MEASURING CROSSWALK SAFETY AT NON-SIGNALIZED CROSSINGS DURING NIGHTTIME BASED ON SURROGATE MEASURES OF SAFETY: A CASE STUDY IN MONTREAL

Ting Fu, Corresponding Author, PhD Candidate
Department of Civil Engineering and Applied Mechanics, McGill University
Room 391, Macdonald Engineering Building, 817 Sherbrooke Street West
Phone: (514) 632-1633
Montréal, Québec, Canada H3A 0C3
Email: ting.fu@mcgill.ca

Luis Miranda-Moreno, Associate Professor
Department of Civil Engineering and Applied Mechanics, McGill University
Room 268, Macdonald Engineering Building, 817 Sherbrooke Street West
Montréal, Québec, Canada H3A 0C3
Phone: (514) 398-6589
Fax: (514) 398-7361
Email: luis.miranda-moreno@mcgill.ca

Nicolas Saunier, Associate Professor
Department of Civil, Geological and Mining Engineering
Polytechnique Montréal, C.P. 6079, succ. Centre-Ville
Montréal, Québec, Canada H3C 3A7
Phone: (514) 340-4711 x. 4962
Email: nicolas.saunier@polymtl.ca

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ABSTRACT

This paper proposes a methodology to evaluate crosswalk safety at nighttime using surrogate safety measures and thermal video sensors. The methodology is illustrated using two non-signalized crosswalk locations in downtown Montreal, Quebec. Video data recordings from the thermal camera were used to compare nighttime and daytime safety conditions using different surrogate safety measures including vehicle crossing speed, post encroachment time (PET), as well as the yielding compliance and the conflict rate. A new way of measuring pedestrian exposure is also proposed which excludes non-interacting road users. A thermal camera was used in an effort to alleviate issues pertaining to low visibility at night for video analysis when road users, especially pedestrians, are difficult to detect and track. The results showed that the proposed thermal-video-based surrogate safety methodology is effective to collect and analyse pedestrian-vehicle interactions at night regardless of lighting conditions. From the study crossings, results also showed that that average vehicle crossing speeds and percentage of dangerous conflicts were higher during nighttime compared to daytime, indicating that pedestrians were at higher risks during nighttime. The proposed methodology can be used to evaluate the performance of different crosswalk treatments on pedestrian safety at night.

Keywords: Nighttime Safety, Crosswalk Safety, Video Analysis, Thermal Videos, Surrogate Safety Measures, Interactions, Risk Rate, Post Encroachment Time

INTRODUCTION

Pedestrian safety has become a priority for many cities due to increased awareness of their vulnerability compared to other road users. In the U.S, 14 % of total road crash fatalities were pedestrians in 2013 (*1*). Meanwhile 15.6 % of road crash fatalities in Canada were pedestrians in 2013 (*2*). Studies indicated that nearly half (46 %) of pedestrian fatalities in the US (*3*) and 57 % of pedestrian fatalities in Ontario, Canada (*4*) occurred at nighttime. Most crashes happen when pedestrians are crossing the streets when they are exposed to motorized traffic. A study in Europe showed that roughly 31 % of all pedestrian victims of road crashes were injured on marked crosswalks (*5*). Pedestrians are also vulnerable at locations with non-signalized crossings. For instance, Hunter et al. found that 40 % of intersection crashes and 93 % of midblock crashes occurred at non-signalized locations (*6*). Compared to daytime, there is less motorized and pedestrian traffic at nighttime, which generally leads to higher vehicle speeds as well as lower levels of driver awareness and attention. This difference in traffic and driving behavior leads to an increase in crash frequency and severity especially when pedestrians are involved (*7*) (*8*). In addition, Huang et al. point out that at nighttime, crosswalks and pedestrians can be less visible for drivers to see in time for a stop (*9*). Crosswalk safety has been looked into by numerous studies, and different treatments have been implemented and evaluated for different crosswalk locations; however, evaluating the safety of the treatment is challenging, in particular at night time, because of the sparse nature of the crash data and the lack of exposure measures (e.g., count data during night time). Most often, short-term counts for safety analysis are taken only during day time (*10*).

Moreover, the pedestrian safety literature has been built mainly through the use of historical crash data, focusing on crash frequency and severity as direct measures for road safety (*11*) (*12*) (*13*). However, vehicle-pedestrian crash data is not always available in sufficiently large quantity and suffers from known problems such as low-mean small sample, underreporting, mislocation and misclassification. Tarko et al. list the limitations of using crash data for road safety analysis (*14*). In addition, the low mean problem (sparse nature of the crash data) can represent a statistical issue when working with pedestrian crash data during nighttime, in which given the low level of exposure, the mean number of crashes is typically very low. Using historical data for pedestrian safety analysis requires long periods of observation (many years); thereby recent treatments cannot be quickly evaluated from crash data due to the lack of after-treatment crash data (*15*). In order to overcome this problem, proactive methods have been proposed that do not require waiting for crashes to happen. They rely on surrogate measures of safety that may provide better and more precise alternative road safety indicators.

Surrogate safety measures that rely on automated video analytics are gaining increasing popularity in road safety analysis for their various benefits (*14*) (*15*). Some studies have used such measures for identifying risk factors or evaluating treatment effectiveness using a before-after or control-case study approach (*15*) (*16*) (*17*) (*18*) (*19*). St-Aubin et al. developed a trajectory-based algorithm to measure Time-to-Collision (TTC) and carried out a Montreal case study to evaluate a safety treatment on highway ramps (*15*). This work has been extended by using realistic motion prediction methods (motion patterns learnt from observation) for the evaluation of the safety performance of roundabouts (*16*). Despite the important developments on surrogate safety analysis, there has been little nighttime safety evaluation using surrogate measures. Among the reasons, one can mention the technological limitations of regular video cameras (in the visible spectrum) that are unable to provide high quality data at night.

