

Video-based Conflict, Speeding, and Crash Correlation in Bellevue (WA) United States

Correlation Report | July 2020



City of Bellevue



TRANSOFT SOLUTIONS™



TOGETHER FOR
SAFER ROADS



Contents

Key Terms	3
Executive Summary	5
Introduction	7
1.1 Project Motivation and Objectives	7
1.2 Conflicts as a Safety Indicator	8
1.3 Past Studies and Research on the Relationship Between Traffic Conflicts and Crashes	8
1.4 Speeding in the City of Bellevue	9
1.5 Past Studies and Research on the Relationship Between Driver Speeds and Crashes	9
1.6 Methodology	10
Network Traffic Data	11
2.1 Crash Data	11
2.2 PET Data	12
2.3 Summary of Excessive Speeding Findings in Bellevue	13
Statistical Analysis	15
Intersection Analysis	17
Conclusion	19
5.1 Lessons Learned	19
5.2 Limitations	19
5.3 Related Work	20
5.4 Future Work	20
5.5 Acknowledgements	20
Bibliography	21
Appendix	23

Key Terms

Conflict

an observable event which would end in a collision unless one of the involved road users changes their trajectory or speed. In this paper conflicts are measured using post-encroachment time (PET)

Critical Conflict

Conflicts with PETs lower than 2 seconds

Driver

A legacy term for what is now more formally known as a motorized road user. In reality traffic data acquisition is performed on vehicular-shaped objects of various (FHWA-compliant) classifications (passenger cars, pickups, single-unit trucks, etc.) which usually (but not always) have at least one operator (the now more formal definition of “driver”) and which may or may not have other occupants on board. The traffic data acquisition system does not observe vehicle operators/drivers directly, nor does it count onboard passengers, and therefore cannot distinguish between vehicles operating in autonomous mode and manual mode, if that vehicle model supports CAV functionality. Any and all references to “drivers” in text are made with the assumption that the number of motorized road users operating in autonomous mode is insignificant at the time of data collection and therefore does not skew human behavior analysis results.

Excessive Speed

The median speed of the road user’s speed while they are speeding

High Injury Network (HIN)

A specific subset of the roadway network in Bellevue used to prioritize for proactive education, enforcement, engineering, and engagement for the benefits of all modes. The HIN was created weighing killed or severely injured collisions more heavily than less-severe collisions

Post-Encroachment Time (PET)

The time between when the first road user leaves the conflict point and the second road user arrives at that point. Dangerous interactions tend to have lower PETs

Road User

A road user is any entity moving along the road. The video analytics detects and tracks all motorized vehicles (cars, buses, pickup trucks, work vans, single-unit trucks, articulated trucks, and motorcyclists), bicyclists, and pedestrians

Scenario

An event involving two different road movements.

Speed

The video analytics platform used defines a road user’s speed as the median speed of the road user while they are in motion

Speeding

A road user is speeding when they are traveling above the posted speed limit for more than 20-percent of their moving trajectory

Speeding Incidence Rate

The proportion of the speeding road users from all the roads. In this report, speeding incidence rates are given per 10,000 road users.

Trajectory

A road user's path

Video Analytics

Automatic video content analysis using machine learning to provide temporal and spatial information about traffic events

Executive Summary

As part of the City of Bellevue's Vision Zero goal to eliminate traffic deaths and serious injuries by 2030, the City has partnered with Together for Safer Roads and Transoft Solutions (ITS) Inc., formerly Brisk Synergies, on a network-wide traffic conflict screening using video analytics. This project leverages video footage from existing traffic cameras to obtain useful data that can be searched, managed, and used to provide traffic management centers with detailed information on traffic volumes, speeds, and other conditions, and allow a more rapid response to traffic incidents. Two additional reports have been produced throughout this partnership and presented the results of a network screening and conflict analysis (Video-based Network-wide Conflict Analysis to Support Vision Zero in Bellevue (WA) United States) and on speed and speeding analysis (Video-based Network-wide Speed and Speeding Analysis to Support Vision Zero in Bellevue (WA) United States). This third and last report explores a correlation between conflict and speeding measurements generated by BriskLUMINA, and crashes from the data obtained from a sample of intersections in the City of Bellevue, WA, United States.

For the first two reports, video footage was obtained for 40 intersections. For this third report, only 10 intersections with both conflict and crash data were used. These 10 intersections were those in which crash data by scenarios was matched to conflict scenarios and, more importantly, for the top 10 intersections with the highest number of crashes that were correlated with scenarios identifiable by the video analysis. The footage was taken daily (16 hours per day) for the months of August and September 2019, resulting in just under 40,000 hours of footage. Using video analytics, data was obtained on road user counts, road user speeds, and conflicts (measured using post-encroachment time or "PET"). Results from the entirety of the footage were used to gain insight; however, the data presented in this report is from a full week in September 2019 (1,120 hours). The general summary statistics were obtained from September 13th to September 19th. Two correlations, between conflict rates and crash rates and speeding incidence rates and crash rates, were performed.

