Identification of Pedestrians Non-Conforming Behavior at Urban Intersections using Computer Vision

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Abstract

The detection and the understanding of non-conforming behavior (violations) can be beneficial for a sound safety diagnosis as well as for developing safety countermeasures. Traffic violations occur when road users including pedestrians seek an increased mobility, by disregarding existing traffic laws and regulations. This behavior can come at the expense of accepting additional collision risk. The objective of this paper is to demonstrate the automated identification of pedestrian crossing violations using computer vision techniques. Two types of violations are considered. The first is spatial violations where pedestrians decide to cross in non-designated crossing regions. The second is temporal violation when pedestrians cross an intersection during an improper signal phase. The methodology relies primarily on the discrimination of road-users trajectories and separating pedestrians with non-conforming behavior. The methodology is demonstrated on two distinct urban intersections in Downtown Vancouver, Canada and Kuwait City, Kuwait. The results show satisfactory accuracy of detecting both spatial and temporal violations with about 90% correct violation detection rate in both case studies.

keywords. Computer Vision, Violations Detection, Road-Users Classification, Trajectories Analysis

1 INTRODUCTION

Walking is a reliable activity that connects the different modes of travel and interfaces with external activity areas. In modern urban planning, the function and mode-assignment of streets are being redefined to accommodate the pedestrian as a key road user (1). However, non-motorized modes of travel such as walking, may expose the road-user to severe consequences, when involved in traffic collisions. A study compromising 38 cities in developing countries, has shown that pedestrian fatalities is the highest among all modes; accounting for 41% to 75% of all fatalities (2). The problem of pedestrian vulnerability is also present in developed countries. Approximately 22% of fatal road collisions in Canada and 30% of fatal road collisions in British Columbia involve vulnerable road users; respectively 13% and 15% of which are pedestrians (3). Maintaining a safe pedestrian walking environment is vital for a sustainable transportation system and represents a challenge for promoting sustainable travel modes.

Traffic violations occur when road users including pedestrians seek an increased mobility, by disregarding existing traffic laws and regulations. This behavior can come at the expense of accepting additional collision risk. The detection and the understanding of non-conforming behaviors (violations) can therefore be beneficial for a sound safety diagnosis as well as for developing safety countermeasures. This practical benefit of observing violations as surrogates to traffic conflicts, and consequently road collisions, is especially realized when observational periods are limited. In situations where it is likely that road collisions are attributable to violation actions, traffic violations can provide a reliable and timely surrogate road safety measure. Several studies argued on conceptual and empirical grounds that traffic violations are valid indicators of road safety ((4) (5) (6)).

Unfortunately, one of the main challenges in conducting detailed pedestrian road safety analysis is the lack of reliable data (7). Examples of desired data include pedestrian volume and measures of exposure to collision risk (8). Yet, current field based methods for collecting pedestrian data is labor-intensive, suffer from reliability issues, time consuming and costly. Reliability issues stem from the fact that pedestrians move in a less organized fashion than vehicles, at higher densities, and in more complex and constrained spaces than vehicular traffic. Video sensors have become popular for recording different events for offline analysis, solving much of the above-mentioned issues. However, the manual inspection of the video data suffers from some of the shortcomings of the field based methods, more precisely the subjectivity and timing issues. Computer vision provides an automated based interpretation of the different scenery. It has been an active research area that found applications in different disciplines including transportation engineering. It is advocated that the automated observation and analysis of road user violations may help improve our understanding of pedestrian safety issues. Moreover, such automation can enable the processing of extended observational periods while consuming limited time and staff resources.

This paper presents a methodology for the automated detection of pedestrian spatial and temporal violations at urban intersections. Spatial violations occur when pedestrians decide to cross in non-designated crossing regions. Temporal violations occur when pedestrians cross an intersection during an improper light phase. The methodology relies on: First, the discrimination of pedestrian trajectories and segregating the ones with non-conforming behavior. Second, the identification of pedestrian locations during different light phases by analyzing their coordinates. The analysis is performed on video segments of two urban intersections in Downtown Vancouver, Canada and the city of Kuwait, Kuwait to illustrate the methodology. In addition to its importance to safety analysis, this line of research can be beneficial to other applications including data collection to support pedestrian behavioral studies as well as calibration and validation of pedestrian simulation models.

2 RELATED WORK

Pedestrian crossing behavior is important for the design of urban intersections and signalized crossings, in addition to its role as a safety surrogate indicator of the intersection. For example, the results in (9) suggested a relation between pedestrian crossing conformance and traffic conflicts. e.g., non-conforming pedestrian is more likely to be trapped in the middle of the street. That leads to an increase in collision exposure. The main factors that affect pedestrian behavior at intersections were studied in (10). Several parameters, such as waiting time, crossing time, and arrival rate were suggested as key variables for describing pedestrian characteristics and improving crossing design and signal timing plan (10). In (11), models were developed to study the relationship between the pedestrian waiting time at the curbside and the number of crossing attempts. The study revealed that the expected waiting time influenced the number of crossing attempts of the pedestrian. In line with this work, a system was developed as an observatory system dedicated to pedestrian mobility at signalized intersections (12). The system focuses on the assessment of time sharing between pedestrians and road trafc. Data collection in the above studies did not employ computer vision techniques and relied on field observations for data collection and analysis.

The literature covering transportation applications of computer vision techniques is steadily growing. A useful recent overview of work developed in the realm of computer vision on pedestrian detection, classification and tracking can be found in (13)and (14). Malinovskiy *et.al.* (15) present a computer-vision based approach for collecting pedestrian arrival rate and headway information. Road-users including pedestrians are identified via background extraction and are subsequently tracked. A waiting zone is selected at the beginning of the analysis and is used for pedestrian tracking initialization as well as a starting point for recording the arrival rate as well as the headway. The shortcoming for the waiting zone is the assumption that a pedestrian starting from one region will reach the other region. This technique may be challenged duo to the non-compliance behavior of certain road users.

Beyond basic pedestrian behavior characterization, discriminative methods for pedestrian classifications were proposed using movements' characteristics (16) and motion spatial patterns (17). While this is suitable for identifying pedestrians and is found practical for exposure measures like pedestrian counting, it is not clear how it can be used to identify more complex movement patterns like road-crossing. Template motion patterns extracted from video scenes in unsupervised manner have been applied extensively for road-users classification and (18) as well for predicting conflicts between road-users (17). In Ismail *et.al.* (17), as a prerequisite step to analyze pedestrian-vehicle conflicts, the authors combined LCSS based classification and speed threshold in order to discriminate between motorized road users and pedestrians.