The objective of this work is to propose a surrogate safety methodology to quantify pedestrian safety on crosswalks during nighttime using thermal video sensors. To get effective video data under nighttime conditions, this paper used a thermal-camera based system; the details of this system are reported in (*20*). The trajectories were then extracted from video data and analyzed by calculating speeds of crossing vehicles and Post-Encroachment Time (PET).

This paper begins with a literature review; it then describes the thermal camera system used to obtain usable nighttime data and measures for crosswalk safety based on video data. A case study conducted as an example of using thermal videos for crosswalk safety evaluation at night is presented. Finally, conclusions and future works are discussed.

LITERATURE REVIEW

Using traffic trajectory data obtained from video recordings is the most widely adopted method for automatically calculating surrogate safety measures. Different trackers have been developed and used to obtain trajectory data (*21*) (*22*) (*23*) (*24*) (*25*). Saunier et al. adapted this method to intersections to track all road users by continuously detecting new features and adding them to current feature groups (*22*) (*23*). An improved multiple object tracking system, named Urban Tracker, was developed for tracking different types of road users in urban mixed traffic (*25*). In addition, in order to count different road users in mixed traffic conditions and to identify interactions based on their trajectories and between different types of road users, Zangenehpour et al. developed a classification algorithm to distinguish between three types of road users: pedestrians, vehicles and cyclists (*26*). The proposed classifier in this study uses the occurrence area, speed distribution and presence (appearance) of the road users to classify them. The data can then be used for surrogate safety analysis of the interactions between different road users. The overall accuracy of the classification algorithm at intersections with high volumes and mixed road user traffic was approximately 93 %. This algorithm was trained for thermal video in (*20*) and results for mixed traffic conditions demonstrated an overall accuracy of 70 %.

Different studies have also used trajectory data for obtaining traffic information such as volume, speed and conflict measures, which are fundamental for surrogate safety measures (*15*) (*16*) (*17*) (*26*) (*27*) (*28*) (*29*). Laureshyn looked at different indicators in behavioral and road safety research in terms of validity and reliability (*30*), and the indicators include time to collision (TTC), post-encroachment time (PET), gap time (GP), encroachment time (ET), time headway/time gap, compliance with the yielding rules and stop sign requirements and etc. Different studies used different measures for different conditions. In (*15*) (*16*), St-Aubin et al. computed TTC using the equations presented in (*30*) for highway safety. Tang and Nakamura relied on PET for evaluating conflict severity at signalized intersections(*31*). For pedestrian safety at crosswalks, PET has been widely used (*17*) (*29*). For instance, Alhajyaseen et al. (*29*) used PET and vehicle speed at a crosswalk as validation parameters to assess pedestrian safety at intersections.

Another important concept is the exposure of pedestrian to the risk of collision with motor vehicles (*32*). Exposure is traditionally measured through the pedestrian and vehicle volumes passing the area of interest, i.e. crosswalks for our study, or their product. But exposure is a general concept that represents the opportunities or necessary conditions for a collision to occur: it can be measured in various ways which depend on the purpose of the study. Pedestrians' exposure was already used in 1989 in a study of pedestrian safety at traffic signals using a manual traffic conflict technique (TCT) (*33*). In 1998, Silcock et al (*34*) proposed a method that used video recording as a data collection method to automatically extract data from video tapes describing the number of crossing movements and pedestrian-vehicle interactions. However, the definition of the conflicts (e.g. the threshold used on the surrogate measure of safety to distinguish from other events) was not clarified (*35*). Exposure is generally used to calculate pedestrian risks of collision with vehicles through crash or conflict ratios. The ratio is calculated based on the number of crashes or conflicts over the total exposure, which reflects the probability dimension of risk, i.e. the probability of a crash or conflict per unit of the chosen exposure. The most recent work using surrogate safety analysis with rate calculations can be found in (*26*). In this paper, the authors used the ratio of the total number of conflicts and severe conflicts divided by the product of the pedestrian and vehicle volumes. Other indicators such as speed and yielding compliance to evaluated crosswalk safety have been used extensively in similar studies.

Different measures of pedestrian exposure have been proposed (*35*). In the literature, the number of pedestrian crossings (per hour), vehicle volume, or their product have been used as the key indicators; however, these measures do not correspond to events where a pedestrian and a vehicle may actually interact, i.e. they are close enough to each other at the site of interest that they are at least aware of each other. There is a huge gap between the product of traffic volumes and an actual interaction between a pedestrian and a vehicle. This gap is even larger during nighttime in which pedestrian and vehicle flows are much lower and can present more temporal variability. Vehicle-pedestrian interactions change from site to site and from time to time due to many conditions at different sites. Besides, upstream signalization has a large impact on the arriving time of the pedestrians and the vehicles, which also influences pedestrian exposure. All these uncertainties may explain the low or unreported model fitness in past studies. All these require proposing and testing existing and new exposure measures.

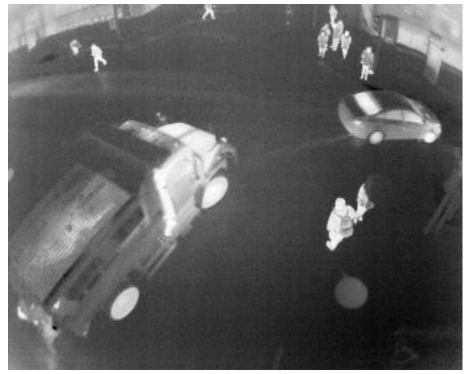
METHODOLOGY

The methodology consists of three key steps: thermal video data collection, trajectory extraction, and computation of surrogate safety measures.

