AUTOMATED ANALYSIS OF PEDESTRIAN-VEHICLE CONFLICTS: A CONTEXT FOR BEFORE-AND-AFTER STUDIES

By

Karim Ismail *, M.A.Sc.
Research Assistant
Department of Civil Engineering
University of British Columbia
Vancouver, BC, Canada V6T 1Z4
karim@civil.ubc.ca

Tarek Sayed, PhD. P.Eng.
Professor, Dept of Civil Engineering
University of British Columbia
Vancouver, BC, Canada V6T 1Z4
604-822-4379
tsayed@civil.ubc.ca

Nicolas Saunier, PhD.
Assistant Professor, Department of Civil, Geological and Mining Engineering
École Polytechnique de Montréal
Montréal, Québec
(514) 340-4711 (#4962)
nicolas.saunier@polymtl.ca

*** Corresponding Author**

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ABSTRACT

This paper presents novel application of automated video analysis for the Before/After safety evaluation of a scramble phase treatment. Data availability has been a common challenge to pedestrian studies, especially for proactive safety analysis. The traditional reliance on collision data has many shortcomings in terms of the quality and quantity of collision record. Qualitative and quantitative issues with road collision data are more pronounced in pedestrian safety studies. In addition, little information could be drawn from collision reports regarding the implicated mechanism of action. Traffic conflict techniques have been advocated as a supplement to or an alternative to collision-based safety analysis. Automated conflict analysis has been advocated as a new safety analysis paradigm that empowers the drawbacks of survey-based and observer-based traffic conflict analysis. One of the focus areas of pedestrian safety that could greatly benefit from vision-based road user tracking is before-and-after (BA) evaluation of safety treatments. This paper demonstrates the feasibility of conducting BA analysis using video data collected from a commercial-grade camera in Chinatown, Oakland, California. Video sequences for a period of two hours before and two hours after scramble were automatically analyzed. The before-and-after results of the automated analysis exhibit a declining pattern of conflict frequency, a reduction in the spatial density of conflicts, and a shift in spatial distribution of conflicts further from crosswalks.

INTRODUCTION

> *"[Pedestrian exposure to the risk of collision is] very difficult to measure directly, since this would involve tracking the movements of all people at all times"* (1).

The challenge of gaining insight into the mechanism of action that endangers road users transcends the focus on pedestrian exposure to the entire realm of road safety. The accurate estimation of exposure as well as other quantities fundamental to road safety analysis, e.g. severity of a traffic interaction, can greatly benefit by analyzing road users' positions in space and time, i.e. road user tracks (2). Manual annotation of road user positions is time- and resource-expensive, especially when pedestrians are studied, e.g. (3)(4). Therefore, the automated extraction of road users' positions from video observations has been advocated as a resource-efficient and potentially more accurate alternative (5).

Video sensors are selected as the primary source of data in this research. Video data is rich in details, recording devices are becoming less expensive, and video cameras are often already installed for monitoring purpose. Pedestrian tracking in video sequences is traditionally more challenging than other road users (6). Pedestrians are locally non-rigid, are prone to visual occlusion due to crowdedness, and are more variable in shape and appearance. Despite these challenges, vision-based applications in the field of pedestrian studies have been demonstrated with an increasing level of practical feasibility, e.g. (5)(7)(8)(9)(10). One of the focus areas of pedestrian safety that could greatly benefit from vision-based road user tracking is before-and-after (BA) evaluation of safety treatments. BA studies are a key component of road safety programs that aim at measuring the safety benefits (or absence thereof) derived from a specific engineering treatment.

Catering for the safety of non-motorized modes of travel, in particular for walking, is essential to meet the ever-growing demand for building a sustainable transportation system. The prevalent collision-based paradigm of BA studies is based on estimating the reduction in collisions, in terms of frequency and consequence, which can be attributed to the evaluated treatment. In order to draw statistically stable conclusions, e.g. explicating the effect of the treatment away from all other confounding factors, collisions are typically observed for relatively long period (1-3 years) before as well as after the introduction of the treatment. However, the reliance on collision data for BA analysis has the following shortcomings (11):

1. **Attribution**. The information obtained by police reports and interviews often does not allow the attribution of road collisions to a single cause. It is sometimes difficult to pinpoint the failure mechanism that lead to a road collision. In that, it is often required to remedy or prevent events of which causes are not precisely known.

2. **Data Quantity**. Road collisions are rare events and are therefore subject to randomness inherent to small numbers(12). Drawing statistically stable inferences from such data is typically challenging and costly in its own right. While the object of road safety analysis is the reduction of the risk of road collisions, it is typically based on the road collision as the main data unit. That is, collisions have to occur and be recorded over an adequately long period in order to conduct safety diagnosis. This gives rise to a paradoxical situation in which the safety analyst, for the sake of methodological correctness, strives to observe events that ought to be prevented.

3. **Data Quality**. Road collision reporting is based on post-hoc descriptions, witness accounts, and site observations. The process is fundamentally deductive and subjective. Collision records are often incomplete and lack details. The quality of road collision

reporting has been deteriorating in many jurisdictions. Reporting is also biased toward highly damaging collisions, while non-injurious collisions may go unreported.

Shortcomings in collision-based BA studies are even more pronounced in the study of pedestrian safety. Pedestrian-involved collisions are more injurious and less frequent than vehicle collisions (13). Exposure measures, such as pedestrian volume, are often difficult to obtain and expensive to collect through in-field surveys (14). Surrogates and/or statistical predictors of these types of data are often used in practice, e.g.(1). It is often the case that the safety analysis may not afford long-term collision observation after the introduction of a measure (15).

Arguments that support the adoption of traffic conflict techniques find more ground in BA studies that concern pedestrian safety. Traffic Conflict Techniques (TCTs) are based on analyzing the frequency and severity of traffic conflicts at an intersection, typically by a team of trained observers. Traffic conflict is defined as “an observable situation in which two or more road users *approach* each other in space and time to such an extent that there is a *risk of collision* if their movements remained *unchanged*” (16). Traffic conflicts are more frequent than road collisions and are of marginal social cost. Traffic conflicts provide insight into the failure mechanism that leads to road collisions. BA studies based on traffic conflicts can be conducted over shorter periods. A theoretical framework, advocated in this study, ranks all traffic interactions by their severity in a hierarchy, with collisions at the top, undisturbed passages at the bottom, and traffic conflicts in between (12).

