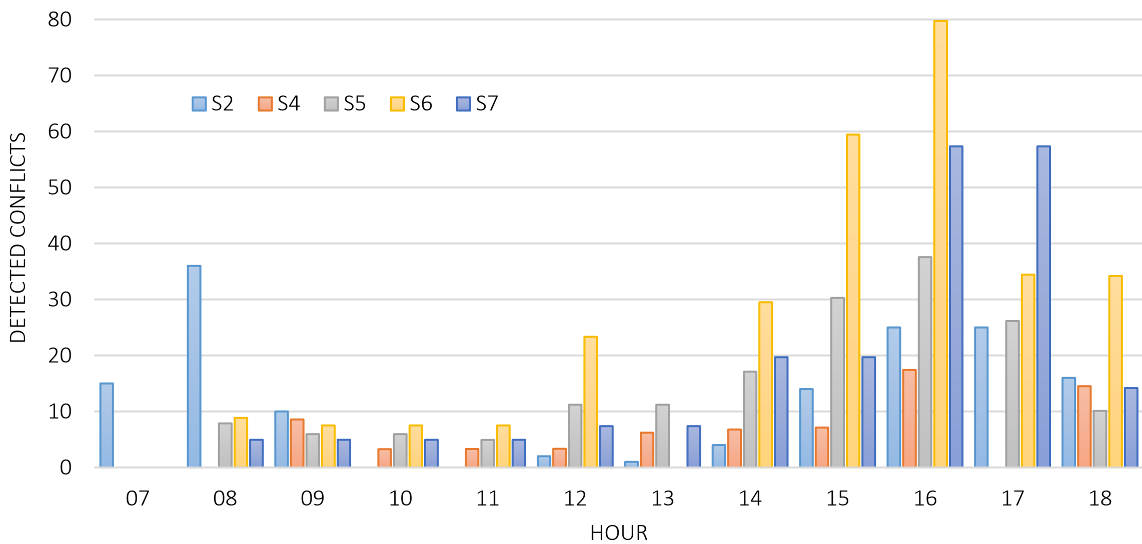

Figure 3-40: Vehicle-pedestrian and vehicle-bicycle conflicts distributions per scene throughout the day.

In Figure 3-39, it can be seen that most vehicle-vehicle conflicts occur during the afternoon peak hours. Scene 5, which covers the merger between the On-ramp and the Burrard St. SB traffic flows, shows the most detected conflicts. In Figure 3-40, it can be seen that most conflicts involving active transportation users occur during the afternoon peak hours. Scene 6, which covers the vehicle-bicycle conflicts in the bike lane's crossing through the On-ramp, is the scene with most detected conflicts.

3.3.5 Intersection conflict zones: violations

A comprehensive traffic violation analysis is applied, based on both manual observation and automated detection, to identify road users who are presenting non-conforming behavior to the location's traffic regulations. Table 3-3 and Table 3-4 summarize the vehicle, bicycle, and pedestrian spatial and temporal violations. Manual detection is used for most of the violation identification process, while automated detection helps to validate vehicle not-yielding and bicycle speeding violations. Automated not-yielding violation detection proved to have a 90% accuracy by comparing automated detection with manual observations, and was done using video components from Scene 2.

Vehicle violations

Table 3-3 Most relevant vehicle violations.

	Type of traffic violation	Location/ Approach	Count of traffic violations	Traffic volume	Inappropriate Negotiation Rate (per 1000 vehicles)
1	Stopping over the bicycle crossing or not yielding	On-ramp	495	6,136	80.67
2	Arriving on a red light	Pacific EB	245	4,348	56.35
3	Stopping over the South crosswalk or not yielding	On-ramp	242	4,736	51.10
4	Stopping over the North crosswalk or not yielding	On-ramp	178	5,972	29.81
5	Changing lanes over solid lines into Pacific St.	Off-ramp	163	7,112	22.92
6	Crossing the stop line on a red light	Pacific WB	171	7,532	22.70
7	Changing lanes over solid lines or using the wrong lane	Pacific WB	165	7,532	21.91
8	Driving on the bike lane	On-ramp	8	900	8.89
9	Stopping over the bicycle crossing or not yielding	Off-ramp	56	7,632	7.34
10	Driving on the bike lane	Off-ramp	2	444	4.50
11	Performing illegal turns into Pacific St.	Pacific WB	16	4,348	3.68
12	Changing lanes over solid lines into the Off-ramp	Pacific EB	7	2,900	2.41

Several vehicle violation types are identified at the intersection that are considered as a safety problem. In some cases, the safety problem arises due to the violation’s frequency. Good examples are vehicles not yielding for active road users or stopping beyond the crossing traffic lines.

Figure 3-41: Examples of violations: not-yielding (top-left), cross blocking (top-right), stopping beyond the crossing traffic lines (mid-left), changing lanes over solid traffic paint lines (mid-right), using the wrong lane (bottom-left), and illegal right-turn (bottom-right).

In other cases, the safety problem arises due to the violation's potential for causing a severe conflict with a pedestrian or bicycle. These are the cases for motor vehicles driving along bike lanes and crosswalks, or vehicles crossing under a red light.

Figure 3-42: Examples of violations: motorcycle on bicycle crossing (top-left), car driving on bike lane (top-right), car arriving on a red light (bottom-left), and motorcycle driving on bike lane (bottom-right).

Cyclist and pedestrian violations

When addressing the violations related to active transportation users, such as cyclists and pedestrians, defining non-conforming behavior becomes a bigger challenge than when analyzing vehicle violations. This is because of the active road user movement's complexity and lack of physical environmental constraints.

Table 3-4: Most relevant bicycle/pedestrian violations.

	Type of traffic violation	Location/ Approach	Count of traffic violations	Traffic volume	Inappropriate Negotiation Rate (per 1000 users)
1	Pedestrian crossing through the ramp	Off-ramp	51	444	114.86
2	Cyclist not dismounting for the South crosswalk	On-ramp	26	248	104.84
3	Bicycle crossing out of bounds through the approach	Pacific WB	33	336	98.21
4	Bicycle crossing outside the bike lane or bicycle crossing	Off-ramp	39	444	87.84
5	Bicycle speeding in the bike lane (speed over 50 km/h)	Pacific EB	31	988	31.38
6	Pedestrian crossing on 'do not walk' phase	Pacific EB	22	1,980	11.11
7	Cyclist not dismounting for the crosswalk	Pacific EB	21	1,980	10.61
8	Bicycle crossing on a red light	Pacific EB	7	1,032	6.78
9	Cyclist not dismounting for the North crosswalk	On-ramp	10	1,548	6.46

By not having a marked bicycle crossing through the Pacific St. WB approach and in combination with the East traffic island's sidewalk, out-of-bounds violations are recurrent among cyclists. Moreover, the lack of clear signage for northbound pedestrians at the Off-ramp fails to prevent pedestrian use of the East traffic island's sidewalk and crossing through the Pacific St. WB approach. Examples of these situations are shown in Figure 3-43.

Figure 3-43: Examples of violations: bicycle on the East traffic island's sidewalk instead of using the bike lane (top-left), bicycle crossing out-of-bounds (top-right), pedestrian crossing the Off-ramp (bottom-left), and pedestrian crossing through the Pacific St. WB approach (bottom-right).

Another safety problem arises when addressing the speed of cyclists going downhill on the Burrard St. SB bike lane. Cyclists have the same rights and responsibilities as drivers, including speed limits, according to the Motor Vehicle Act (Province of British Columbia, 2016), and there is a precedent of cyclists getting fined for speeding in British Columbia (McArthur, 2016). Using automated detection and relating the bicycle speed to the speed limit stated by the City of Vancouver (50 km/h), bicycle speed violations can be detected. Bicycle speed measurement is explained in section 3.3.6 and illustrated in Figure 3-46.

An example of bicycle speeding is shown in Figure 3-44, where a comparison is made between two pairs of bicycles. The first pair of bicycles, after stopping for the traffic signal, is crossing at 15 km/h;

while the second pair of bicycles, after not stopping for the traffic signal, is crossing three times faster, at 45 km/h. When combined with vehicles crossing under a red light and illegal turns from Burrard St. into Pacific St., high bicycle speeds represent a safety problem. It is estimated that for every 1,000 cyclists crossing through the Pacific St. EB's bike crossing, 31 will be going over 50 km/h. Figure 3-45 shows the cyclist speed distribution at this location.

