AUTOMATED SAFETY ANALYSIS USING VIDEO SENSORS: TECHNOLOGY AND CASE STUDIES

Karim Ismail, M.A.Sc.
University of British Columbia

Tarek Sayed, PhD, P.Eng.
University of British Columbia

Nicolas Saunier, PhD
École Polytechnique de Montréal

Abstract

Over the last decade, substantial technological progress has been achieved in the discipline of computer vision, driven by the inexpensiveness of video sensors and of computer processing. Techniques of particular importance have been developed in the area of automated road user detection and tracking in video sequences. The applications of computer vision techniques in the disciplines of traffic engineering and road safety are numerous and effectively address well-entrenched challenges in these fields. Traditionally, traffic conflict techniques (TCT) have been advocated to empower the weaknesses of collision data by relying on relatively more frequent and costless events. Traffic conflict techniques have been challenged since their inception by observer subjectivity and the costliness of conducting field surveys. The adoption of computer vision techniques in conducting TCT has been advocated by the authors and demonstrated in a number of successful applications. This study demonstrates an extended before-and-after analysis for the evaluation of a pedestrian safety treatment. The results obtained using the automated video analysis system are consistent with previously published results using based on human observers.

Résumé

Au cours de la dernière décennie, de grands progrès technologiques en vision par ordinateur ont été permis par la baisse des coûts des capteurs vidéo et de la puissance de calcul. En particulier, des techniques ont été développées pour la détection et le suivi automatiques des usagers de la route dans des séquences vidéo. Les applications des techniques de vision par ordinateur dans les disciplines de l'ingénierie du trafic et de la sécurité routière sont nombreuses et permettent de traiter efficacement des problèmes tenaces dans ces domaines.

Les techniques des conflits de trafic (TCT) ont été traditionnellement mises en avant pour remédier aux faiblesses des données de collision en reposant sur des événements relativement plus fréquents et sans conséquences. Les TCTs ont été contestées depuis leur origine à cause de la subjectivité des observateurs et du coût de la collecte de données sur le terrain. L'adoption de techniques de vision par ordinateur pour l'utilisation de TCTs a été recommandé par les auteurs et illustrée dans plusieurs applications. La présente étude est une analyse avant-après étendue pour l'évaluation d'un aménagement pour la sécurité des piétons. Les résultats obtenus à l'aide du système d'analyse automatique de données vidéo sont en accord avec les résultats publiés précédemment qui reposaient sur des observateurs humains.

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 studying the mechanism of action that exposes road users to the risk of collision transcends the focus on pedestrians to all other road users. The accurate estimation of exposure as well as other fundamental quantities in road safety analysis can greatly benefit by analyzing the microscopic positions of road users, i.e. road user tracks [2]. The automated extraction of road users' positions from video data using techniques in the discipline of computer vision has been advocated as a resource-efficient and potentially more accurate alternative [3]. Video sensors are selected as the primary source of data due to advantages of richness in details, inexpensiveness, and ubiquitous usage for monitoring purposes. Despite the technical challenges of pedestrian tracking in video data, such as visual occlusion and non-rigidity, vision-based applications in the field of pedestrian studies have been demonstrated with an increasing level of practical feasibility, e.g. [3,4]. One of the focus areas of pedestrian safety that can 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.

The classical collision-based approach to BA studies is based on estimating the reduction in the frequency and consequences of collisions attributable to the evaluated treatment. In order to draw statistically stable conclusions, e.g. explicating the effect of a treatment from confounding factors, the observational period for collisions extends for relatively long period (1-3 years) before as well as after the introduction of the treatment. The reliance on collision data for BA analysis invites the following shortcomings [5]: **Attribution**) police reports and interviews often do not enable the attribution of road collisions to a single cause or a set of causes with satisfactory accuracy, **Data Quantity**) road collisions are rare events that are subject to randomness inherent to small numbers [6], and **Data Quality**) collision records are often incomplete and lack important details, and the quality of road collision reporting has been deteriorating in many jurisdictions.

Classical shortcomings in collision-based BA studies are even more pronounced when studying pedestrian safety. Pedestrian-involved collisions are more injurious and less frequent than vehicle collisions. Exposure measures, such as pedestrian volume, are often difficult to obtain and expensive to collect through in-field surveys. It is often the case that the safety analysis may not afford long-term collision observation after the introduction of a measure. To address previous shortcomings, Traffic Conflict Techniques (TCTs) have been advocated as an alternative approach to road safety analysis. Classically, TCTs are based on in-site observation of traffic conflicts at an intersection by a team of trained observers. Traffic conflicts are more frequent and less costly than road collisions. Traffic conflicts also provide useful 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 [6]. The classical observer-based TCT is challenged on several accounts due to: inter- and intra-observer disagreement, cost of field observation, demand for staff training, and difficulty of in-field estimation of objective conflict indicators, such as the Time to Collision.

Automating the process of traffic conflict analysis is greatly appealing in the context of BA studies of treatments intended to enhance pedestrian safety. The automation of TCT enables the objective analysis of pedestrian-vehicle conflicts in an accurate 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 [7]. This study provides extended analysis of previous work [8] on longer video sequences involving more in-depth analysis based on the development of an aggregate severity index. This study is another step in a unique research direction in the field of road safety. The objectives of this study are to: 1) Provide a description of the methodology of analysis. 2) Provide more in-depth analysis of the aggregation of conflict data into a severity index.

PREVIOUS WORK

There is a significant body of work on the evaluation of pedestrian safety treatments using non-collision data. The literature contains studies that rely on traffic conflicts and behavioral surrogates such as motorist yielding rate [9]. Studies on the evaluation of pedestrian scramble treatment were mainly conducted using traffic conflicts, e.g. [10]. The work by Malkhamah et al. [11] was the only one found in the literature in which safety evaluation data 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 [12]. The authors noted issues of observer subjectivity and the labor cost of extracting observations from video data. The application of computer vision techniques is being increasingly advocated to overcome these shortcomings. In order to study pedestrian-vehicle conflicts, all conflicting road users must be detected, tracked in subsequent frames, and classified into pedestrians and motorized road users. This is a challenging task in busy outdoor urban environments. Common problems are global illumination variations, multiple object tracking, and shadow handling [13]. Several approaches for road user tracking have been noted in the literature [3], amongst which feature-based tracking has been adopted in this study.