The traditional way of collecting traffic conflict data is challenged on several accounts. Inter- and intra-observer variability is a common challenge for the repeatability and consistency of results from traffic conflict surveys (17). Field observations are costly to conduct and demand staff training. Despite decades of conceptual developments, there is no universal *operational* definition of a traffic conflict, e.g. objectively measurable interpretation of words “approach”, “risk of” and “unchanged” in the previous conceptual definition, (11). Finally, the estimation of objective conflict indicators, such as Time to Collision (18) using field observations can be difficult.

Automating the process of traffic conflict analysis is greatly appealing in the context of BA studies of treatments intended to enhance pedestrian safety. Process automation can enable the objective analysis of pedestrian-vehicle conflicts in an accurate, objective, and cost-efficient way. The goal of this study is to demonstrate a novel application of automated video analysis for the BA analysis of a scramble phase treatment analyzed manually in previous work (19). In later stage, the practical use of the developed system as an assisting tool is demonstrated. The length of the video sequence to be reviewed by an observer could be greatly reduced. This study is another step in a research direction that is, to the best of the authors’ knowledge, unique in the field of road safety and pedestrian studies.

The objectives of this study are to: 1) Report several technical improvements to the video analysis system. 2) Demonstrate the feasibility of conducting BA analysis using video data collected from a commercial-grade camera, from a relatively low altitude, and using a video not collected initially for the purpose of automated video analysis.

PREVIOUS WORK

Conflict-based Before-and-After Studies

There is a significant body of work on the evaluation of pedestrian safety treatments using non-collision data. The literature contain studies that rely on traffic conflicts (15)(19-27) and behavioral surrogates such as motorist yielding rate (28). The difficulties in relying on collision data in conducing BA studies is acknowledged in the literature, e.g. (28) (15), in which surrogates safety measures were used. The studies that concerned the evaluation of pedestrian scramble were predominantly conducted using traffic conflicts (25) (26) (19) (27) (except for (29)). There is some agreement that scramble phase treatment reduces pedestrian-vehicle conflicts except when pedestrian compliance rate is low (30) (25). Among the reviewed studies, the study by Malkhama et al. (23) was the only one in which data required for evaluation, motorist deceleration, was automatically collected.

The previously identified issues with the observer-based traffic conflict analysis were echoed by a recent evaluation study of pedestrian treatments in San Francisco (15). The authors noted issues with the subjectivity of the definition of traffic conflict, inter-observer agreement, and the labor cost of extracting observations from video data were highlighted. The use of automated video analysis tools is being increasingly advocated to overcome these shortcomings.

Video-based Road User Detection and Tracking

The previous work reported in (5) is updated in this paper. To study pedestrian-vehicle conflicts, all road users must be detected, tracked from one video frame to the next, and classified by type, at least as pedestrians and motorized road users. This is a challenging task in busy outdoor urban environments. In addition to specific problems when tracking pedestrians, common problems are global illumination variations, multiple object tracking, and shadow handling (6). The different approaches are classified into (6):

- Tracking by detection: detection of objects is done using background modeling and subtraction with the current image (7)(31), or deformable templates, i.e. an appearance model using color distribution, edge characteristics, and texture.
- Tracking by flow: selecting features on moving objects, and matching them between successive images provide feature tracks that can be clustered into object trajectories. This approach is also called feature-based tracking and has been applied to traffic monitoring in (32), and pedestrian safety analysis (5).
- Tracking with probability: tracking is represented as a probabilistic inference problem in a Bayesian tracking framework, e.g. (33). This approach may fail in scenes where the objects interact and occlude each other. This is problem can be addressed using particle filters and Markov chain Monte Carlo methods for sampling.

Despite recent progress, tracking performance of the various systems is difficult to report and compare. This is likely because many of these systems are not publicly available or their details disclosed, and benchmarks of comparison are rare and not systematically used. Tracking pedestrians and mixed traffic in crowded scenes is still an open problem. To the authors' knowledge, (5) was the first attempt to develop a fully functional video-based pedestrian conflict analysis system.

METHODOLOGY

Previous work has been performed to develop a video analysis system that can automatically detect, classify, and track road users and interpret their movement (5). The core of the system for the detection and tracking of road users relies on feature-based tracking (32) and a system developed at the University of British Columbia. Following is a brief description of improvements in the system, mainly to meet video analysis challenges faced in this study.

Road User Classification

To analyze pedestrian-vehicle conflicts, it is necessary to identify pedestrians and motorized vehicles. The system described in (5) (34) used a speed classifier, a threshold on the maximum speed reached by road users during their existence for classification. This "speed classifier" however proved inadequate for the BA dataset available for this study.

A new method was developed for that purpose, inspired by previous work done by the authors. In (35), the distribution of road users' trajectories is learnt to allow the prediction of road users' future positions to estimate the probability of collision and analyze road users' interactions. A small subset of actual road users' trajectories, called *prototype* trajectories, is identified using an incremental unsupervised algorithm described in (35), relying on the Longest Common Subsequence (LCSS) similarity (36). The LCSS is a variation of the edit distance. The intuitive idea is to match two sequences by allowing them to stretch, without rearranging the sequence of the elements, but allowing some elements to be unmatched. Let *A* and *B* be two trajectories of moving objects with size *n* and *m* respectively, $A = [(a_{x,1}, a_{y,1}), \dots, (a_{x,n}, a_{y,n})]$ and $B = [(b_{x,1}, b_{y,1}), \dots, (b_{x,n}, b_{y,n})]$. For a trajectory *A*, let $Head(A)$ be the sequence $Head(A) = [(a_{x,1}, a_{y,1}), \dots, (a_{x,n-1}, a_{y,n-1})]$. Given a real number $\varepsilon \geq 0$, the basic similarity measure $LCSS_\varepsilon(A, B)$ is defined as follows (36):

- *0* if *A* or *B* is empty,
- $1 - LCSS_\varepsilon(Head(A), Head(B))$ if $|a_{x,n} - b_{x,n}| < \varepsilon$ and $|a_{y,n} - b_{y,n}| < \varepsilon$,
- $\max\ (LCSS_\varepsilon(Head(A), B), LCSS_\varepsilon(A, Head(B)))$ otherwise.

