Large Scale Automated Analysis of Vehicle Interactions and Collisions

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ABSTRACT
Road collisions represent a worldwide pandemic which can be addressed through the improvement of existing tools for safety analysis. The paper presents a refined probabilistic framework for the analysis of road user interactions. In particular, the identification of potential collision points is used to estimate collision probabilities and their spatial distribution can be visualized. A probabilistic time to collision is also introduced, and interactions are categorized in four categories: head-on, rear-end, side and parallel. The framework is applied to a large dataset of video recordings containing more than 300 severe interactions and collisions collected in Kentucky. The results demonstrate the usefulness of the approach in studying road user behavior and mechanisms that may lead to collisions.

INTRODUCTION

The importance of improving the understanding of the mechanisms that lead to road collisions cannot be overstated. Various approaches have been tried to achieve this task. An important distinction is whether the analysis relies on microscopic data collected from the field. There is a recent increase of interest in using traffic simulation for safety analysis (*1, 2, 3*). One of the reasons for this trend is attributed to the difficulty to collect adequate microscopic data, as stated in a recent work (*2*):

> "Ideally, it would be preferable to obtain measures of traffic turbulence [i.e. safety performance] directly from field studies. However, such an approach [is] still not feasible given that it would require real-time monitoring of vehicles in the traffic stream, including those rare combinations of events when a crash is observed and this type of information is not readily available"

This work attempts precisely to tackle the challenge of automatically monitoring all road users, including pedestrians, and extracting their trajectories for safety purposes. The data is collected using video sensors and computer vision techniques to process the video data (*4*).

A probabilistic framework was proposed in (*5*). It relies on the concept of the *safety hierarchy*, i.e. that there is a continuum of all road users' interactions with collisions at the top, undisturbed passages or "safe interactions" at the bottom and traffic conflicts in between (*6*). The safety hierarchy is matched by a *severity hierarchy*, based on *severity indicators* that measure the proximity of an interaction to a collision. It is thought that the observation of all interactions, and traffic conflicts in particular, can be an alternative or complementary approach to analyze road safety from a broader perspective than collision statistics alone. The widely accepted definition of a conflict is "an observational situation in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged" (*7*). The core concept of this definition is the *collision course*, and the fact that various chains of events may lead road users to collide. This observation led to propose a probabilistic framework to predict road users' positions and evaluate their probability of collision. This paper refines and expands the previous framework, adding more severity indicators, and applies it to explore a large dataset of video recordings of collisions and conflicts.

The rest of the paper is organized as follows. The next section will cover briefly recent work on safety modeling. The refined framework and formulation of the severity indicators are presented in Section 4. The large video dataset of collisions and conflicts is explored in section 5. Section 6 concludes and proposes future research directions.

RELATED WORK

Road safety studies rely traditionally on historical collision data. As reported in (*8*), significant effort has been put to develop a reference Highway Safety Manual (HSM): the main tools are statistical models of observational data, using generalized linear models to describe baseline associations between collision frequency and observable road features, and the effect of countermeasures is captured through empirically-determined collision modification factors. Yet there are well-recognized problems of availability and quality associated with collision data. Collision data is also intrinsically ill-suited to understand the mechanisms that lead to collisions.

An important concept to model is exposure (*9*). Recent work has shown that elementary units of exposure can be developed on the basis of known aggregate measures, such as annual average daily traffic (*10*). The framework is interesting and supports choices for the categories of interaction made in this paper, but it is completely disconnected from microscopic data collected in the field.

Davis and Morris expect that the statistical models proposed in the HSM "will be replaced by models explicitly describing mechanisms underlying crash occurrence" and advocates simulation models, in particular because those that "capture underlying mechanisms are usually able to represent a richer and more detailed set of alternatives than are statistical models" (*8*). Using microscopic traffic simulation for safety analysis is not a new idea (*11*), yet it has recently seen renewed interest. A large project called Surrogate Safety Assessment Model (SSAM) was funded by the Federal Highway Administration to develop a program to automate conflict analysis from the vehicle trajectory data generated by traffic simulations (*3*). Two Ph.D. theses have been undertaken on the topic (*1, 2*), demonstrating that microscopic traffic simulation may be used for the estimation of road safety and performance effects of changes in the transportation system.