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 [3]. The core of the system for the detection and tracking of road users relies on feature-based tracking [14]. Figure 1 illustrates the architecture of the video analysis system. Following is a brief description of improvements in the system to meet challenges faced in this study.

1. Road User Classification

To analyze pedestrian-vehicle conflicts, it is necessary to identify pedestrians and motorized vehicles. The system described in [3] 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 by the authors. In [15], a small subset of actual road users' tracks, called *prototype* trajectories, is identified using an incremental unsupervised algorithm relying on the Longest Common Subsequence (LCSS) similarity [16]. The object is assigned the type of the closest prototype similar to the methodology described in [8]. An object trajectory that does not have a matched prototype is classified using the default speed classifier. Labeling of prototypes is performed once, where the prototype trajectories are first classified using the speed classifier, then reviewed and corrected, if required, by a human observer. A comparison of the classifiers on a subset of 1063 manually annotated trajectories was done and the results presented in Table 1 show clear superiority of the prototype classifier over the speed classifier. Examples of pedestrian prototypes are shown in Figure 2.

2. Validation of Tracking Performance

The safety analysis presented in this paper relies on road users' tracks extracted using an optimized set of parameters. The obtained tracking parameters minimize the difference between a sample of observed tracks and ground truth (manually annotated) tracks. A new algorithm was developed to automatically assign detected objects (the output of the system) to manually annotated tracks [17]. The assignation results can be used to calculate various tracking performance measures, such as the numbers of 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:

$$Cost = \frac{\alpha_{fd} * N_{fd} + \alpha_{md} * N_{md}}{N} \quad \ldots(1)$$

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. This framework was used to optimize the cost function over a range of values for key tracking parameters.

3. Camera Calibration

The positional analysis of road users requires accurate estimation of real-world coordinates of road users' positions as they appear in the video. This can be achieved by conducting camera calibration. The camera parameters recovered 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 map points in the image space back to real-world coordinates assuming that they lie on a reference surface with known model (pavement surface). The camera calibration algorithm used in this study was developed by the authors in [18].

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 PCC: Percentage correct classification **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.

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

The calibration error is 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. Visual depiction of camera calibration is presented in Figure 3.

a) **b)**

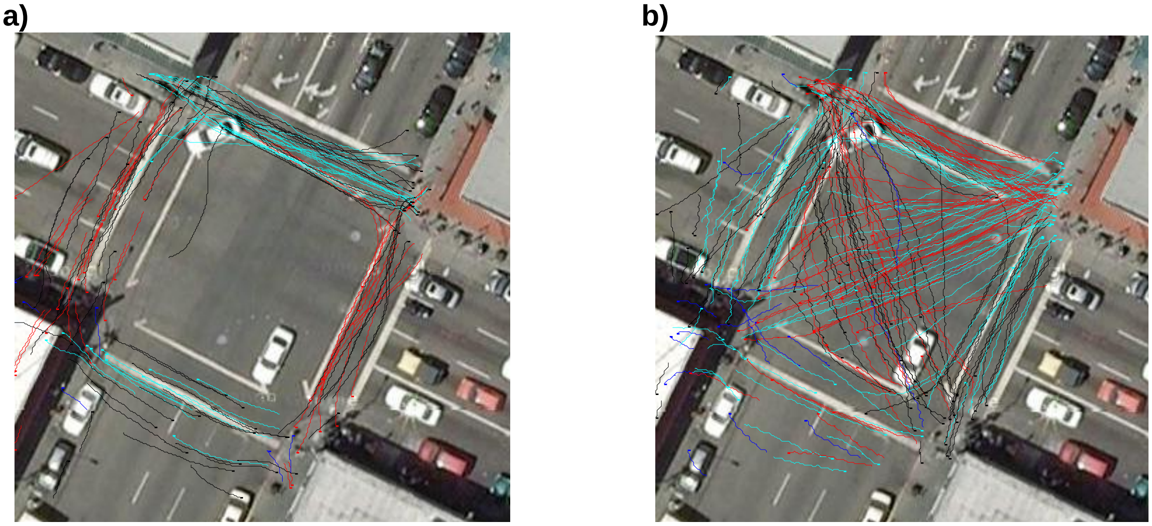


Figure 2 - Pedestrian prototypes for the before-and-after scramble phase. Figure a) shows the pre-scramble prototypes and Figures b) shows post-scramble prototypes.

Conflict Indicators

Conflict indicators are advocated as an objective and quantitative measure of the severity (proximity to collision) of a traffic event [6]. 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". 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. GT is a variant of PET calculated at each instant by extrapolating the movements of the interacting road users in space and time. 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. The definitions and calculation of conflict indicators are presented in previous work by the authors [3][8].

a) b)