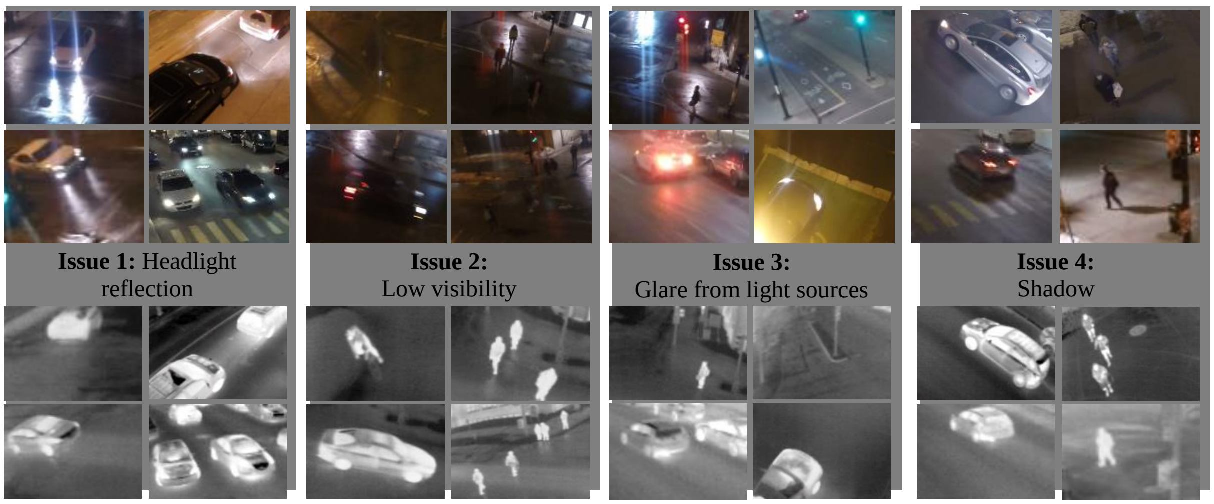
Thermal Video System, Object Tracking and Validation of Detection Performance

A thermal camera system was used for data collection. For details about the system and its performance in nighttime conditions, one can refer to (*20*). The system components are presented in **FIGURE1 a)**. For field measuring purposes, the camera was mounted on an adjustable mast against existing poles (i.e. lamppost or telephone pole) with an ideal coverage area and camera angle. **FIGURE 1 b)** shows a sample snapshot from the thermal video which was taken at nighttime where regular cameras in the visible spectrum fail to provide enough details about road users because of the darkness, reflection, and shadow and glare from different light sources. **FIGURE 1 c)** presents the issues of using regular videos for video data collection at night, and how thermal video is not affected by these lighting issues.

a) Camera system and installation



b) Sample of thermal video



c) Issues for using regular videos at night paired with the corresponding thermal videos

FIGURE 1 Thermal camera system and a comparison with regular videos at nighttime

Once video was collected, video data processing was carried out using the tracker in the open source Traffic Intelligence project (*22*); as an outcome, road user trajectories were obtained. The techniques used in the tracker are explained by Shi and Tomasi (*21*) and Saunier(*23*). (*20*) has validated the performance of video analysis using thermal video for traffic data collection in multi-modal environments in various lighting and temperature conditions, and has shown the reliability of this technique. Compared with mixed traffic conditions at intersections, non-signalized crosswalks are much simpler because road users travel in fixed directions along fixed segregated paths. Therefore, the performance of the tracker for detecting road users at crosswalks is expected to be higher. This study uses the performance measures introduced in (*20*). Miss rate was defined in (*20*) as “the proportion of road users whose movement is not captured by any trajectories”, and “was used to quantify detection performance. For pedestrians, the detection performance was evaluated at the group level, i.e. a group of pedestrians not tracked is counted as one miss”. Precision and recall for detection are also reported.

Safety Measures

For evaluating the safety status of a crosswalk during night time, the following three measures were defined.

Pedestrian-Vehicle Interaction

FIGURE 2 describes an interaction between a pedestrian and a vehicle at a crosswalk. PET is defined as "the time gap" between two road users "arriving" and "leaving" the crossing area; PET is used in this study as the surrogate safety measure for interactions between pedestrians crossing the street and vehicles since their trajectories will always intersect and PET can thus always be computed. The fact that PET may not be computed for some interactions is otherwise a known shortcoming of that measure. Based on the road user classification and the trajectory data of each road user, the PETs of pedestrian-vehicle interactions is calculated as:

$$PET = \begin{cases} T_{CF} - T_P, if\ T_P < T_{CF} \\ T_P - T_{CR}, if\ T_{CR} < T_P \end{cases} \quad (1)$$

Where the notations are defined and illustrated in **FIGURE 2**: $T_P < T_{CF}$ indicates the situation where the pedestrian arrives at the crossing area before the vehicle, while $T_{CR} < T_P$ means the opposite. The study used the trajectory data to measure the PET between each pedestrian crossing the street and vehicle crossing the crosswalk at a same time. This study used a computer vision safety analysis tool to automatically calculate the PET values for each pair of interacting vehicle and pedestrian. Interactions with PETs less than 5 seconds were considered as conflicts, and those with PETs less than 1.5 seconds were defined as dangerous conflicts. For details about the PET thresholds for the conflicts, see (*19*). With the computer vision software, pedestrians may be tracked in a group, in which case only one interaction with the whole group will be counted - in real situation, a small group pedestrians walking together could be regarded as one road user as they have the same chance in interactions with passing vehicles.