The constant ε controls the matching threshold for the Chebyshev distance used by default (it is chosen over the Euclidean distance because it is less expensive to compute while yielding good results), but can be replaced by any distance, and more conditions can be added. In this work, a second similarity measure $LCSS_{\varepsilon,\theta}(A, B)$, with $0 \leq \theta \leq 1$, is used by supplementing the trajectories with the velocity at each instant and adding the condition that the cosine of the velocities be below θ. The associated distances are obtained by scaling the similarities to [0,1]

$$D_\varepsilon(A, B) = 1 - \frac{LCSS_\varepsilon(A,B)}{\min\ (n,m)} \quad \dots (1)$$

$$D_{\varepsilon,\theta}(A, B) = 1 - \frac{LCSS_{\varepsilon,\theta}(A,B)}{\min\ (n,m)} \quad \dots (2)$$

The prototypes are learnt using $D_\varepsilon(A, B)$ to yield a smaller set. The "prototype classifier" uses the 1 nearest-neighbor method with the distance $D_{\varepsilon,\theta}(A, B)$ and a threshold δ $(0 \leq \delta \leq 1)$ on the distance to limit the matches to the closest prototypes. The object is assigned the type of the closest prototype. Given that a threshold is used, an object trajectory may have no prototypes with a distance of δ, in which case it is classifier using the default speed classifier.

The prototypes need therefore to be labeled. This labeling is a one-time semi-automated operation, where the prototype trajectories are first classified using the speed classifier, then reviewed and corrected if needed by a human annotator. An example of labeled prototypes is given in Figure 1. A comprehensive comparison of the classifier on a subset of 1063 manually annotated trajectories was done and the results are presented in Table 1 and Figure 2. It shows the clear superiority of the prototype classifier over the speed classifier.

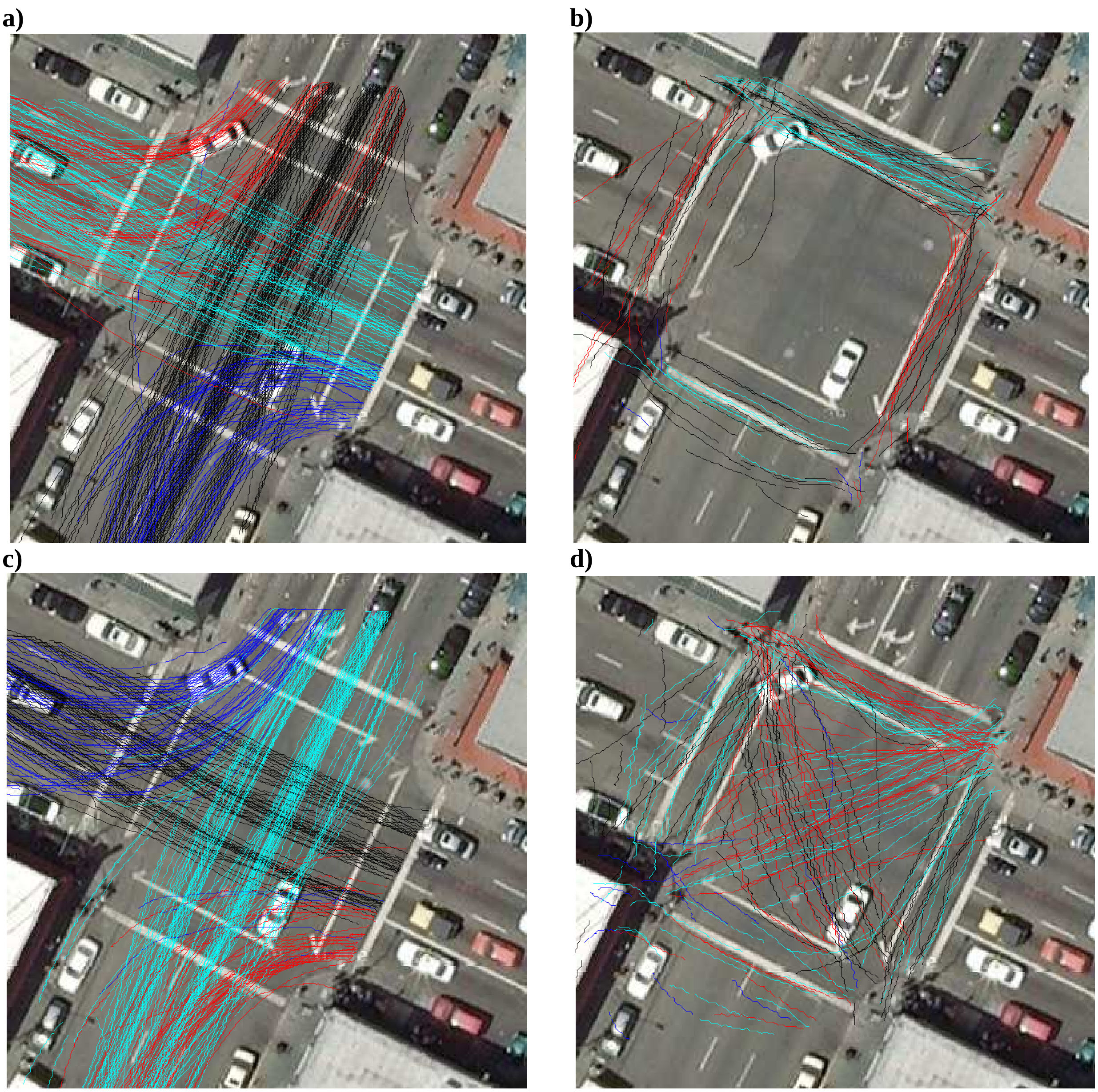


FIGURE 1 Road user prototypes for the before-and-after scramble phase. Figure a) shows the pre-scramble vehicle prototypes (pre-scramble/veh). Figures b, c, and d show pre-scramble/ped, post-scramble/veh, and post-scramble/ped, respectively. The color coding is the result of a k-means clustering in 4 classes based on the prevalent prototype direction.

TABLE 1 Results of the comparison of the speed and prototype classifiers

Classifier	Speed Threshold	Max *PCC*[1]	Max K-statistic	True positive rate[2]	False positive rate
Speed classifier	2.90 m/s	0.85	0.70	0.96	0.26
Speed classifier with a moving average filter	2.30 m/s	0.87	0.73	0.93	0.21
Prototype classifier	-	0.97	0.95	0.98	0.04

1 Percentage correct classification (PCC) represents the number of road user trajectories correctly classified (vehicle into vehicle and pedestrian into pedestrian) over the total number of trajectories.