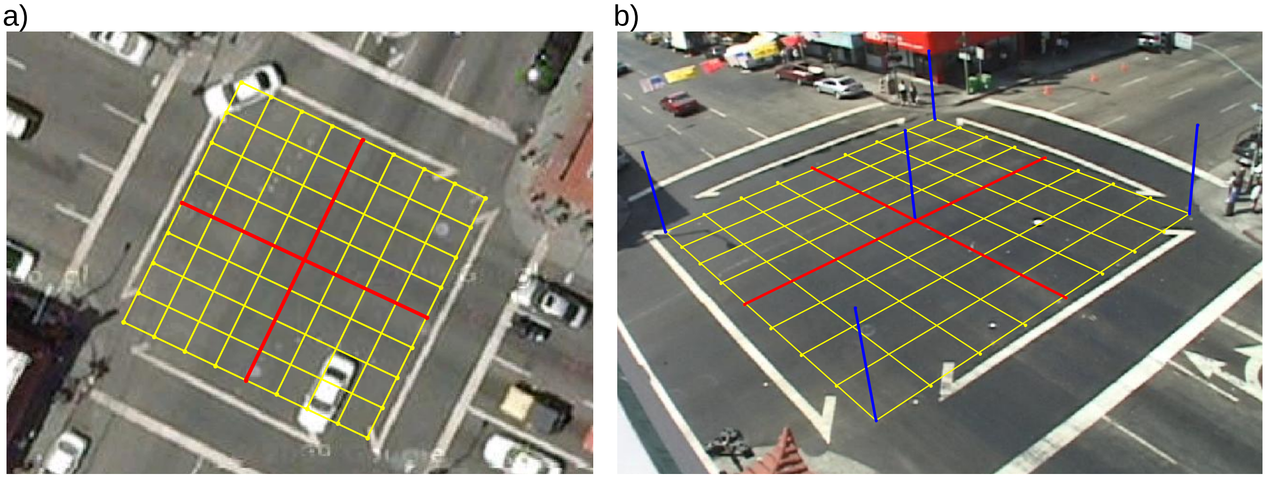


Figure 3 - Calibration of the video camera. Figures a) and b) show the projection of a reference grid from the world space in a) to image space in b). Reference grid (2.0m spacing – 4.0m vertical line) in world space (left) and image space (right)

ANALYSIS AND RESULTS

The analysis of three hours of video was conducted automatically at processing pace of approximately one hour of video per day per machine (Pentium Dual Core 1.8 GHz, 2GB memory, C++ implementation relying on the OpenCV library). Sample frames with superimposed road user tracks are shown in Figure 4. The spatial distribution of traffic conflict positions is shown in Figure 5. 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 a discernable 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.

One of the important contributions in this study is the development of a methodology for mapping conflict data into a unitless severity index. Admittedly, every indicator measures different severity aspect and there is no unified framework for combining these safety cues. The mappings presented later are intended to enable a unified integration of severity cues or information contained in each conflict indicator. Also, different measures can be extracted from the severity indices data at different aggregation levels. In the most aggregate form, a single unitless severity measure can represent the safety level in a specific treatment period. This leads to intuitive interpretation of the results obtained from the video analysis system and provide support for further decisions. The mappings and the aggregation strategies proposed later are the main novelties of this work. Severity measures are calculated as follows:

Algorithm 1: Algorithm for calculating aggregate severity measures

Definitions: 1) A traffic events is a data point that comprise the temporal, spatial, typical, and safety aspects of a traffic interaction between two road users.
2) A severity index I is a measure defined over the domain of individual conflict indicators that maps from its current value to [0,1], with 1 being the most severe.
3) A severity measure is a general term for the outcome of different aggregation methods that combine information on severities of traffic events.

Input: A list of all traffic events and the corresponding set of attributes, such as road users, type, location, time, and conflict indicators.

Output: An aggregate severity measure distributed over time or over road users.

begin

1- Create a data structure (**struct**) that contains the set of all traffic events and their attributes. Some attributes of a traffic event are static, e.g. PET, and others are a dynamic or function of time, e.g. location.

2- **For all** traffic events in **struct** and **for all** of their static and dynamic conflict indicators, calculate the corresponding severity index I using one of the following mappings:

a. **Mapping 1:**

$$I(TTC = x) =* e^{-\frac{x}{p1}} \qquad \forall TTC > 0 \qquad \ldots(2)$$

$$I(PET|GT = x) = e^{-p3*(p4*x+e^{-p4*x}-1)} \qquad \forall GT > 0 \qquad \ldots(3)$$

$$I(DST = x) = (1 - \frac{e^{p5-x}}{e^{p5}})^{\frac{1}{p6}} \qquad \forall DST > 0 \qquad \ldots(4)$$

where $p1{:}\,p6$ are specific mapping parameters that define its shape.

b. **Mapping 2:** Estimate the Gamma distribution parameters ($\propto, \beta$) that represent the distribution of conflict indicators. Find the severity index I as based on its relative frequency in the distribution of all recorded conflict indicators as follows:

$$I(x) = 1 - \Gamma(x, \propto, \beta) \qquad \ldots(5)$$

where $\Gamma(x, \propto, \beta)$ is the cumulative distribution function of the Gamma distribution with parameters ($\propto, \beta$) and random variable value x.

3- Calculate the average of all severity indices $\bar{I}$ (mapped from every conflict indicator). Ignore conflict indicators that do not report a calculable value.

4- Create an aggregation table that contains records of the summation of all severity indices of all events along one of the following dimensions:

a. Aggregation per time: for each frame in the video sequence, calculate the summation of average severity indices $\bar{I}$ of all extant traffic events.

b. Aggregation per road user: for each pedestrian road user in **struct**, calculate the summation of $\bar{I}$ of all traffic events in which the road user is involved.