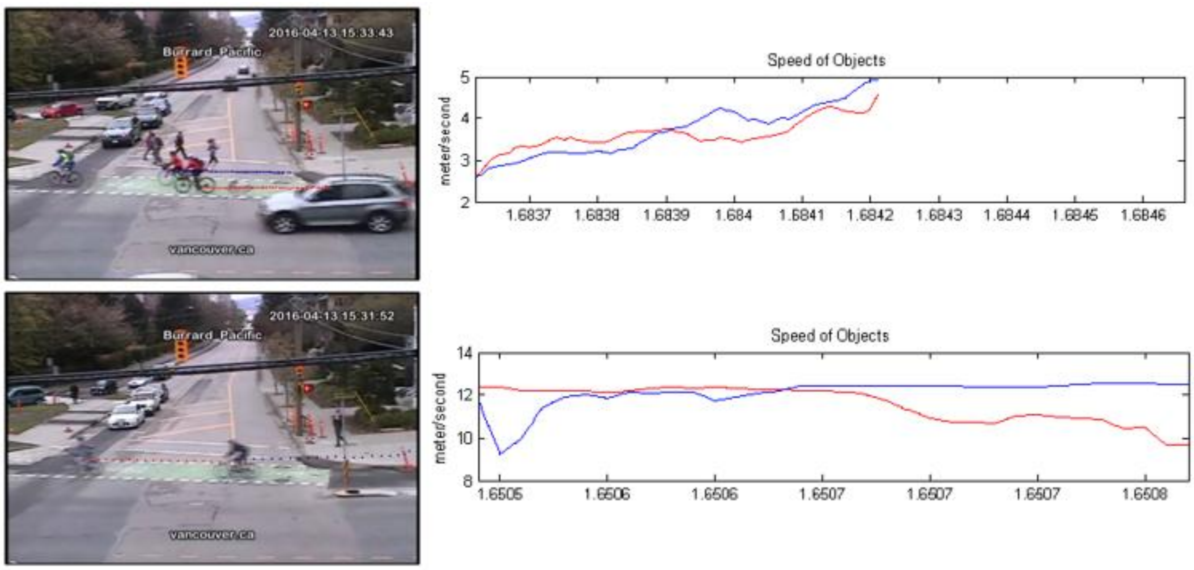

Figure 3-44: Speed comparison between two bicycles stopping before the intersection (top) and two bicycles not stopping before the intersection (bottom).

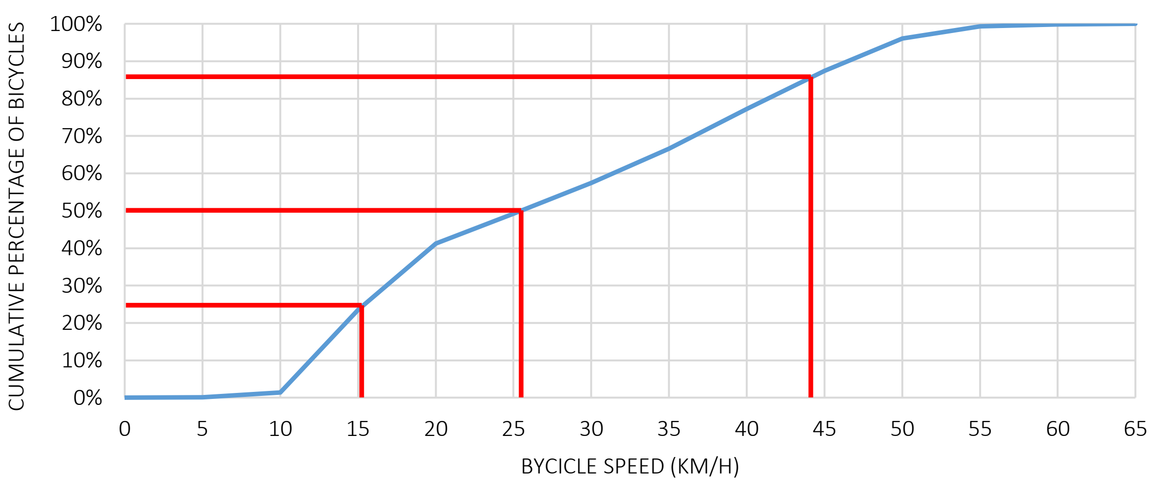

Figure 3-45: Bicycle speed cumulative distribution for Pacific St. EB' bicycle crossing.
25th percentile: 15 km/h, 50th percentile: 25 km/h, 85th percentile: 44 km/h.

3.3.6 Speed validation

To calculate the speed of each road user, two imaginary parallel lines (screens) are placed across two selected sections of the intersection: on the Off-ramp (for vehicles) and on the Pacific St. EB approach's bicycle crossing (for cyclists). Dividing the distance by the time it takes for each tracked feature to pass through both lines will generate the average speed of the road user through the segment (Zaki and Sayed, 2016b).

This procedure is applied to selected road users. 4,173 vehicles and 790 cyclists with good tracking (continuous throughout) are selected for their respective validation. The distance between the screens in the Off-ramp is determined to be 7.9 m, while the distance between the screens in the bike crossing is 7.3 m.

Figure 3-46: Speed screens for S2 (left) and S7 (right).

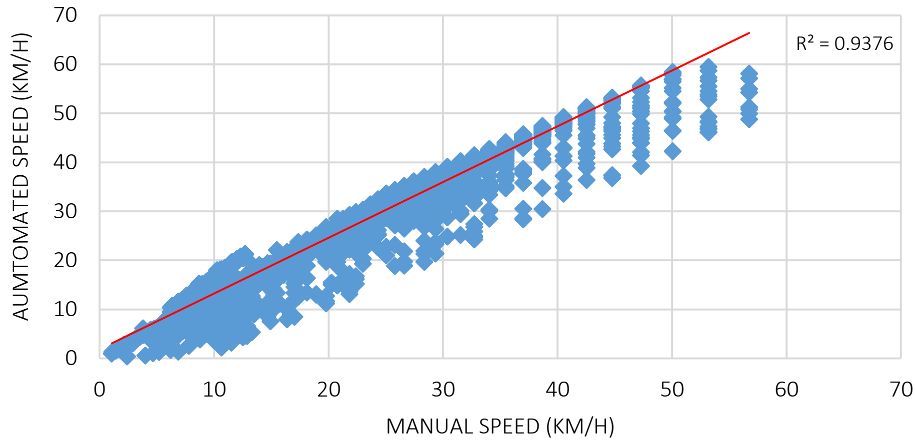

Figure 3-47: Speed validation for vehicles.

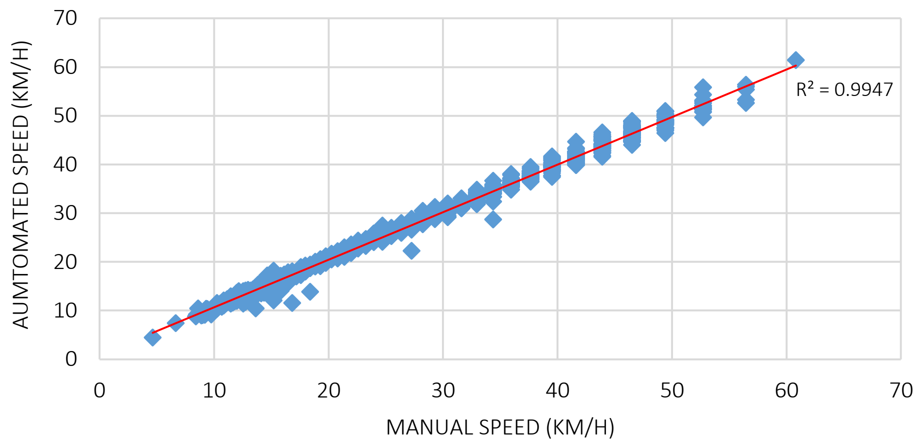

Figure 3-48: Speed validation for bicycles.

3.3.7 Challenges encountered during the traffic conflict analysis

During the course of the analysis, several challenges are encountered related to the video footage. Factors such as the camera's distance to the tracked road users, camera angle, lighting, and occlusions, as well as the overall low definition of the cameras, affected the capability for analysis and limited its accuracy. The impact of these factors vary depending on the camera and/or the scene, forcing the analysis to occasionally rely on manual video observations.

Road users' occlusion

Due to cameras' angle and height, road users going on paths further away from the camera can get temporary occluded by road users going on nearer paths. Even though most times road user occlusion is only partial (i.e. parts of the occluded road user are still visible), it is enough to affect the feature tracking procedure. Figure 3-49 shows two examples of occlusion caused by road users: on the left, a transport truck is occluding other road users behind it, and on the right, a small white truck is occluding a conflict region while stopping for the red light.

Figure 3-49: Occlusion caused by road users.

Fixed objects' occlusion

With the exemption of Scene 2, all video footage has occlusion issues due to fixed objects. In Figure 3-50, fixed objects for scenes 4 to 7 are identified in yellow (for segments of power-line cables) and red (for traffic control elements such as signs and posts, as well as power-line cable loops). Fixed objects are one of the biggest challenge to address since they are present during the entire footage. For the *after* analysis, it might be useful to consider relocating the cameras (if possible) to minimize the occlusion caused by fixed objects.

Figure 3-50: Occlusion caused by fixed objects in S4 (top-left), S5 (top-right), S6 (bottom-left), and S7 (bottom-right).

Other challenges

Weather-related challenges such as rain and sun glare can also affect automated detection. In both cases, video image tends to blur and vehicles may go undetected during short periods of time. To address these issues, manual video observation is conducted alongside automated detection. Traffic control was also being implemented during the field survey, which might limit the validity of the results. Traffic control operations resulted in temporary changes in road user paths, additional sources of occlusion, and often false positive detections. To minimize their effect on the counting validation, traffic control personnel is filtered out of the analysis.