2 A positive is the classification of a road user into a pedestrian and a negative is the classification of a road user into a vehicle. A true positive is a pedestrian classified into a pedestrian (ped-ped). A false positive is vehicle into pedestrian (veh-ped). A true negative is veh-veh and a false negative is ped-veh. The rates are computed by dividing over the number of trajectories in the respective classes.

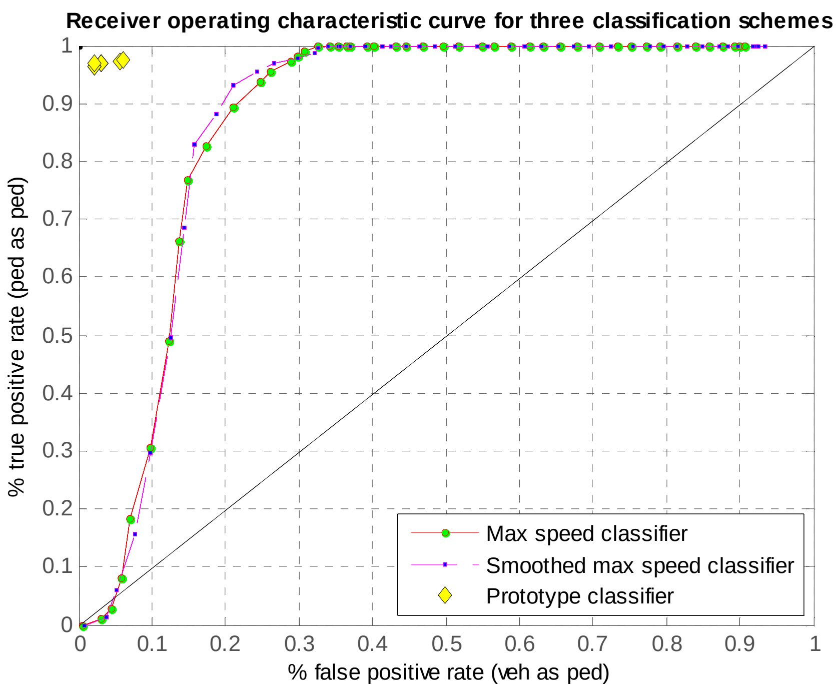


FIGURE 2 Receiver Operating Characteristic (ROC) Curve for the speed and prototype classifier (for the smoothed max speed classifier, the road user speed is smoothed with a moving average filter). The threshold for the speed classifiers is 3m/s. The ROC curve is the plot of the true positive rate versus the false positive rate (the ratio of the number of false positives over the total number of vehicles), for various settings of the classifiers' parameters. A perfect classifier would yield a point in the upper left corner of the ROC space, at coordinate (0,1) meaning no missed pedestrian and no false positives. A completely random guess, would give a point along the diagonal line from the left bottom to the top right corners, also called line of no-discrimination (represented in the graph).

Validation of Tracking Performance

The tracking results of the system need to be evaluated. The safety analysis presented in this paper relies on road users' tracks. Since most existing research has embraced instantaneous per-frame performance measures, a new algorithm was developed to automatically assign detected objects (the output of the system) to ground truth objects (manually annotated tracks) (37). The results are the unique assignment of these objects: correct assignments (one detected object-to-one labelled object), over-segmentations and over-groupings (one-to-many and many-to-one), missed and false detections (one-to-zero and zero-to-one). For this work, the results were condensed into correct assignments, missed and false detections, and the performance measure is the following cost function that measures the overall tracking error:

$$Cost = \frac{\alpha_{fd} * N_{fd} + \alpha_{md} * N_{md}}{N} \qquad \ldots(3)$$

where N is the number of annotated objects, N_{fd} and N_{md} are respectively the number of false and missed detections, α_{fd} and α_{md} are respectively the weights for false and missed detections, set respectively to 0.25 and 0.75 in this study.

The choice of weights is prompted by a target of minimizing missed detections, which might translate into missed pedestrian-vehicle interactions, while still trying to minimize, to a lesser extent, the number of false detections, to reduce the number of falsely detected interactions, called false alarms. This framework was used to optimize the cost function over the space of a few key tracking parameters, namely the connection distance $D_{connection}$, the maximum distance between two features for their connection, and the segmentation distance $D_{segmentation}$, the maximum difference between the minimum and maximum distance between two features. Data was annotated for 1495 frames, resulting in 41 tracked objects. The space of ($D_{connection}$, $D_{segmentation}$) was search systematically (See Figure 3) and yielded the selection of (0.45, 0.12). Figure 4 presents sample frames with manually annotated data and the result using the automatically tuned parameters.

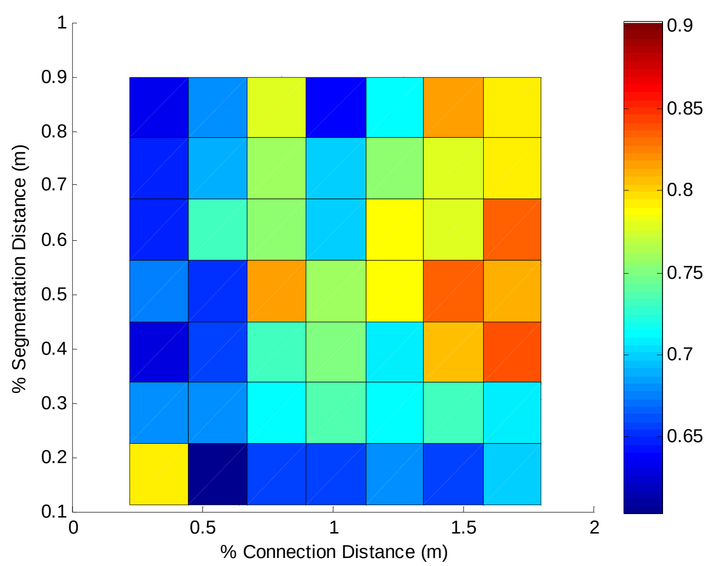


FIGURE 3 Plot of the cost function with respect to ($D_{connection}$, $D_{segmentation}$).

a)

b)

FIGURE 4 Sample frames from validation results. The number of missed detections is 3/32 with 29 false detections mainly due to over-segmentation. Figure a) shows a sample frame from a post-scramble sequence with labeled pedestrians. Figure b) shows the pedestrians tracked in the same frame using the optimized tracking parameters. The bicyclist annotated with a box in Figure b) is correctly identified as a non-pedestrian (given a screen label '`ca`').