Interactions between motorized road-users and pedestrians have been analyzed in (19) and (20). In (20), an analysis was conducted of pedestrian-vehicle conflicts and pedestrian violations occurring at the intersection before and after the introduction of a pedestrian scrambling phase. The introduction of the scramble signal phase resulted in a statistically significant reduction in conflicts between pedestrians and vehicles. The conflicts analysis results were validated using automated computer vision detection system in (19).

3 METHODOLOGY

3.1 Detecting Road-Users Using Computer Vision

An outline of the video analysis procedure is shown in Figure 1. At first, video data is encoded to a pre-defined format. Subsequently, feature tracking is conducted where important points are tracked on moving objects. The subsequent step is to select a point that moves at similar speed and satisfy other motion constraints to the same coherent object. This step is called feature grouping. The subsequent step is to distinguish between read-users types and finally classify pedestrians as violating and non-violating pedestrians.

The road user detection and tracking module relies on a feature-based tracking method described in (21). Feature-based tracking is preferred because it can handle partial occlusion. The tracking of features is done through Kanade-Lucas-Tomasi feature tracker. Stationary features and features with unrealistic motion are filtered out, and new features are generated to track objects entering the field of view. Since a moving object can have multiple features, the next step is to group the features, i.e., decide what set of features belongs to the same object, using cues like spatial proximity and common motion. A graph connecting features is constructed over time. A detailed description of the tracking algorithm is presented in (21).

An important component in the methodology is the camera calibration (22). A Homography matrix is generated to provide a transformation used to convert the image coordinates to physical coordinates on a world map. This step is important because a mandatory perquisite of the analysis is to have speed measured in real world coordinates rather than pixel based coordinate. The main objective of camera calibration is to find a set of parameters that constitute a mapping from world coordinates to image plane coordinates, so that world coordinates can be recovered from video image. The parameters can be categorized as extrinsic or intrinsic. The extrinsic parameters specify the translation and rotation of the camera coordinates relative to the world coordinates. The intrinsic parameters describe the perspective projection of the road scene onto the image plane. Estimation of the parameter values is usually set as a minimization problem of the difference between selected projected geometric features (e.g., points, lines) onto world or image plane spaces and the actual measurements of these entities in projection space. A detailed description of the adopted camera calibration algorithm is described in (22).

3.2 Detecting Violations

Figure 2 illustrates the general procedure for the violation detection methodology. Road users are classified into vehicles and pedestrians. Once an acceptable correct road-users classification level is achieved, only pedestrian tracks are kept for further analysis. Pedestrians are classified as either spatially violating or non-violating. This is done by comparing the pedestrian tracks against a given set of predetermined tracks representing standard pedestrian movements. Simultaneously, pedestrian are classified as either temporally violating or non-violating. This is achieved by automatically capturing the temporal and spatial information of each pedestrian and comparing this information against the provided traffic signal cycles and specified screen lines.

Road Users Classification Based on Prototypes Matching

Classification of road-users based on trajectory prototypes is performed in two consecutive steps. First, a set of trajectories representing a specific reference type of interest is selected. Second, a comparison procedure to classify road-users based on their similarity to those prototypes is then applied. Similarly, violation detection starts with identifying set of movement prototypes that

