Video-based Network-wide Surrogate Safety Analysis to Support a Proactive Network Screening Using Connected Cameras: Case Study in the City of Bellevue (WA) United States

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ABSTRACT

Surrogate road safety approaches, as part of road improvement programs, have gained traction in recent years. Thanks to emerging technologies such as computer-vision and cloud-computing, surrogate methods allow for proactive scanning and detection of safety issues and address them before collisions and injuries occur. The objective of this paper is to propose an automated and continuous monitoring approach for road network screening using connected video cameras and a cloud-based computing analytics platform for large-scale video processing. Using the wide network of traffic cameras from cities, the proposed approach aims to leverage video footage to extract critical data road network screening (ranking and selection of dangerous locations). Using the City of Bellevue as an application environment, different safety metrics are automatically generated in the platform such as traffic exposure metrics, frequency of speeding events, and conflict rates. Using Bellevue's camera network, the proposed approach is demonstrated using a sample of 40 cameras and intersections. The results and platform provide a proactive tool that can constantly look for dangerous locations and risk contributing factors. This paper provides the details of the proposed approach and the results of its implementation. Directions for future work are also discussed.

Keywords: Computer vision, video-based traffic monitoring, network screening, surrogate safety, vision zero

INTRODUCTION

Road safety has been a fundamental concern globally, costing most countries around 3% of their gross domestic product. Road crashes kill approximately 1.35 million people annually, placing them in the top ten causes of death, and making them the leading non-disease cause of death world-wide. More than half of these deaths are among vulnerable road users, making them more high risk (*1*). In the United States, the annual death rate due to road crashes is 38,000 (resulting in 12.4 deaths per 10,000 inhabitants). 4.4 million additional road users have injuries requiring medical attention. This amounts to $871 billion in societal and economic costs, making the United States the most affected high-income country by the consequences of crashes. In addition, the number of pedestrian and cyclist fatalities have been on the rise since 1990 (*2*).

In response to these road safety concerns, many cities have adopted road safety programs to achieve Vision Zero. One of the main goals of Vision Zero is to eliminate traffic fatalities and serious injuries to ensure that all road users can safely move around their communities. This concept was introduced in 1995 and has since been adopted in 24 countries world-wide and in over 40 cities in the United States alone (*3*). Vision Zero recognizes that road users make mistakes or can be confronted with dangerous situations and that public roads should be designed to accommodate for these modes of failure—in the jargon of safe systems engineering, public roads should be *fault tolerant*.

Two major components of the program include managing safe travels and collecting, analyzing, and using data to understand the causes of traffic deaths and their effects. This requires the establishment of safety programs and goals that include educational, enforcement, and engineering countermeasures. This implementation requires following the road safety management process (RSMP) which offers a systematic approach to the site identification, improvement selection, and evaluation (*4*). The process starts with a network screening process to determine the locations of interest. Once the locations are selected, diagnosis is performed to identify the crash-risk contributing factors in order to then select the proper countermeasures. A cost-benefit analysis is then performed, and projects are prioritized. Finally, safety effectiveness evaluations are performed at multiple levels – on the project level, countermeasure level, and/or program level (*5*).

Several steps in the RSMP are currently heavily reliant on the use of crash data. This creates a significant obstacle for achieving Vision Zero, due to the long time required to obtain this data, in addition to the issues surrounding data gaps, under-reporting, cross-jurisdictional inconsistencies, and the ethical concerns with acting on crashes only after they happen. This necessitates the use of more proactive measures, known as surrogate safety measures. These measures are used to reflect the current state of road safety by providing information on crash risk (*6*). Due to the granular nature of the data required to provide these measures, various technologies have been used in the context of diagnosis and safety evaluation. These include cameras, LIDAR, and GPS, each with its documented advantages and shortcomings (*7*)(*8*)(*9*)).

Additionally, obtaining surrogate safety measures for network screening purposes adds another layer of complexity as massive amounts of data need to be derived in a systematic and continuous manner. Previous works have investigated the use of GPS data for network screening purposes with documented success (*9*). However, despite the latest research developments, a limited number of studies have explored the use of computer vision and available city infrastructure (network of traffic video cameras and management center facilities) to perform continuous and automatic network screening. Traditional network screening methods can only be performed at discretized intervals on a scale of years. With the use of connected city cameras, computer vision, and surrogate safety measures, network screening can be performed on a daily-, hourly-, or minute-by-minute-basis if desired. This new approach enables city engineers to monitor changes in traffic patterns and respond proactively to emerging safety warnings with countermeasure improvements.

The objective of this paper is to introduce the concept of automated and continuous monitoring for road network screening using available infrastructure (connected cameras and cloud computing) and a video analytics software solution referred to as BriskLUMINA. Using the wide network of traffic cameras from cities, the proposed concept aims to leverage video footage to obtain useful data that can be searched, managed, and used to provide city road safety authorities with detailed information on traffic volumes, speeds, conflicts and other driver behaviors so that they can respond more rapidly to road safety issues. This paper presents the concept using the City of Bellevue as an application environment and using various traffic flow and safety metrics (such as traffic exposure, over-speeding, near-miss indicators based on frequencies and rates, etc.). This screening provides the City with data on which locations experience road safety issues for motorized and vulnerable road users for a particular time, day, or traffic movement.

LITERATURE REVIEW

In recent years, many communities have been looking beyond crash records for data-driven safety analysis. 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. Additionally, 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 these locations may change significantly. Furthermore, 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 (*10*).

These concerns have led Vision Zero cities to use surrogate safety measures to proactively identify locations that have a high risk of crashes but where the risk has not yet resulted in actual crashes. These surrogate safety metrics are collected from analysis of road-users' trajectory data and near-collision data. A wide variety of surrogate safety measures exist, including speed, delay, violations, deceleration distribution, etc. (*6*). Two very popular metrics of crash risk are divided into measures of proximity and crash severity with time-to-collision (TTC) and post-encroachment time (PET) being measures of proximity and speed, and with acceleration, object size, and collision angle being measures of severity. TTC is "the time required for two vehicles to collide if they continue at their present velocity and on the same path" (*11*). PET is the time difference between when the first road user leaves the conflict point and the second road user arrives at the conflict point (*12*). TTC is computed continuously and depends on the predicted motion of the two road users whereas PET requires the two road users to have intersected paths at some point. TTC is better suited for road users whose paths coincide for more than a single point of their trajectories such as two road users originating from the same lane or merging into the same lane.

Many research groups have researched and developed the applications of computer vision to surrogate safety with promising results (*13*). The use of video analytics to obtain surrogate safety data has been growing in popularity due to the richness and granularity of the data that can be obtained. This approach offers an alternative method of obtaining the desired metrics that is relatively inexpensive and quick. Unlike traditional traffic safety evaluation methods, video-based monitoring is detailed enough to identify near-crashes, classify road user types and their movements, and detect speeding infractions and lane violations. Cameras capture high-resolution data for all road users and modes of transportation within the field of view of the camera, compared to GPS sensor data, which only capture some of the road users (*8*)(*9*). Unlike LIDAR, cameras are relatively easy to deploy and maintain alongside a traditional surveillance system (*7*). Lastly, videos are easy for people to review and understand, unlike many other data collection technologies that simply provide numerical data.

Despite recent developments in the literature on surrogate safety, most of the work has been focused on the proposition of new surrogate safety methods or the use of surrogate approaches for safety diagnosis or before-after studies (*14*)(*15*). Very little work has been published using large-scale studies. In particular, to our knowledge, no studies have been published using a large network of connected cameras for proactive network screening – which is the first step of the classical RSMP.

METHODOLOGY

The implementation of the network-wide continuous monitoring system with connected cameras consisted of several steps. For the methodology implementation, the City of Bellevue's connected camera network was used as an application environment. First, the locations at which the analysis was to be performed were selected. Then, the analytics system was deployed at those locations and calibration was performed. Finally, the numerical and visual data were generated and then analyzed.

Location Selection

The criteria for location selection were: 1) presence of a camera at the road segment, 2) camera having an appropriate field of view, 3) rank with respect to the High Injury Network (*16*), and 4) variation in land use, urban density, and road geometry.

The City of Bellevue's up-to-date camera infrastructure and modern traffic management centers ensured the smooth implementation of the system. The city has a network of high resolution connected cameras at approximately 110 of its 200 intersections with fibre optic video streaming capabilities. All cameras are mounted on traffic signals or poles between 20 and 40 feet high making them appropriate for this type of deployment.