Camera Calibration

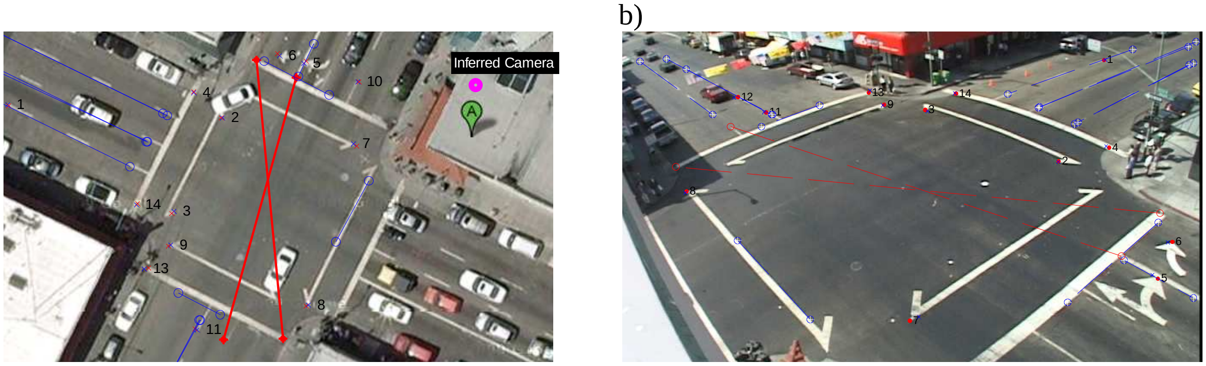
The positional analysis of road users requires accurate estimation of the camera parameters. The camera parameters calibrated in this study are six extrinsic parameters (that describe the location and orientation of the camera) and two intrinsic (that represent the projection on the image space). Once calibrated, it is possible to recover real-world coordinates of points in the video sequence that lie on a reference surface with known model (pavement surface).

Since videos were collected by a third party, access to the camera was not possible and therefore all camera parameters must to be inferred from video observations and an orthographic image of the intersection. A mixed-feature camera calibration approach was introduced in previous work (5). Each calibration feature imposes a condition based on its shape, position, and length in both image and world spaces. An additional calibration feature was necessary to enhance the accuracy of the camera calibration based on the parallelism of calculated vertical line (depicted in blue in Figure 5d) to a manually annotated vertical direction (observed from light poles).

The accuracy of the estimated parameters was tested using a set of 12 lines segments of true length estimated from the orthographic image. This set of observations was not used in calibration. The calibration error is represented by the discrepancy between calculated and annotated segment lengths normalized by the length of each segment. The accuracy of the final estimates was satisfactory (0.096 m/m) and no further error in conflict analysis was attributed to inaccurate estimated camera parameters.

Calibration Features (points, distances, and angular constraints) in world space (left) and image space(right).

a) b)



Reference grid (2.0m spacing – 4.0m vertical line) in world space (left) and image space (right)

c) d)

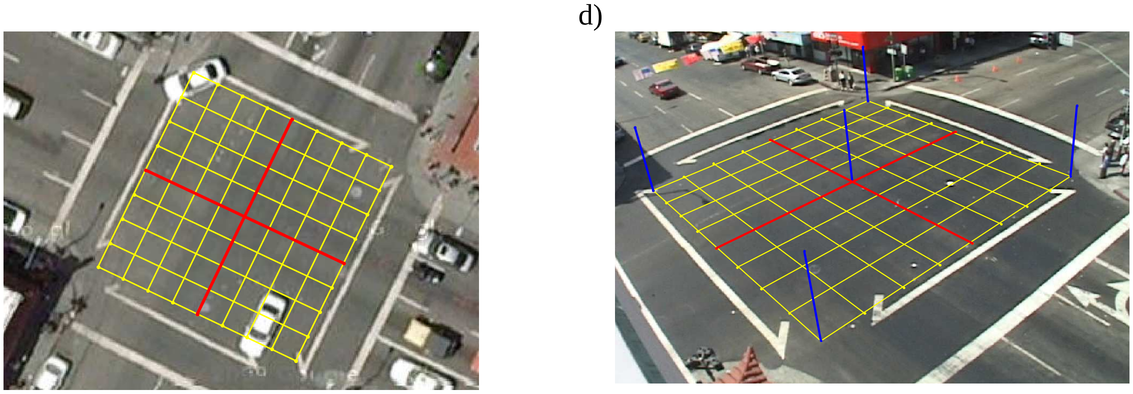


FIGURE 5 Calibration of the video camera. Figure a) and b) shows the calibration features. Points are labelled, lines in red are two distance constraints, and lines in blue constitute angular constraints. The inferred camera location is marked. Figures c) and d) show the projection of a reference grid from the world space in c) to image space in d). World images are taken from Google Maps.

Conflict Indicators

Conflict indicators are advocated as an objective and quantitative measure of the severity (proximity to collision) of a traffic event (12). This study concerns traffic events that include a potential conflict between a pedestrian and a non-pedestrian road user. The four conflict indicators calculated in this study are: Time to Collision (TTC), Post-Encroachment Time (PET), Deceleration-to-Safety Time (DST), and Gap Time (GT).

TTC is defined as "…the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained." (38). PET is the time difference between the moment an offending road user leaves an area of potential collision and the moment of arrival of a conflicted road user possessing the right of way (39). GT is a variant of PET calculated at each instant by extrapolating the movements of the interacting road users in space and time(40). Deceleration to Safety Time (DST) is defined as the necessary deceleration to reach a non-negative PET value if the movements of the conflicting road users remain unchanged.