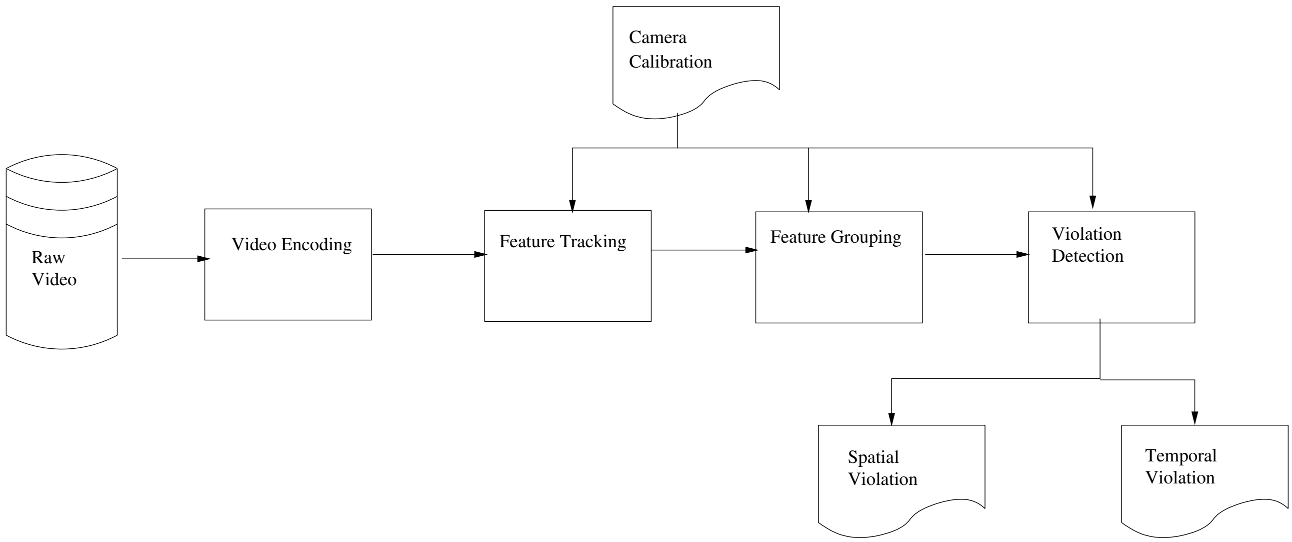


FIGURE 1 Computer Vision System Modules

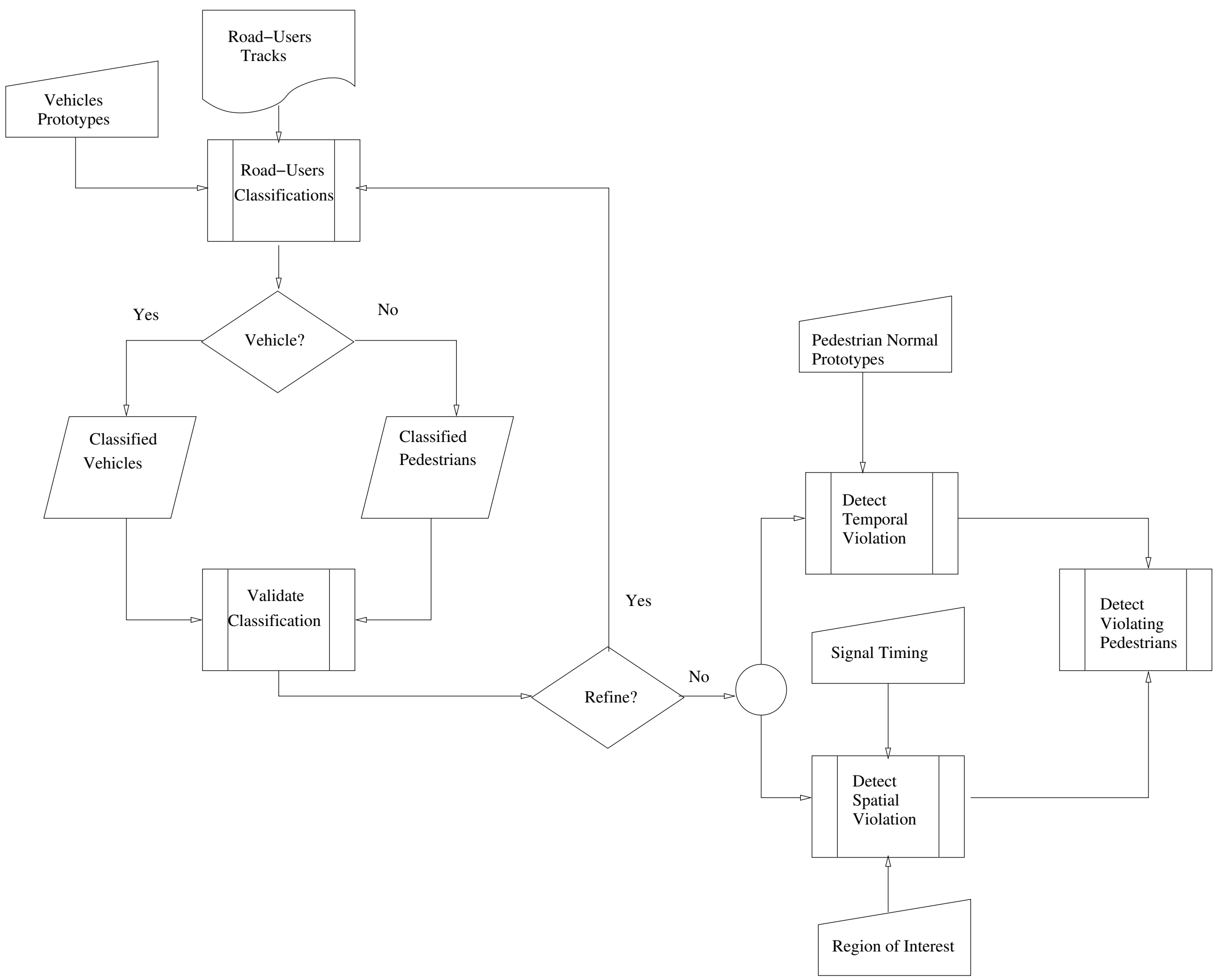


FIGURE 2 Violation Detection Procedure

represent what are considered as normal movement prototypes. Subsequently, a comparison is conducted between a given track and normal movement prototypes. For example, any significant disagreement between both sequences of positions is interpreted as evidence that the given track represents the movement of a road user performing a traffic violation. In this paper, the longest common sub-sequence algorithm (LCSS) is adopted for both road-users classification and violation detection. More specifically, the comparison relies on an LCSS similarity measure between the movement prototypes and the trajectories to make decision about the classification.

LCSS Algorithm

Let τ be a finite set of road user tracks $\{T_i | i \in 1, 2, \ldots, N(\tau)\}$, with $N(.)$ is a measure on a finite set that returns the number of the set elements. Let each road user track T_i be composed of a set of coordinate tuples such that $T_i = \{t_{ik} | k \in 1, 2, \ldots, N(T_i)\}$ and each coordinate tuple t_{ik} be defined as $t_{ik} = (x_{ik}, y_{ik})$. Two points t_{ik} and t_{jl} to be matched if $max\{|x_{ik} - x_{jl}|, |y_{ik} - y_{jl}|\} < \epsilon$, where ϵ is some spatial proximity bound called hereafter matching distance. The LCSS of two road user tracks T_i and T_j, $LCSS_\epsilon(T_i, T_j)$ of respective lengths m and n, is defined recursively as follows:

- 0 if $m = 0$ or $n = 0$,
- $1 + LCSS_\epsilon(Head(T_i), Head(T_j))$, if the points t_{in} and t_{jm} match,
- $max\{LCSS_\epsilon(Head(T_i), T_j), LCSS_\epsilon(T_i, Head(T_j))\}$, otherwise.

where $Head(T_i) = \{t_{ik} | k \in 1, 2, \ldots, N(T_i) - 1\}$ and the definition is identical for all tracks other than i.

In the process of violation detection, the function $LCSS_\epsilon(T_i, T_j)$ defines the LCSS between a road user track T_i and a previously learned movement prototype T_j. Matching decision can be complicated due to non-ideal tracking of road-users. For instance, the case $LCSS_\epsilon(T_i, T_j) < T_j$ likely involves a partial road user track. On the other hand, the case $LCSS_\epsilon(T_i, T_j) < T_i$ could occur if T_j is a partial road user track that was included in the set of prototypes. This case can also occur if T_i is in fact a violation track that contains sub-sequences that are not matched to any prototype. In order to explicate the two cases, a different normalization strategy is used for violation detection. The non-metric LCSS similarity measure DLCSS (more precisely a dissimilarity measure) used in violation detection is defined as follows:

$$DLCSS(T_i, T_j) = 1 - \frac{LCSS_\epsilon(T_i, T_j)}{N(T_i)} \tag{1}$$

Therefore, the LCSS is normalized by the length of the sub-sequence of the tracked object. LCSS-based violation detection is conducted on all road user tracks $T_i \in \tau$ by matching against the set of normal prototypes $T_j \in \tau_{normal}$. The latter set can be created by incrementally learning prototypes for a period of time and then manually removing prototypes that represent road user violations. For a given similarity threshold $\sigma \in [0, 1]$, a road user track T_i is identified as a violation track if the following condition is met:

$$min\{DLCSS(T_i, T_j) | j = 1, 2, \ldots, N(\tau_{normal})\} > \sigma \tag{2}$$

If the condition in Equation 2 is not met, then a road user track T_i is considered to represent a normal road user movement. Furthermore, in order to take into account the similarity in movement directions between two matched prototypes, an additional condition on the directional cosine of road user movements is augmented to Equation 2. A minimum threshold α is imposed on the directional cosine of a pair of positions that belong to the same common sub-sequence.

A key challenge in the adaptation of the LCSS algorithm is the choice of the set of matching parameters track ϵ, σ, α that maximizes the number of correct violation detections and minimizes the number of missed violation detections. Relevant to this challenge is the study of the sensitivity of results to the selection of the matching parameters. In the case studies presented in this paper, sensitivity to matching parameters is investigated by detecting violations using a sample of all feasible selections of the matching parameters.