The presence of a camera was the most important selection criteria, narrowing down the number of possible locations. Of these locations, the fields of view of all the cameras were assessed to eliminate the locations where the camera's field of view did not cover the entire intersection. Another important criterion was the inclusion of a variety of locations along the City's High Injury Network (HIN) (and with a variety of ranks within that network – high, medium, and low) and locations not on the HIN (*16*). Additionally, the intersections selected were also geographically spread out throughout the city, had varying urban densities, and different land uses. Finally, the selection of intersections took into consideration varying road geometry and infrastructure.

Video-based Traffic Monitoring Platform Deployment

After the locations of interest were finalized, vision-based traffic monitoring was performed. This process involves 1) livestreaming the video footage, 2) calibration and validation, 3) video-based AI processing and safety analysis, 4) quality control and data filtering, and 5) presentation of analytics results on the dashboard. This process is depicted in Figure 1.

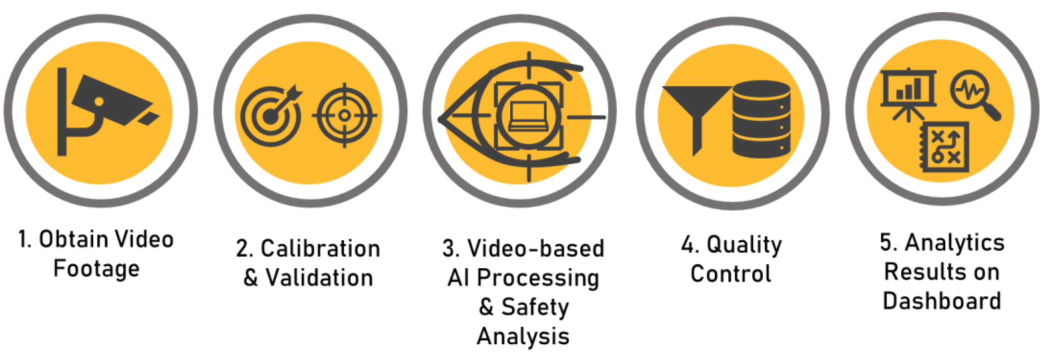


Figure 1 Video-analytics process for safety analysis

The video footage from the intersections of interest was live streamed. The intersection meta-data, alongside a short sample of video footage, was then input on the platform to perform the calibration. During the calibration process, a coordinate transformation is performed using the camera view and an aerial image for mapping purposes. The portion of the camera's field of view of interest is then isolated and the relevant movements are defined. Once calibration is complete, result validation is performed to ensure accurate results (proper mapping and movement definition). Additionally, random 15-minute manual traffic counts are compared to automatic counts to ensure count accuracy.

Once the validation process is complete, the video footage can be continuously processed. During processing, computer vision is used to detect, classify, and track each of the road users in the traffic stream. For this purpose, state-of-the art algorithms have been developed and integrated in the BriskLUMINA platform. (*17*) Once the detection and tracking algorithms are implemented, the platform automatically generates a set of traffic flow and safety outcomes. This includes graphs, heat maps, and video clips as well as risk indicators at different levels (scenario and intersection level). The results are then quality controlled to ensure a high-level of accuracy, removing any false positives in the outcomes. Once all of this is complete, the results are available on the online safety dashboard.

Output Analytics

The outputs from the video-analytics cloud platform (BriskLUMINA) provide information on traffic flow (volumes and speed measures) and safety (in the form of near-misses and violations). The outputs of the video analytics provide granular information on every single road user observed in the video footage as well as more aggregate data at the scenario and intersection level in the form of charts and heatmaps. Some of the typical outputs of the analytics are provided in Figure 2.

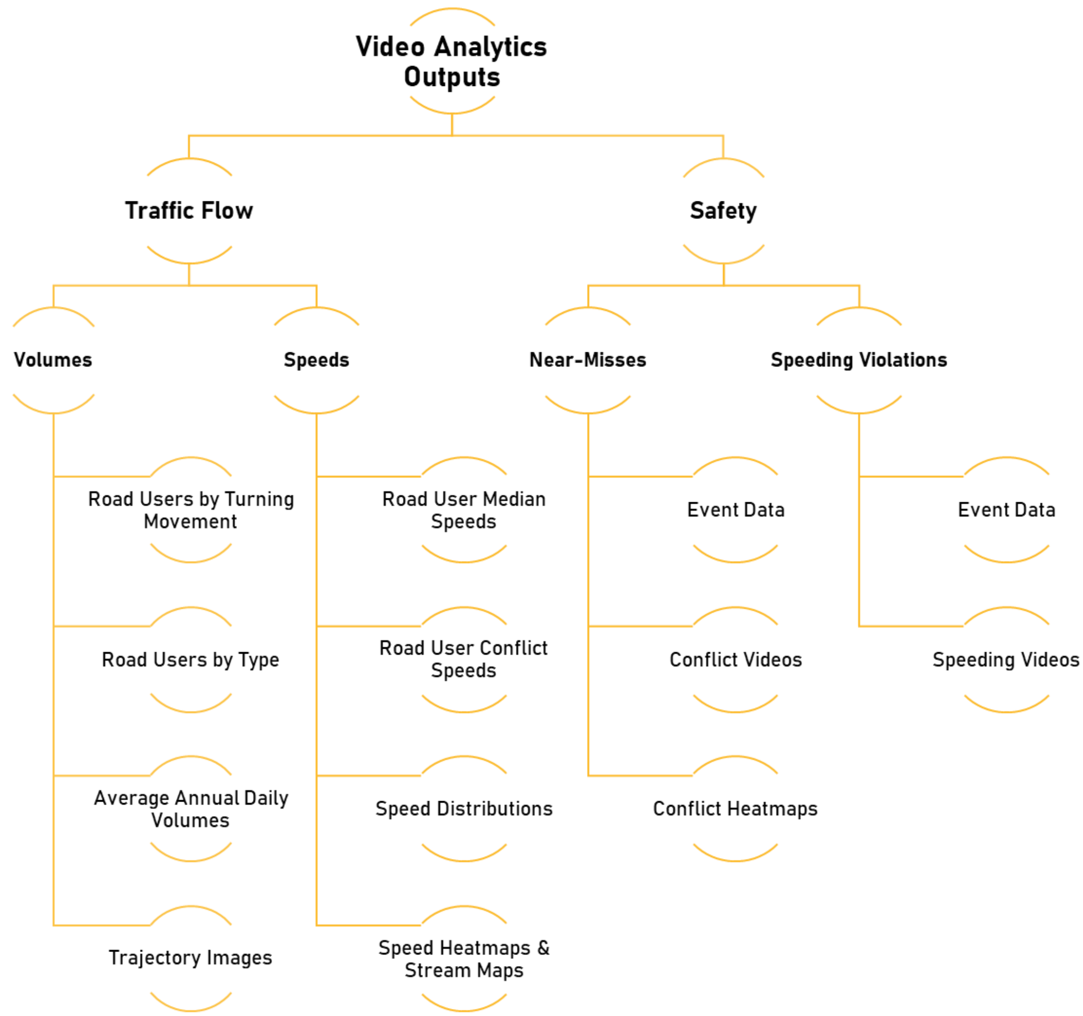


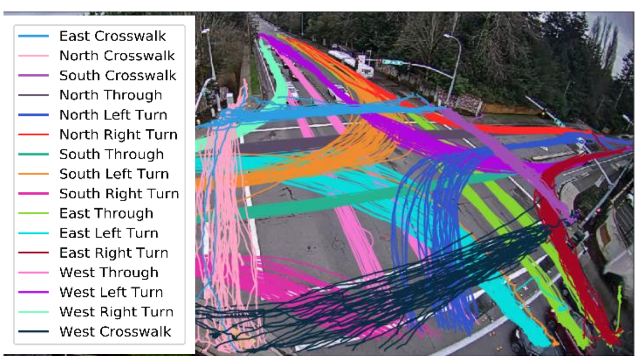
Figure 2 Output analytics

The following data was used throughout the network screening process.