Figure 3-51: Challenges caused by bad weather (top-left), sun glare (top-right), traffic control personnel (bottom-left), and traffic control operations (bottom-right).

3.4 Analysis of proposed safety improvements

This research has the particularity of taking place once the countermeasures' development has started. Furthermore, construction takes place during the field survey process. Therefore, instead of proposing a new design or recommendations for the intersection based on the results of the conflict analysis and violations, these results will be compared to the design made by the City of Vancouver (2015b) to understand how the new alignment will affect the conflict zones and non-conforming behavior present in the current design.

3.4.1 New intersection design

Figure 3-52 shows the new design for the Burrard St. and Pacific St. intersection and its surroundings. Proposed improvements will address vehicle, bicycle, and pedestrian facilities. The most significant modification will be the elimination of both ramps, introducing new right-turn exclusive lanes in the Pacific St. EB approach (to replace the On-ramp) and in the Burrard St. NB approach (to replace the Off-ramp). The elimination of the ramps will enable a better spatial distribution at the intersection, providing a larger vehicle capacity and new protected bike lanes, isolating the three types of road users in an effective way.

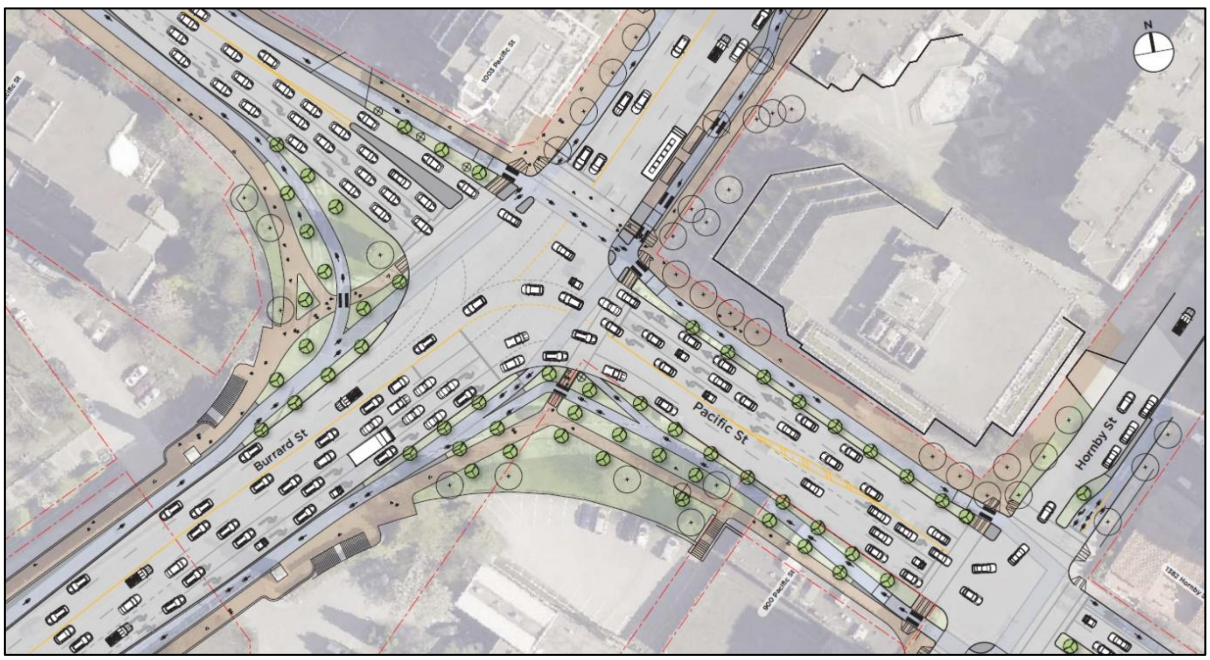

Figure 3-52: Proposed design for the Burrard St. and Pacific St. intersection. Source: City of Vancouver, 2015b.

Burrard St. NB

The Burrard St. NB approach will consist of a total of four lanes: two for crossing straight through the intersection and two for right-turn only. Pedestrian and bicycle crossings through this approach will not be allowed. The current area of the Off-ramp will be used for a new bike lane and sidewalk configuration.

Pacific St. WB

The Pacific St. WB approach will maintain its current three-lane configuration: two left-turn lanes, and one straight and right-turn lane. The bicycle crossing through this approach will be marked with horizontal signage, and a new exclusive crosswalk will be introduced.

Burrard St. SB

The Burrard St. SB approach will maintain its current two-lane configuration: right- and left-turns will not be allowed. The current crosswalk will be eliminated to introduce separated bicycle and pedestrian crossings. Thus, separating bicycles and pedestrians flows.

Pacific St. EB

The Pacific St. EB approach will experience drastic changes. The On-ramp will be removed to make space for two new right-turn lanes, in addition to the existing one to go through the intersection. Left-turns will not be allowed. The current area of the On-ramp will be used for a new bike lane and sidewalk configuration. After crossing the intersection, Pacific St. will have two lanes to accommodate the vehicles coming from the Pacific St. EB approach and the vehicles coming from the new right-turn lanes in the Burrard St. NB approach. Bicycle and pedestrian crossings through this approach will maintain their current design.

3.4.2 Expected safety effects

Several conflicts and violations are identified throughout the analysis. For vehicle-vehicle conflicts, four zones are considered to have high conflict frequency: the merger between the On-ramp and the Burrard St. SB traffic flows, the Pacific St. WB approach, the beginning of the On-ramp, and the end of the Off-ramp. For conflicts involving active transportation users, four zones are again considered to have high conflict frequency: the bicycle crossing through the Off-ramp, the bike lane through the On-ramp, and the crossings through both Pacific St. WB and EB approaches. Non-conforming behavior is detected along the intersection.

The new design is expected to address many of the safety problems at the intersection. Still, there are some problems not addressed in the proposed improvements or that are likely to migrate to a different zone of the intersection. Moreover, it is possible that the new design will generate new problems or ease different non-conforming behavior. The safety improvements will be further evaluated in the *after* analysis, by comparing the frequency and severity of traffic conflicts before and after the improvements. The expectations for the safety problems encountered in this project are presented in Table 3-5 (for vehicles) and Table 3-6 (for bicycle and pedestrians).

Vehicle safety problems

Table 3-5: Expected vehicle-related current safety problems' status under the new design.

	Type of safety problem	Location/ Approach	Addressed (*)	Potential migration	New problem
1	Merging conflicts	On-ramp	●		
2	Rear-end conflicts	On-ramp	●	X	
3	Stopping over the bicycle crossing or not yielding	On-ramp	●	X	
4	Stopping over the South crosswalk or not yielding	On-ramp	●		
5	Stopping over the North crosswalk or not yielding	On-ramp	●		
6	Driving on the bike lane	On-ramp	●		
7	Rear-end conflicts	Off-ramp	●		
8	Stopping over the bicycle crossing or not yielding	Off-ramp	●		
9	Changing lanes over solid traffic lines into Pacific St.	Off-ramp	●		
10	Changing lanes over solid lines into the Off-ramp	Pacific EB	●		
11	Rear-end and side-swipe conflicts	Pacific WB	◖		
12	Crossing the stop line on a red light	Pacific WB	◖		
13	Driving on the bike lane	Off-ramp	○		
14	Arriving at the other side of the intersection on a red light	Pacific EB	○		
15	Changing lanes over solid lines or using the wrong lane for their movements	Pacific WB	○		
16	Performing illegal turns into Pacific St.	Pacific WB	○		
17	Changing lanes over solid lines or using the wrong lane for their movements	Pacific EB			X
18	Changing lanes over solid lines or using the wrong lane for their movements	Burrard NB			X

(*) ● : Fully addressed - ◖: Partly addressed - ○ : Not addressed.

Since both ramps are to be replaced, traffic conflicts and violations in these locations are expected to be addressed. In the Pacific St. WB approach, lane-switching violations and side-swipe conflicts will be reduced by the introduction of a new traffic island on the Pacific St. EB approach (illustrated in Figure 3-53), but rear-end conflicts caused by right-turn interruptions in the traffic flow of the Pacific St. WB approach will remain. This latest conflict could be solved by restricting the right-turn movement or by protecting the bicycle and pedestrian crossings with an additional signal phase. Important violations such as motor vehicles going in the Burrard St. bike lane will be corrected, while illegal turns, stopping over the lines, and arriving on a red light will not. In the *after* analysis, particular care will be required in the conflict and violation analyses for the new right-turn movements at the Pacific St. EB and Burrard St. NB approaches (Figure 3-54), as they are expected to become new safety problems (rear-end and side-swipe conflicts and lane-switching over solid lines violations).

Figure 3-53: Lane-switching correction for the Pacific St. WB approach by the new traffic island.