Prototype Tracks

Compared with vehicle movements, pedestrian movements is more complex. Vehicles usually move in predefined pathways and limited number of turning movements. On the other hand, pedestrians move freely and do not have environment constrains on turn movements, reverse directions and sudden stops. More important, is the difficulty to predict a pedestrian trip as the pedestrian during the trip might combine multiple sub-trips that involve stops of indeterminate length.

The LCSS algorithm compares the tracks against a set of templates (prototypes) of expected road-user behavior at the given intersection. The computer vision system described earlier has a built-in procedure to extract a set of common tracks of road-users. However, more often the set of generated prototypes do not provide adequate representative of the road-user tracks. This is primary depending on the footage length used in the prototype generation as well as the distinct tracks found in the footage. An iterative procedure may be implemented to ensure a certain behavior coverage. An alternative procedure, would be synthesize prototypes to cover certain behavior that deemed hard to extract from the footage. An algorithm is developed to generate prototypes representing pedestrian behavior crossing at the designated crossing area. Currently linear tracks with additive positional noise mimic pedestrian ambulation are generated based on starting and ending world coordinate points. Deflection points can be used to represent pedestrians changing directions or making turns. The speed of the prototype is extracted from the average pedestrian speed at the intersection.

Spatial Violation Procedure

Spatial violation detection based on LCSS matching is summarized as follows. The algorithm requires as inputs the list of road user tracks, minimum possible speed for vehicles as well as set of vehicles movement prototypes. The algorithm returns as output two complimentary sets for tracks associated with violating and non-violating pedestrians. The algorithm consists of three main procedures. The first part of the algorithm classifies the road-users as vehicles and pedestrians and store them into the appropriate list. The classification is based on the movement prototypes and the provided speed threshold. The next stage is to create a list of prototypes for non-violating pedestrians. Those prototypes can be synthetically obtained or automatically generated form sample pedestrian tracks. Those prototypes are subsequently used for pedestrian violation classification.

While it would have been reasonable to have the classification procedure identifies specific movement patterns for particular road-users (pedestrians in this case) in one step, several challenges hindered this process. First, the movement prototype generation necessitates the manual intervention in order to exclude prototypes representing movements not deemed normal in the current study. Pedestrian movement variations are less regular when compared with vehicles which are confined to travels in limited regions defined by the lanes in the road segments. Second, the lack of adequate normal pedestrian prototypes in some locations made it difficult to have a representative set to compare against. To overcome this shortfall, prototypes were synthesized as described earlier. A validation procedure against ground truth (manual) classification was done to provide an insight about the usefulness of the algorithm by analyzing the false positive and false negative rates of the results as demonstrated in the case studies section.

Temporal Violation Algorithm

The basic idea of the algorithm for detecting temporal violation is to detect pedestrian tracks traversing an intersection segment during an improper signal phase. The Algorithm requires primarily as inputs the list of pedestrians tracks, as well as the signal timing information. The output consists of two non-disjoints lists that include the tracks associated with pedestrians violators and non-violators, respectively. The first step of the procedure is to specify the boundaries of the intersection segment. The violation detection is then implemented in two consecutive steps. First, the tracks of the pedestrians crossing the region of interest, at any given time, are identified. This is simply achieved by intersecting the tracks coordinates with those of the intersection segment. The next step is to identify the time period within which the pedestrian tracks existed in this segment. This period is then compared against the corresponding signal timing phase. If the time period intersects with a phase when the pedestrian is prohibited to cross, then the pedestrian is labeled as violator, otherwise it is labeled as non-violator.

4 CASE STUDIES

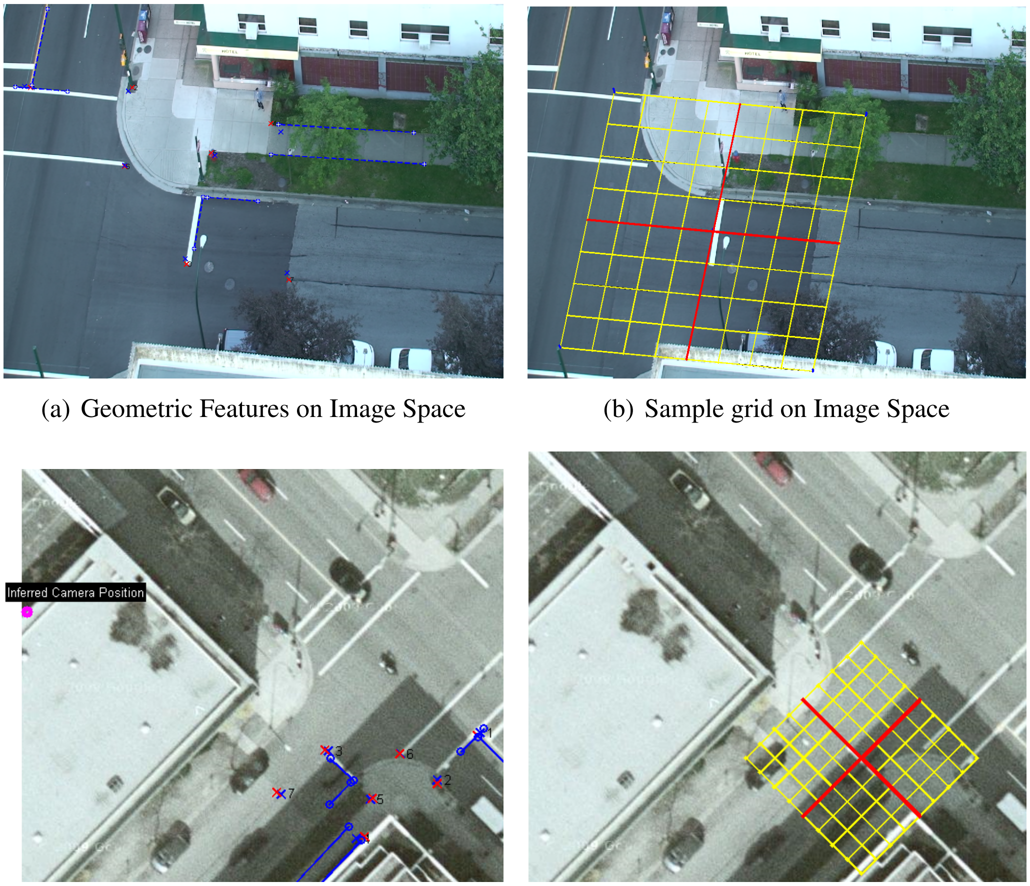
This section describes the analysis of video sequences collected from two distinct open busy intersections with different characteristics and different pedestrian crossing patterns. The first intersection is in Downtown Vancouver and is characterized by a large pedestrian sample size. The second intersection is in the city of Kuwait and is characterized by a sparse pedestrian volume.