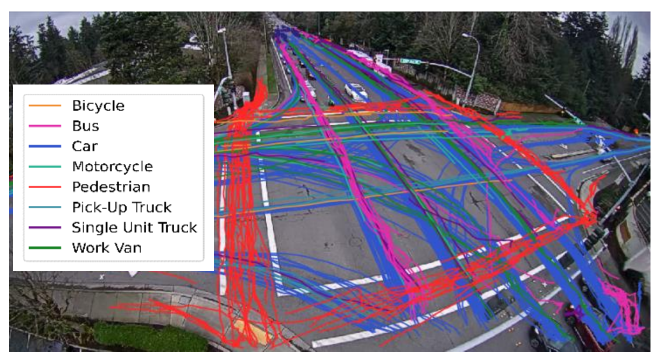
- Traffic volumes: Data is available on every road user captured. The road users observed are bound by the field of view of the camera. Depending on the intersection, this extends between 0 to 30-feet from the stop line of each approach. Each road user is identified as a road user type (truck, bus, car, motorcycle, cyclist, pedestrian, etc.) and is associated with a movement (eg. northbound through or East crosswalk). The data can be obtained on more aggregate bases, such as on a 15-minute, daily, site, or network basis.

- Speed measures: For each road user, speed measures are calculated on a frame by frame basis. Ultimately the speed vector assigned to each road user can be used to compute mean, median speed, 85^{th} percentile or other measures of speed using their trajectory data. Just as with the volume data, this data can be obtained for each road user or aggregated over various desired parameters.
- Near-misses or conflict events: Near-miss events are quantified using PET as the indicator (or optionally, also using TTC). Data is available for all events that involve the interactions of two road users with a PET < 10 s, for relevant scenarios. Relevant scenarios are scenarios involving two road users whose trajectories intersect, excluding events involving two pedestrians. In this paper, events with PETs < 2 s are denoted as critical conflicts. Critical conflict rates were calculated based on the total number of critical conflicts per 10,000 road users for the study period.
- Speeding events: Speeding violations or events, as defined by the traffic video analytics output, occur when a road user is traveling above the posted speed limit for more than 20% of their moving trajectory. Speeding is limited to motorized road users and uses the speed limits of through movements as the assigned speed limit for the intersection. Anyone driving above the speed limit will have an excessive speed value, defined as the median speed value of the vehicle's speeding trajectory. In this paper, speeding incidence rates were calculated based on the total number of speeding road users per 10,000 road users for the week of the study period. Other traffic violations can be extracted in an automated way but this application is limited to over-speeding.

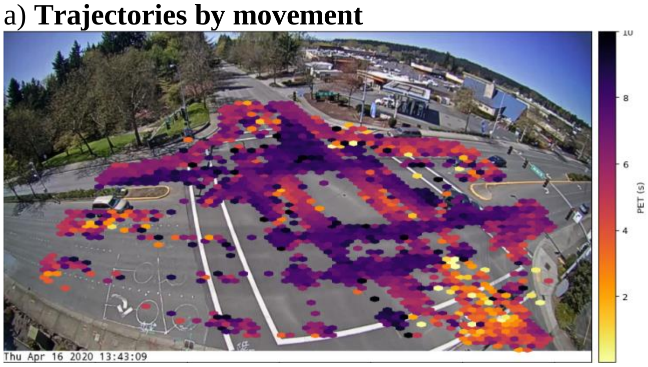
Figures 3 a-e show some sample platform outputs for the week of analysis at different study locations. Figures 3.3a and b show the detected trajectories superimposed onto the camera's field of view. Figure 3.3c shows a conflict heatmap, indicating the frequency of more critical conflicts at specific locations within the intersection. Figure 3.3d aggregates all the road user speeds to show a speed heatmap. Lastly, Figure 3.3e shows a screenshot of a car exceeding the speed limit by more than 30 mph.



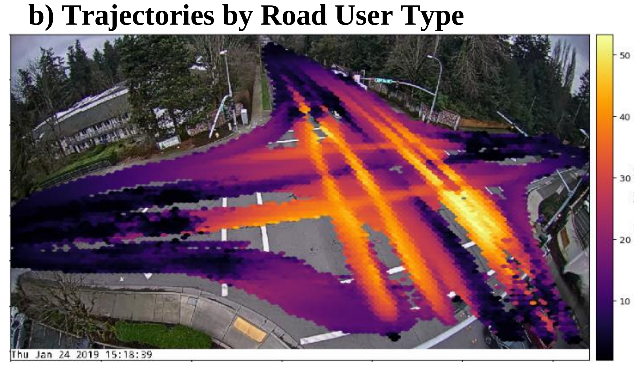
a) **Trajectories by movement**



b) Trajectories by Road User Type



c) Conflict heatmap



d) Speed Heatmap

e) Speeding violation video

Figure 3 Sample analytics platform outputs

Analyses

In addition to looking at the raw-data indicators mentioned before (e.g., the frequency or rates of conflicts or speeding events), a statistical regression model can be used to estimate the frequency of events for each intersection after controlling for other factors. In this case, a multi-level regression model is used to perform a network-wide analysis. Multiple geometric and non-geometric variables were considered as explanatory variables when fitting these models. The explanatory variables include urban density (high or medium), land use (commercial or residential), whether or not a school is present within less than 0.125 miles from the intersection, road user types (car driver, bus or truck operator, motorcyclist), road user movement (through, left turn, or right turn), protected vs non-protected left turns, pedestrian traffic phasing, number of lanes, lane width, crosswalk width, presence of bike infrastructure (dedicated bike path, shared bike path, both, or neither), time of the day, and days of the week.

The multilevel regression analysis was estimated with intersection fixed and random effects using the independent variables as surrogate safety measures.

$$y_i = \beta_0 + \beta_1 x_{i\,1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \alpha Zi + \varepsilon_i, \qquad \text{i=1, 2,…..,n}$$

Where:

y_i – surrogate safety measure of interest for site i, for all conflicts

x_{ij} – regressor for explanatory variable j

β_j – coefficient for explanatory variable j

αZ_i - fixed effects error for site i

ε_i – random error of the regression estimate

Using the expected frequency of events at the site level, the sites under study were ranked to identify the most dangerous locations according to the specific indicator.

APPLICATION

Between 2009 and 2018, 66% of all fatal and serious-injury collisions in the City of Bellevue occurred along just 9% of streets (*16*). Vulnerable road users (pedestrians and cyclists) made up 5% of all collisions during this time but comprised 46% of all serious injuries and fatalities. An analysis of the collisions indicated that the following five road user behaviors contributed to 70% 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 (*16*). 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 2019, the City of Bellevue conducted 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. Camera footage was analyzed to obtain data about surrogate safety indicators including road user speeds and near-misses. Results are used to validate road improvements, determine high-risk locations, and determine the most severe conflicts and interactions at an intersection.

For the implementation of the proposed approach, a sample of 40 intersections were selected, from the City's 200 intersections. Figure 4 depicts the study intersections. The selection was based off of the aforementioned factors:

- All intersections were signalized with a connected camera with the appropriate field of view.
- From those, 34 are four-legged intersections, 5 are three-legged, and 1 is five-legged.
- Most of the intersections (31) were part of the High Injury Network.
- The majority of the intersections (31) were not in the downtown area, defined here as the area bordered by Main St. & NE 12 and 100th Ave & 112th Ave.
- Priority was given to intersections located in commercial areas given the high pedestrian presence. In the sample, 28 intersections were located in commercial areas as opposed to residential areas.
- 28 intersections were in medium density locations (suburbs, big-box stores, and/or factories) while the rest were in high density locations (multi-story dwellings and/or businesses).