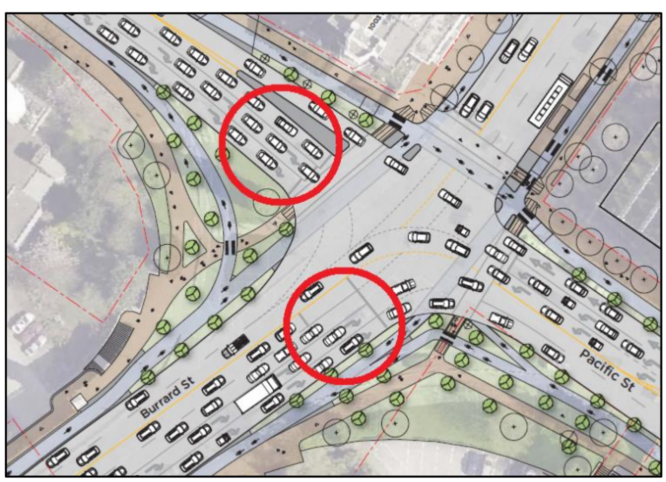

Figure 3-54: Expected new safety problems for vehicles based on the new design.

Bicycle and pedestrian safety problems

Table 3-6: Expected active road user-related current safety problems' status under the new design.

	Type of safety problem	Location/ Approach	Addressed (*)	Potential migration	New problem
1	Vehicle-bicycle conflicts	On-ramp	●		
2	Vehicle-bicycle conflicts	Off-ramp	●		
3	Bicycle crossing outside the bike lane or bike crossing	Off-ramp	●		
4	Pedestrians crossing through the ramp	Off-ramp	●		
5	Vehicle-bicycle conflicts	Pacific WB	●		
6	Bicycle crossing out of bounds through the approach	Pacific WB	●		
7	Cyclist not dismounting for the North crosswalk	On-ramp	◖	X	
8	Cyclist not dismounting for the South crosswalk	On-ramp	◖	X	
9	Cyclist not dismounting for the crosswalk	Pacific EB	○		
10	Pedestrian crossing on 'do not walk' phase	Pacific EB	○		
11	Bicycle crossing on red light	Pacific EB	○		
12	Bicycle speeding in the bike lane (speed over 50 km/h)	Pacific EB	○		
13	Bicycle-bicycle and vehicle-bicycle conflicts	Pacific EB	○		
14	Vehicle-bicycle and vehicle-pedestrian right-turn conflicts	Burrard NB			X

(*)● : Fully addressed - ◖: Partly addressed - ○ : Not addressed.

Since both ramps are to be replaced, the conflicts and violations in these locations are expected to be addressed, while the introduction of protected bike lanes on Pacific St. will help to reduce vehicle-bicycle conflicts along the street. Safety problems will remain in the Pacific St. EB approach's bicycle and pedestrian crossings, with the possibility of increasing the conflict frequency since more vehicles will be entering the intersection from this approach due to the added right-turn lanes. From the new design, is unclear how cyclists going along Pacific St. on an eastbound direction will cross the intersection since no protected bike lane is provided at the Burrard St. NB approach. Speed reduction elements could be introduced to slow down bicycles coming from the Burrard St. SB approach. Placing dismounting signage for cyclists when they are moving northbound through the Pacific St. EB approach's crosswalk will help to minimize cyclist not-dismounting violations. In the *after* analysis, particular care will be required in the conflict and violation analyses for the new right-turn movement at the Burrard St. NB approach, as it is expected to become a new safety problem with a high frequency of right-turn vehicle-pedestrian and vehicle-bicycle conflicts, as showed in Figure 3-55.

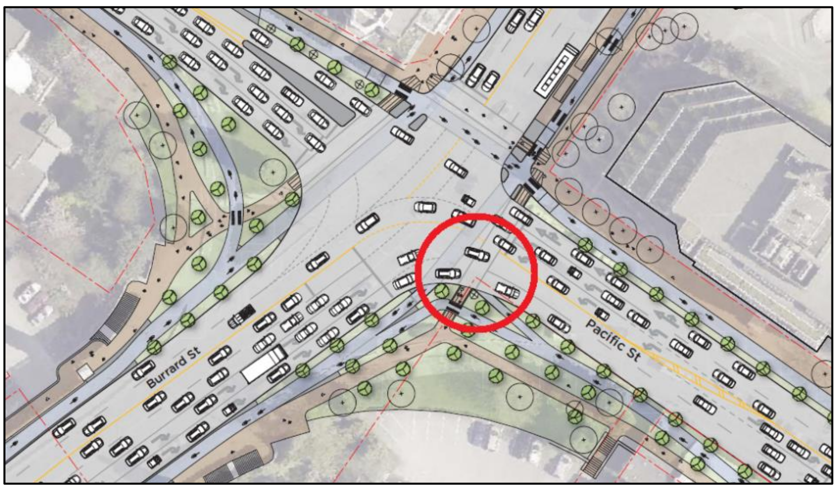

Figure 3-55: Expected new safety problems for active road users based on the new design.

4. CYCLIST YIELDING BEHAVIOR ANALYSIS

This chapter evaluates microscopic cyclist yielding behavior by analyzing vehicle and bicycle yielding rates. Most conventional models based on the Highway Capacity Manual (Transportation Research Board, 2010) neglect how yielding rates change the dynamics of vehicle-bicycle interactions (Huff and Liggett, 2015), and how important these rates can be when accounting for safety. Cyclist compliance with traffic regulations is also studied by looking at how cyclists truly operate at intersections despite the formal traffic rules.

The objective of this chapter is to provide insights of what leads a cyclist to make the decision to yield, by observing two complementary intersections (i.e. bicycle crossings) between bicycle paths and one-way vehicle paths. Understanding the relevance of yielding rates and cyclist compliance with traffic regulations can enable engineers to design and build safer intersections which are consistent with road users' expected behavior, and to develop more realistic and accurate behavior models.

4.1 Site characteristics and data collection

The research is conducted in the bicycle crossings of the Off-ramp and On-ramp (Figure 4-1). Each location constitutes an intersection between a one-way single-lane and a one-way bicycle path and are selected due to their spatial proximity and because traffic regulations are different. The bicycle crossings have approximated widths of 2.5 and 7 meters in the Off-ramp and the On-ramp, respectively. Both bicycle crossings are approximately 4.5 meters long.

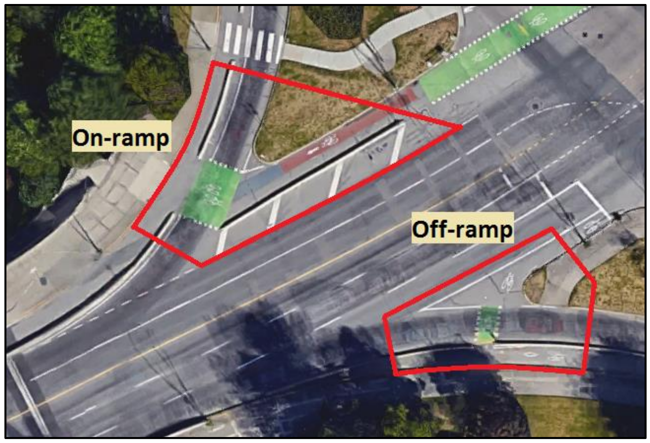

Figure 4-1: Areas of interest on the northeast end of the Burrard Bridge.

Data collection is performed as previously explained in section 3.2. As shown in Table 3-1, the Off-ramp video footage was recorded on April 13th, 2016, for a total of 12 uninterrupted hours between 7 AM and 7 PM. The On-ramp video footage was recorded on April 11th, 2016, for a total of 9 intermittent hours between 8 AM and 7 PM. In total, 399 crossing cyclists are captured on the Off-ramp and 409 crossing cyclists are captured on the On-ramp for the cyclist yielding behavior analysis.

Figure 4-2: Conflict regions of interest in the Off-ramp (left) and On-ramp (right).

4.2 Traffic signage and right-of-way

Traffic signage is different at each intersection. Thus, it is expected for road users to behave differently. Defining who has the legal right-of-way by traffic signage becomes useful to understand road user's compliance with traffic regulations and the yielding rates' analysis. Dotted white lines delimit the crossings. Traffic signage is indicated in Table 4-1.

Table 4-1: Available traffic signage at the time of data collection.

Off-ramp	Vehicles	No signage instructing drivers to yield or to stop.
	Bicycles	Two stop signs at the beginning of the bicycle crossing ([a]).
On-ramp	Vehicles	A yielding sign and a 'bicycles coming from the left' sign ([b]).
	Bicycles	No signage instructing cyclists to yield or to stop.

([a]) and ([b]) are showed in the left and right pictures of Figure 4-3, respectively.

Figure 4-3: Traffic signage in the Off-ramp (left) and in the On-ramp (right).

The stop signs in the Off-ramp indicate that bicycles must stop before the crossing, regardless of whether a vehicle is coming or not. Vehicles are not instructed to yield to cyclists, nor are they previously warned of the presence of the bicycle crossing before the pavement markings. In contrast, the On-ramp does not present any signage for bicycles, while providing vehicles with a yield sign and a 'bicycles coming from the left' sign. Based on the traffic signage, vehicles have the legal right-of-way at the Off-ramp and bicycles have the legal right-of-way at the On-ramp. It is possible that drivers are unaware of the bicycle stop signs on the Off-ramp because of their relatively sub-standard size and angle in relation to the driver's perspective. In addition, the pavement markings are identical at both locations and drivers could interpret the markings as an indication to yield, similar to a pedestrian crosswalk.