4.1 Downtown Vancouver

Site Characteristics

Videos were selected from a library collected for pedestrian movement analysis at a traffic intersection on Robson Street. This intersection is a major commercial and business corridor in Vancouver Downtown area with active walking environment. The intersection is a four-legged signal-controlled intersection. The two-way streets are line separated. Each leg has one traffic lane and one parking/reserved lane. A 2-phase signal control the traffic flow at the intersection. A total of 31 minutes video footage was selected and the timing of the video survey was intended to be concurrent with a nearby major event (fireworks) in order to capture higher pedestrian volumes and to provide walking speed information. This case study is concerned only with spatial violation. Signals cycle timing was unavailable and it was not possible to estimate it from the video footage.

The camera calibration data used in this study was composed of a set of 7 points selected from salient features in the monitored traffic scene that appear in the video image, as well as two parallel lines, one 90 degree angles as shown in Figure 3(a) and 3(c). The world coordinates of the calibration points were collected from an orthographic image of the location obtained from Google Maps. The intrinsic parameter considered in this study is the camera focal length. The accuracy is



(a) Geometric Features on Image Space

(b) Sample grid on Image Space

(c) Projected Geometric Features on World Space

(d) Projected Sample Grid on Orthographic World Space

FIGURE 3 Camera Calibration Illustration

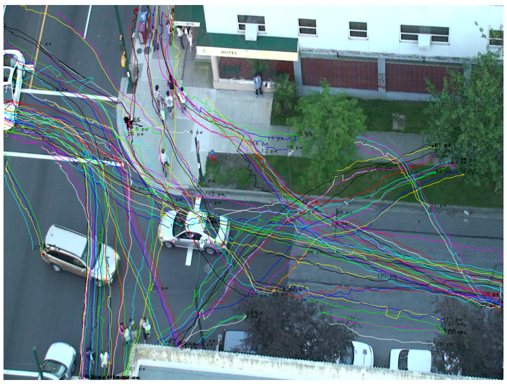
demonstrated by the sample grid and its projection in Figures 3(b) and 3(d) respectively.

Data Analysis

Pedestrians in the scene are tracked and classified according to the violation methodology developed in Section 3. Due to the high definition properties of this video, the majority of the pedestrians in the scene were tracked. Out of 593 total pedestrians, only 4 were missed. Figures 4(a) and 4(b) shows all the normal and spatial violation tracks analyzed in this case study.

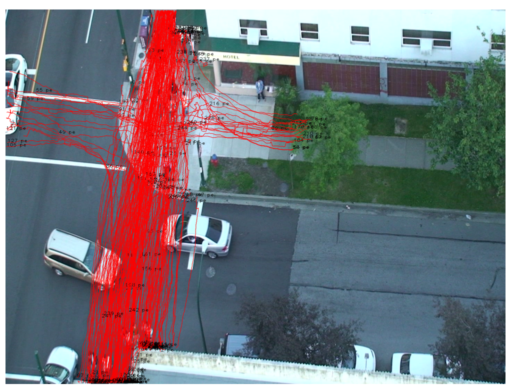
Movement prototypes were learned for a total of 250 prototypes. Those prototypes are used to identify and classify objects as normal pedestrians. All prototypes representing vehicle movements are removed. Figure 4(c) displays a super-imposition of all normal pedestrian prototypes used in LCSS-based classification. The richness of the pedestrian behavior in this scene made the synthesis of prototype an unnecessary step. For validation purposes pedestrians in the scene were manually identified and classified to be used as ground truth. Ground truth data revealed that of the total pedestrians in the scene, 30 were considered violators.

To identify the best parameters values for the violation classification, various combinations of LCSS matching parameters are used. The range for matching distance ϵ is 2-10m with increment 1m. The range for maximum similarity threshold σ is 0.05-0.85 with increment 0.1. The value of



(a) Spatial Violating Pedestrian Track

(b) Normal Pedestrian Track



(c) Pedestrian Prototypes

FIGURE 4 Pedestrian Tracks

the directional cosine threshold α is fixed at 0.95. Figure 5(a) displays the performance LCSS-based violation detection when ϵ and σ varies in the specified intervals while α is kept constant at 0.95. In general, for a given short matching distance ϵ and low α, the incidence of false detection of normal tracks as violation tracks is negatively related to the value of the similarity threshold σ. The same effect on the incidence of false detection, albeit at less sensitivity, is observed for larger values of ϵ. On the other hand, reducing the value of σ under the previous conditions is found to increase missed detection of violation tracks. Similar but more pronounced effect is observed for the selection of ϵ. The performance of the violation detection using the LCSS matching is shown in Figure 5(b) representing the receiver operating characteristics (ROC) curve for the LCSS different parameters choice. At 16% false detection rate (non-violating pedestrian as violating), a 90% of correct detection rate of true violator can be achieved.

The main factor affecting the false detection rate is the pedestrians moving very close to the crosswalk. Those pedestrians were labeled in the ground truth annotation as non-violating pedestrians. The nature of crossing marking in the east-west (up-down in the Figure 4(b)), makes it difficult to have a conclusive ground truth labeling for this kind of crossing scenario. Those "corner cases" were included in the analysis data set in order to have a more thorough performance evaluation of the classification. This reason, combined with a parameter sweeping with larger step size, attributed to the relative degradation of the performance.