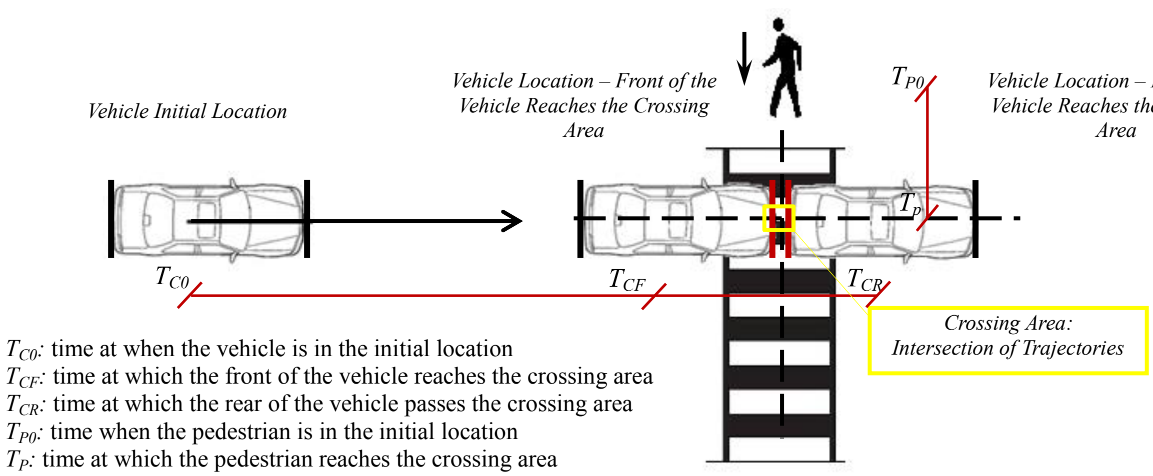


FIGURE 2 Description of pedestrian-vehicle interactions at a crosswalk

Pedestrian Exposure Measure

Exposure measures, in most of the literature, are based on traffic volumes. Different exposure measures can be used depending on the purpose and can be considered in the traditional safety hierarchy framework of surrogate safety analysis based on earlier work by Hydén among others **(*36*)** illustrated in **FIGURE 3**, with collisions as the most severe events at the top and undisturbed passages at the bottom. Using microscopic trajectory data, this work can measure exposure at the level of road user interactions, when two road users are close enough in time and space. This paper sets an arbitrary threshold of 20 s on PET for interactions considered as exposure to pedestrian-vehicle collisions.

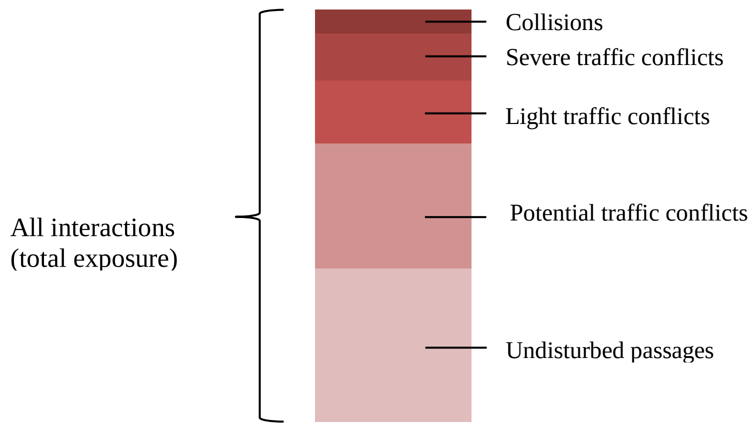


FIGURE 3 Pedestrian-vehicle interactions in the safety hierarchy (*36*)

Safety Measures

Safety measures are analyzed by visualizing the cumulative distribution functions (CDFs) and the interaction rate based on the exposure measure defined above: this paper calculates the interaction rate at crosswalks as the number of conflicts over the number of interactions used as exposure.

Cumulative Distribution Functions (CDFs)

Visualization has been proved to be powerful for comparison purposes. CDFs are used in this study as a way to understand pedestrian risk at crosswalk. **FIGURE 4** demonstrates the principle of this analysis method. The elevated line indicates a higher proportion of dangerous conflicts. The grey line in the figure represents the dangerous conflict threshold and the right border of the figure is the conflict threshold. This method of showing safety is intuitive; however, as (*37*) illustrated, using cumulative distribution is not always conclusive.

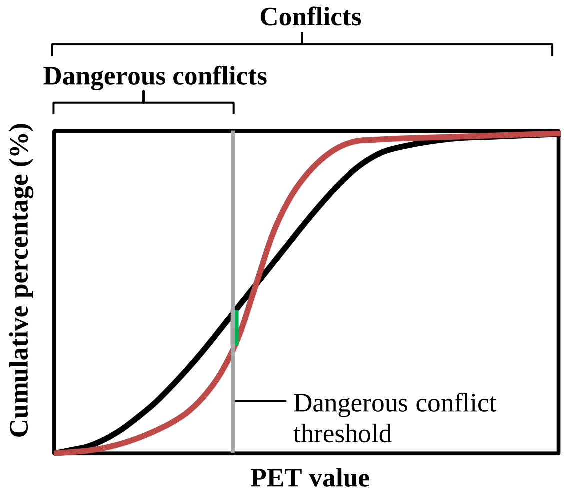


FIGURE 4 Illustration of different cumulative distribution functions

Conflict Ratio

Two conflict rates are used. For a given site i, the conflict rate (R_{Ci}) is defined as the number of pedestrian-vehicle conflicts, which are the interactions with PETs less than 5 s, divided by the number of interactions with PET less than 20 s denoted N_{Ei} (exposure). The dangerous conflict rate (R_{DCi}) is defined as the number of dangerous conflicts, which are the interactions with PET less than 1.5 s, divided by the same exposure measure N_{Ei} .