4.3 Classification of yielding interactions

A typical yielding definition indicates that a road user will be considered as yielding if they allow the other road user to cross first (Svensson and Pauna-Gren, 2015). However, defining yielding based on the outcome of who crosses first fails to address more complex situations. Consider the following questions:

- If both road users completely stop to let the other one go first, then should the road user who crosses first be considered as not yielding the right-of-way?
- If none of the road users stop or adjust their speed to let the other one go first, then should the road user who crosses second be considered as yielding the right-of-way?
- If a road user stops to yield the right-of-way, but by doing so blocks the crossing, then should this road user still be considered as yielding the right-of-way?

Different logical interpretations can challenge the previous definition of yielding. To address yielding interactions and their potential outcomes, a more flexible yielding definition from Silvano, Koutsopoulos, and Ma (2016) is adopted, which states that a road user's yielding process is divided into two parts: a conflict decision and a yielding decision. The decision to yield begins at some distance upstream of the conflict region of the intersection.

First, the road user must recognize a potential for collision between themselves and another incoming road user on an intersecting trajectory. In case the road user decides there is potential for collision, then they must decide if the potential for collision requires yielding by completely stopping or adjusting their speed and trajectory to allow the other road user to traverse safely the conflict region. From this concept, a two-step methodology was developed to classify different types of interactions:

4.3.1 Identifying a yielding-required situation

The first step is to identify if a vehicle-bicycle interaction constitutes a *yielding-required situation*, which are those interactions in which it is expected for at least one road user to yield. Three requirements were identified as necessary for an interaction to be considered as a yielding-required situation for analysis purposes:

- Relevant proximity: There must be relatively close proximity between vehicle and bicycle near the conflict region of the intersection. What is considered as sufficient spatial and temporal proximity vary depending on the geometric configuration of the intersection, as well as each road user's position and speed.
- Potential for collision: Relevant proximity by itself does not guarantee potential for collision. Road users' speeds and trajectories can be observed to evaluate if such potential exists.
- Yielding must be a choice: There must be room for both road users to move forward. Road users need to be able to move forward without blocking the intersection in case they decide not to yield. If yielding is imposed due to traffic, then it will not be considered as a yielding-required situation.

These requirements become useful to filter those interactions which are not considered to be yielding-required situations. A definition is made for what a yielding-required situation is: *a yielding-required* *situation will be considered as such if a pair consisting of one vehicle and one bicycle are in proximity to each other and both have the opportunity to move forward through or towards the conflict region while presenting the potential for collision in case none of them decides to yield.*

4.3.2 Classifying a yielding-required situation

A yielding maneuver is defined as stopping or slowing down with the intention to allow the other road user to traverse safely the conflict region (Silvano, Koutsopoulos, and Ma, 2016). By defining yielding as a maneuver rather than an outcome, it becomes possible for a road user to make a yielding maneuver despite the outcome of who ends up crossing first. Furthermore, Forester (2012) explains that cyclists are not required to stop to be considered as yielding since they are best able to get moving again if they are still riding with their feet on the pedals. A cyclist will find a benefit in moving slowly towards the intersection, waiting for an acceptable gap in the traffic to cross, rather than completely stopping before the traffic line. If the cyclist gets close to the traffic line and no gap comes along, the cyclist must stop to wait.

A methodology is developed to classify different yielding interactions acknowledging the following guidelines:

- A yielding maneuver must be clear: The yielding road user must slow down or stop if necessary to give the other road user the opportunity to cross. Since there is no unique and objective standard to state how much an approaching road user must slow down to be considered as yielding, the interpretation of what a yielding maneuver is might be subjected to the road user's or the observer's preferences and experiences.
- Crossing intentions must be clear: It should not be expected for a road user to yield to another until it is clear that the later has the intention of crossing the intersection.

- It is possible for a road user to yield to another road user and, after evaluating the other's response, decide whether to go in first or in second. In the same way, it is possible for a road user to yield or not regardless having the legal right-of-way. Thus, a separation between yielding maneuver, legal right-of-way, and crossing order must be acknowledged.
- If a driver has the option to choose between waiting behind the dotted white line or to move the vehicle forward and temporarily block the intersection and it chooses the later one, then the vehicle will be considered to have failed to yield to all its interacting cyclists.

From these classification rules, a yielding definition can be developed to be used to assess the different types of vehicle-bicycle yielding-required situations: *a road user will be considered as yielding the right-of-way if it makes a clear attempt, by slowing down or stopping if necessary, to let another road user cross in a safe and undisturbed manner without blocking the intersection.*

By combining both definitions, yielding-required situations can be classified in one of four different categories or interaction types, as showed in Figure 4-4.

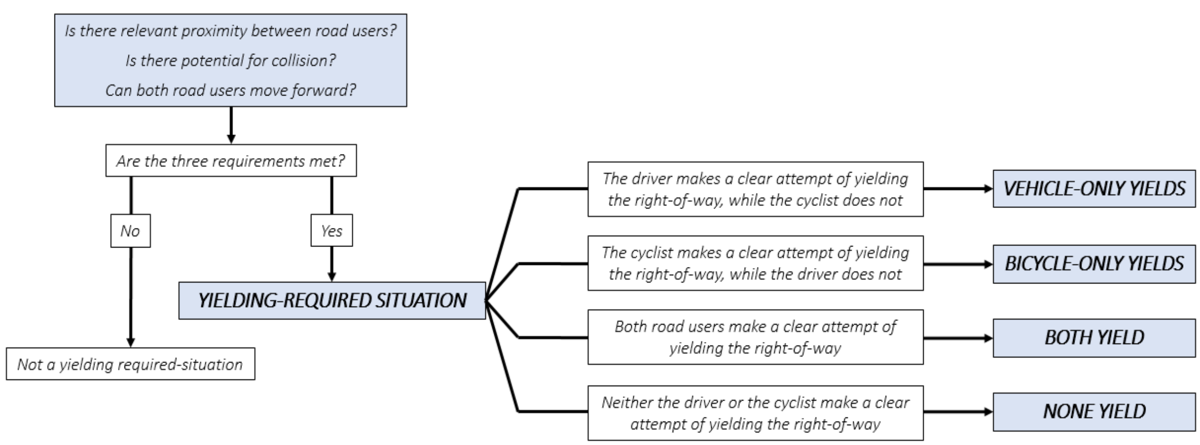

Figure 4-4: Yielding interactions' classification methodology.

4.4 Summary of findings

The following section summarizes the results obtained from the cyclist yielding behavior analysis. Findings include vehicle and bicycle yielding rates, modeling the observed cyclist's probability of yielding, and the effects of bicycle yielding on the severity of conflicts. Furthermore, different observed cyclist behavior components are identified and analyzed: cyclist compliance with stop signs, cyclist use of hand gestures, and cyclist behavior when facing a blocked intersection.

4.4.1 Vehicle and bicycle yielding rates

A total of 881 vehicle-bicycle interactions are considered for the analysis, but only 705 meet the requirements to be classified as yielding-required situations. From these yielding-required situations, the yielding rates are extracted. The results presented in Table 4-2 and Figure 4-5 show consistent vehicle yielding rates in both ramps: almost 70% of vehicles yield, regardless of who has the legal right-of-way or the geometric configuration of the ramp. A different situation can be observed in bicycle yielding rates. When vehicles have the legal right-of-way, less than 60% of bicycles yield. When bicycles have the legal right-of-way, only 6% of bicycles yield.

The results suggest that drivers are likely to keep a consistent behavior when approaching an intersection with more vulnerable road users, although similar analyses should be conducted in more locations before generalizing. It is a safety problem that 3 out of 10 drivers fail to yield for bicycles, which is hazardous when accounting for cyclist vulnerability in vehicle-bicycle collisions. In contrast, cyclists seem to be highly unlikely to yield when having the legal right-of-way. Bicycle yielding rates at the On-ramp might be affected by the cyclist's expectations for vehicles to yield. Despite having the legal right-of-way, the low bicycle yielding rate is a safety problem in light of the 30% vehicle not-yielding rate.

Table 4-2: Yielding rates.

	Off-ramp	On-ramp	Total
Analyzed interactions	372	509	881
Yielding-required situations	300	405	705
Vehicles yielding (yielding rate)	207 (69.00%)	278 (68.64%)	485
Bicycles yielding (yielding rate)	177 (59.00%)	25 (6.17%)	202

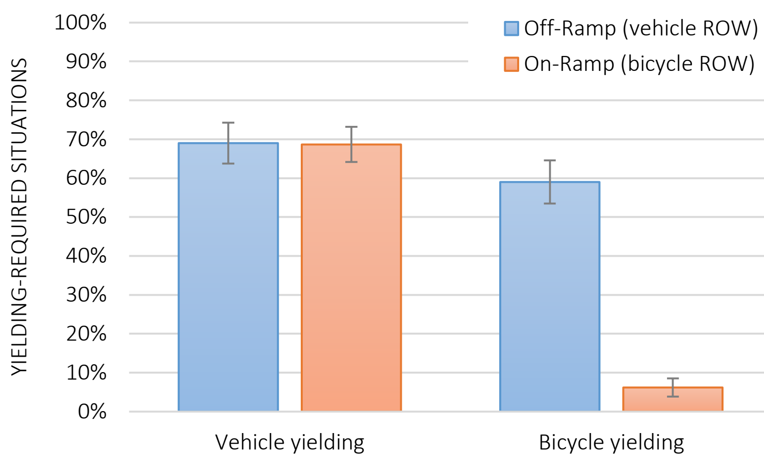

Figure 4-5: Yielding rates (with error bars).