An accurate in-field estimation of objective conflict indicators is challenging and inherently subjective. Semi-automated methods have been used in previous studies in which road user positions are manually annotated (12). This process is time-consuming and does not support large-scale data collection. The calculation of conflict indicators in this study follows main lines of an algorithm presented in previous work (8). The videos analyzed in this study include significantly large number of road users - especially pedestrian movement during pedestrian scramble. Issues with large data structures arose and the following measures were taken:

1. Road user tracks are extrapolated at their extremities in time by the amount of 3 seconds assuming constant velocity. This extension of the observed road user tracks was conducted to detect conflicts in the further crosswalks of the intersection that occur after vehicle yielding. Vehicles are not tracked when stationary and the image quality at further crosswalks could not enable instant re-tracking when movement is resumed.
2. The list of traffic events to be analyzed is reduced based on the following proximity heuristic:
    a. Collect five sample frame numbers selected uniformly from the time span in which the two road users co-exist.
    b. Calculate at every point the spacing S_i between the pedestrian and the potentially conflicting vehicle.
    c. Discard this event if $\min(S_i) > 10m$.
3. The remaining list of events is further reduced using the following motion similarity heuristic:
    a. For each of the previous sample frame numbers, calculate the smoothed average (window of 10 frames) of the direction of movement.
    b. Calculate the angle between the average movement directions of the pedestrian and the vehicle.
    c. If the cosine of this angle is greater than 0.9, discard this event.
4. Road users are assumed to be represented by points, e.g. centroid.
5. The collision area is the *point* of intersection of pedestrian and vehicle tracks.
6. The objective definition of a collision course is the extrapolation of road user positions that leads to a minimum spacing shorter than the distance traversed by the

conflicting vehicle at current speed in 1.5 sec. Extrapolation of road user positions are based on assuming they will maintain a constant velocity.

The tracking parameters used in this study lean toward over-segmentation of road users, i.e. tracking of multiple objects over the same road user. An example is show in Figure 6**.** This was increases the chance of tracking of road users, especially pedestrians, at further crosswalks. To reduce this effect, events with calculable conflict indicators that involve road users within a proximity constraint are grouped into one event.

This is implemented by creating a graph connecting pedestrian objects and interacting vehicle objects for which there are calculable conflict indicator. All pair-wise spacing between vehicle objects at the moment of their *min* TTC and *min* GT are computed. Vehicle objects are further connected if their spacing is below a threshold of 3m. The subgraph of connected vehicle objects is replaced by a new vehicle object which conflict indicators resultant conflict indicators are taken as the minima of TTC, PET and GT and the maximum of DST. Details of this grouping are presented in Appendix 1. Figure 4 provides additional illustration.

a) b)

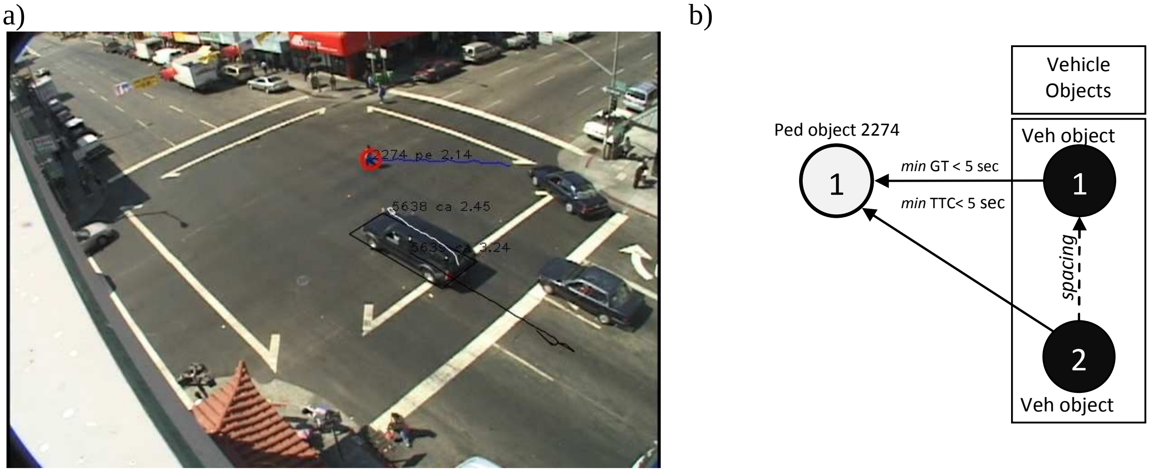


FIGURE 6 Conflict clustering. Figure a) shows an interaction between a pedestrian and an over-segmented vehicle (tracked twice, object 5638 on the front side and the other 5639 encompasses its horizontal projection). The spacing between these vehicle objects and the pedestrian at minimum TTC and GT are 2.18m and 1.53m respectively. Both are below a spacing threshold of 3m and are therefore grouped. Figure b) shows an illustration of the graph implementation.

ANALYSIS AND RESULTS

The analysis of four hours of video was conducted automatically at a pace of approximately one hour of video/day/machine. Sample frames with superimposed road user tracks are shown in Figure 7. The spatial distribution of traffic conflict positions is shown in Figure 8. A conflict position is taken as the location of the conflicting vehicle at the moment when there was a minimum time separation from the pedestrian. The time separation is measured by TTC as well as GT. There is an evident change in the density of traffic conflicts per unit area and time. The spatial distribution of traffic conflicts migrated away from the crosswalks after the scramble phase. The density of traffic conflicts per unit area was also reduced.

The distributions of the calculated conflict indicators before-and-after scramble are shown in Figure 9. There is an evident reduction in the frequency of traffic conflicts. It was not attempted to conduct statistical analysis of this data for two reasons:

1. Validation of the video analysis system on this data sequence was not conducted to measure the reliability of the estimates. To meet this purpose, an expert opinion is to be sought on the detection and severity ranking of the traffic conflicts in the video sequences.
2. It is not clear how the severity of traffic events measured by the calculated conflict indicators should be inducted in a statistical analysis.

Misclassification of pedestrians into vehicles was still evident, however at a much lower frequency than speed-based classification. Figure 7 shows a sample frame in which a pedestrian is misclassified as a vehicle while walking in a scramble phase.

CONCLUSIONS AND FUTURE WORK

This study demonstrates the feasibility of conducting before-and-after evaluation of pedestrian safety measures using automated analysis of video data. Pedestrian tracking in video data is an open problem for which some improvements have been investigated. The reliance on motion prototypes demonstrated a clear advantage over classification methods used in previous studies.

The context of this study is the evaluation of the safety benefit of the introduction of the pedestrian scramble phase. A two-hour video sequence was analyzed for pre- and post-scramble. Despite that the video analyzed in this study was not collected initially for the purpose of automated analysis, tracking accuracy was satisfactory. The automated analysis of four conflict indicators shows a reduction in conflict frequency. In addition, there was a general reduction in the spatial density of conflicts after the safety treatment.