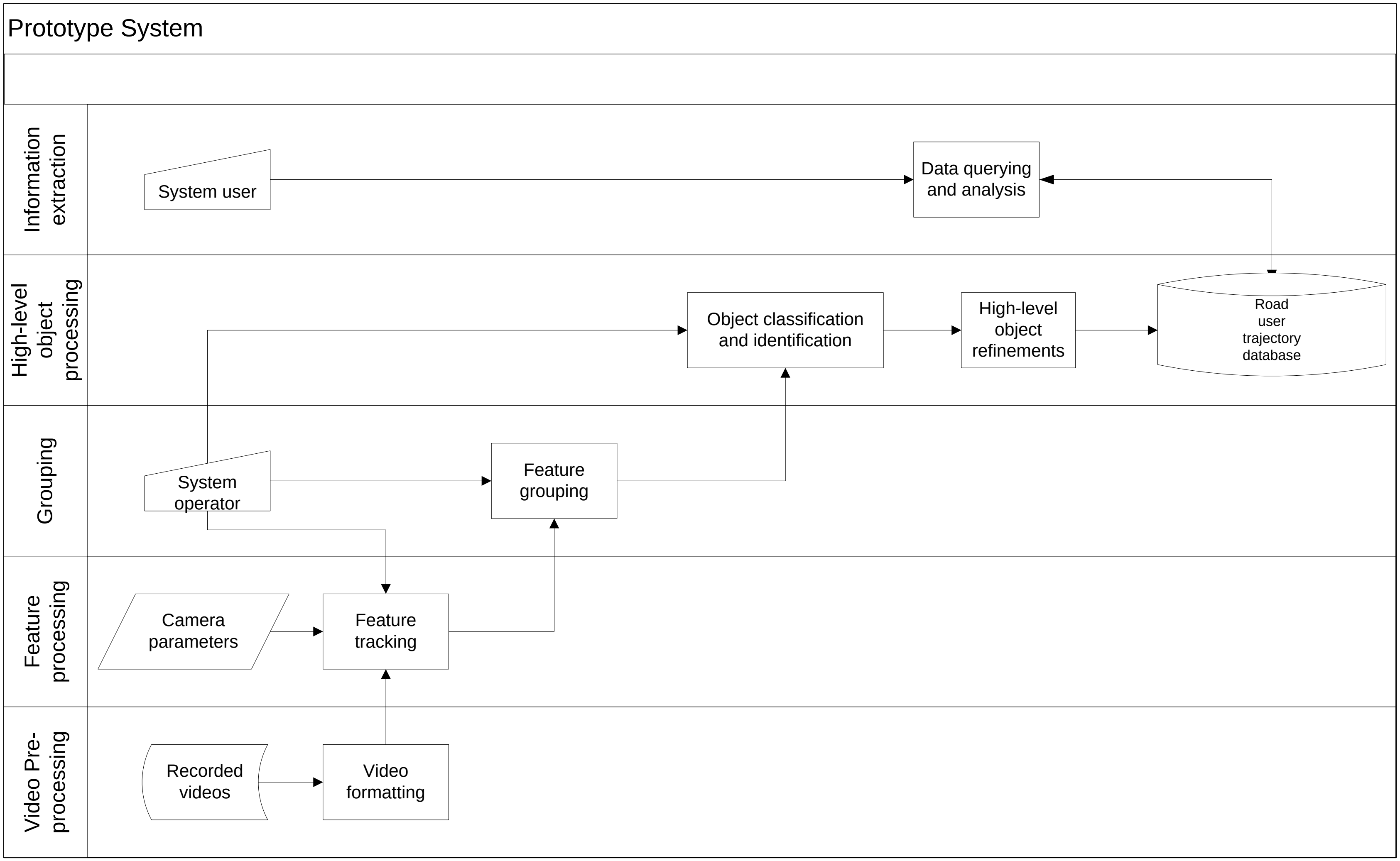


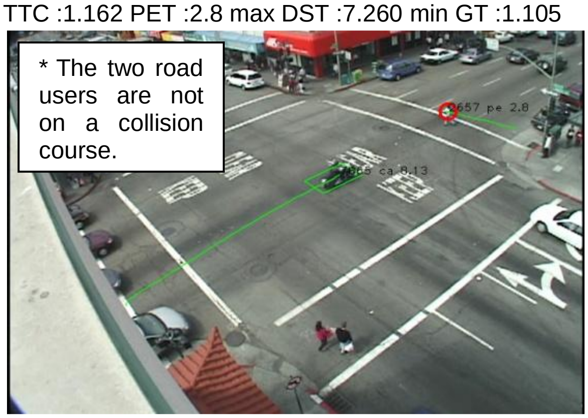
Figure 1 - Layout of the pedestrian detection and tracking system. The figure shows the five main layers the make up the system. Depicted also is the data flow among system modules from low-level video data to a position database of detected, tracked, and classified road users.

A depiction of Mappings 1 and 2 are shown in Figure 6. Both mappings are based on observing the abnormality of a conflict indicator in comparison to a distribution of typical values for this indicator. Mapping 1 relies on subjective assessment of the level of abnormality, or rather severity, measured in terms of each conflict indicator. The functional form of Mapping 1 is selected to enable flexibility in shape while relying on few parameters, thus relaying the definition of the mapping to the issue of parameter estimation. The estimation of parameters $p1{:}\,p6$ can be conducted more rigorously if there is training data. In this study, their selection was based on previous experience and subjective assessment. Mapping 2 compares the conflict indicator of current event to the distribution recorded for all other events. Mapping 1 was used for further analysis.

A summary of results is shown in Table 2. Figure 7 shows the distribution of aggregate severity indices for all events in the before as well as after periods. There is a clear and statistically significant (paired *t-test*: *p-value* 2.0981e-005) reduction in severity per unit time after treatment. Figure 9 shows the temporal distribution of aggregate severity measures for the before as well as after periods. Figure 9 shows a clear reduction in the magnitude of pedestrian exposure and severity of events. While no further analysis of the rich data shown in this figure was attempted, it foreshadows the significant level of details (superior to collision records) that can be examined using automated safety analysis. Figure 8 shows the distributions of the calculated conflict indicators. There is an evident reduction in the frequency of traffic conflicts after the treatment.

TTC :1.162 PET :2.8 max DST :7.260 min GT :1.105

TTC :3.318 PET :2.266 max DST :3.355 min GT :1.198



TTC :0 PET :1.53 max DST : 0.0 min GT :0.0

TTC 0 PET 2.07 DST -0.075 GT 2.83

Figure 4 - 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.