In Table 4-3 and Figure 4-6, the 705 yielding-required situations are distributed according to the classification given in Figure 4-4. The distribution can be attributed to a combination of different factors, related to the geometric configuration of the intersection and road users' behavior (Bjorklund and Aberg, 2005). An example of the geometric configuration effect on yielding is illustrated in Figure 4-7, where the cyclist's field of vision changes as the cyclist moves towards the intersection. In the On-ramp, the cyclist's detection of an incoming vehicle can occur early in the approaching trajectory and is continuous along the path, giving the cyclist adequate time to assess whether the vehicle will yield and then, if necessary, to adjust their speed and trajectory accordingly. In the Off-ramp, vehicles are coming from behind the cyclist's normal field of vision, hindering their ability to track the vehicle.

In addition to the geometric configuration, other factors can contribute to cyclists' decision to yield, including: traffic signage, vehicle approaching speed, width of the bicycle crossing, the complexity of the maneuvers near the crossing (e.g. the sharpness of the left-turn bicycles have to make to access the Off-ramp bicycle crossing), among others.

Table 4-3: Yielding distribution (by interaction type).

	Off-ramp	**On-ramp**
Vehicle-only yields	115 (38.33%)	269 (66.42%)
Bicycle-only yields	85 (28.33%)	16 (3.95%)
None yield	8 (2.67%)	111 (27.41%)
Both yield	92 (30.67%)	9 (2.22%)
Total	300	405

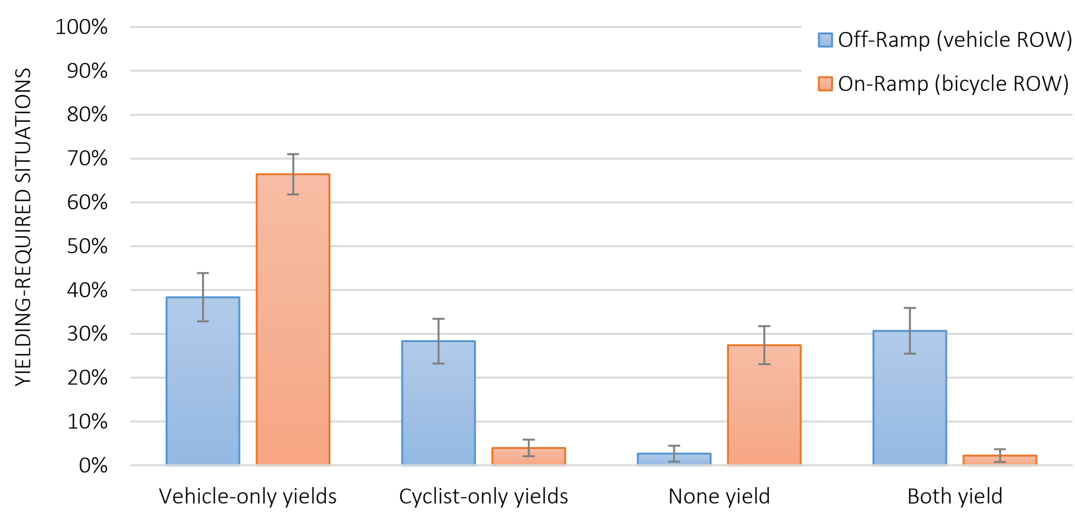

Figure 4-6: Yielding distribution by interaction type (with error bars).

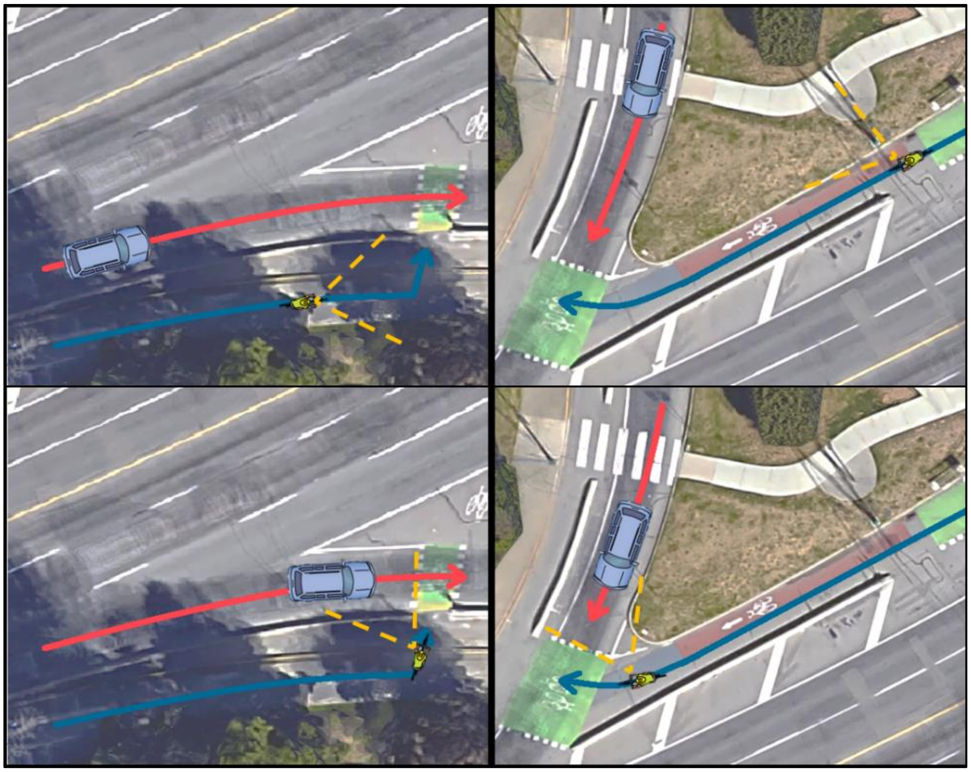

Figure 4-7: Change in cyclist's awareness of vehicles in the Off-ramp (left) and On-ramp (right).

Because of the geometric configuration, it was expected for at least one road user to yield in the Off-ramp interactions: in 97% of the yielding-required situations, at least one road user yields. A different situation occurs in the On-ramp, where in 27% of the yielding-required situations, neither of the road users yield. Also, *both yield* cases are a rare situation in the On-ramp, meaning that if one of the two road users yield, it is highly unlikely for the other to yield as well. Despite the analysis taking place in only two intersections, understanding how and why this distribution changes depending on the intersection's configuration and rules of priority might help to increase the accuracy of microscopic behavior models and software.

4.4.2 Modeling cyclist yielding behavior

To develop a behavior model for the cyclist's probability to yield, 9 different variables are considered, which are presented in Table 4-4. The speed variables are obtained through computer vision techniques and consisted of the bicycle and vehicle approaching speeds and the difference between them. The rest of the variables are obtained through manual observation of the road user trajectories obtained from the vision systems. Only the On-ramp is modeled, as the Off-ramp bicycle's approaching speed was not measurable using the available video footage due to the available camera angle.

Table 4-4: List of variables for cyclist yielding behavior models.

C_S	Independent	Approaching speed of the interacting bicycle, in km/h.
V_S	Independent	Approaching speed of the interacting vehicle, in km/h.
C_S-V_S	Independent	Difference in approaching speeds of interacting road users, in km/h.
V_N	Independent	Bicycles passing in front of the same yielding vehicle before current interaction.
V_{WT}	Independent	Vehicle waiting time since previous interaction, in seconds.
C_N	Independent	Vehicles passing in front of the same yielding bicycle before current interaction.
C_{WT}	Independent	Bicycle waiting time since previous interaction, in seconds.
C_G	Independent	Bicycle group size. A single cyclist is accounted as C_G=1.
V_Y	Independent	Vehicle yielding. Binary variable: if yielding, V_Y=1; if not yielding, V_Y=0.
C_Y	Dependent	Bicycle yielding. Binary variable: if yielding, C_Y=1; if not yielding, C_Y=0.

The models are developed using a binary logit model structure with the *Real Statistics Resource Pack* (Zaiontz, 2017a). The goodness-of-fit is tested using the Pearson's chi-square test (χ^2) and the Hosmer-Lemeshow test, which is essentially a Pearson's chi-square test for grouped data. Additionally, three pseudo coefficients of determination (pseudo-R^2) are presented: the log-linear ratio R^2 (also known as McFadden's R^2), the Cox and Snell's R^2, and the Nagelkerke's R^2 (Zaiontz, 2017b). Because of occlusion and miss-detection issues, only 171 yielding-required interactions in the On-ramp are assessed in the analysis. Only in 9 (5%) of these interactions did the bicycles yield, while in 162 (95%) the bicycles did not. Table 4-5 shows the model estimation results for four developed models.