It was not attempted in this study to draw a statistical inference regarding the safety benefit of the pedestrian scramble. It represents an important continuation of this work, and potentially a different paradigm of safety diagnosis that considers the frequency as well as severity of traffic events. A framework for safety diagnosis places all traffic events on a continuum of severity from uninterrupted passages to traffic collisions (12). Such framework can clearly benefit from automated video analysis.

An important continuation of this work can also be to conduct a comparison between the severities of traffic interactions measured by the system against expert rating. Ongoing research is planned to be conducted on this subject.

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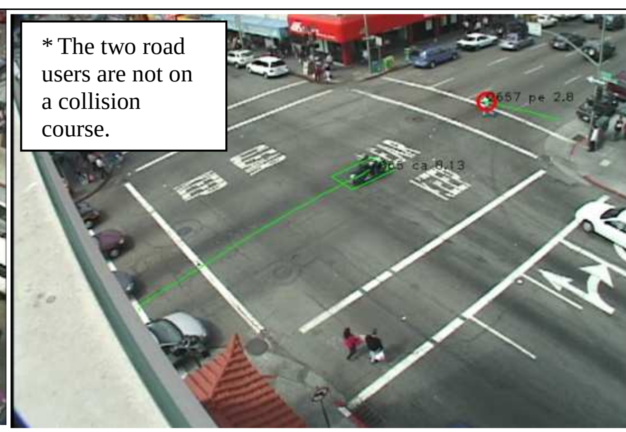
Event :2939 objects: 1501 | 5074 | TTC :1.162 PET :2.8 max DST :7.260 min GT :1.105

Event :2609 objects :1317 | 4966 | TTC :3.318 PET :2.266 max DST :3.355 min GT :1.198

Event :2913 objects :1496 | 4992(*unseen*)| TTC :1.815 PET :0 max DST :0.437 min GT :1.113

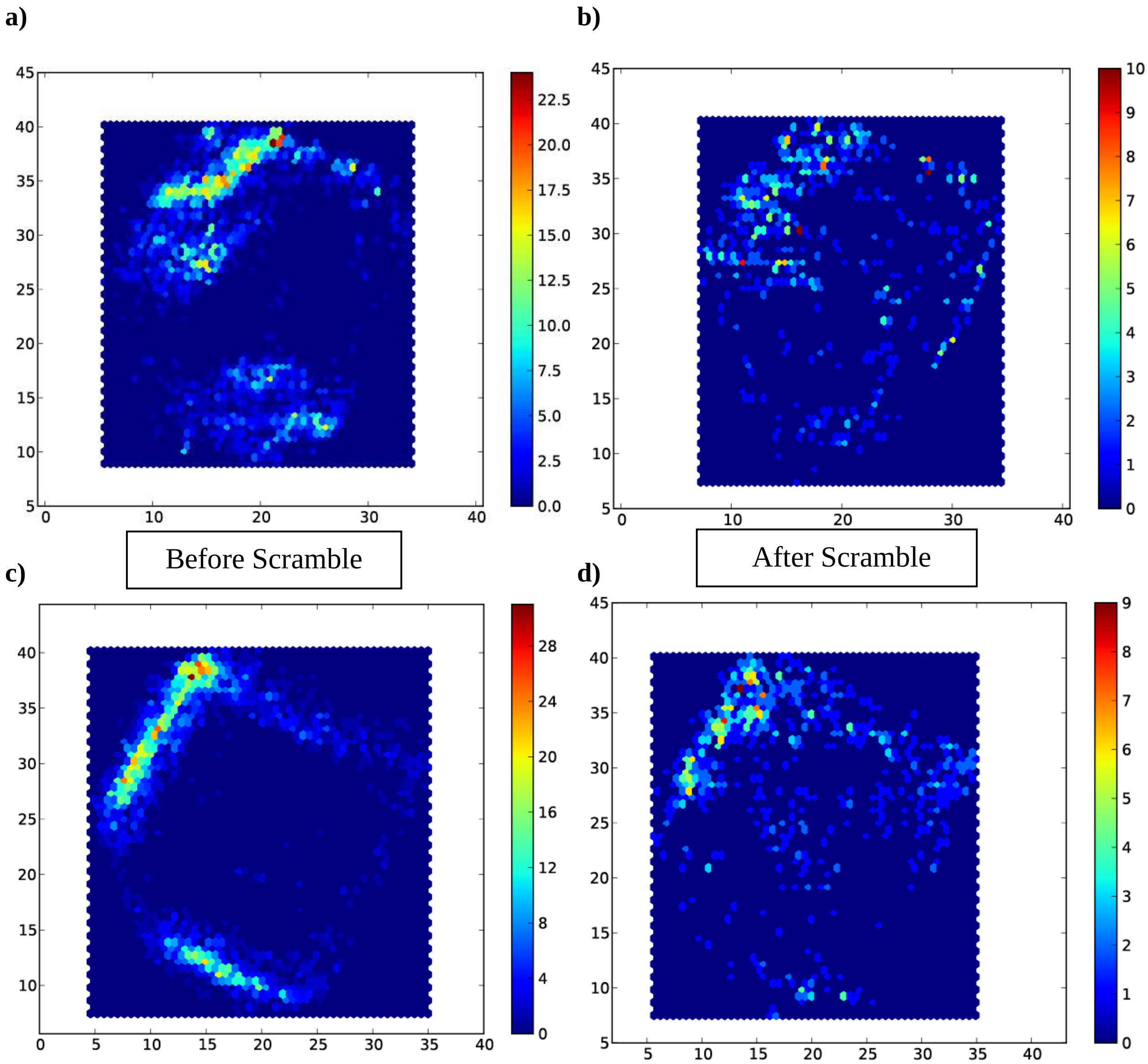
Event: 2306 objects: 1313 | 4812 TTC 0 PET 2.07 DST -0.075 GT 2.83

Event :2372 objects :1167 :4804 | TTC :2.973 PET :0 max DST :-0.379 min GT :1.473



Event :14292 objects :2657 :7865 | TTC :0 PET :1.53 max DST : 0.0 min GT :0.0

FIGURE 7 Sample frames with automated road user tracks. The captions display "Event" the event order in the list of potential interactions, "objects" the numbers of the interacting objects, and the indicated conflict indicators.