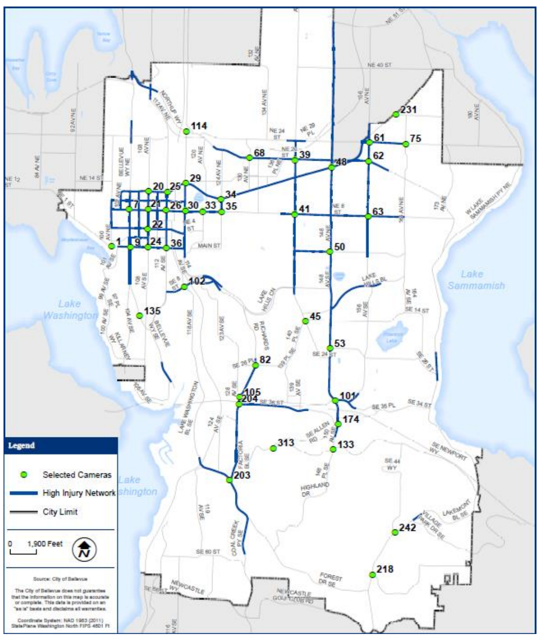


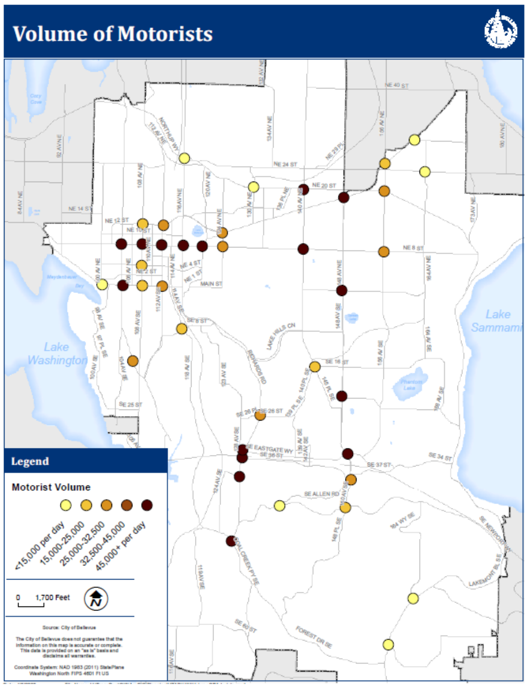
Figure 4 Study locations

Results

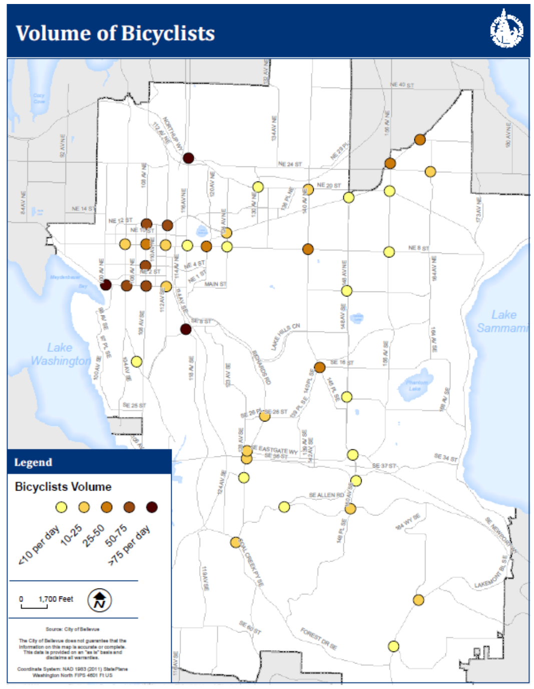
Video data was processed using the analytics platform defined earlier. For each intersection, 112 hours of video data (6AM to 10PM) were collected and automatically processed for a total of 4,500 hours of video footage. This corresponds to seven consecutive days of data from September 13th to 19th, 2019. Once data was streamed to the cloud analytics platform, each camera was calibrated and detection/ tracking algorithms were implemented. This was followed by the generation of traffic flow and safety analytics metrics. A multitude of analyses can be performed on the data obtained; however, the section will provide a set of outcomes for illustrative purposes.

4.1.1 Volumes

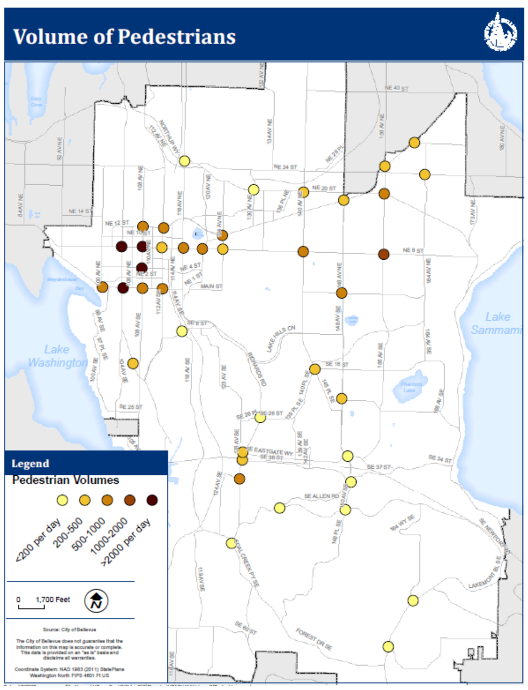
During the week of data collection, over 8.25 million road users were observed. From the total, 97.3% were motorized road users and 2.7% were vulnerable road users (2.6% pedestrians and 0.1% cyclists). Figures 5 a-c show the concentration of each road user type across the network.



a) Motorist volumes across network



b) Bicyclist volumes across network



c) Pedestrian volumes across network

Figure 5 Concentration of each road user across network

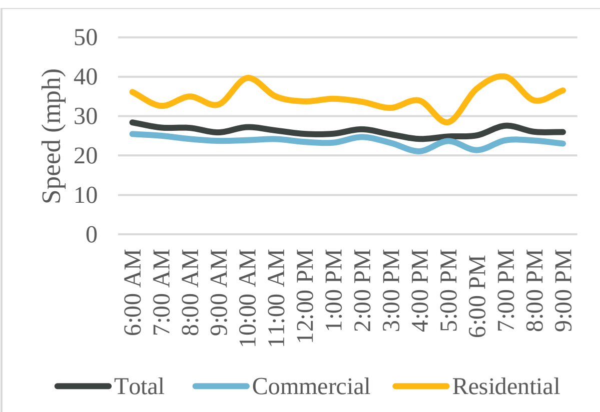
The average total vehicular volume per intersections was between 0.2 and 0.25 million for the entire week of analysis. The 2 intersections with the highest volumes, at around 0.4 million, were 112th Ave & NE 8th St and 116th Ave & NE 8th St. These high volumes were observed as both intersections are adjacent to interstate ramps. Pedestrian volumes were less uniform throughout the study locations. Over half of all the pedestrian volumes observed were at four downtown, high density intersections

(Bellevue Way & NE 8th St, 108th Ave & NE 8th St, 108th & NE 4th St, and Bellevue Way & Main St). For more than two-thirds of the selected locations, pedestrian volumes made up less than 2% of the total traffic. Cyclist volumes were very low throughout all study intersections, and cyclists made up more than 1% of road user volumes at only 2 intersections (116th Ave NE & Northup Way and 100th Ave & Main St).

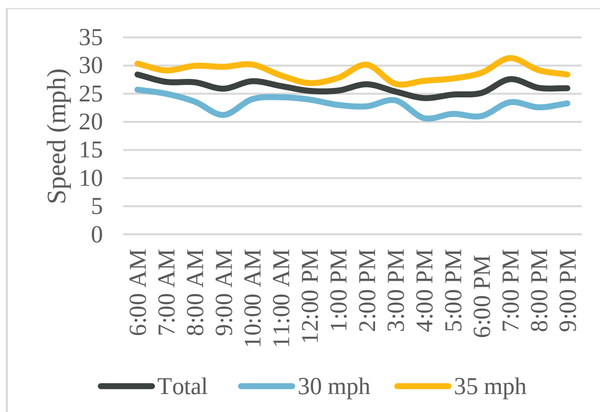
Speeds

The speed for all the road users was obtained on a road user basis and was aggregated for a network-wide analysis by road user type and movement type. This section looks at the temporal variation in through vehicular speeds by land use, speed limit, and intersection location along the HIN. Other analyses can be performed by looking at different road users and/or turning movements and other metrics such as 85th percentile speeds, free flow speeds, coefficient of variation etc.