Table 4-5: Model of the On-ramp cyclist's probability of yielding.

Model		1	2	3	4
Intercept	(coef.)	**0.859**	**0.527**	**-2.097**	**-2.448**
	(s.e.)	1.550	1.080	0.763	0.354
	(p-value)	0.580	0.626	0.006	4.64E-12
C_S	(coef.)	**-0.201**	**-0.217**		
	(s.e.)	0.086	0.079		
	(p-value)	1.91E-02	6.04E-03		
V_S	(coef.)	**0.006**			
	(s.e.)	0.039			
	(p-value)	0.883			
C_S-V_S	(coef.)			**-0.059**	**-0.069**
	(s.e.)			0.029	0.026
	(p-value)			4.23E-02	7.86E-03
V_N	(coef.)	**-0.014**		**-0.014**	
	(s.e.)	0.186		0.186	
	(p-value)	0.941		0.942	
V_{WT}	(coef.)	**-12.352**		**-12.267**	
	(s.e.)	1264		1074	
	(p-value)	0.992		0.991	
C_N	(coef.)	**0.839**		**0.888**	
	(s.e.)	0.969		0.933	
	(p-value)	0.386		0.341	
C_G	(coef.)	**0.164**		**0.262**	
	(s.e.)	0.436		0.418	
	(p-value)	0.707		0.531	
V_Y	(coef.)	**-1.290**		**-1.134**	
	(s.e.)	0.805		0.770	
	(p-value)	0.109		0.141	
χ^2	(α=0.05)	Significant	Significant	Significant	Significant
Hos-Lem	(α=0.05)	Not significant	Significant	Not significant	Not significant
$R^2_{(LL)}$		0.269	0.169	0.203	0.110
$R^2_{(CS)}$		0.105	0.067	0.080	0.044
$R^2_{(N)}$		0.311	0.200	0.237	0.131

The cyclist waiting time is discarded as no cases were detected in which a cyclist rejected a gap between two crossing vehicles. To model the cyclist decision to yield, models 1 and 2 use approaching speeds individually, while models 3 and 4 use the speed difference. Model 1 and 3 include all considered variables. Models 2 and 4 include only the significant variables (p<0.05) of Models 1 and 3, respectively. Model 2 is preferred over Model 4 because of its better goodness-of-fit statistics. Based on the modeled cyclist behavior, the probability of yielding at the On-ramp crossing is given by the following equation and plotted in Figure 4-8.

$$P(Y_C) = \frac{1}{1 + exp^{-(0.527 - 0.217 * C_S)}}$$

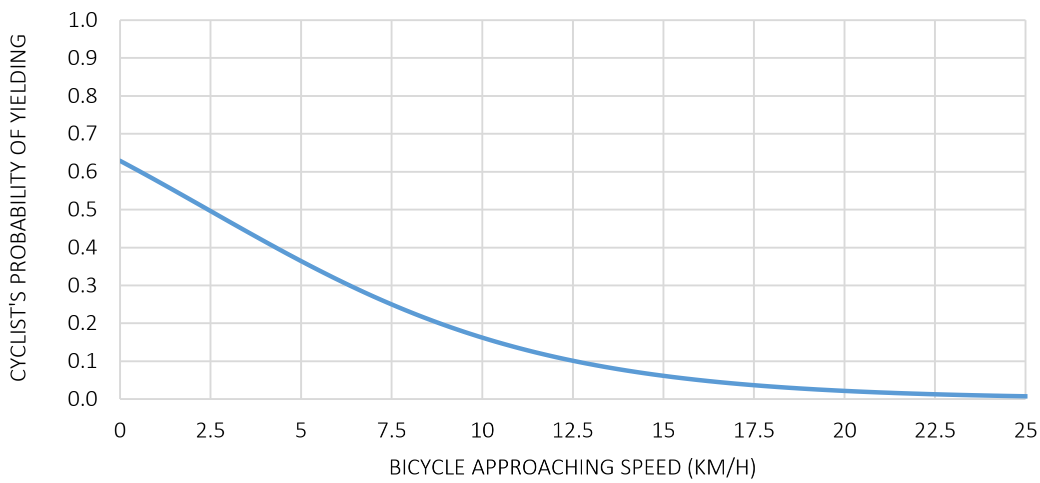

Figure 4-8: On-ramp cyclist's probability of yielding in the On-ramp according to Model 2.

The only statistically significant variable in the model at p<0.05 is the bicycle approaching speed. Vehicle approaching speed and vehicle yielding variables are not significant, which is somewhat unexpected. The lack of significance for vehicle variables could be related to the limited number of observed bicycle yielding events in the On-ramp data set (9 out of 171 interactions).

4.4.3 Conflict severity by cyclist behavior

Previous research (Svensson and Pauna-Gren, 2015) suggests a relationship between vehicle yielding rates and the severity of the vehicle-bicycle conflicts. This section investigates the relationship between bicycle yielding rates and the severity of conflicts. The TTC was measured in 74 yielding-required situations (24 in the Off-ramp and 50 in the On-ramp). The other vehicle-bicycle interactions did not have sufficiently accurate feature-tracking to measure TTC. The mean TTCs by bicycle yielding conditions are given in Table 4-6 and Figure 4-9.

Table 4-6: Mean TTC.

		Off-ramp	On-ramp
Bicycle not-yielding	Sample	18	48
	Mean	2.863	2.250
	Std. Dev.	0.912	0.847
Bicycle yielding	Sample	6	2
	Mean	3.026	3.687
	Std. Dev.	0.942	0.489

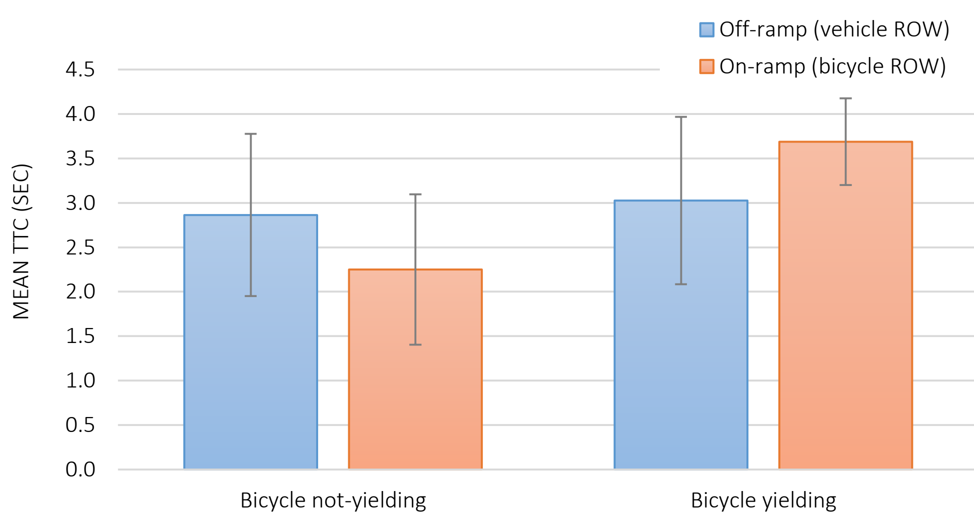

Figure 4-9: Mean TTC (with standard deviations).

The Off-ramp conflict severity does not seem to change whether the bicycle yields or not, having a mean TTC of approximately 3 seconds in both scenarios with slightly higher values when bicycles yield. This suggests that the Off-ramp is operating consistently under double-yield informal traffic rules, as conflict severity does not seem to be affected by the use of informal traffic rules. On-ramp conflict severity changes depending on bicycle yielding: yielding-required situations in which the bicycle yields are safer than those in which not (mean TTCs of 3.7 and 2.2 seconds, respectively). If conflict severity is combined with the low bicycle yielding rates for the On-ramp, it becomes a concern that despite the increase in safety resulting from bicycle yielding, cyclists are still unlikely to make the decision to yield to vehicles in the On-ramp.

These conflict-related findings are limited by the low number of observed bicycle yielding events in the location. A larger sample would be required to assess the TTC distribution according to the yielding interaction types and evaluate in a detailed manner how conflict severity changes as result of cyclist yielding behavior.

4.4.4 Cyclist behavior and compliance with traffic regulations

Additional useful information for understanding cyclist behavior can be obtained from the videos. This information includes: stop sign compliance, use of hand gestures, and swerving maneuvers.

Stop sign compliance

The observed stop sign compliance rate was low. For research purposes, a cyclist full stop is defined as "*at least one foot on the ground*" (Pein, 1997), although other definitions could have been used to address bicycle stopping maneuvers. Out of 399 crossing cyclists in the Off-ramp, only 105 (26%) fully stopped before the crossing. However, only 4 of those 105 (4%) stopped under uninfluenced circumstances (i.e. when there was no vehicle present to influence cyclist behavior). This suggests that the compliance rate to the stop signs is rather a stopping necessity due to the circumstances of the vehicle-bicycle interaction. This may be the case of formal versus informal traffic rules, as described in the study by Bjorklund and Aberg (2005). In this case, the informal rules of priority seem to be controlling the intersection: cyclists assess the stop signs as if they were yield signs since virtually no cyclist stops unless it is to yield to incoming vehicles. At the same time, vehicles yield for bicycles despite having no signage indicating the requirement to yield. Evaluating the vehicle and bicycle yielding rates of the Off-ramp while replacing the stop signs for yield signs might provide useful insights on what may happen when informal traffic rules are formalized.