4.2 Kuwait City Durwaza Intersection

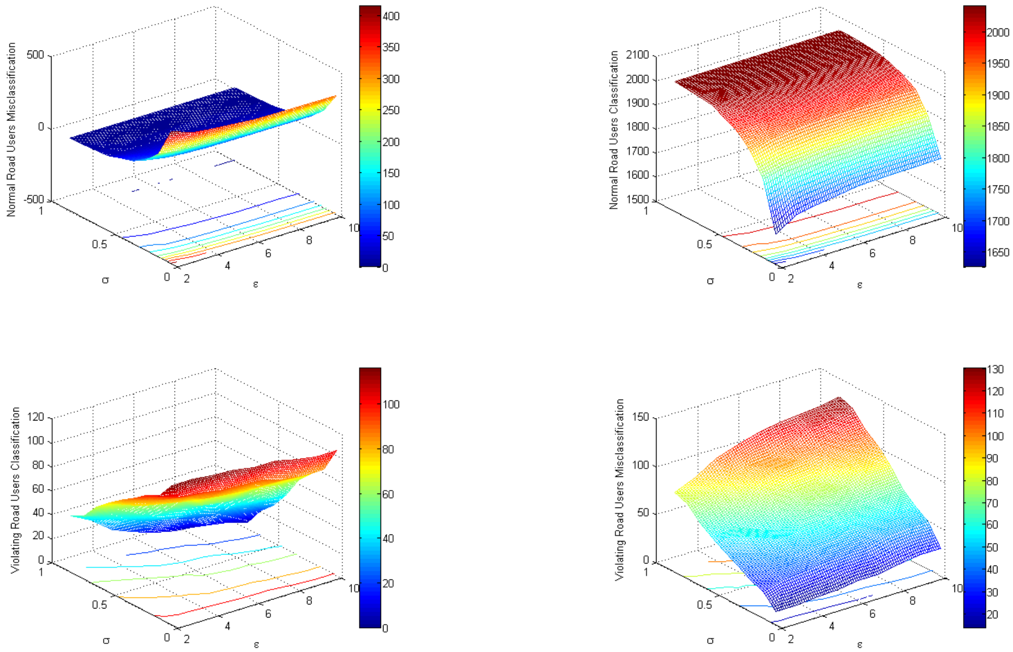
Site Characteristics

The Darwaza intersection is a four-legged signal-controlled intersection in Downtown Kuwait City. The two-way streets are separated by elevated median. Each leg has a three traffic lanes and a reserved median-separated lane for right turn. A 4-phase signal scheme is used for the intersection.

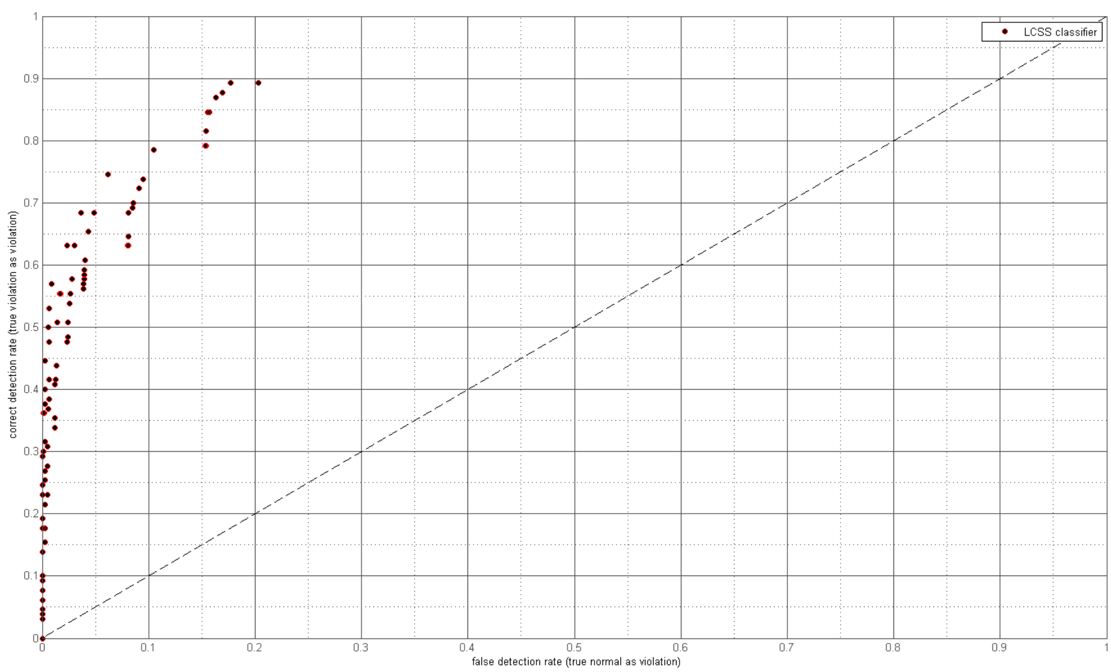
The calibration data used in this study was composed of a set of 8 points selected from salient features in the monitored traffic scene that appear in the video snapshot, as well as one set of parallel lines and five 90 degree angles as shown in Figure 6(a). The world coordinates of the calibration points were collected from an orthographic image of the location obtained from Google Maps. (See Figure 6(c)). The intrinsic parameter considered in this study is the camera focal length. The calibration accuracy using the procedure in (22) was satisfactory. The camera calibration problem faced in this case study was relatively simple due to the abundance of lane marking features that appear in the orthographic image of the traffic scene. The accuracy is demonstrated by the sample grid and its projection in Figures 6(b) and 6(d) respectively.

Data analysis

Pedestrians in the scene are tracked and classified according to the violation methodology developed in Section 3. Despite a low resolution quality, a large percentage (around 80%) of the pedestrians in the scene were detected and tracked during their trip in the region of interest (shaded region in Figure 7). Of the 251 total pedestrians in the scene, 79 pedestrians passed through this region. Out of 79 pedestrians , 16 were not detected. Proper tuning for feature grouping ensured that poor isolated features were single out and each pedestrian is attributed at least one object. On the other hand, sparsity and scattering of pedestrians in the scene as well as fine tuning narrowed the effect of over-grouping. Over segmentation was not an issue in the scene. Yet, multiple objects were associated with each pedestrian track. A total of 108 tracks were associated with the 63 pedestrians. This large number is mainly due to the occlusions by the traffic light as well as light-



(a) LCSS Parameters Sweeping using a range of values for matching distance ϵ in meters and similarity threshold σ

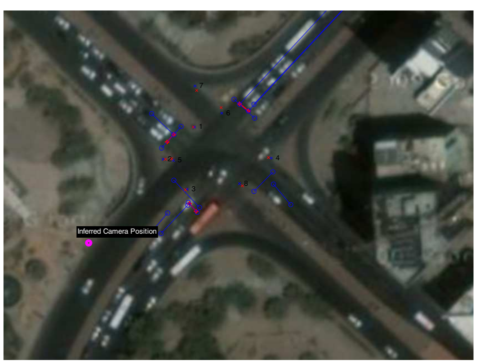


(b) Receiver Operating Characteristics Curve

FIGURE 5 Classification Performance Analysis

(a) Geometric Features on Image Space

(b) Sample grid on Image Space



(c) Projected Geometric Features on World Space

(d) Projected Sample Grid on Orthographic World Space

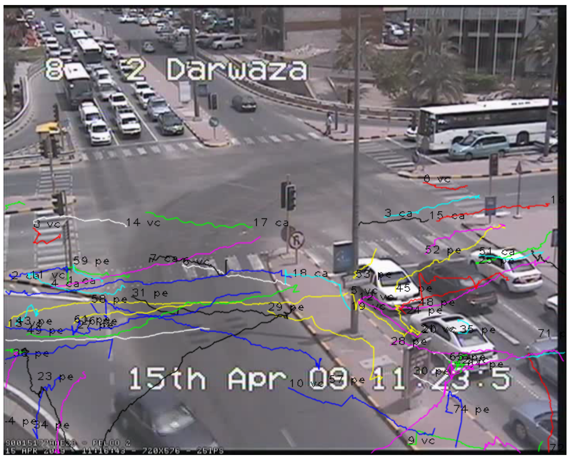
FIGURE 6 Camera Calibration Illustration