Other Safety Measures: Crossing Speed and Yielding Compliance

Crossing Speed

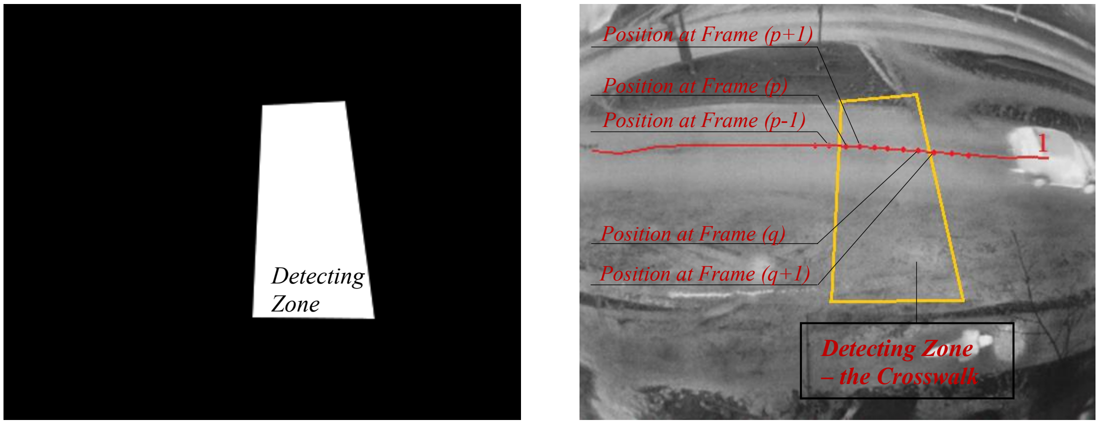
The crossing speed of vehicles passing the crosswalk was used as a safety measure in this paper. Crossing speeds were automatically extracted from the videos through the computer vision software and have been shown to be reliable in (*20*). A script was used for extracting velocities and calculating the speeds for vehicles passing the crosswalk. **FIGURE 5** presents how the crossing speeds were extracted. A mask was prepared for the detection zone – the crosswalk in this case, shown in **FIGURE 5** a). In video collected from site i, for a certain vehicle j, $j = (1, \ldots, N)$, where N is the total number of vehicles, if its trajectory falls in the detecting zone in video frame m, $m \epsilon (p, p+1, \ldots, q)$, its velocity $\overrightarrow{v_{ijm}}$ is extracted and the instantaneous speed s_{ijm} is calculated. The crossing speed is calculated by averaging the instantaneous speeds in these frames, as presented in the following equation:

$$s_{ij} = \frac{1}{q-p+1} \sum_{m=p}^{q} (s_{ijm}) \qquad (2)$$

The average crossing speed for site i would be:

$$s_i = \frac{1}{N} \sum_{j=1}^{N} (s_{ij}) \qquad (3)$$

Speed distributions and average crossing speeds of all the passing vehicles were compared.



a) Mask for detecting zone b) Sample of a trajectory

FIGURE 5 Sample of speed extraction through the computer vision software

Yielding Compliance

The law requires vehicles to yield to a pedestrian when he is starting or indicating the intension to cross the road. In this case, yielding compliance refers to the rate of drivers' yielding behavior among the pedestrian-vehicle interactions which require the drivers to slow down or stop to give pedestrians the right-of-way. Yielding compliance rate (YCR) was calculated by manually counting the vehicle yielding maneuvers. For site i, if a pedestrian arrives at the crosswalk before a certain vehicle j, the yielding behavior of this vehicle involved in an interaction with a pedestrian can be quantified by the following measures

$$X_{ij} = \begin{cases} 1 \; if\ the\ vehicle\ yields\ and\ gives\ right\ of\ way\ to\ the\ pedestrian \\ 0 \; otherwise \end{cases}, j = (1, \dots, M_i) \quad (4)$$

$$Y_i = \sum_1^M X_{ij} \quad (5)$$

$$YCR_i = \frac{Y_i}{M_i} \quad (6)$$

Where M_i is the total number of interactions between the crossing vehicle and the pedestrian already starting or indicating his intention to cross and, to avoid a collision, at least one involved road user must yield. Y_i is the total number of yielding drivers and YCR_i is the yielding compliance rate.

Validation of the Classification Tool for Pedestrian-Vehicle Interactions at Crosswalks

In order to calculate the PETs, a classification method is required to identify the vehicle-pedestrian interactions. A modification of a previously developed method for object classification in video (*26*) was used in this study. The modification was done by changing the image database for detecting road user presence in thermal videos (*20*). One can refer to (*26*) and (*20*) for details. **FIGURE 6** presents a sample snapshot of tracking and classification results.

In (*20*), the overall accuracy of the classification algorithm in terms of classification performance measures has been shown to be over 80 % for mixed traffic with the average precision of 70.9 % and the average recall of 99.5 % for vehicles, the average precision of 73.2 % and the average recall of 89.2 % for cyclists and the average precision of 98.6 % and the average recall of 72.0 % for pedestrians. While the rates are relatively high, they are not high enough to conduct a safety analysis. However, with the simpler traffic conditions at non-signalized crosswalks, the performance of classification algorithm is expected to be better. Similarly to (*20*), the classification performance was validated in terms of precision, recall and overall accuracy, and was measured by extracting frames at every 10 consecutive seconds of video.

FIGURE 6 Tracking & Classification process with video - Sample of tracking and classification. The red line represents the trajectories of the moving objects up to the time of the image; P stands for pedestrians and C stands for cars

CASE STUDY

Site Selection and Data Description

FIGURE 7 shows the locations of the selected sites. For testing the thermal camera system and investigating the crosswalk safety, two crosswalk locations with different traffic and environmental conditions were selected in downtown Montreal:

- **Site du Fort:** This crosswalk is located on Rue du Fort at the intersection of Rue du Fort and Rue Baile. It is a painted crosswalk crossing two one-way lanes and a median between the two lanes. Since the left lane was observed to have very little traffic, only the right lane was analyzed. Located on a secondary road, this site has a relatively low traffic volume.
- **Site St-Laurent:** The crosswalk is located on one of the main arteries in downtown Montreal, Boulevard St-Laurent, at the intersection of Boulevard St-Laurent and Rue Bagg. It is a painted crosswalk crossing two one-way lanes. This location is busier than the du Fort site in terms of vehicular and pedestrian traffic.