CONCLUSIONS AND FUTURE WORK

This study demonstrates the feasibility of conducting before-and-after evaluation of pedestrian safety treatments using techniques in the discipline of computer vision. 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. Two three-hour video sequences were analyzed during periods before and after the implementation of a scramble phase. Despite the fact 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 and severity. In addition, there was a general reduction in the spatial density of conflicts after the safety treatment.

a) **b)**

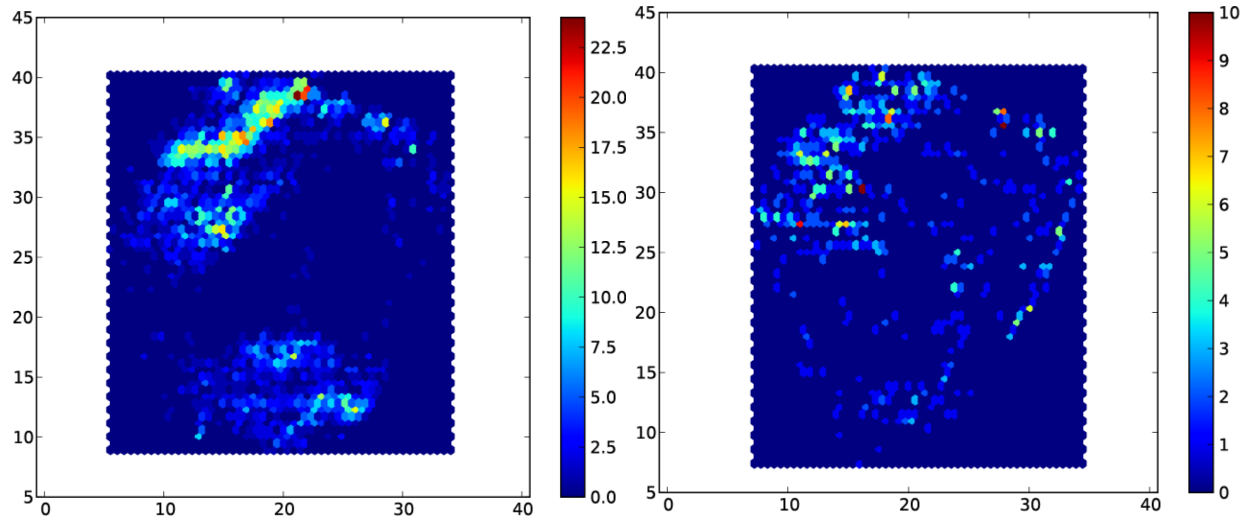


Figure 5 - Before-and-after spatial distribution of traffic conflicts. A conflict position is selected as the position at which the motorist was separated by a minimum Gap Time (GT). Intensities are in number of conflict positions per unit area per first 2 hours.

An important contribution of this study is the development of an aggregation method that integrates various severity aspects represented by different conflict indicators into a single unitless index. Another contribution is the development of two aggregation strategies for combining individual severity indices into severity measures that represent the underlying safety level. This lays the groundwork a new paradigm of measuring road safety in using mixed objective cues and also in terms that can directly and intuitively represent the underlying level of road safety. An important continuation of this work will explore methods to conduct a comparison between the severities of traffic interactions measured by the system against expert rating and collision-based measures. The parameter estimation of Mapping 1 can be conducted in a more rigorous fashion by estimating these parameters based on data obtained from a larger pool of expert opinions. In this paper, a simple average of individual severity indices was conducted. There are practical reasons to believe that some indicators are relatively more capable of comprehending the severity of traffic events, and therefore should be assigned more weight. Again, this represents an important future development.

Summary Statistic		Video 1		Video 2		Video 3		Video 4		Video 5		Video 6	
		S1	***S2***	***S1***	***S1***	***S1***	***S1***	***S1***	***S2***	***S1***	***S2***	***S1***	***S2***
Length (min)		30.08	30.13	29.96	30.27	29.29	30.84	29.79	29.64	30.62	28.23	30.37	29.61
Exposure Events		24584	27324	24413	24918	19366	18225	5356	5336	6401	6192	13110	15703
Events		13608	15023	13854	14118	11853	10915	2756	2782	2993	3268	6488	7576
Per time	**Mean**	5.1	5.2	5.5	5.4	4.5	4.0	0.89	0.87	1.3	1.2	2.6	2.6
	Median	2.5	3.2	3.2	3.2	2.6	2.2	0	0	0	0	0	0
	Mad	2.5	2.9	3.1	3.1	2.6	2.2	0	0	0	0	0	0
	Std	6.7	5.9	7.9	6.7	5.4	5.3	2.3	3.1	5.9	3.32	7.4	6.3
Per ped	**Mean**	0.62	0.67	0.69	0.67	0.80	0.73	0.17	0.16	0.20	0.17	0.27	0.29
	Median	0.037	0.17	0.05	0.054	0.23	0.19	0	0	0	0	0	0
	Mad	0.037	0.17	0.05	0.054	0.23	0.19	0	0	0	0	0	0
	Std	1.1	1.0	1.2	1.1	1.3	1.1	0.49	0.52	0.63	0.55	0.70	0.71

S# is the number of the analyzed half-hour, **Exposure Events** is the number of pedestrian-vehicle events in which the former was exposed to the risk of collision (decreasing relative velocity and minimum spacing < 10m), **Events** is the number of events with at least one calculable conflict indicator, **per time** is the results category with statistics aggregated over time, **per ped** is the results category with statistics aggregated over pedestrians, **Mad** is median absolute deviance.