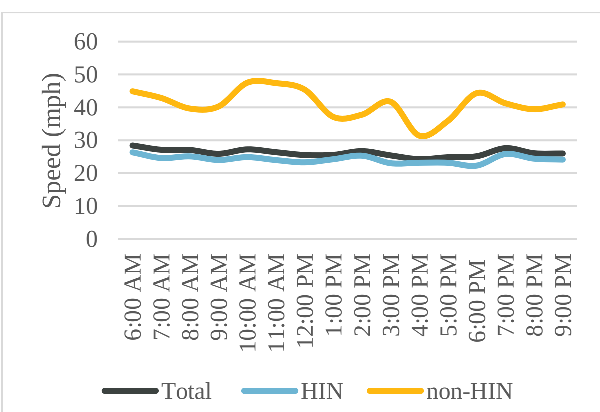
Figures 6a-c display the temporal variation of through vehicle speeds with respect to different factors. On a network-wide basis, through movement speeds were relatively constant throughout the day. Vehicles at residential locations had higher speeds and fluctuations compared to commercial locations. As would be expected, speeds were lower at intersections with posted speed limits of 30 mph compared to intersections with posted speed limits of 35 mph. Fluctuations in speeds throughout the day were slight for both posted speed limits and do not appear to have a clear correlation with the time of day. Speeds along the HIN were observed to be lower than speeds not on the HIN. This is due to speeds and speeding limits being higher at residential land use and two-thirds of the selected locations not on the HIN were in residential areas.



a) Average speed (mph) by land use



b) Average speed (mph) by speed limit



c) Average speed (mph) by High Injury Network

Figure 6 Weekday through average vehicle speeds with respect to different factors

Conflict Frequency and Rates

Near-misses

The safety indicator used to quantify near-misses was PET. Approximately 1.5 million events with PETs < 10s were observed across the week of analysis. Figure 7 shows the distribution of the PET values of these events. For this paper, data will be provided based on the number of conflicts with a PET < 2s. This value was selected because it is slightly higher than 1.5s, the average human reaction which is a common threshold use to identify conflicts with a relatively high-risk level, (*18*)(*19*) to ensure that no conflicts with a slightly higher reaction time are not overlooked. These will be called critical conflicts hereon. Twenty thousand (1.4% of all interactions) of these events were observed, while more than 80.7% of interactions had PETs between 5 and 10 seconds which is considered to be safe passage. As would be expected, the distribution of conflicts/interactions across the threshold values follows a pyramidal shape.

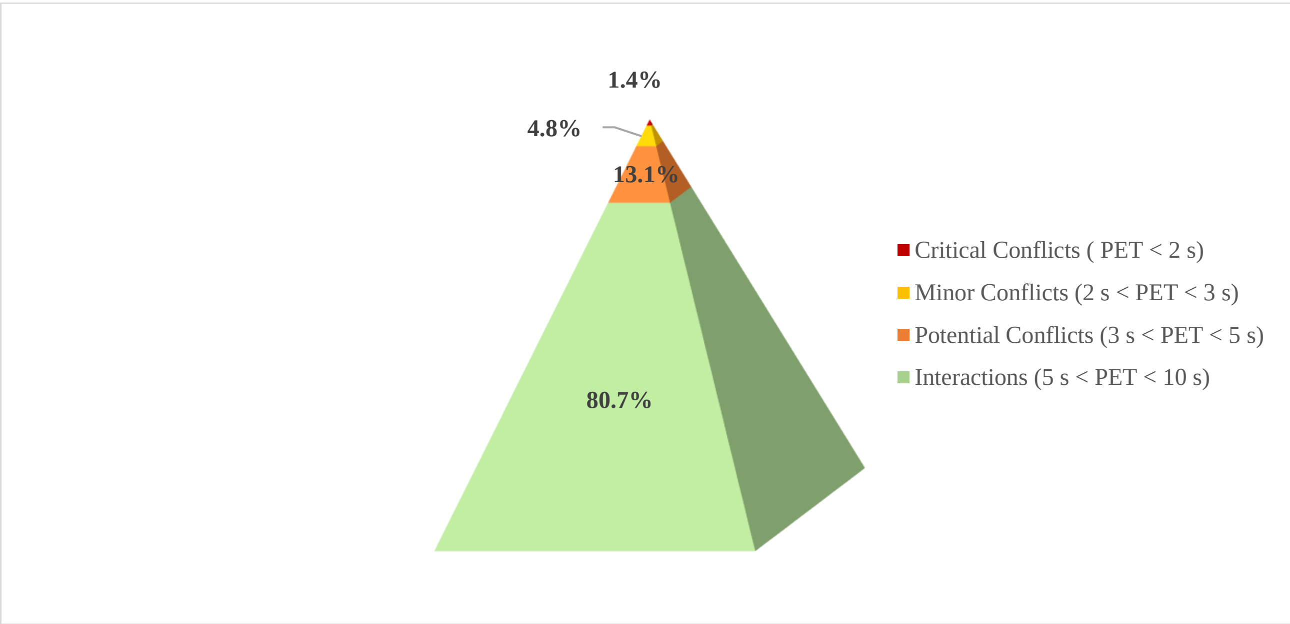


Figure 7 Distribution of PET value of all events

Based on the video analytics data, several ranking criteria could be derived for identifying the most prone intersections for safety improvements, this includes critical conflict rates defined as the number of conflicts observed with PETs < 2s per 10,000 road users for the week of analysis. Figure 8 presents a map showing the concentration of the total number critical conflict rates per intersection. This map is useful for identifying those intersections with a high frequency of critical conflicts. The map indicates that 7 intersections had more than 150 critical conflicts daily.

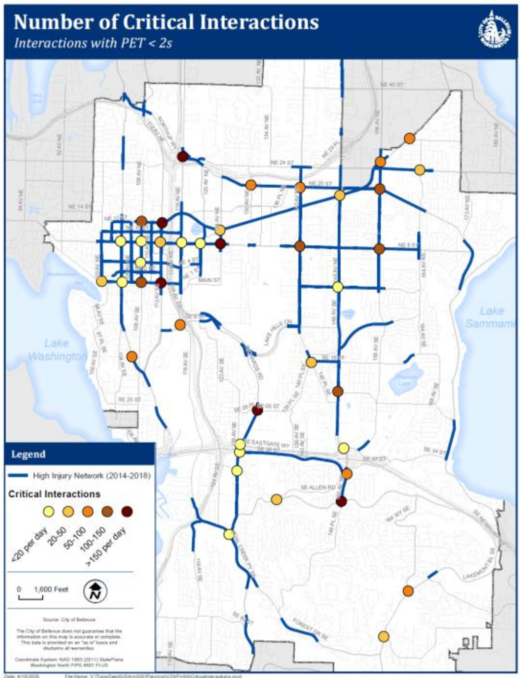
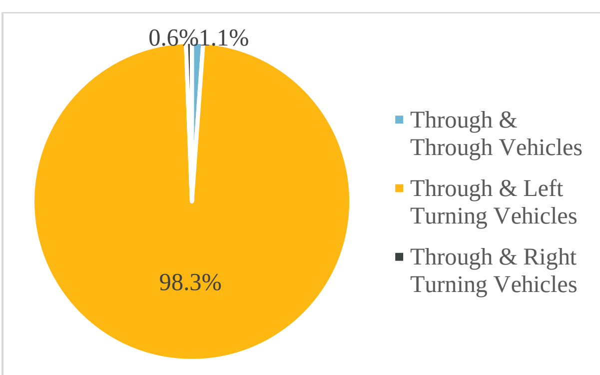
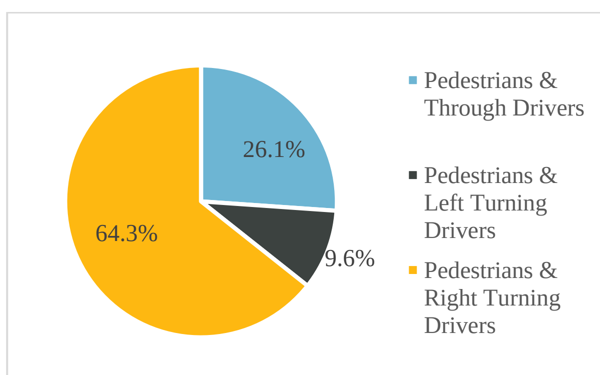


Figure 8 Concentration of critical conflicts across network

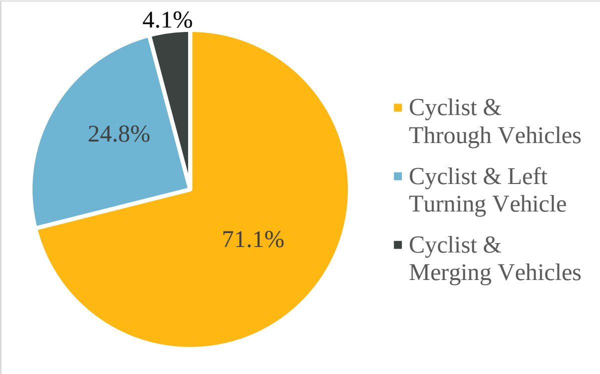
When exploring conflicts by mode, vehicular conflicts made up 97.5% of all critical conflicts observed. Pedestrian conflicts made up only 1.9% of all these conflicts, and cyclist conflicts made up 0.6%. Even though cyclists were involved in the least number of critical conflicts, they had the highest critical conflict rates. When comparing the critical conflict rates for each road user, cyclists were 6.5 times more likely to be involved in a conflict than a pedestrian and 8.7 times more likely to be involved in a conflict than a vehicle. Additionally, pedestrians were 1.3 times more likely to be involved in a conflict than a vehicle.