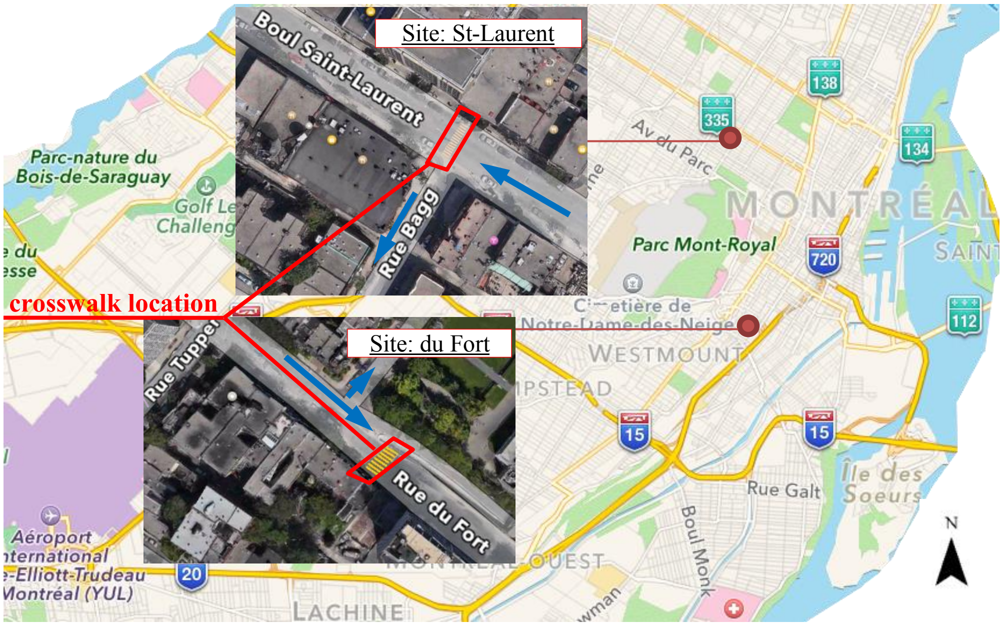


FIGURE 7 Locations of the selected sites

For each site, thermal video data were collected in both daytime and nighttime conditions. A total number of 16.8 hours of video data were collected. For comparison purposes, all video data were collected in the same season with similar traffic, weather and road surface conditions (i.e. collected on good weather conditions with bare pavement in winter). All the videos were recorded during the afternoon peak period and at nighttime on weekdays when higher crash rates were observed. Details of the video data are presented in Table 1.

TABLE 1 Description of the Video Recorded from Each Site

Site name	du Fort	St-Laurent
Camera View		
Total hour collected at night	4.6 hrs	6.0 hrs
Total hour collected during the day	2.6 hrs	3.6 hrs

Site name	Date	Period of a Day	Time	Duration (hour)
du Fort	11-Nov-2014	Day	03:00-04:40pm	1.6
		Night	07:00-08:15pm	1.2
	14-Jan-2015	Night	06:30-08:20pm	1.8
	15-Jan-2015	Day	03:30-04:30pm	1.0
		Night	07:00-08:40pm	1.6
St-Laurent	31-Dec-2014	Day	03:00-04:10pm	1.2
		Night	06:30-09:15pm	2.8
	01-Jan-2015	Day	02:00-04:30pm	2.4
		Night	06:00-09:15pm	3.3

Detection and Classification Validation

The tracker and the classification algorithm were validated using 30 minute video samples from each site. Results of the detection and classification performance are provided in Table 2.

TABLE 2 Classification Accuracy Validation Results

	No. of Presence	No. of Missed /Miss Rate	Detection Performance Precision	Detection Performance Recall	Classification Performance Precision	Classification Performance Recall
du Fort *(Video length of 30 minutes, from night, 14-Jan-2015)*						
Vehicle	68	1 / 1.7%	97.1%	97.1%	98.5%	98.5%
Pedestrian	60	1 / 1.6%	100%	81.1%	100%	98.3%
Overall	128	2 / 1.6%	91.4%	98.4%	*Global Accuracy = 97.7%*	
St-Laurent *(Video length of 30 minutes, from night, 31-Dec-2014)*						
Vehicle	205	0 / 0%	97.6%	98.6%	94.8%	97.6%
Pedestrian	104	1 / 1.0%	100%	80.0%	100%	93.0%
Overall	309	1 / 0.3%	93.1%	98.4%	*Global Accuracy = 91.7%*	

Based on the results, the tracker and the classification algorithm worked almost perfectly in detecting and classifying the pedestrians and vehicles at each crosswalk – very few misses and around 95 % of precision, recall and global accuracy rates in most cases, except for the lower recall values in detecting pedestrians (around 80 %) mainly resulting from the over-grouping of pedestrians moving together (***20***). These values are much higher than those for mixed traffic tested in (***20***), indicating the reliable performance of using the tracker and the classification algorithm at crosswalks. The small portion of the misclassified road users could be easily corrected in the output SQLite file.

Results and Analysis

The proposed methodology was applied to the selected sites and video data were processed. Mean vehicle speed over the vehicle trajectory within the marked crosswalk area was calculated as the crossing speed for each vehicle, and PETs between vehicles and pedestrians were computed. For the du Fort site, an average of 319 vehicles and 161 pedestrians per hour were detected during the 2.6 hours of video data collected in daytime conditions while a volume of 414 vehicles and 127 pedestrians per hour were detected from the 4.6 hours of video taken at night. The St-Laurent site had a volume of 848 vehicles and 994 pedestrians per hour during 3.6 hours of daytime video recordings, and a vehicle flow of 833 vehicles and 407 pedestrians per hour during 6.1 hours of nighttime video recordings. Table 3 presents a summary of the results of different safety measures, which includes the vehicle crossing speed, vehicle yielding compliance rate, exposure measured in the traditional way using the product of pedestrian and vehicle volume, number of the conflicts, conflict rate, number of dangerous conflicts and rate of dangerous conflicts, for both sites. **FIGURE 8** presents the distributions of speeds and the CDFs of PET for conflicts for both day and night.