Figure 4-10: Cyclists stopping under uninfluenced (left) and influenced (right) scenarios.

Use of hand gestures

The use of hand gestures (i.e. hand signals) in the Off-ramp was rarely done to announce the cyclist's intentions. The analysis lies in the moment when the cyclist's hand gesture is made: if it is done while the bicycle is already crossing or when the vehicle has already yielded, it is considered as a 'thank you' gesture rather than a statement of the cyclist's crossing intentions. Out of 278 cyclists who crossed in proximity to a vehicle, only 61 (22%) used hand gestures. Furthermore, only 17 of those 61 (28%) used a hand gesture to announce their crossing intentions, while the rest of the cyclists who used hand gestures did so to thank the driver for yielding. Bicycle good-practice manuals (City of Vancouver, 2004) recommend doing hand signals well in advance of any turn. Because cyclists need their hands on the handlebar to break before the sharp left-turn into the Off-ramp bicycle crossing, it becomes difficult for cyclists to use their hands to inform the driver about their crossing intentions. Detected hand gestures were done no farther than 5 m away from the bicycle crossing. Cyclist hand gestures may be of importance as a study by Westerhuis and De Waard (2016) on cyclist behavior's prediction concluded that drivers rely on cyclist body movements and perceived bicycle speed to predict their movements.

Figure 4-11: Cyclists using hand gestures to indicate their crossing intentions (left) and to thank the driver for yielding (right).

Cyclist behavior when facing a blocked intersection

On-ramp cyclists tended to swerve around vehicles which were blocking the intersection instead of waiting for the vehicle to move out before crossing. Out of 93 cyclists facing a blocked intersection, only 2 (2%) of them decided to wait for the vehicle to move out of the intersection before crossing. Out of the 91 bicycles crossing through a blocked intersection, 34 (37%) seemed to require some degree of swerving maneuvers to avoid the blocking vehicle. The side to which bicycles swerve seems to be circumstantial, as observed swerving maneuvers were evenly distributed (17 bicycles swerved to their left and 17 bicycles swerved to their right). The location of the blocking vehicle may be the reason behind the cyclist's decision on which direction to swerve, as it is expected for a cyclist to choose the path that requires less physical effort or less travel time.

Figure 4-12: Cyclists waiting for a vehicle to move out of the intersection (left) and swerving to cross through the intersection despite the blocking vehicle (right).

5. CONCLUSIONS

5.1 Summary and conclusions

The first application demonstrated the latest developments in automated computer vision systems at a complex urban intersection that is known to have safety issues for cyclists and pedestrians. The diagnosis identified the safety problems at the Burrard St. and Pacific St. intersection by locating conflict regions and non-conforming behavior patterns. These were studied through traffic conflict and violation analyses. The diagnosis revealed that the Burrard Bridge's access and exit ramps were the main sources of conflicts at the intersection, and their design encouraged many non-conforming behavior patterns. Given the results of the analysis and the new design for the intersection, it can be expected that, by removing both ramps and replacing them with exclusive right-turn lanes, a significant amount of conflict regions will be addressed and non-conforming behavior at the intersection will be reduced. However, there are some conflict regions and violation patterns that are likely to remain after the improvements have been developed. Particular care should be given to the new Burrard St. NB approach's EB movement (the new right-turn movement introduced as replacement of the Off-ramp), since it is expected to have vehicle-vehicle, vehicle-bicycle, and vehicle-pedestrian conflicts. The *after* analysis of this before-and-after study will be conducted in late 2017, after the implementation of the proposed improvements, and will provide valuable ex-post comparison for the ex-ante assessment presented in this thesis. The diagnosis can serve as a successful case study to show the capabilities of automated video-based computer vision techniques for data collection and traffic conflict analysis.

The second application demonstrated that understanding bicycle yielding rates and cyclist behavior at intersections can be of importance when evaluating how vehicle-bicycle interactions take place. It was shown that cyclists can appeal to informal traffic rules of priority that contradict traffic signage and expected behavior. Bicycle yielding rates were shown to change significantly depending on the intersection's configuration and legal right-of-way (53% difference between the Off-ramp and the On-ramp). Vehicle yielding rates were consistent around 69% on both ramps. Low bicycle yielding rates in combination with consistent but unsatisfactory vehicle yielding rates were a safety problems: despite an increase in conflict severity as a result of bicycle-yielding (a mean-TTC difference of 1.4 seconds), bicycles had only a 6% yielding rate when having the legal right-of-way. In contrast, in the Off-ramp location bicycle-yielding did not appear to affect conflict severity, despite non-yielding being a non-conforming maneuver. The large discrepancy between traffic controls and actual operation of these two intersections has important implications for traffic operations modeling, as assumptions of control-conforming behavior by either drivers or cyclists may not be valid.

In a binary logistic regression model of cyclist yielding decisions, the only statistically significant variable was the bicycle's approaching speed. The cyclist's modeled probability of yielding decreases as bicycle approaching speed increases. Observations of bicycle yielding events were limited to identify significant effects of the vehicle approaching speed or the driver yielding decision, among other variables.

In other behavioral observations, virtually all cyclists facing a partially or fully blocked intersection managed to cross through despite the presence of one or more blocking vehicles. Cyclist compliance with stop signs in the Off-ramp was low and appeared to be primarily related to the presence of a crossing vehicle. Approximately 25% of cyclists in proximity of an incoming crossing vehicle used hand gestures, although most appeared to be acknowledgments rather than indications of intentions to cross. Further analysis is required to determine if the use of hand gestures at intersections is done in response to the driver's behavior.

5.2 Limitations

Camera height, angle, resolution, and location were limited for the analysis to settings pre-determined by the City of Vancouver. Issues with camera parameters hindered the capability to conduct a more in-depth and accurate analysis, as some of the identified conflict regions could not be studied using the available video footage. Limitations associated with road user tracking using automated computer vision techniques (over-segmentation, over-grouping, and miss-detection) are detailed in section 3.3.1.

In the cyclist yielding behavior analysis, vehicle-bicycle interactions were studied in only two locations, preventing the generalization of the results to intersections with different geometric configurations, population characteristics, and rules of priority. The relatively small sample size of bicycle-yielding events may have limited the capability to obtain statistical significant effects of different variables in addition to the bicycle approaching speed. Moreover, limitations in computer vision techniques hindered the ability to detect road users continuously across the intersection, preventing to measure road user speeds while approaching the intersection.

The identification and classification of yielding-required situations involved a certain degree of subjectivity, as different observers may have different interpretations of what is expected in a yielding maneuver and when or where it should be performed. Despite this research not having a quantitative benchmark to classify vehicle-bicycle interactions as yielding-required situations, the use of a quantitative benchmark does not guarantee objectivity. Different road user profiles based on personal experiences and preferences may have a strong impact on the perception of and need for yielding, as seen in Bjorklund and Aberg (2005). Thus, it becomes unlikely to reach a quantitative benchmark that fits all road user profiles due to the subjective nature of yielding behavior.

Road user yielding intentions were assumed based on observable behavior in the video footage. Video footage alone does not provide information of a road user's intention, as it only allows to observe its maneuvers. If a road user is stopping or slowing down while approaching the intersection in proximity of another incoming road user in an intersecting trajectory, the maneuver can be interpreted as yielding the right-of-way. However, it is possible that the maneuver was performed for reasons beyond yielding. For research purposes, it was assumed that all stopping or slowing down maneuvers while in proximity of another road user in an intersecting trajectory were done with the purpose of yielding the right-of-way.

5.3 Recommendations and future work

Future work, including the planned post-implementation study, should prioritize better quality of video data, particularly for automated conflict analysis involving cyclists and pedestrians. In addition, further research in computer vision is required to develop a more efficient software to conduct automated road safety analysis, as the current method relies on manual video observations to filter false positive conflict detections. The capacity to detect and track stopped road users also requires improvement, as it is limited under current tracking algorithms and can cause missed-detections in conflicts involving stopped road users. More generally, the quantitative relationship among collisions, traffic conflicts, and traffic violations requires further research, particularly for intersections between motorized and vulnerable road users.

A survey among transportation experts may be useful to develop a more concise and robust yielding classification methodology based on road users' maneuvers. Furthermore, an experiment could be designed to measure additional relevant yielding parameters and estimate a yielding model for application in microscopic simulations. From the road user perspective, a cyclist survey could be conducted to identify factors related to the cyclist's decision to yield. Expanding the analysis to different intersections could help explain how the yielding distribution changes with intersection geometry and traffic controls. Finally, understanding how cyclist yielding affect conflict severity is yet to be studied in greater depth.

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