Depending on the countermeasures or policies in place, hotspot intersections with the highest frequency of a specific conflict scenario can be identified. Figures 9 a-c indicate the frequency of the main conflict scenarios and their frequency for each road user, on a network-basis. The vehicular conflicts were predominantly between through and left turning vehicles. Additionally, pedestrian conflicts with left turning vehicles were also most common. The most common cyclist conflicts were between cyclists and through vehicles.





a) Vehicular conflict scenarios **b) Pedestrian conflict scenarios**



c) Cyclist conflict scenarios

Figure 9 Conflicts by scenario for every road user

Based on the above information, multiple countermeasures can be proposed in the diagnosis stage to address the safety of these scenarios. With respect to vehicle-bicycle interactions, as cyclist volumes were very low throughout the intersections studied, the number of conflicts observed was also low. If the priority is targeting bicycle safety, longer periods of video data could be processed to increase the number of observations. Given the accessibility to video data from connected cameras, extending the period of observation is not an issue.

If the interest is to identify hotspots during critical hours of the day, critical days of the week, and/or by land use type, conflict frequency or rates per intersection can be generated per hour or per weekday. For instance, in this sample of intersections, conflict rates were highest in the morning around 7 AM and were the lowest after 7 PM. Intersections in residential areas had higher conflict rates than commercial areas throughout the day, as is depicted in Figure 10.

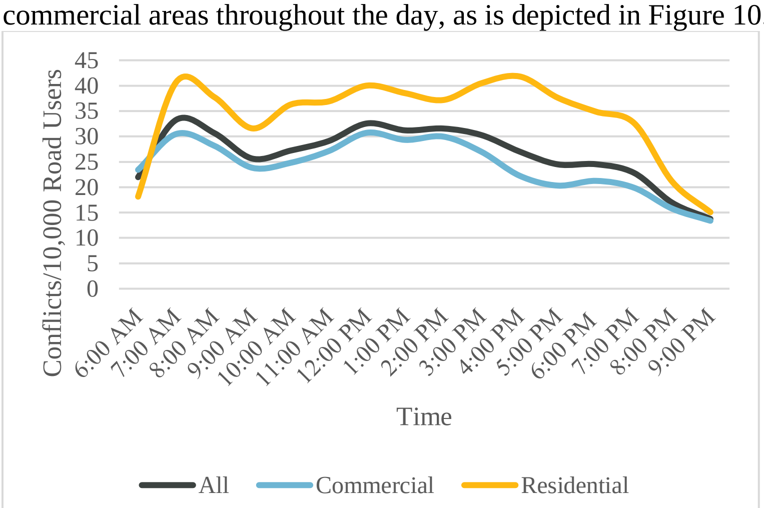


Figure 10 Hourly distribution of conflict rates by type of land use

Speeding

As in the case of conflicts, ranking criteria for hotspot identification could be derived from over-speeding events – which are defined based on speed limits for each particular approach when vehicles enter-exit the intersection. Throughout the network, around 870,000 instances of driver exceeding the speed limit were observed, indicating that approximately 10.8 % of motorized vehicles were speeding. The number of road users speeding at each intersection is listed in Figure 11 and the top 5 intersections with the most speeding incidence rate can be identified.

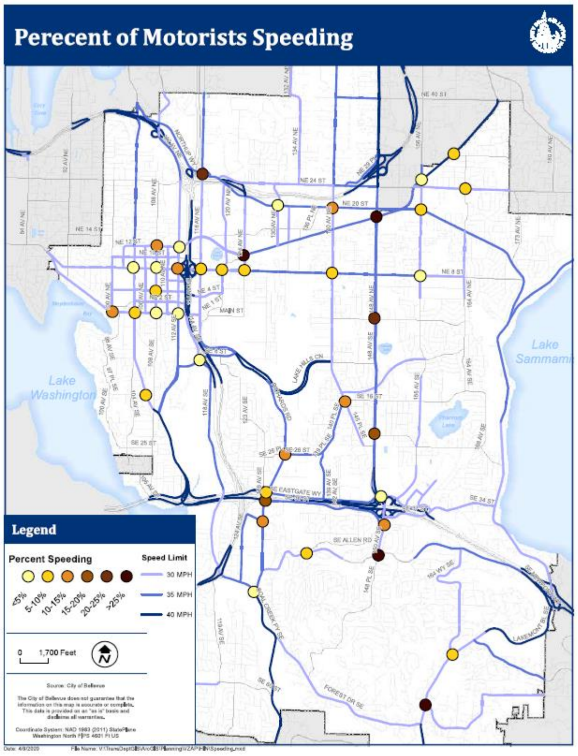


Figure 11 Concentration of speeding throughout network.

Depending on the city of interest, alternative ranking indicators can be derived from the data based on factors of interest, such as the identification of those hours or days of the week in which over-speeding occurs for each intersection. Figure 12 depicts the hourly speeding distribution across the entire network. A volume trendline was added to the graph. The trendline only depicts the change in volume pattern to look for clear correlations between volume and speeding. The figure shows that speeding incidence is lowest during peak hours, closer to 5 PM.

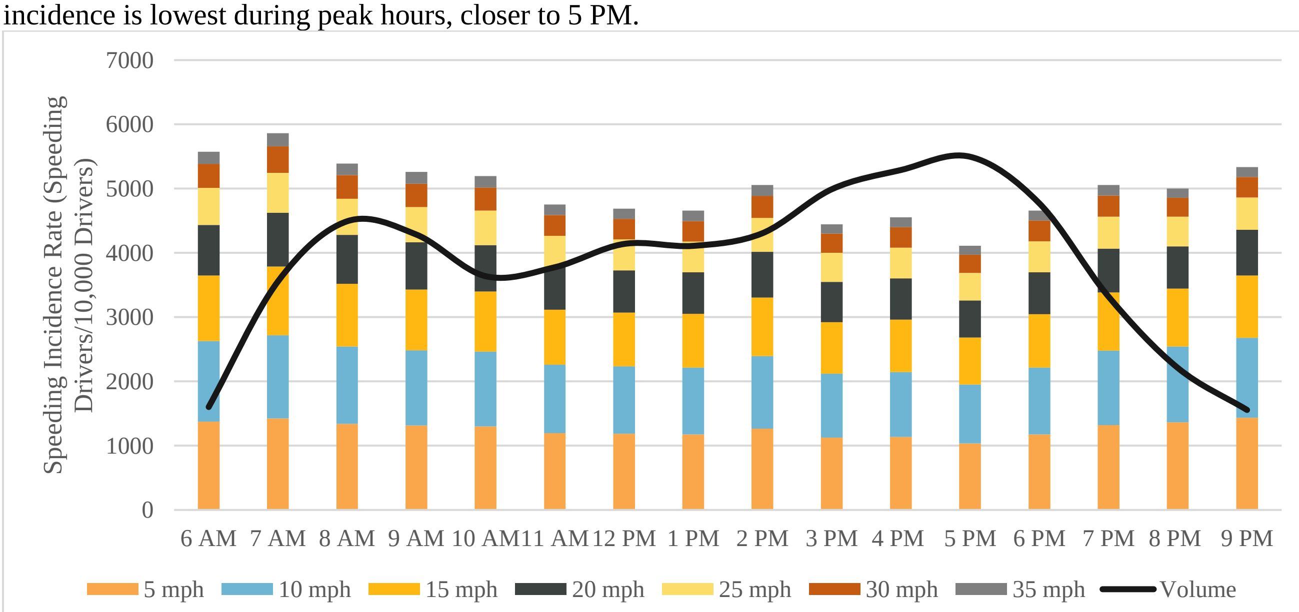
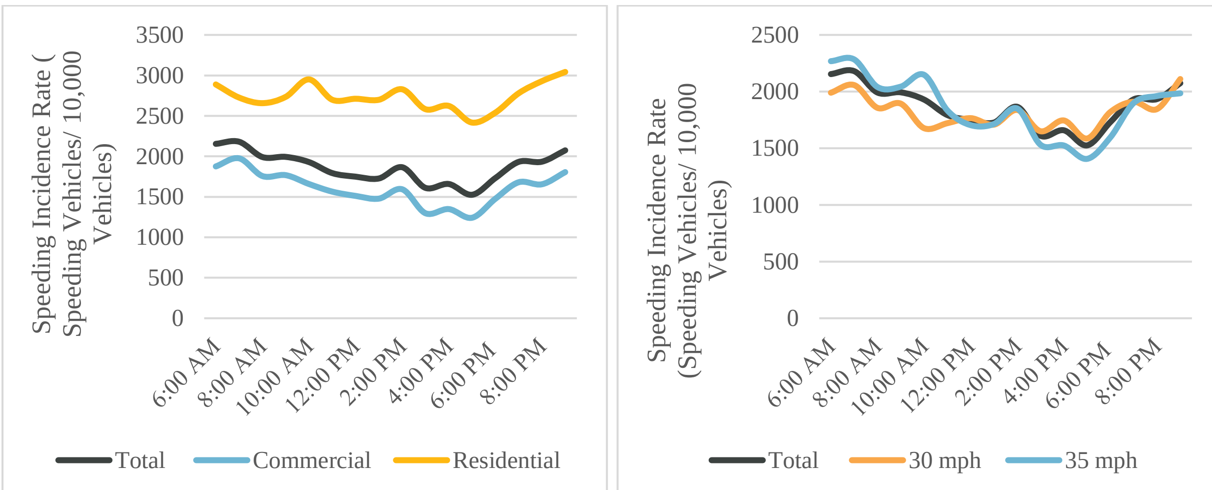