Key findings

The following are conclusions derived from the data summaries:

- Preliminary success was achieved in modeling collisions using collision indicators including traffic conflicts based on PET.
- Of the crash data that was correlated to scenarios identifiable by BriskLUMINA, the most frequent crashes were between left-turning and through drivers (driver-driver crashes). Driver-pedestrian crash rates were found to be 1.6 times higher than driver-driver crash rates.
- Conflict data indicates that conflicts between left-turning and through drivers were the most frequent throughout the network, which matched the crash data findings.

Count regression models (e.g., Poisson and Negative Binomial or NB models) were generated using data

of the top 10 intersections with the most crashes. The models found a positive and statistically significant non-linear association between conflict and crash rates; however, no statistically significant correlation was found between speeding incidence and crash rates. Not surprisingly, increased volumes were found to have a statistically significant correlation with increased conflict frequency as well as with increased crash rates in a non-linear way. In addition, a hotspot analysis was performed on the intersection with the highest number of crashes, 112th Ave & Main St. It was found that the movements with the highest crash rates at the intersection were in line with the movements found to have the highest critical conflict, but not enough data was available to make a conclusive inference about speeding incidence rates.

1

Introduction

1.1 Project Motivation and Objectives

As pedestrian and bicycle fatalities continue to rise nationwide, there is a need for improved data driven approaches to achieve our collective goal of Vision Zero – eliminating traffic fatalities and serious injuries to ensure that everyone can safely move around in our communities. Between 2009 and 2018, 66-percent of all fatal and serious-injury collisions in the City of Bellevue, Washington occurred along just 9-percent of streets (Breiland, C., Weissman, D., Saviskas, S., & Wasserman, D., 2019). Pedestrians and cyclists are vulnerable road users (RUs) and made up 5-percent of all collisions during this time but comprised 46-percent of all serious injuries and fatalities. An analysis of the collisions indicates that the following five road user behaviors contributed to 70-percent of all fatal and serious injuries: driver’s failure to yield to a pedestrian, failure to grant right-of-way to a motorist, driver distraction, intoxication, and speeding.

In response to these road safety concerns, the City of Bellevue passed a Vision Zero resolution in 2015 to strive to eliminate traffic fatalities and serious injuries by 2030. In 2018, the City of Bellevue partnered with Transoft Solutions (ITS) Inc., formerly Brisk Synergies, to conduct a citywide network screening analysis to better understand the factors that impact the safety of its transportation system and leverage this insight to identify improvements and evaluate outcomes. BriskLUMINA, a product of Transoft Solutions (ITS) Inc., uses computer vision and artificial intelligence to analyze traffic video. Camera footage is analyzed to obtain data about surrogate safety indicators including road user speeds and near-misses. Results are often used to validate road improvements, determine high-risk locations, and determine the most severe conflicts and interactions at an intersection, roundabout, or road segment.

The objective of this report is to study the association between conflict and speeding data with crashes from the data obtained in Bellevue. Count regression models were generated from the data of the top 10 intersections with the most crashes. The results of this analysis are presented in section 3 of this report.

1.2 Conflicts as a Safety Indicator

Many governmental agencies continue to rely on traditional traffic safety approaches. They intervene only after enough police crash reports are filed to trigger a High Crash Corridor designation. This reactive approach to prevent crash recurrence has well documented limitations.

- Studying collision data is reactive; safety evaluation takes place after collisions occur, making it nearly impossible to achieve the goal of zero traffic deaths and serious injury collisions;
- The infrequent nature of traffic collisions necessitates years of observation to achieve statistical significance — up to 5 or even 10 years of data in the cases of studies involving single sites and/or low-traffic volume locations - during which time locations can change significantly.
- It is well-documented that traffic crashes and injuries are under-reported in many localities and
- There are societal barriers in using the general public to test unknown safety countermeasures.

Although traffic collisions can happen anywhere, conflicts at specific locations are often early warning signs - e.g. recurring instances where a driver abruptly stops because a bicyclist turned in front of them, a pedestrian steps into the path of a bicyclist, or one bicyclist or driver passes by another or a static object at very close spacing. These surrogate warning indicators provide insight into when, where, and why crashes are most likely to occur. Understanding the root causes for traffic conflicts enables local agencies to take proactive, corrective actions to reduce the potential for future crashes.

1.3 Past Studies and Research on the Relationship Between Traffic Conflicts and Crashes

The concept of measuring road safety indirectly, a process which came to be known as the Traffic Conflict Technique (TCT), was first implemented at General Motors (Perkins and Harris, 1968). The technique is based on tabulation of manually observed evasive maneuvers such as braking or lane changes at an intersection. From the observed data, collision rates per “x” number of conflicts for various interaction types were calculated, essentially developing a coefficient that linearly relates conflicts to collisions. The interest in using traffic conflicts rather than crash data to measure safety caught on quickly, and sparked more testing of the TCT in the following years (Baker, 1972; Paddock, 1974; Hauer, 1982).

Shortly thereafter, Hydén (1987) developed the Swedish Traffic Conflicts Technique (Swedish TCT). In this paper, Hydén points out that the proximity to a collision only covers one dimension of a conflict; The potential consequences (severity) in the case that a collision had taken place is another aspect that should be taken into account.