Intensities are in *number of conflict positions per square meter per 2 hours.*

FIGURE 8 Before-and-after spatial distribution of traffic conflicts. A conflict positions is selected as the position at which the motorist was separated by either a minimum Gap Time (GT) or minimum Time to Collision (TTC). Figure a) shows the *before* spatial distribution of conflict locations based on min GT. Figure b) shows the *after* distribution of conflict positions based on min GT. Figure c) shows the *before* distribution of motorist position at min TTC. Figure d) shows the *after* distribution of conflict positions based on min TTC.

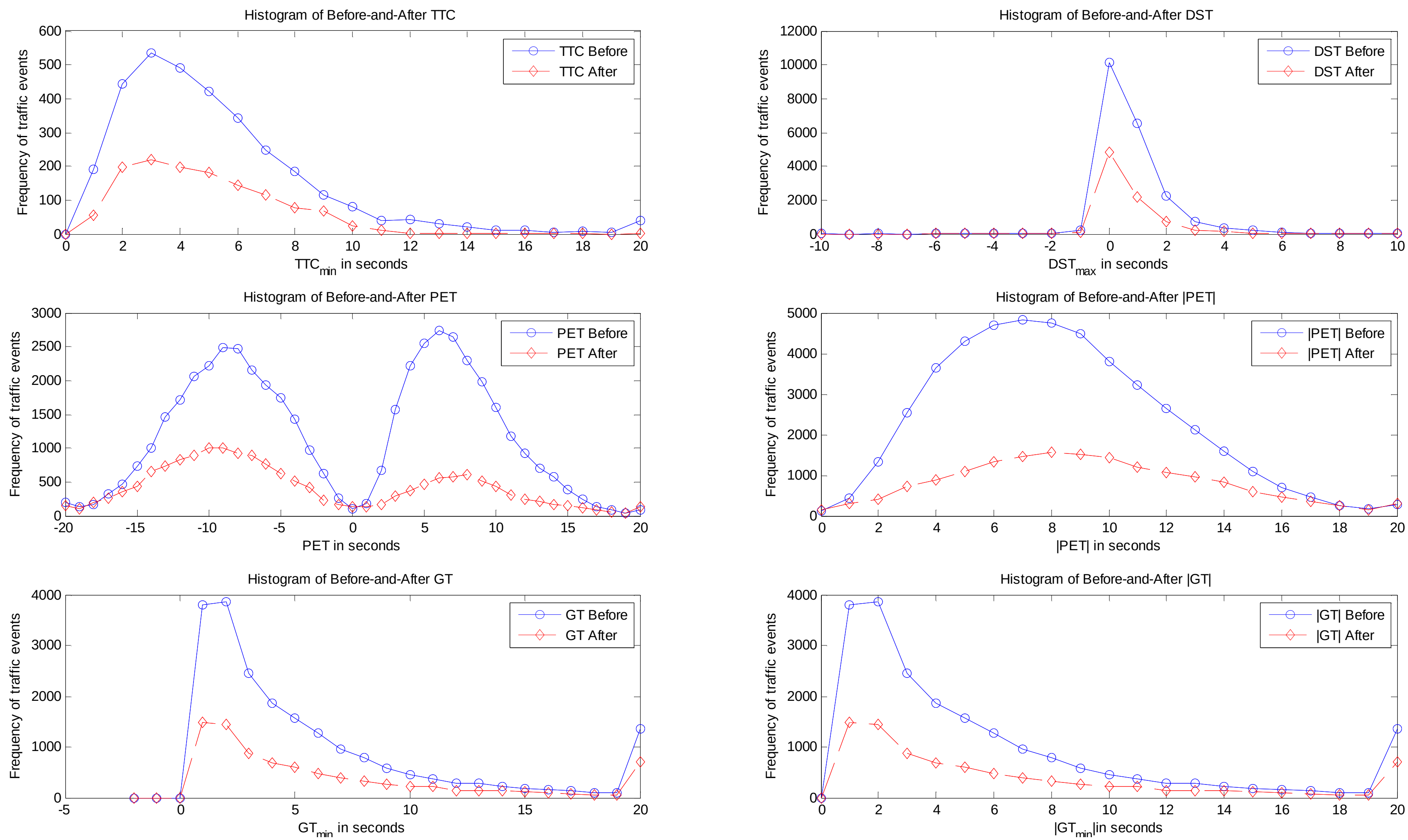


FIGURE 9 Distribution of different conflict indicators values for before and after scramble phase. Analyzed video durations are 2 hours before and 2 hours after. |PET| and |GT| are the modulus (unsigned) value of the Post Encroachment Time and Gap Time conflict indicator.

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APPENDIX 1

Algorithm 1: Algorithm for grouping pedestrian-vehicle event

Definitions: 1) A pedestrian object P_i is i^{th} in the list of all pedestrian objects that exist in the list of traffic events to be analyzed.
2) A vehicle object V_j is j^{th} in the list of all vehicle objects that exist in the list of traffic events to be analyzed.

Input: Let $V_{j,TTC}$ be the position of the j^{th} vehicle object at the position that exposed the interacting pedestrian with the shortest Time to Collision (TTC).
Let $V_{j,GT}$ be the position of the j^{th} vehicle object at the position that exposed the interacting pedestrian with the shortest Gap Time (GT).

Output: An updated list of traffic events that does not contain, but one, the grouped traffic events.

begin

1- **for each** pedestrian object P_i find within the list of vehicle objects the subset of n vehicle objects $V_{i,j}$ that coexist with P_i in the same traffic event.
2- Create an adjacency matrix A_{nxn} that represent the spacing between the positions of every pair of vehicle object $V_{i,j}$ at the time of minimum TTC. Elements in A that correspond to vehicle objects that do not possess a calculable TTC (not on a collision course) are assigned a token value (0) that is discarded later.
3- Find the connected graphs of all vehicle objects in $V_{i,j}$ in which every pair l, m of connected nodes satisfied the condition $A_{lxm} \leq connection\_threshold$. The threshold is taken 3.0m in this study.
4- Repeat steps 2 and 3 for vehicle positions at the moment of minimum GT.
5- Combined the list of connected graphs and remove redundancies.
6 - Create a new event with TTC at every time step equals the minima at each common time instant of all sequences of TTC observations for all $V_{i,j}$, PET equals the minima of all PET, GT equals the minima of GT observations at every time instant, and DST equals the maxima of all sequence.
7- Remove but one from the list of events all recorders that contains $V_{i,j}$.
8 - Add the new events created in 6 to the list of traffic events to be analyzed.