Figure 12 Weekday hourly speeding incidence distribution

Figures 13 a and b display the hourly variation of speeding incidence rates by land use and speed limit. Speeding incidence rates appear to be lowest during the peak hours between 3 and 6 PM. Speeding was more prevalent in residential areas, with 14% of vehicles speeding compared to commercial areas where 10.6% of vehicles were observed speeding. In terms of speeding at locations with different speed limits, speeding incidence rates did not appear to be more prevalent at either location. Looking at the temporal variation, speeding incidence rates were slightly higher at locations with speed limits of 35 mph in the morning; however, later in the afternoon, speeding incidence rates were slightly higher at locations with speed limits of 30 mph. Additionally, vehicular speeding incidence was found to be higher downtown with 15% of the vehicles speeding compared to the areas outside of downtown where 10.5% of the vehicles were speeding.



a) Speeding incidence rates by land use **b) Speeding incidence rates by speed limit**

Figure 13 Weekday speeding incidence rates by different factors

Hotspot Identification

To create both the network-wide model for the conflict data, two surrogate safety measures were analyzed, vehicle speed and PET. These two measures were considered as PET alone is insufficient to estimate the injury risk of a potential collision. The modeling approach, as described in the methodological section, involves fitting a multilevel regression model to the data with random and fixed effects at the intersection level. Once alternative models are fitted, the model with the best combination of variables is identified based on goodness-of-fit measures. Using the model outcomes, the expected number of conflicts or rates are estimated after controlling for other variables. This approach is similar to the classical regression approach using safety performance functions and Empirical Bayesian models with observed crash data.

The outputs of the network-wide PET and Speed models are listed in Table 1. The model indicated that the top 5 high-risk intersections were 116th Ave NE & Northup Wy, 124th Ave NE & NE 8th St, Richards Rd & 26th St, 145th PI SE & SE 16th St, and 130th Ave NE & Northup Wy.

With respect to the linear regression model used for the network-wide analysis, lower PETs and higher vehicle speeds are less desirable (i.e. indicative of more high-risk situations). Higher traffic volumes led to a reduction in speed and in PET severity. Speeds were lowest at locations with speed limits of 30 mph followed by 40 mph and then 35 mph. PET values were lowest (indicating more critical interactions) at locations with speed limits of 35 mph, followed by 30 mph and are highest at speed limits of 40 mph. Both the speed and PET models indicated that motorcyclists were the most high-risk road user as they increased the average speed by 1.15 mph and reduced PETs by 0.21 seconds. Through and through interactions with PET >2s were observed to be the most prone to higher speeds but happened at higher PETs (closer to 10 s) indicating they were not as critical of conflicts.

TABLE 1 PET and Speed Network-wide Model Outputs

Model	Parameter		Coef.	Std. Err.	t	P>t	95% Conf. Interval	
PET Model	1-hour Volumes		0.002	0.0001	32.38	0.000	0.000	0.000
	Peak Hour	0	0	(base)				
		1	0.055	0.005	11.43	0.000	0.0453	0.064
	Day of Week	Weekday	0	(base)				
		Weekend	-0.034	0.005	-6.68	0.000	-0.0442	-0.024
	Speed Limit	30	0	(base)				
		35	1.316	-0.037	33.6	0.000	1.244	1.389
		40	0.805	0.032	25.13	0.000	0.742	0.867
	Road User Type	Car	-0.064	0.059	-1.14	0.225	-0.183	0.049
		Bus	0.079	-0.056	5.34	0.000	0.0499	0.1079
		Bicycle	-0.143	0.0307	-4.65	0.000	-0.2027	-0.082
		Motorcycle	-0.207	0.04	-5.12	0.000	-0.286	-0.128
		Pedestrian	0	(base)				
		Truck	0.028	0.0105	2.67	0.007	0.008	0.0490
	Scenario	Through & Through	0	(base)				
		Through & Left Turn	-0.661	0.006	-115.95	0.000	-0.672	-0.650
		Left Turn & Through	-0.780	0.006	-136.71	0.000	-0.791	-0.769
		Left Turn & Left Turn	0	(base)				
Speed Model	1-hour Volumes		0.004	0	-22.61	0.000	-0.002	-0.002
	Peak Hour	0	0	(base)				
		1	-0.617	0.038	-16.83	0.000	-0.689	-0.545
	Day of Week	Weekday		(base)				
		Weekend	0.714	0.039	18.22	0.000	0.637	0.791
	Speed Limit	30	0	(base)				
		35	10.876	0.283	38.37	0.000	10.32	11.431
		40	-7.854	0.246	-31.99	0.000	-8.336	-7.37
	Road User Type	Car	-0.428	0.454	-0.94	0.346	-1.318	1.462
		Bus	-2.391	0.113	-21.1	0.000	-2.614	-2.169
		Bicycle	-5.63	0.235	-23.94	0.000	-6.091	-5.169
		Motorcycle	1.849	0.309	5.97	0.000	1.241	2.456
		Pedestrian	0	(base)				
		Truck	-1.851	0.081	-22.96	0.000	-2.009	-1.693
	Scenario	Through & Through	0	(base)				
		Through & Left Turn	-10.019	0.044	-229.13	0.000	-10.105	-9.933
		Left Turn & Through	-6.501	0.044	-148.61	0.000	-6.567	-6.415
		Left Turn & Left Turn	0	(base)				

In a similar manner, network-wide hotspot identification models were created based on speeding data. To create the network-wide mode; for the violation data, the surrogate safety measure analyzed was the speeding incidence rate. The output of the network-wide speeding model is listed in Table 2. The model indicated that the top 5 intersection prone to speeding behavior are Bel-Red Rd & NE 30th St, 145th Pl SE & SE 16th St, 118th Ave SE & SE 8th St, 150th Ave Se & SE 38th St, and 140th Ave NE & NE 20th St.

The explanatory variables (vehicle speeding rate, maximum speed, time of day, weekday vs. weekend, user type, and road user type) were found to be statistically significant at 99% except for the weekend at 94% significance. Vehicular speeding rates were found to cause an increase in speed by 0.23 mph for every 1% increase in speeding rate. Peak hours, between 3 PM and 6 PM, led to a small, but statistically significant decrease in speed by 0.15 mph compared to non-peak hours. Motorcyclists were found to be the fastest road users, with speeds 0.97 mph higher compared to vehicles, and the slowest motorized road users were busses, with speeds 0.69 mph lower compared to vehicles. Through vehicle movements were found to be the fastest. Right turning and left turning movements were found to have lower speeds by 4.82 mph and 4.27 mph, respectively. Weekends caused only a very minor reduction in vehicle speed.