Sayed (1997) estimated the safety at unsignalized intersections using time-to-collision traffic conflicts. Similarly, Sayed and Zein (1998) applied the traffic conflict technique, using data collected from 94 conflict surveys. Regression analysis was used to develop models which relate the number of traffic conflicts to traffic volume and collisions. The regression analysis results indicate that the average hourly conflict rate and the average hourly severe conflict rate correlated reasonably well with traffic volume for both signalized and unsignalized intersections. Strong relationships between collisions and conflicts were obtained for signalized intersections only.

In more recent years, a variety of other models have been applied to study the relationship between conflicts and collisions. Davis et al (2011) and other researchers have developed methods for predicting crash frequency based on structural modelling, or, using probability distributions and simulating thousands of sequences to estimate the probability of each event.

Extending this work, Tarko (2012) modeled the crash probability using the Pareto distribution, which is well-suited to model extremely rare events. Shahdah et al (2014) estimated crash modification factors (CMF) using data before and after treating a sample of intersections in Toronto by changing left turn signal priority at signalized intersections from permissive to protected-permissive.

While the relationship between traffic conflicts and collisions has been studied in various ways, and it is generally accepted that there is some relationship between the two, previous studies have applied the models to data that is specific to a particular method of measuring conflicts (i.e. manual observation, time-to-collision, post-encroachment time, etc.). Conflict data is unique to the methodology of data collection, as well as the

methodology and/or software used to process the data. Results from BriskLUMINA are dependent on the camera calibration and Transoft's specific definition of the surrogate safety metrics. Therefore, it is valuable and important to find a relationship between the conflict metric and observed collisions for data from the City of Bellevue.

1.4 Speeding in the City of Bellevue

Speeding is a major concern to many cities around the world. According to the National Highway Traffic Safety Administration (2019), driver speeding was a contributing factor in more than 26-percent of all traffic fatalities in the United States. For driver to driver crashes, the likelihood of fatality increases as speed increases, therefore it is important to assess safety with respect to speed. Speeding is defined as traveling too fast for conditions or in excess of the posted speed limits (ITE, 2016). The motorist must take into consideration a variety of factors such as vehicle capability, roadway features, environmental conditions, surrounding context, presence of other road users, and the speed limit. Even though any type of driver is susceptible to speeding, more common offenders have been found to be young, male drivers; Collision-involved teens have been found to be less likely to obey the speed limit, and generally more likely to take part in risky driving behavior (The Traffic Injury Research Foundation, 2007).

The City of Bellevue has several existing programs managed by Neighborhood Traffic Safety Services that help with speed management. One of the existing programs is the installation of permanent (stationary) radar feedback signs that tell drivers how fast they are going. Additionally, to manage driver speeds and speeding around schools, the City has installed flashing speed zone signs around schools. In another program, residents can request temporary radar signs or police speed enforcement. The City plans on expanding these efforts as part of its Vision Zero Action Plan.

1.5 Past Studies and Research on the Relationship Between Driver Speeds and Crashes

The relationship between driver speeds and crashes has been extensively quantified in the literature. However, the relationship between speed and crash risk is complex, due to the fact that there are many factors that determine to what extent driving speed affects crash risk. For instance, the geometric layout and design speed of a road, traffic volume, and traffic composition all have an effect on the crash risk.

In 1964, an American study (Solomon, 1964) gave substantial weight to the idea that collision rates may be affected not only by mean speeds but also by the "spread" of speeds. The study concluded that most collisions involved drivers who were travelling either much faster or much slower than the mean traffic speed. This relationship was confirmed by Hauer (1971). However, the study was criticized for using drivers' mean traffic speeds rather than those occurring at the time of the collision. That same year, an American study by the Research Triangle Institute (1971) used driver's actual speeds rather than reported speeds, and confirmed this relationship between speeds and collisions. However, after eliminating collisions involving turning maneuvers, the relationship was not so pronounced. These studies were the first to begin looking at the relationship between crashes and speeds. However, they were limited to studying data from rural highways.

Looking at studies performed at urban signalized intersections, Tian (2013) collected crash and speed data at 65 urban signalized intersections, and found that both mean speed and speed standard deviation are positively correlated to crash frequency.

Islam (2016) investigated the relationship between speed and rear-end collisions at urban signalized intersections. The study found that increases in the average, 85th, and standard deviation of speed were associated with increases in the frequency of total, injury, and property-damage-only (PDO) rear-end collisions. Moreover, as the level of speeding increased, collision frequencies were found to increase exponentially.

Other analyses have shown that a change in average speed tends to have a larger effect on crashes and crash severity on rural roads and motorways than on urban and residential roads (Elvik, 2009; Cameron & Elvik (2010). Nilsson (2004) acknowledged that it is difficult to estimate representative speed or speed changes in urban areas due to the variation of speed in space compared with rural areas.

In this report, preliminary analysis will be done to look at the existence of a significant statistical correlation between crash rates and speeding incidence rates at intersections in the City of Bellevue. Excessive speeding infractions are primarily characteristic of through movements at signalized intersections.