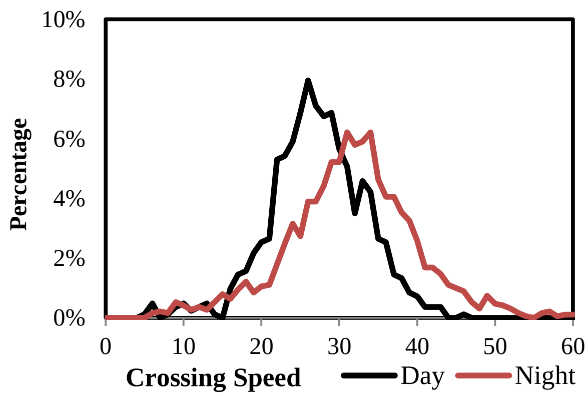
Looking at **FIGURE 8 a)** and **c)** it can be observed that increases in the crossing speed were detected at night for both sites. Also, from Table 3, for the crosswalk safety situation, the average crossing speeds were found to be higher (by 9.3 % - 16.8 %) at the crosswalk of the du Fort site at nighttime compared to daytime; for the St-Laurent site, the average crossing speeds increase by around 30 % at night compared to daytime. Possible reasons for this observation could be: 1) although the traffic flow is similar between afternoon peak hours and early nighttime hours for both sites, the volumes at the second site are higher during the afternoon peak hours, which leads to the congestion of the adjacent road segments; 2) during the afternoon peak hour, a large number of vehicles are searching for parking spots and their parking maneuvers block the traffic. This phenomenon is especially evident for the site of St-Laurent, where a pharmacy and many restaurants are located. Many parking maneuvers were observed in the daytime while fewer occurred at night; 3) Because of lower traffic volumes and less pedestrian activity at night, drivers drive faster. This increase in the average crossing speeds of the passing vehicles at the crosswalks at nighttime indicates that pedestrians are exposed to higher probabilities of severe crashes at night.

Exposure was measured in both the traditional way using the pedestrian-vehicle volume product and the exposure using PET. The ratio of the "real" exposure number over the second definition was calculated to compare the exposure measures in different situations. From Table 3, most of the values were less then 1 and these ratios actually varied from case to case. The exposure of the number of interactions with PET less than 20 s is used in the study to compute the rates and evaluate the safety performance. From the results, a higher exposures can be observed in daytime compared to nighttime in most cases except for data collected at the du Fort site on Wednesday, January 14th when a hockey game brought about a large number of people at nighttime, and data collected from the St-Laurent site on Thursday, January 15th when people went out clubbing.

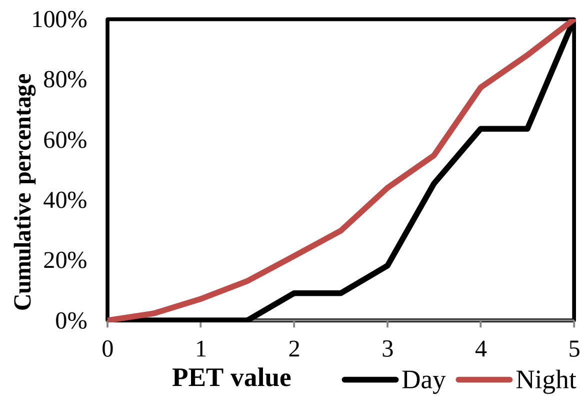
From **FIGURE 8 b)** and **d)**, among all interactions, a higher percentage of dangerous conflicts (with PET less than 1.5 seconds) were observed at nighttime compared to daytime, which indicates that pedestrians were involved in more dangerous interations with vehicles at the crosswalks at night. Looking at the rates, R_C values do not necessarily change from daytime to nighttime, while the R_{DC} values indicate that pedestrians experience higher risks of being involed in a dangerous conflict at night.

These results concerning the speeds and conflict rates seem to indicate that at these two locations, pedestrians were at higher risks of being involved in a dangerous interaction at night, when crossing speeds were on average higher.

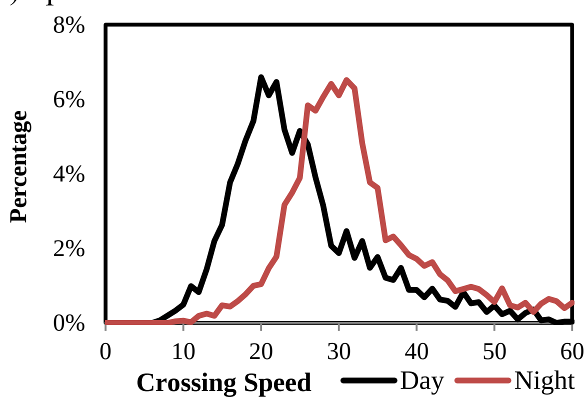
However, regarding the yielding behavior of the drivers, people's yielding compliance varies from site to site. Site du Fort had a higher yielding rate at nighttime, while the yielding rate is reduced at night at site St-Laurent. Upon a field inspection or Rue du Fort, in daytime, vehicles were parked near the crosswalk along the sidewalk, which was free of parked vehicles at night. This observation might explain the increase in yielding rate at night at this site as pedestrians were easier to detect in advance by drivers. Regardless the results indicated overall that the yielding compliance of the drivers at these two locations were both low (on an average of 15 % - 38 % for the two sites).