Table 2 Summary of before-and-after statistics (3 hours before and 3 hours after)

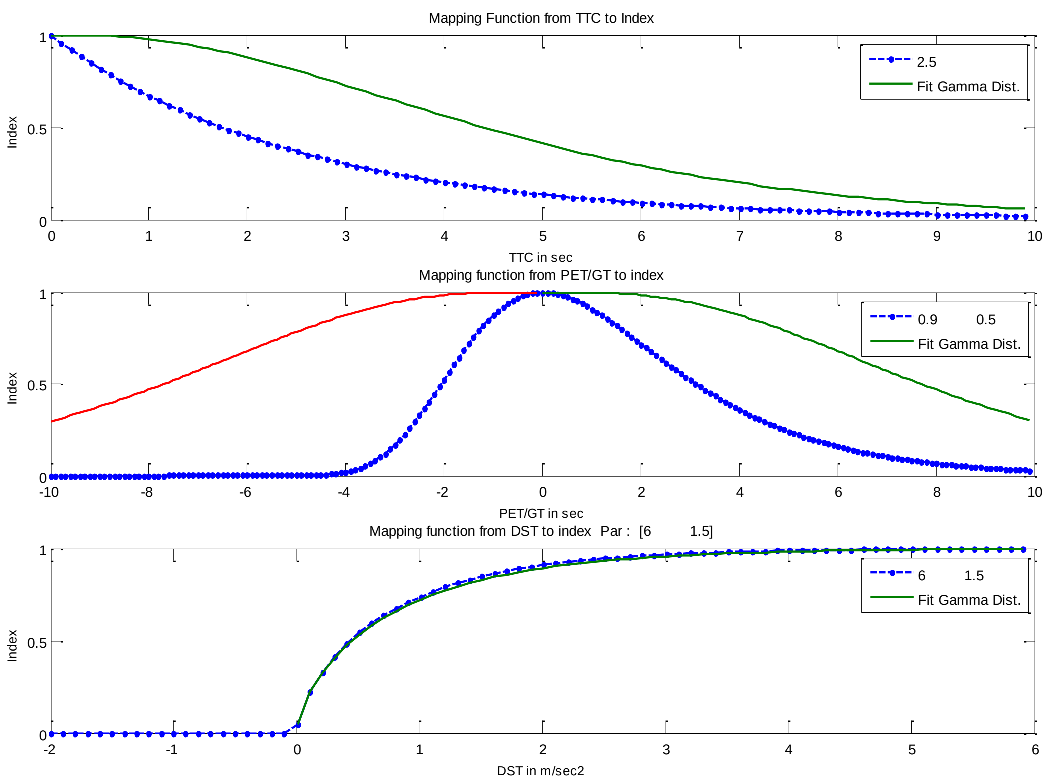


Figure 6 – A depiction of two mappings from conflict indicators to severity index. Shown also are the parameters used for the shown mapping depictions (Mapping 1: Algorithm 1). Mapping parameters (p1:p6) are shown in the legend. For example p1 = 2.5.

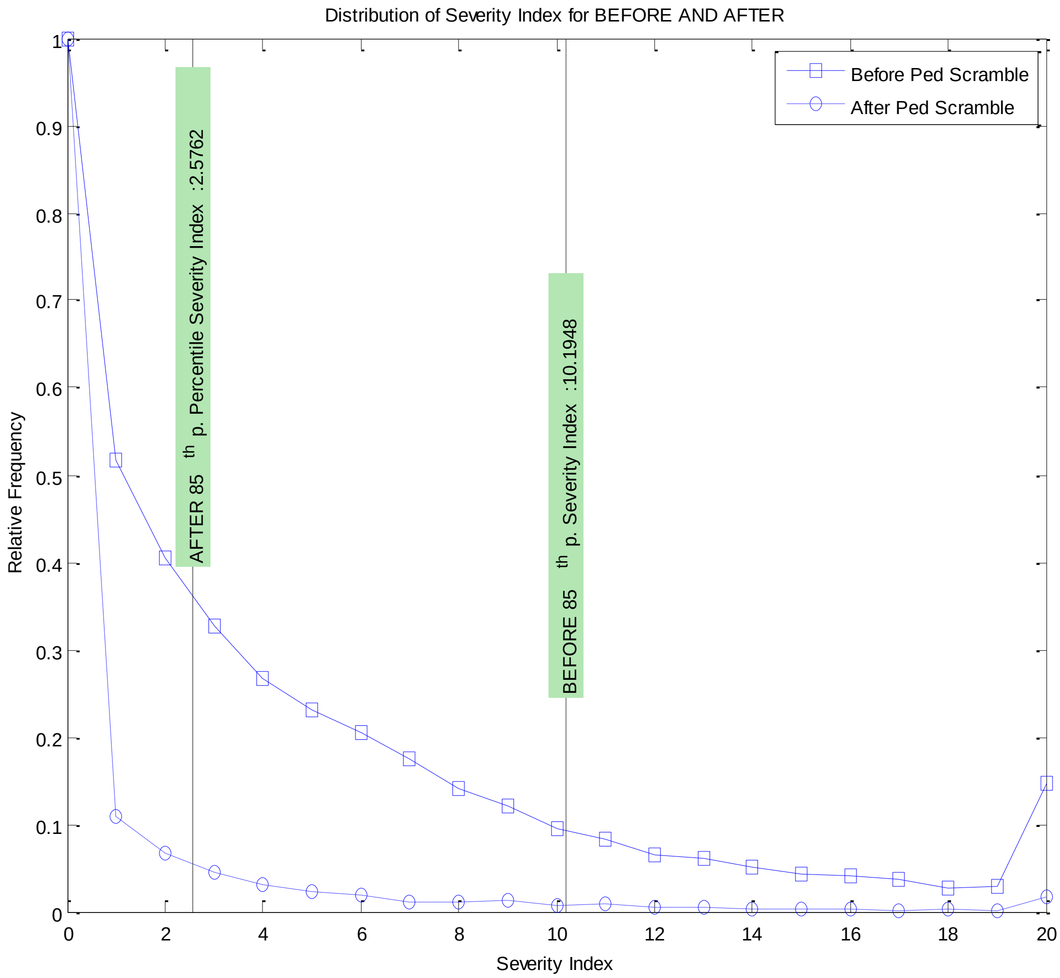


Figure 7 – Distribution of aggregate severity measures (summation of severity indices) for before and after. Vertical lines show the 85th percentile values for the severity measures.