1.6 Methodology

For this project, cameras were selected from various intersections throughout the City of Bellevue. After camera selection, the network camera feeds were shared with Transoft Solutions (ITS) Inc. and the video footage was recorded. Traffic cameras recorded footage at the intersections daily for 16 hours, from 6 AM to 10 PM, for the months of August and September in 2019, resulting in just under 1,000 hours of footage for each intersection. The footage was then calibrated on an intersection basis, after which it was processed using LUMINA. Lastly, the data was quality controlled, extracted, and analyzed.

2

Network Traffic Data

In this section, crash data from the City as well as conflict and speeding data generated by BriskLUMINA is summarized. The following analysis was completed for seven consecutive days of footage from September 13th to 19th, 2019. This amounted to 112 hours for each intersection, just under 4,500 hours of footage in total. One week of footage was used as some cameras disconnected or had inconsistent frame rates at times.

2.1 Crash Data

Crash data was obtained from the City for all the study intersections for the duration of video recording in addition to the 3 prior years. This amount of data was obtained to ensure that the crash data was abundant yet still relevant to the current state of the intersection and conflict data obtained. Three intersections were omitted from this analysis because they experienced major changes affecting their traffic patterns during the analysis period: 120th Ave NE & NE 8th St, 164th Ave SE & Lakemont Blvd SE, and Lakemont Blvd SE & Cougar Mt Way.

The data was then filtered to match the data to the conflict scenarios defined by the analytics. Rear-end crashes were removed from the crash data, due to the fact that the surrogate safety metric used in this analysis (post-encroachment time) is not fit to analyze rear-end conflicts. Driver-cyclist crashes were also removed from the data due to the lack of reporting of cyclist directionality in the crash data. Lastly, any scenarios that could not be observed due to the field of view of the camera were also removed. With this criteria, 172 crashes were observed at the 37 intersections of this study. The specific movements and road users involved in these crashes are summarized in Table 2.1 and Figure 2.1.

Table 2.1 - Crash Data by Road Users Involved

	Scenario	Crash Count
Merging	Through and Right Turning Drivers	27
	Left Turning and Right Turning Drivers	5
T-Bone	Through and Left Turning Drivers	95
	Through and Through Drivers	33
Drivers and Pedestrians	Left Turning Drivers with Pedestrians	7
	Right Turning Drivers with Pedestrians	4
	Through Drivers with Pedestrians	1

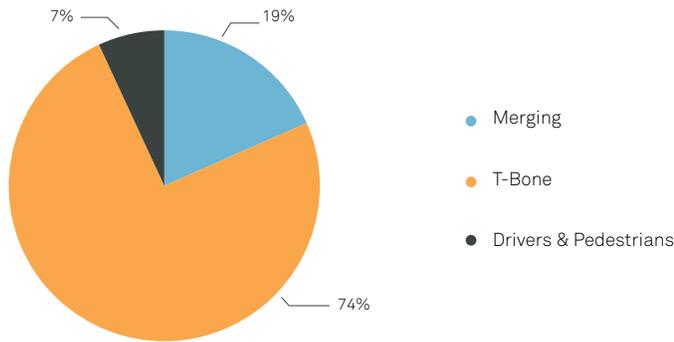


Figure 2.1 – Crash Types

Using the FHWA intersection crash rate calculation (Golembiewski & Chandler, 2011), crash rates were obtained for each road user. These rates expressed as accidents per million entering vehicles (MEV) are displayed in Table 2.2. Results indicated that pedestrians were the more vulnerable road user. On average, a pedestrian was 1.6 times more likely to be involved in a crash than an arbitrary driver was. However, when separating drivers by turning movements, left turning drivers were found to be the most vulnerable road user overall. They were more than 2.5 times more likely to be involved in a crash than either a through driver or a right turning driver and were 1.3 times more likely to be involved in a crash than a pedestrian.

Table 2.2 – Average Crash Rates by Different Road Users			
Crash Type	Movement	Number of Road Users involved in a Crash	Crash Rates (MEV)
Driver-Driver	Through	189	0.181
	Left Turning	107	0.463
	Right Turning	36	0.169
Driver-Pedestrian	All	12	0.362

2.2 PET Data

BriskLUMINA provides information on safety using post encroachment time (PET) as the conflict metric. PET measures the time between successive arrivals at a common location of two crossing road user trajectories. The PET value obtained for conflicts is unique to the calibration performed using BriskLUMINA and is dependent on the speed and location of both road users. A lower PET indicates a situation where a collision was more likely to occur. PETs below 1.5s are considered events of concern, as 1.5s is considered to be the standard human reaction time (Taoka, 1989). PETs below 2 will be denoted as critical conflicts. The number is slightly higher than 1.5s to ensure that conflicts with a slightly higher reaction time are not overlooked. Twenty thousand critical

conflicts were observed during the week of analysis. PETs between 5 and 10 seconds, are simply considered interactions. Figure 2.2 displays the frequency of conflicts at thresholds of 2s, 3s, 5s, and 10s to observe various trends.