TABLE 2 Speeding Network-wide Model Outputs

Parameter		Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Speeding Rate		0.371	0.001	1196.84	0	0.371	0.372
Maximum Speed		0.021	0.001	38.60	0	0.020	0.022
Peak Hour	**0**	0	(base)				
	1	-0.249	0.015	-16.40	0	-0.278	-0.219
RU Type	**Car**	0	(base)				
	Motorcycle	1.560	0.143	10.88	0	1.279	1.841
	Bus	-1.100	0.089	-12.42	0	-1.274	-0.927
	Truck	0.441	0.056	7.83	0	0.331	0.552
Movement	**Through**	0	(base)				
	Right Turn	-7.755	0.041	-189.66	0	-7.836	-7.675
	Left Turn	-6.869	0.046	-147.38	0	-6.960	-6.778
Day of Week	**Weekday**	0	(base)				
	Weekend	-0.028	0.015	-1.94	0.053	-0.0579	0.000

CONCLUSIONS

This work introduces a novel network screening approach based on connected cameras and using an automated video-analytics road-safety platform. The different steps in the systematic proposed approach are presented through an application environment using the City of Bellevue infrastructure. These steps include: video footage streaming, video camera calibration, video processing using state-of-the-art computer vision algorithms, quality control, and analytics outcomes which include raw data and ranking criteria automatically generated. Among those metrics that are used for ranking and identification of hazardous locations one can mention: traffic volumes by mode as an exposure measure, speed measures, near misses and violations (such as overspeeding). These metrics were generated and analyzed for a network of 40 intersections throughout the City of Bellevue.

The most critical intersections based on each ranking criterion were identified. Following, the road safety management process, those intersections could be considered for safety diagnosis in which potential crash contributing factors and potential solutions are proposed. In addition to aggregate ranking criteria such as the total number of critical conflicts or rates, disaggregate criteria with respect to categories of interest can be easily generated for identifying salient contributing factors and prone locations. For instance, if an interest to identify locations with a high concentration of left-turn-through conflicts exists, vehicle-vehicle conflict rates could be determined according to different scenarios (through vehicles with left turning vehicle, right turns, or other through vehicles). This can help identify the most dangerous types of scenarios and the locations in which conflicts of this type are concentrated. In a similar fashion, the identification of hotspots for vulnerable road users or hotspots with safety concerns related to night time or weekdays could be done using the appropriate category of conflicts or speeding events.

In this application, the majority of the critical conflicts observed were between two vehicles, and particularly between through and left-turning vehicles. Pedestrian conflicts primarily involved right turning vehicles, followed by conflicts involving through vehicles (potentially indicating red light violations). Cyclists were found to be most at-risk despite their low volumes. Conflict rates were found to be highest at 7 AM and lowest past 7 PM, and throughout the day were observed to be higher in residential areas compared to commercial areas. Instances of speeding were more prevalent in residential areas as opposed to commercial areas; however, speeding was more prevalent in the downtown intersections as opposed to the non-downtown intersections. Speeding incidence rates were not affected by the posted speed limit at an intersection. Weekday hourly speeds and speeding incidence rates were constant with the exception of a decrease around peak hours.

A network-wide hotspot modeling was performed using regression techniques with conflict and speeding data. The results of the statistical models showed that higher traffic volumes and peak hours were related to decreased PETs and speeds. Other factors affecting these outcomes are type of road user, land use type, etc. From the models and using expected values, ranking criteria were also derived based on the estimated frequency or rates of events. Similar to the traditional approach, regression models were used to derived safety performance functions that then can be used to identify contributing factors and hotspots using a Bayesian approach.

The power of surrogate safety using connected cameras and video analytics is demonstrated using a network-wide approach for network screening for the first step of the road safety management process. This work may be extended in various forms for future work. Longer periods of observation or a larger set of cameras may be considered with low computing costs, given that the automated process and availability of the analytics platform solution and connected cameras. The use of regression analysis for hotspot identification may be expanded to the use of full Bayesian approaches considering the state of the literature on this topic. Many other different metrics and their combinations may be derived and used for network screening such as different violations (jaywalking, red light running, double parking, etc.) performance metrics that affect safety such as pedestrian waiting or crossing times.

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REFERENCES

1. World Health Organization. Road Traffic Injuries. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries. Accessed Jul. 15, 2020.

2. Association for Safe International Road Travel. Road Safety Facts. https://www.asirt.org/safe-travel/road-safety-facts/#:~:text=More than 38%2C000 people die,for people aged 1-54. Accessed Jul. 15, 2020.

3. Vision Zero. Vision Zero Communities Map. https://visionzeronetwork.org/resources/vision-zero-cities/.

4. AASHTO. *The Highway Safety Manual, American Association of State Highway Transportation Professionals, Washington, D.C.* 2010.

5. Tingvall, C., and N. Haworth. Vision Zero-An Ethical Approach to Safety and Mobility. 1999.

6. Trentacoste, M. F. *Surrogate Safety Measures From Traffic Simulation Models Final Report*. 2003.

7. Wu, J., H. Xu, Y. Zheng, and Z. Z. Tian. A Novel Method of Vehicle-Pedestrian near-Crash Identification with Roadside LiDAR Data. *Accident Analysis and Prevention*, Vol. 121, 2018, pp. 238–249. https://doi.org/10.1016/j.aap.2018.09.001.

8. Ismail, K. A. *Application of Computer Vision Techniques for Automated Road Safety Analysis and Traffic Data Collection*. University of British Columbia, Vancouver, Canada, 2010.

9. Stipancic, J., L. Miranda-Moreno, N. Saunier, and A. Labbe. Network Screening for Large Urban Road Networks: Using GPS Data and Surrogate Measures to Model Crash Frequency and Severity. *Accident Analysis and Prevention*, Vol. 125, No. July 2018, 2019, pp. 290–301. https://doi.org/10.1016/j.aap.2019.02.016.

10. Guo, F., S. G. Klauer, M. T. McGill, and T. a Dingus. Evaluating the Relationship Between Near-Crashes and Crashes: Can Near-Crashes Serve as a Surrogate Safety Metric for Crashes? *Contract No. DOT HS*, Vol. 811, No. October, 2010, p. 382.

11. Fu, T., L. Miranda-Moreno, and N. Saunier. A Novel Framework to Evaluate Pedestrian 11 Safety at Non-Signalized Locations. *Accident Analysis and Prevention*, Vol. 111, 2017, pp. 23–33. https://doi.org/10.1016/j.aap.2017.11.015.

12. Peesapati, L., M. Hunter, and M. Rodgers. Evaluation of Postencroachment Time as Surrogate for Opposing Left-Turn Crashes. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2386, 2013, pp. 42–51. https://doi.org/https://doi.org/10.3141/2386-06.

13. Saunier, N., T. Sayed, and K. Ismail. Large-Scale Automated Analysis of Vehicle Interactions and Collisions. *Transportation Research Record*, Vol. 2147, No. 1, 2010, pp. 42–50. https://doi.org/10.3141/2147-06.

14. St-Aubin, P. *Driver Behaviour and Road Safety Analysis Using Computer Vision and Applications in Roundabout Safety*. Ecole Polytechnique De Montreal, 2016.

15. Johnsson, C., A. Laureshyn, and T. De Ceunynck. In Search of Surrogate Safety Indicators for Vulnerable Road Users: A Review of Surrogate Safety Indicators. *Transport Reviews*, Vol. 38, No. 6, 2018, pp. 765–785. https://doi.org/10.1080/01441647.2018.1442888.

16. Breiland, C., D. Weissman, S. Saviskas, and D. Wasseman. *Task 3A – Value Added Research*

Findings. 2019.

17. Zangenehpour, S., L. Miranda-Moreno, C. Chung, J. Clark, and L. Ding. Apparatus and Method for Detecting, Classifying and Tracking Road Users on Frames of Video Data, , 2020.

18. Hydén, C. *The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique*. Lund Institute of Technology, 1987.

19. Green, M. How Long Does It Take to Stop?" Methodological Analysis of Driver Perception-Brake Times. *Transportation Human Factors*, Vol. 2, No. 4, 2010, pp. 195–216. https://doi.org/10.1207/STHF0203_1.