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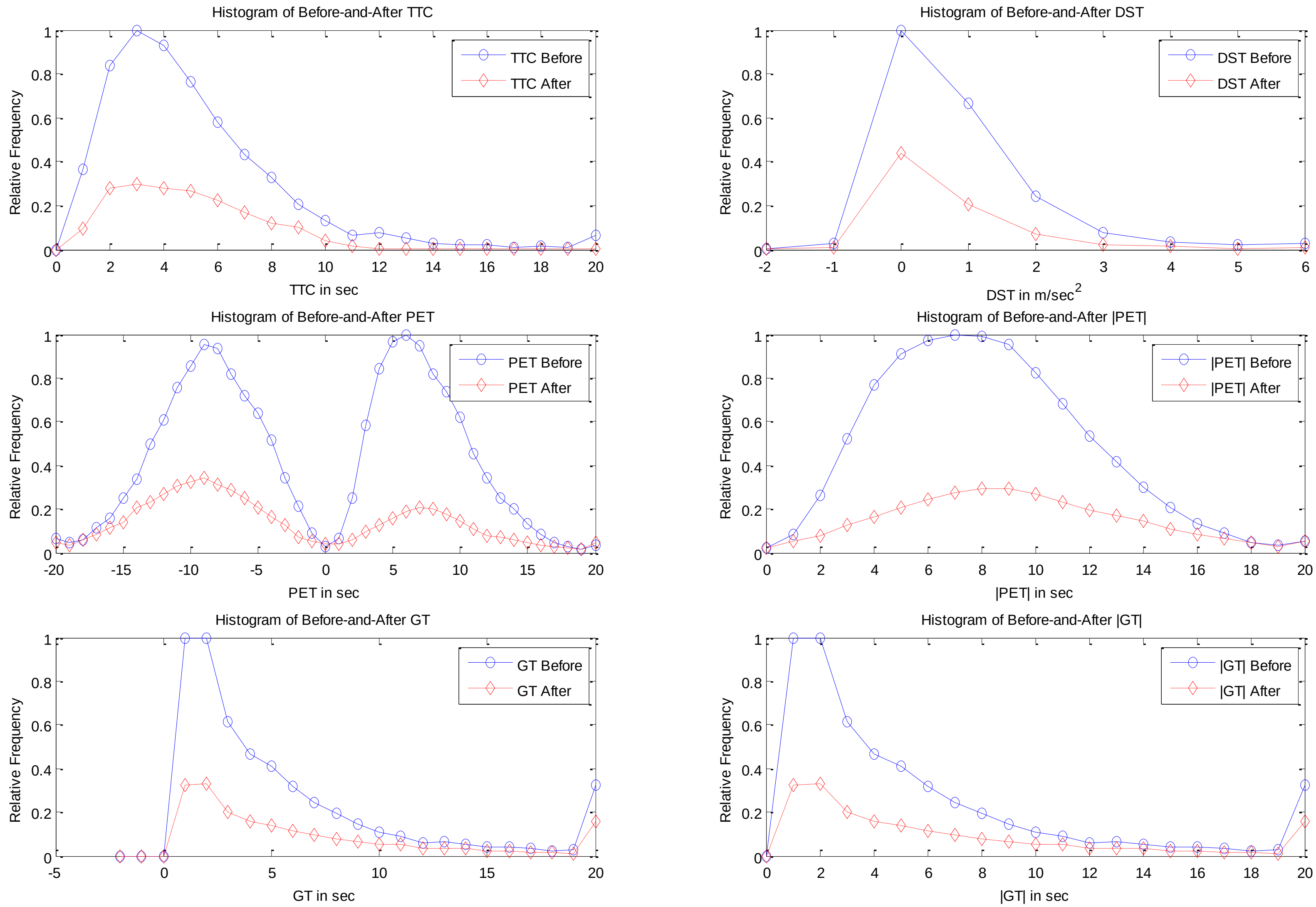

FIGURE 8 - Distribution of different conflict indicators values for before and after scramble phase. Analyzed video durations are 3 hours before and 3 hours after. |PET| and |GT| are the moduli (unsigned) values of the Post Encroachment Time and Gap Time conflict indicator.