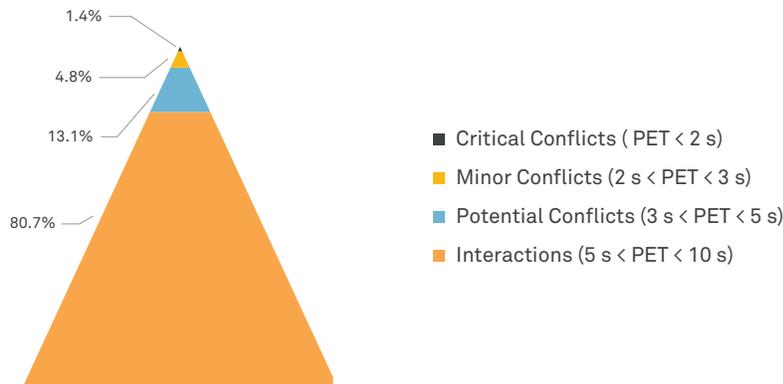


Figure 2.2 – Frequency of interactions with different PET values

Driver-driver conflicts made up 97.5-percent of critical conflicts observed. Driver-pedestrian conflicts made up only 1.9-percent of all these conflicts, and driver-cyclist conflicts made up 0.6-percent. Figure 2.3 depicts the conflict breakdown by road user type. Even though cyclists were involved in the least number of critical conflicts, they had the highest conflict rates. Cyclists were 6.5 times more likely to be involved in a conflict with a driver than a pedestrian was and 8.7 times more likely to be involved in a conflict than two drivers. Pedestrians were 1.3 times more likely to be involved in a conflict with a driver than a driver was with another driver.

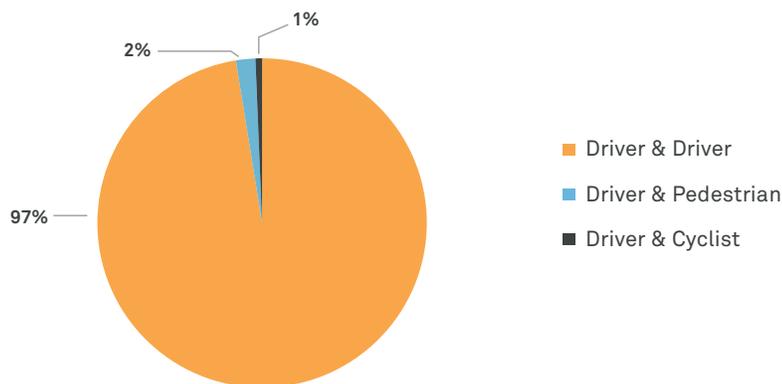


Figure 2.3 - Critical conflicts by road user types across network

Please refer to *Video-based Network-wide Conflict Analysis to Support Vision Zero in Bellevue (WA) United States* for a more detailed analysis of conflicts throughout this network.

2.3 Summary of Excessive Speeding Findings in Bellevue

Driver speeding, as defined by BriskLUMINA, occurs when a road user is traveling above the posted speed limit for more than 20-percent of their moving trajectory. This 20-percent is defined as the 'speeding rate' by BriskLUMINA. A driver's trajectory is bound by the field of view of the camera. Depending on the intersection, it extends between zero to 30-feet from the stop line of each approach. Speeding is limited to motorized road users and uses the speed limits of through movements as the assigned speed limit for the intersection. Any driver driving above the speed limit will have an excessive speed value, defined as the median speed value of the driver's speeding trajectory.

Throughout the network, 870,000 speeding events were observed in August and September 2019, indicating that approximately 10.8-percent of drivers were speeding. The analytics indicated that the majority of the speeding drivers were speeding for only a small portion of their trajectory. This is expected to be the case at intersections as the drivers are not at free-flow conditions. Figure 2.4 depicts the hourly speeding distribution of speeding drivers, and by how much they were driving above the speed limit across the entire network. A volume trendline is added to the graph. The trendline only depicts the change in volume patterns and does not correspond to the actual network volume.

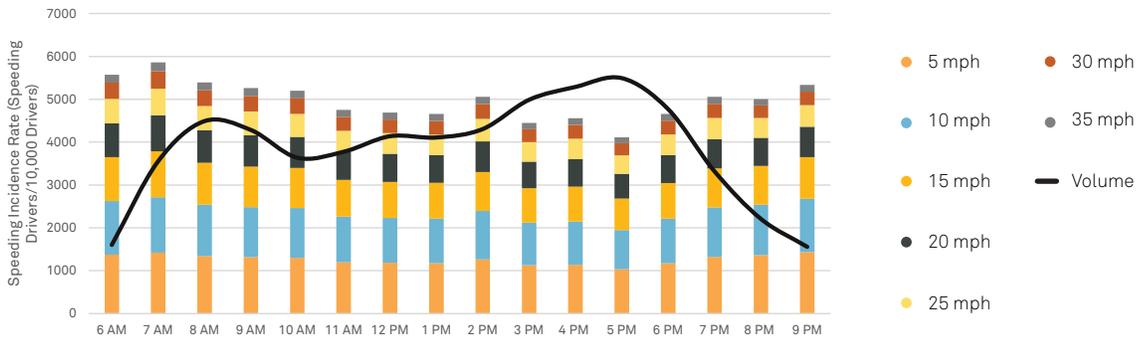


Figure 2.4 – Weekday hourly speed distribution

Please refer to *Video-based Network-wide Speed and Speeding Analysis to Support Vision Zero in Bellevue (WA), United States* for a more detailed analysis of speeding throughout this network.