FIGURE 7 Region of Interest

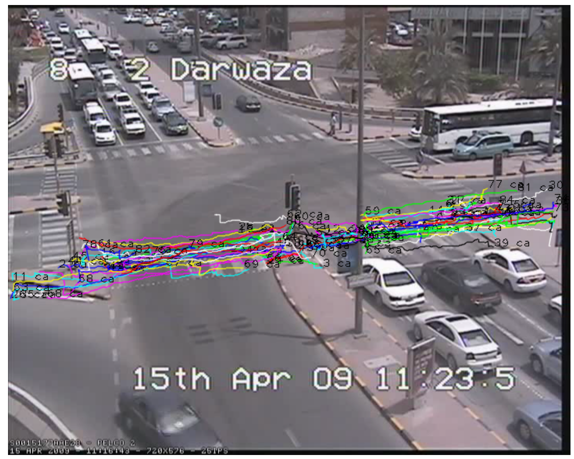
ing pole installed in the elevated median. Overcoming the occlusion was with limited success and introduced over-grouping elsewhere in the scene, which was not desirable for the current analysis.

Figures 8(a) and 8(b) show all the pedestrian tracks (normal and spatial violation tracks, respectively) analyzed in this case study. Unlike spatial violations, it is not informative to display all temporal violating tracks. Some of the pedestrians in both Figures are considered temporally violating. An illustrative pedestrian which is both spatially and temporally violating is illustrated in Figure 9(a). The pedestrian in this case started the intersection crossing journey outside the designated cross-walk area and as it shows from the background vehicles are moving towards this pedestrian (Traffic Signal was green for those vehicles). Figure 9(b) shows the interaction of the pedestrian track with the road-segment boundary.

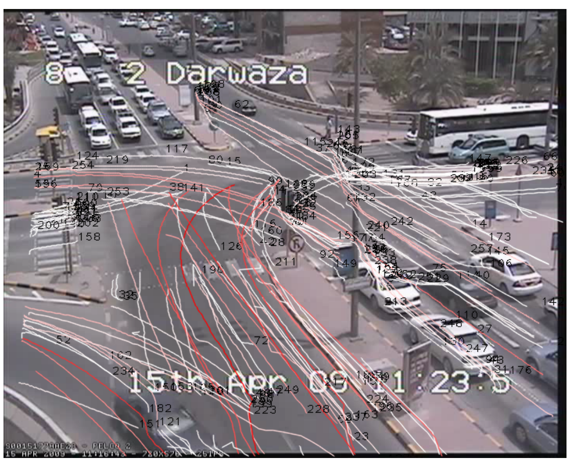
In the 4-hours components a total of 13953 objects were tracked, including over-segmentation and multiple tracks per objects. Movement prototypes for road-users are learned for a period of 5000 frames selected at random from the video sequence. A total of 189 prototypes are recorded. Those prototypes are used to identify and classify objects as vehicles. No trajectory prototypes were generated for pedestrians. This is due to the sparsity of the pedestrians present in the scene. Figure 8(c) displays a super-imposition of all vehicle prototypes. Figure 8(d) shows the pedestrian synthetic prototypes used in LCSS-based classification. For validation purposes pedestrians in the scene were manually identified and classified to be used as ground truth. The 108 tracks associated with the pedestrians included false negative results (16 pedestrian tracks identified as vehicles) as well as multiple tracks per pedestrians as noted earlier in this section. Vehicles labeled (False positives) as Pedestrians were 478 and those were discarded from the analysis. The vast majority of the false positives were due to vehicles entering the scene with speed relatively low and preparing to stop. Ground truth data revealed that the spatially Violating pedestrians were 21, while the temporally violating pedestrians were 24. Out of those temporally violating, 9 where also spatially violating which shows that a large portion of those temporally violating has a tendency to cross in non-designated area. This is likely due to the tendency of the pedestrian to minimize the



(a) Spatial Violating Pedestrian Track



(b) Normal Pedestrian Track



(c) Vehicle Movements Prototypes

(d) Pedestrian Movements Prototype

FIGURE 8 Road-Users Trajectories

(a) Pedestrian Track

(b) Track inside the Region of Interest

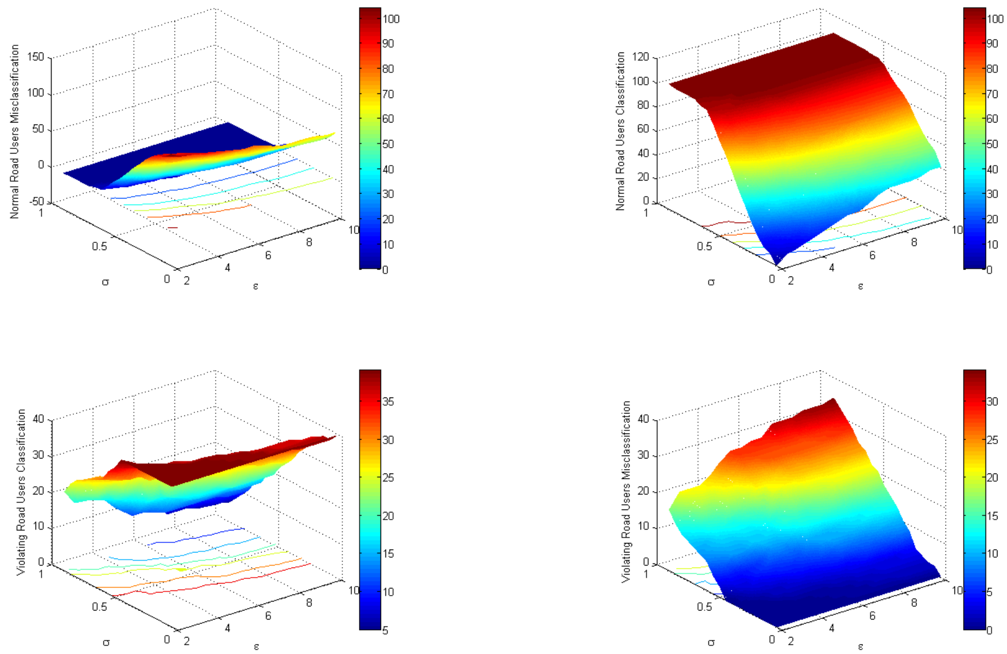
FIGURE 9 A Pedestrian in Spatial and Temporal Violation travel distance. The automated temporal violation methodology detected all the violation correctly with no false detection of non-violator. It is plausible to note that the temporal violation accuracy depends on the precision of the camera calibration as well as the provided signal timing.