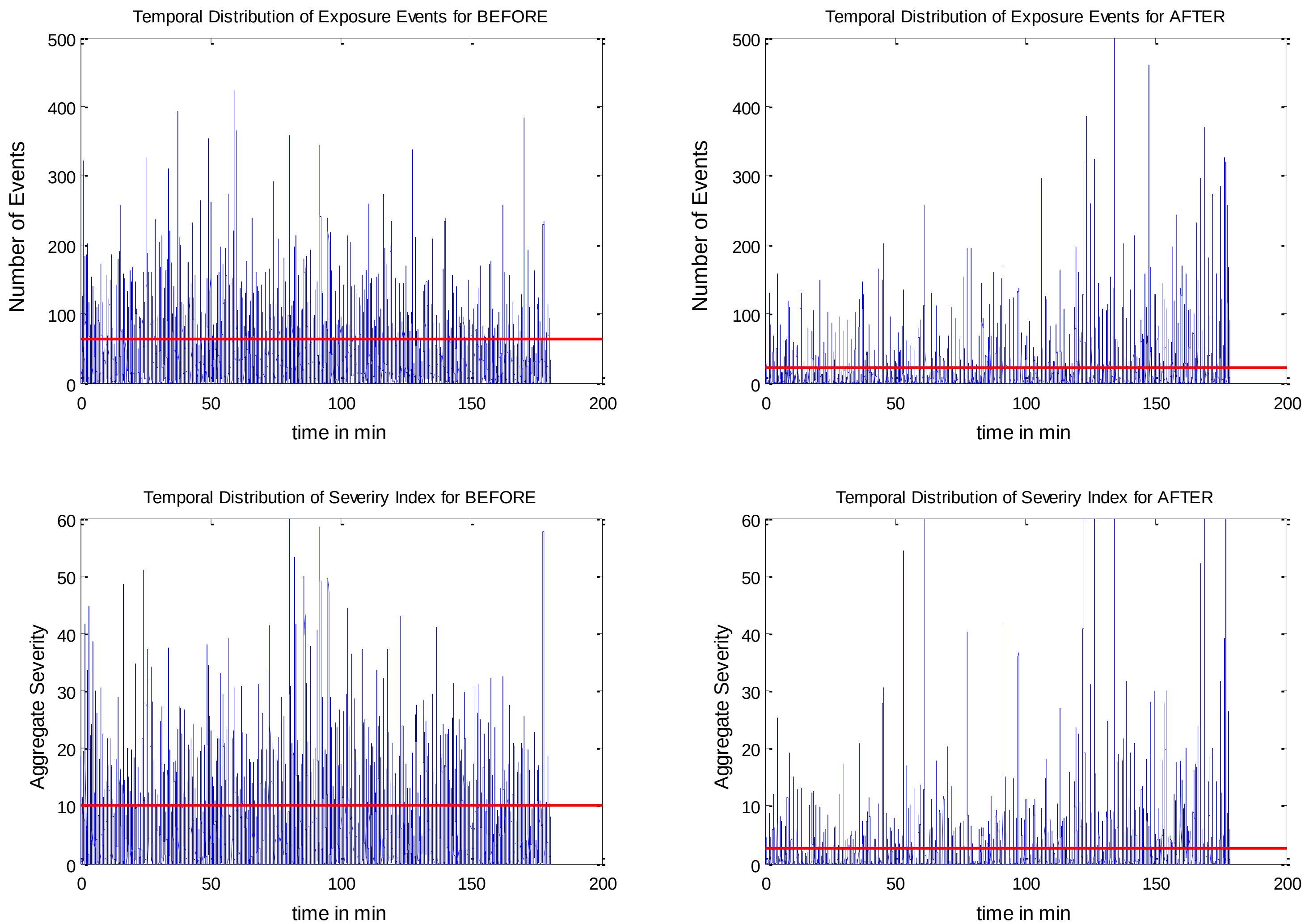

Figure 9 – Temporal distribution for the number of exposure events (first row) and the aggregate severity measures (second row). There is a significant difference in the 85th percentile (red line) value between the before and after (Exposure before: 63 events, exposure after 21 events Severity before 10.19 and severity after 2.576).

REFERENCES

[1] Greene-Roesel, R., Diogenes, M.C. and Ragland, D., Estimating Pedestrian Accident Exposure: Protocol Report. Institute of Transportation Studies. UC Berkeley Traffic Safety Center. s.l. : California PATH, 2007. p. 14.
[2] Saunier, N. and Sayed, T., "Automated Road Safety Analysis Using Video Data." Transportation Research Record, Washington, DC, 2007 : Transportation Research Board, 2007, Vol. 2019, pp. 57-64.
[3] Ismail, K., et al., "Automated Analysis of Pedestrian-Vehicle Conflicts Using Video Data." Transportation Research Record: Journal of the Transportation Research Board, Washington, DC : s.n., 2009, Vol. 2140, pp. 44-54.
[4] Chae, K. and Rouphail, N. M., "Empirical Study of Pedestrian-Vehicle Interactions in the Vicinity of Single-Lane Roundabouts." 2008. Transportation Research Board Annual Meeting Compendium of Papers. 08-2898.
[5] Chin, H.C. and Quek, S.T., "Measurement of traffic conflicts." Safety Science , s.l. : Elsevier, 1997, Vol. 26, pp. 169–185.
[6] Svensson, Å. and Hydén, C., "Estimating the severity of safety related behaviour." Accident Analysis and Prevention, 2006, Vol. 38, pp. 379-385.
[7] Bechtel, A., MacLeod, K. and Ragland, D., Oakland Chinatown Pedestrian Scramble: An Evaluation. UC Berkeley Traffic Safety Center. 2003. Final Report.
[8] K. Ismail, T. Sayed, N. Saunier., "Automated Analysis of Pedestrian-vehicle Conflicts: A Context for Before-and-after Studies." Washington, DC. : TRB, 2010. Transportation Research Board Annual Meeting.
[9] Turner, S., et al., " Motorist Yielding to Pedestrians at Unsignalized Intersections." Washington, DC : Transportation Research Record No. 1982, 2006.
[10] Gårder, P., "Pedestrian Safety at Traffic Signals: A Study Carried Out with the Help of a Traffic Conflicts Technique." Accident Analysis and Prevention, 1989, Vol. 21, pp. 435-444.
[11] Malkhamah, S., Miles, T. and Montgomery, F., "The development of an automatic method of safety monitoring at Pelican crossings." Accident Analysis and Prevention, 2005, Vol. 37, pp. 938-946.
[12] Hua, J., et al., "San Francisco PedSafe II Project Outcomes and Lessons Learned." Washington, DC : TRB 88th Annual Meeting Compendium of Papers DVD, 2009.
[13] Forsyth, D.A., et al., "Computational Studies of Human Motion: Part 1, Tracking and Motion Synthesis." Foundations and Trends in Computer Graphics and Vision, 2005, Vol. 1, 77-254.
[14] Saunier, N. and Sayed, T., "A feature-based tracking algorithm for vehicles in intersections." s.l. : IEEE, 2006.
[15] Saunier, N., Sayed, T. and Lim, C., "Probabilistic Collision Prediction for Vision-Based Automated Road Safety Analysis." Seattle : 10th International IEEE Conference on Intelligent Transportation Systems, 2007.
[16] Vlachos, M., Kollios, G. and Gunopulos, D., "Elastic Translation Invariant Matching of Trajectories." Machine Learning, 2005, Vol. 58, pp. 301-334.
[17] Saunier, N., Sayed, T. and Ismail, K., "An Object Assignment Algorithm for Tracking Performance Evaluation." 2009. Eleventh IEEE International Workshop on Performance Evaluation of Tracking and Surveillance (PETS 2009). pp. 9-16.
[18] K. Ismail, T. Sayed, and N. Saunier., "Camera Calibration for Urban Traffic Scenes: Practical Issues and a Robust Approach." Washington, DC : Transportation Research Board Annual Meeting Compendium of Papers, 2010.