3

Statistical Analysis

Ten intersections with the highest number of crashes over the last 3 years were used for this analysis. These intersections are listed in Table 3.1 alongside their crash rates (as calculated by the FHWA equation) and conflict rates (conflicts with PETs < 3s observed per 1 million road users). All but two intersections (108th Ave NE & NE 12th St and 156th Ave NE & Bel-Red Rd) were also among the ten intersections with the most traffic conflicts with PETs < 3s.

Table 3.1

Intersection	Number of Crashes	Crash Rate (MEV)	Number of Conflicts	Conflict Rate (per 1 million road users)
112th Ave & Main St	14	0.404	5015	26,557
156th Ave NE & Northup Wy	12	0.304	5309	23,650
124th Ave NE & NE 8th St	11	0.332	8766	42,381
108th Ave NE & NE 12th St	10	0.527	3745	26,429
148th Ave SE & SE 22nd St	10	0.213	4234	14,279
156th Ave NE & Bel-Red Rd	9	0.300	2491	14,271
108th Ave & Main St	8	0.386	4795	38,210
140th Ave NE & NE 8th St	8	0.219	4322	18,347
112th Ave NE & NE 12th St	7	0.197	4933	23,012
156th Ave NE & NE 8th St	7	0.196	4118	18,318

Statistical models were fit using the crash data and conflict rates with PETs < 3s (as measured by BriskLUMINA) at the scenario level. Poisson and NB regression techniques were used to investigate the link between crash rates and conflict rates. The following equation shows the basic driver/motor vehicle crash model relating conflict rates observed with the historical crash data in Bellevue:

$$\lambda = V \times e^{-20.74C^{0.298}}$$

Where λ is the total number of crashes (driver-driver or driver-pedestrian) during the study period. V is the total volume at the intersection and C is the total number of conflicts with PETs < 3s during the study period.

The model indicates that a non-linear association between λ and the two predictors exists. An increase in either volume or conflicts with PETs < 3s correlates to an increase in crashes. This relationship is statistically significant and has a pseudo R-squared of 0.380. The outputs of the model can be found in the Table 1 of the appendix. Such an R-squared value is considered high given the nature of the correlation. Modelling human behavior is a complex endeavor and there are potentially thousands of explanatory variables that each capture a small element of the relationship. This strong association indicates that 38% of the relationship between conflicts and crashes at these intersections can be captured using a single variable.

Additionally, another statistical model was fit, using the same techniques, to study the link between speeding incidence rates (as defined and measured by BriskLUMINA) and crash rates at these intersections. As excessive speeding was only observed for through movements, only crashes with through drivers were considered. However, unlike the previous correlation, no statistically significant correlation was found between these two rates. The outputs of the model are in Table 2 of the appendix and show extremely high p-values.

There are a few explanations as to why a relationship between crashes and speeding may have not been found for this study. Firstly, the study looked at the frequency of speeding events. Most research has looked at speed standard deviation, therefore accounting not for the frequency of speeding events, but for the difference in speed of the events compared to the posted speed limit. Additionally, the study does not include crash data for rear-end conflicts. This likely has an effect on the speed-crash relationship. Finally, it is possible that the relationship is not pronounced because the study looks at urban signalized intersections; studies have shown that changes in speed tends to have a larger effect on crashes at rural roads compared to urban and residential roads (Elvik, 2009; Cameron & Elvik, 2010).

4

Intersection Analysis

An analysis was performed on conflict and speeding data at 112th Ave and Main St, which was the study intersection with the highest number of identifiable crashes. The intersection is depicted in Figure 4.1. The road user trajectories are depicted in Figure 4.2 and the average hourly volumes are summarized in Table 4.3.



Figure 4.1 - Aerial image of intersection



Figure 4.2 - Aerial image with aerial trajectories

Table 4.1 – Average Hourly Weekday Driver Volumes

Northbound			Eastbound			Southbound			Westbound			Crosswalks			
LT	Thru	RT	LT	Thru	RT	LT	Thru	RT	LT	Thru	RT	N	E	S	W
119	195	41	99	276	93	50	191	14	72	336	42	10	10	11	7

14 crashes were correlated to scenarios detected by BriskLUMINA. 13 of these were T-bone crashes. Nine crashes were between left turning and through drivers, and 4 crashes were between pairs of through drivers. Five left turning versus through crashes occurred along the North-South corridor and four were along the East-West corridor. A single merging crash was recorded.