To identify the best parameters values for the violation classification, various combinations of LCSS matching parameters are used. The range for matching distance ϵ is 2-10m with increment 0.5m. The range for maximum similarity threshold σ is 0.1-0.9 with increment 0.05. The range for the directional cosine threshold α is 0.7-0.95 with increment 0.05. Figure 10(a) displays the performance LCSS-based violation detection when ϵ and σ varies in the specified intervals while α is kept constant at 0.9. There is little sensitivity of detection performance to α. Similar to the sensitivity analysis for the previous case study, the false detection of normal tracks as violations is negatively related to the value of the similarity threshold σ. On the other hand, reducing the value of σ is found to increase missed detection of violation tracks. The performance of the violation detection using the LCSS matching is shown in Figure 10(b) representing the receiver operating characteristics (ROC) curve for the LCSS different parameters choice. At 14% false detection rate (non-violating pedestrian as violating), a 90% of correct detection rate of true violator can be achieved. It is worth noting that the matching algorithm performance relies, in addition to the LCSS parameters, on the quality of the prototypes.

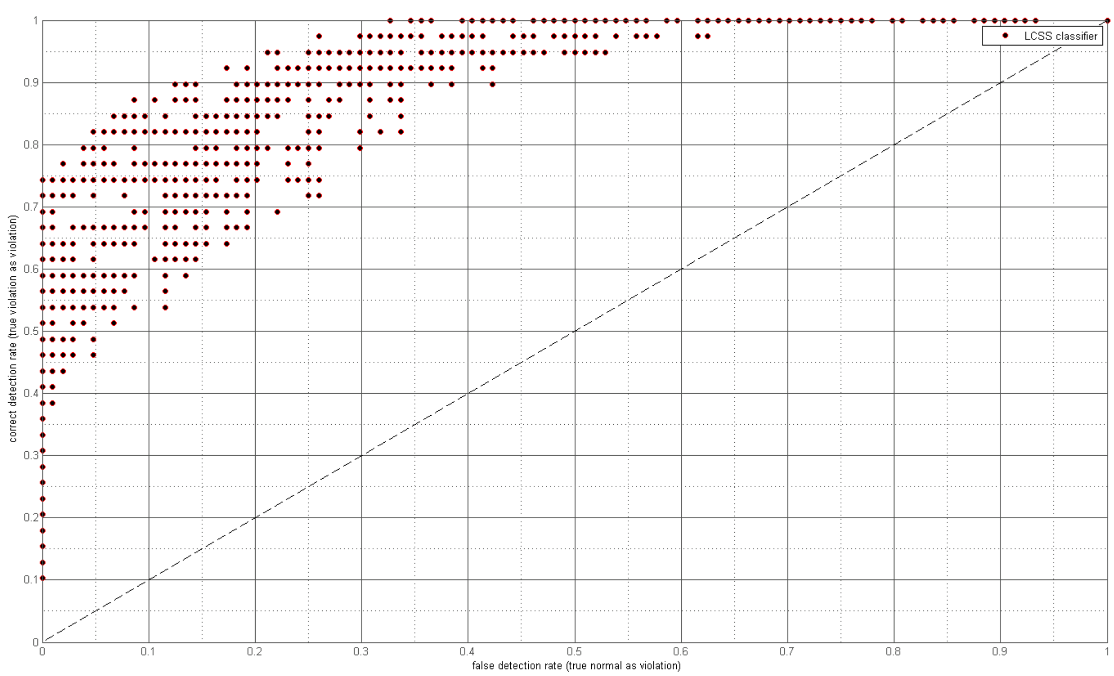
It is worth noting that the accuracy of the analysis is dependent on the quality of the prototypes rather than the number of prototypes. In general, the quality of prototypes covering the normal behavior is subject to the camera angle, the nature of the intersection, and the geometric properties. While, it seems reasonable to assume that the quality increases with the chosen number of prototypes, unfortunately, there is no available mechanism to find the optimum number of prototypes. Any increase above the optimum number will only add to the computation time. In the current case studies, the running time of the algorithm was not considered relatively high to affect its practicality. Due to the over-segmentation issue, the number of pedestrian objects is 143. Classification was performed with 76 synthetic prototypes. The over-segmentation problem, while an important issue in pedestrian analysis, has no impact on the quality of analysis, as the purpose is to identify whether part of a pedestrian trip involved some sort of violations or not.

5 CONCLUSION AND FUTURE DIRECTIONS

The identification of traffic violations as a surrogate safety measure can be an indispensable for a sound safety diagnosis and the initiation of countermeasures solutions. Pedestrians are more vulnerable than other classes of road users and pedestrian violations were shown to have the most significant contributor to pedestrian related crashes (3). While the majority of techniques developed for automatically collecting traffic data focus on vehicular traffic, recent advances in the automated detection of pedestrians expanded the range applications in traffic safety. In this study, an automated system for identifying pedestrian violations using video analysis was developed and tested. A system previously developed for vehicle detection and tracking was significantly modified to adapt for particularities of pedestrian movement and to discriminate pedestrian and motorized traffic as well as different pedestrian behaviors. The reliance on the LCSS matching provides a solid foundation for automated violation detection. Moreover, the practical appeal of LCSS based automated violation detection can be improved if normal prototypes are synthesized from prior knowledge of normal traffic movement. The system was tested on real video data collected at Downtown area of Vancouver, British Columbia, as well as an intersection Kuwait City. The results show satisfactory accuracy of detecting both spatial and temporal violations with about 90%



(a) LCSS Parameters Sweeping using a range of values for matching distance ϵ in meters and similarity threshold σ



(b) Receiver Operating Characteristics Curve

FIGURE 10 Classification Performance Analysis correct violation detection rate in both case studies

In the computer vision research, detecting moving pedestrians is usually based on matching the pedestrian against some predefined shapes or patterns of movements. The common applications of these methods are to differentiate between pedestrians and other road-users like vehicles. Applications like abnormal behaviors detection (e.g., violations) are beyond the capabilities of these methods. The classification presented in this paper is considered a complimentary method that addresses the shortcomings in identifying the conformance of the moving pedestrians. The advantage of the method lies in its generality for deployment at different intersection settings; i.e., signalized 4-legged, roundabout, scrambling settings.

Extending on this work would involve investigating the relation between violations and other traffic factors like wait-time and design characteristics of the intersection. Other directions would involve studying the effect of violations on safety. This can be possible by defining severity profiles as safety measure and by developing relationships between violations and other safety conflict indicators. Finally, more experimental results at different intersections are desirable to have a robust estimation of the practicality of the approach. This includes cyclists' violations detection.

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