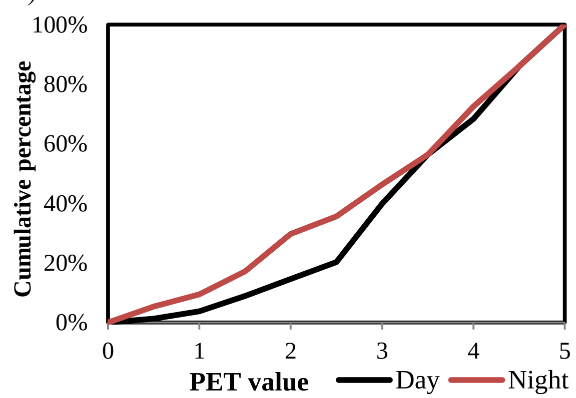
a) Speed distribution – du Fort



b) Cumulative conflict distribution – du Fort



c) Speed distribution – St-Laurent



d) Cumulative conflict distribution – St-Laurent

FIGURE 8 Visualization results of the two sites – speed distributions and PET CDFs

TABLE 3 Results - Exposure Measures and Other Safety Measures for Daytime VS. Nighttime

	Date	**Day**	**Night**	**Day**	**Night**	**Day**	**Night**	**Day**	**Night**
		Vehicle Volume (vph)		***Pedestrian Volume (pph)***		***Average Cro. Speed (km/h)***		***Yielding Compliance***	
du Fort	13-Nov-14	359.4	439.2	53.8	23.3	27.95	30.57	20.83%	50.00%
	14-Jan-15	--	469.4	--	167.8	--	31.22	--	38.52%
	15-Jan-15	331.9	255.0	160.6	127.0	26.56	30.78	11.76%	18.18%
	all	319.2	413.7	81.9	127.6	26.68	31.17	15.52%	37.66%
St-Laurent	31-Dec-14	1333.3	629.3	1087.5	423.2	24.42	32.02	32.69%	18.18%
	01-Jan-15	605.0	1005.8	946.7	392.7	24.97	33.74	30.11%	25.40%
	all	847.8	833.0	993.6	406.7	24.68	33.84	31.47%	22.92%
		Traditional Exposure (per hour)		***Number of Interactions with PET < 20 s (exposure) (per hour)***		***No. Interactions/Trad. Exposure (per thousand)***			
du Fort	13-Nov-14	19316	10247	126.9	114.2	6.6	11.1		
	14-Jan-15	--	78762	--	517.2	--	6.6		
	15-Jan-15	53307	32385	213.1	208.0	4.0	6.4		
	all	26152	52791	158.1	306.3	6.0	5.8		
St-Laurent	31-Dec-14	1450000	266323	6129.2	1758.9	4.2	6.6		
	01-Jan-15	572733	394988	3659.2	5280.9	6.4	13.4		
	all	842361	338779	4531.9	3664.3	5.4	10.8		
		No. Conflicts		***Conflict Rate***		***No. Dangerous Conflicts***		***Dangerous Conf. Rate***	
du Fort	13-Nov-14	2.5	5.0	1.97%	4.38%	0.0	0.0	0.00%	0.00%
	14-Jan-15	--	36.1	--	6.98%	--	3.9	--	0.75%
	15-Jan-15	9.0	8.1	4.22%	3.89%	0.0	2.5	0.00%	1.20%
	all	5.0	18.3	3.16%	5.97%	0.0	2.4	0.00%	0.78%
St-Laurent	31-Dec-14	55.8	27.1	0.91%	1.54%	5.0	2.9	0.08%	0.16%
	01-Jan-15	37.9	44.2	1.04%	0.84%	3.3	9.1	0.09%	0.17%
	all	43.9	36.4	0.97%	0.99%	3.9	6.2	0.09%	0.17%

CONCLUSION

This paper presented an automated video-based methodology for safety analysis for pedestrian crossings at nighttime. This method was based on the use of thermal video sensors for recording video in nighttime. The preliminary results showed that pedestrians were exposed to higher risk levels at the study sites in nighttime as opposed to daytime conditions. The proposed automated methodology can be implemented for assessing different crosswalk treatments, such as LED pedestrian warning signs, an automated pedestrian detection-warning system and geometric/marking treatments for improving crosswalk safety at nighttime. Results from this paper showed that at the studied non-signalized pedestrian crossings, the average vehicle crossing speeds are higher and percentage of dangerous conflicts were higher during nighttime compared to daytime, indicating that pedestrians were at higher risks during nighttime. Not much difference was found concerning the yielding compliance and the conflict rate; however, in both sites the yielding compliance rate was quite low.

Thermal camera sensors provide a reliable solution to the limitation of common video sensors in the visible spectrum when used for nighttime analysis. The main advantage of using thermal cameras over regular ones is their ability to collect useful, high-quality and reliable data under different environmental conditions such as in instances of low visibility and the presence of glare or shadows caused by different light sources. Though the unit price of the thermal camera is relatively high, rapid development of sensor technologies should bring the price down and make them more accessible to institutes, research groups, governments and personal users.

The validation work and the potential future work about the thermal camera have been discussed extensively in (*20*). The use of the thermal camera system for safety analysis at different locations and for different types of road users in nighttime conditions will be explored. The exposure used in this paper potentially provides a more precise measure to describe the pedestrian-vehicle interactions which, compared to exposure measures based on traffic volumes, are more closely related to pedestrian safety. A PET threshold of 20 seconds was set empirically to cover all potential conflicts, while the use of this threshold needs to be further explored and validated. Besides, the methodology and the safety measures used in this paper should be appropriate for the analysis of signalized intersections. However, the performance of thermal videos for safety analysis at busy intersections will be tested and the use of the safety measures should be further validated.

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