Of the 40 intersections, 112th Ave and Main St had the third highest number of critical conflicts. This intersection also had the fourth highest number of conflicts involving through and left turning drivers. At the intersection level, 99-percent of critical conflicts were between left turning and through drivers. The remaining 0.9-percent was between drivers and pedestrians, and 0.1-percent was between through and through drivers. Table 4.2 displays the driver crash rates, critical conflict rates, and speeding incidence rates at this intersection.

Table 4.2

Rates (MEV)	Northbound			Eastbound			Southbound			Westbound		
	LT	Thru	RT	LT	Thru	RT	LT	Thru	RT	LT	Thru	RT
Crash (MEV)	1.14	1.13	0.0	0.99	0.71	0.49	1.74	1.23	0.0	1.20	0.57	0.0
Critical Conflict (per 10,000 Road Users)	8.0	15.0	6.0	10.0	6.0	2.0	57.0	5.0	0.0	23.0	3.0	0.0
Speeding (per 10,000 Road Users)	0.0	1582.0	0.0	0.0	245.0	0.0	0.0	284.0	0.0	0.0	2.0	0.0

The top three movements with the highest crash rates are in line with the top three movements with the highest conflict rates (Southbound left turning movement, westbound left turning, northbound through). Figure 4.3 shows a conflict in which the southbound left turning driver makes a left turn originating from the rightmost lane, and gets into a conflict with a northbound through driver.



Figure 4.3 – Southbound left turning and northbound through driver conflict at 112th Ave & Main St

Figure 4.4 depicts a conflict between a westbound left turning driver and an eastbound through driver.



Figure 4.4 – Westbound left turning and eastbound through driver conflict at 112th Ave & Main St

In terms of speeding, no clear relationship was seen when looking at crash rates and speeding incidence rates. The movements with the highest crash rates were not the same as the movements with the highest speeding incidence rates.

5

Conclusion

This work introduces a unique application of a large-scale network screening using video data from traffic surveillance cameras and BriskLUMINA, a specialized automated-road-safety platform. Over 4,000 hours of video footage from 40 intersections with varied urban densities and land uses were analyzed for conflicts and speeding incidence across the City of Bellevue.

Crash data indicated that the most common road user crash is between left turning drivers and pedestrians. Conflict data showed that left turning drivers are most frequently involved in conflicts. Drivers were slightly more likely to be involved in a conflict with a pedestrian than with another driver. Speeding data indicated that almost one tenth of all drivers were speeding across the network

Crash frequency models using 10 intersections were developed using count regression techniques for investigating the relationship between crashes and conflicts and crashes and speeding. Conflicts and volumes were shown to have a positive non-linear association with crash occurrence. The statistically significant association of these two crashes contributing factors is a first step towards the development of crash prediction models based on conflicts crashes. No statistically significant relationship was found between speeding incidence and crashes at these intersections. Additionally, the intersection with the highest number of crashes, 112th Ave & Main St, was assessed and the movements with the highest crash rates were the same as the top movements with the highest conflict.

5.1 Lessons Learned

This joint project between the City of Bellevue, Together for Safer Roads, and Transoft Solutions (ITS) Inc. is the first of its kind. Tens of thousands of hours of footage were collected and tens of millions of road users were anonymously detected. Due to the extensive amount of data, video processing (and reprocessing) was lengthy and costly. To reduce the cost and time, less hours of footage can be processed, either for a shorter duration or using less hours of footage a day. Additionally, as this study relies on video analytics, the quality of the video footage is extremely important. The network cameras used by the city were of extremely high quality and were located at a height so as to capture the entire intersection and movements clearly. However, issues were encountered as some cameras moved slowly over time resulting in missing data within some regions of the camera's field of view, and delays due to recalibration. Additionally, a few of the cameras had inconsistent frame rates which meant additional quality control was required to delete false positive results. Lastly, weather conditions sometimes led to the obstruction of parts of the camera lens due to snow or rain drops. Similar projects in the future will place greater emphasis on the site selection based on the camera's field of view alongside weather conditions and the data collection period.

5.2 Limitations

The correlations identified in this study are promising but need further validation using data from other cities. Also, the results of the conflict rates from the video analytics are applicable to the trajectory data collection,

filtering, quality control processes, and method of PET estimation used by BriskLUMINA. Additionally, the size of the data, while relatively large compared to other studies, needs to be made larger, with a greater variety of sites, and other explanatory factors to be able to provide conclusive predictive models that are not overfit to the signalized intersection dataset in Bellevue and in this report.

5.3 Related Work

The data used in this report is part of a bigger project with the City of Bellevue, Together for Safer Roads, and Transoft Solutions (ITS) Inc. Two additional reports have been produced on network screening and conflict analysis and speeds and speeding.

5.4 Future Work

While the amount of data used to look at an association between conflicts and crashes in Bellevue is significant, more robust models should be built to generalize the correlation found in this report. Data would need to be obtained from more cities, varied road infrastructure, greater variance in geometry, different weather conditions, more safety indicators, among several other factors.

5.5 Acknowledgements

We would like to thank Dr. Yinhai Wang – director of the Smart Transportation Applications and Research Laboratory (STAR Lab) at the University of Washington (UW) and director for Pacific Northwest Transportation Consortium (PacTrans), USDOT University Transportation Center for Federal Region 10 – for helping in the definition of this project and in the revision of the final report

6

Bibliography

- Baker, William T. (1972). An evaluation of the traffic conflicts technique. *Highway Research Record*, (384);18.
- Cameron, M. H. & Elvik, R. (2010). Nilsson's Power Model connecting speed and road trauma: Applicability by road type and alternative models for urban roads. *Accident Analysis and Prevention*, 42, 1908-1915.
- Davis, G.A., J. Hourdos, H. Xiong, and I. Chatterjee. (2011). Outline for a Causal Model of Traffic Conflicts and Crashes. *Accident Analysis and Prevention*, 43, 1907–1919.
- Elvik, R. (2009). The Power Model of the relationship between speed and road safety: update and new analyses. *TOI Report ; 1034/2009*. Oslo, Institute of Transport Economics TOI.
- Golembiewski, G.A. and Chandler, B. (2011). *Road Safety Information Analysis: A Manual for Local Rural Road Owners*. U.S Department of Transportation Federal Highway Administration.
- Hauer, E. (1971). Accidents, overtaking and speed control. *Accident Analysis and Prevention*, 3, 1-13.
- Hauer, E. (1982). "Traffic Conflicts and Exposure." *Accident Analysis and Prevention*, 14(5), 359–364.
- Hydén, C. (1987). The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique. Ph.D. dissertation. Lund University, Department of Traffic Planning and Engineering.
- Islam, M. T. (2016). Investigating the Speed and Rear-End Collision Relationship at Urban Signalized Intersections. *Transportation Research Record: Journal of the Transportation Research Board*, 2601(1), 10-16. doi:10.3141/2601-02
- ITE. (2016) Speed as a Safety Problem. (n.d.). Retrieved from <https://www.ite.org/technical-resources/topics/speed-management-for-safety/speed-as-a-safety-problem/>
- National Highway Traffic Safety Administration. (2019, December 12). Speeding. Retrieved from <https://nhtsa.gov/risky-driving/speeding>
- Nilsson, G. (2004). Traffic safety dimensions and the power model to describe the effect of speed on safety. *Bulletin 221*, Lund Institute of Technology, Lund.
- Paddock, Richard D. (1974). The traffic conflict technique: An accident prediction method. Department of Transportation, Division of Highways, Bureau of Traffic Control, State of Ohio.
- Perkins, Stuart R. and Harris, Joseph L. (1968). Traffic conflict characteristics-accident potential at intersections. *Highway Research Record*, (225).

Research Triangle Institute. (1971). Speed and Accidents. Vol 1, RTI report Su-409, prepared for the National Highway Safety Bureau, US Department of Transportation.

Sayed, T. (1997). Estimating the Safety of Unsignalized Intersections Using Traffic Conflicts. *Transportation Research Record: Journal of the Transportation Research Board*.

Sayed, T. & Zein, S. (1998). Traffic Conflict Standards for Intersections. *Transportation Planning and Technology*, 22(4), 309-323.

Shahdah, U., F. Saccomanno, and B. Persaud. (2014). Integrated Traffic Conflict Model for Estimating Crash Modification Factor. *Accident Analysis and Prevention*, 71, pp. 228-235.

Solomon, D. (1964). Accidents on main rural highways related to speed, driver and vehicle in Michigan: Effects on injury and death. UMTRI report 89-28.

The Traffic Injury Research Foundation. The Road Safety Monitor: Excessive Speeding. (2007). Retrieved from https://tirf.ca/wp-content/uploads/2017/02/rsm_speeding-2007-final.pdf

Taoka, G. T. (1989). Brake Reaction Time of Unalerted Drivers. *ITE Journal*. Retrieved from <https://pdfs.semanticscholar.org/4f74/cc5b40ce61027e81912db82f305a7f967c11.pdf>

Tarko, A.P. (2012). Use of Surrogates and Exceedance Statistics to Estimate Road Safety. *Accident Analysis and Prevention*, 45, pp. 230-240.

Tian, Z. (2013). Speed-accident Relationship at Urban Signalized Intersections. *Procedia - Social and Behavioral Sciences*, 96, 1383-1388. doi:10.1016/j.sbspro.2013.08.157

Appendix

Appendix | Table 1: Output of Conflict and Crash Correlation

Table 1: Output of Conflict and Crash Correlation

Parameter	Coef.	Std. Err.	z	Pr(> z)
Intercept	-9.578	5.994	-1.598	0.110
log (Volume)	0.351	0.343	1.025	0.305
log (PET < 3s)	0.276	0.049	6.009	0.000
R-squared = 0.38				

Appendix | Table 2: Output of Speeding and Crash Correlation

Table 2: Output of Speeding and Crash Correlation

Parameter	Coef.	Std. Err.	z	Pr(> z)
Intercept	4.091	2.399	1.706	0.088
log(Speeding)	-0.079	0.131	-0.601	0.548
Speeding	0.000	0.000	-0.269	0.788
log(speeding^2)	0.000	0.000	0.263	0.792