The limitation of traffic simulation is related to the difficulty to calibrate the models and the suspicion that the models are too simple to replicate complex behaviors. In-field collection of data, in particular of surrogate safety measures (*14*), is necessary to tackle the problem and diagnose real world situations like existing black spots. Such data is collected with various levels of automation. Traffic conflict collection has been extensively studied since their first conceptualization in the late 1960s, but is still mostly performed manually by on-site observers (*6, 12, 13*). The extreme value method is applied in (*15*) to estimate the frequency of right-angle collisions at signalized intersections, relying on the post-encroachment time, which limits the categories of interaction that can be characterized. Davis et al. outlined a causal theory and built a minimal model capable of rigorously representing traffic conflicts and crashes, relying on the description of the evasive action (*16*). Yet there has been limited work relying on the automated collection of road users' trajectories with the primary goal of safety analysis (*17, 18, 19, 20, 21, 22*). This work and the previous work on which it is built (*4, 5*) are unique in their attempt to develop automated systems supporting a general framework for the analysis of road users' interactions and their severity.

A PROBABILISTIC FRAMEWORK FOR SAFETY ANALYSIS

Moving Object Trajectories

Road users have a certain size, but are represented for simplicity by a point, e.g. their centroid. The measurement of their position in space at each instant constitutes a *trajectory*. A trajectory is a mapping from a finite set $I \subset \mathbb{R}$ (I is typically a finite set of time instants at regular intervals) to $\mathbb{R}^2$ (the two-dimensional plane) (*23*):

$$I \subset \mathbb{R} \rightarrow \mathbb{R}^2 : t \mapsto T(t) = (x(t), y(t))$$

The trajectory T of each road user U is measured for the time of its existence in a region of interest. Let $U(t_0)$ represent the knowledge available about a road user U up to time t_0, e.g. its past n observed positions $T(t_{-n})...T(t_{-1}), T(t_0)$. Studying the probability of collision requires the ability to predict road users' future positions. Let $\hat{T}_{t_0}(t)$ be the prediction made at t_0 for the position of U at $t \geq t_0$, i.e. based on the knowledge available about U at t_0.

General Collision Probability

The probability at time t_0 for two road users U_i and U_j to collide is the probability of the event $Collision(U_i, U_j)$ of the two objects being at the same place at the same time at a later time $t \geq t_0$.

Let $Proximity_\epsilon(A, B)$ be a function mapping from $\mathbb{R}^2 \times \mathbb{R}^2$ to $\{0, 1\}$, called the *proximity function*, defined in the following way for a given distance d and threshold ϵ,

$$Proximity_\epsilon(A, B) = \begin{cases} 1 & \text{if } d(A, B) \leq \epsilon \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The probability at time t_0 of a future collision for two road users U_i and U_j, denoted $P(Collision(U_i, U_j)|U_i(t_0), U_j(t_0))$, is the probability that there exists an instant $t \geq t_0$ such that $Proximity_\epsilon(\hat{T}_{i,t_0}(t), \hat{T}_{j,t_0}(t)) = 1$. It can be written using the complementary event that no collision occurs at any instant $t \geq t_0$ (an upper limit t_1 is added to take into account a reasonable amount of time for the road users to collide during their passing through the scene),

$$P(Collision(U_i, U_j)|U_i(t_0), U_j(t_0)) = \\ 1 - \int_{t_0}^{t_1} P(Proximity_\epsilon(\hat{T}_{i,t_0}(t), \hat{T}_{j,t_0}(t)) = 0|U_i(t_0), U_j(t_0))\, dt \tag{2}$$

In the following, the conditional part of the probabilities is dropped for simplicity of writing. The probability of non collision at t, i.e. of the proximity function $Proximity_\epsilon$ to be 0 at t, is the joint probability of the road users being in positions at t further than the given distance ϵ, that, assuming that the road users move independently, can be computed by

$$P(Proximity_\epsilon(\hat{T}_{i,t_0}(t), \hat{T}_{j,t_0}(t)) = 0) = \\ \int_{A_i \in \mathbb{R}^2} \int_{A_j \in \mathbb{R}^2} P(\hat{T}_{i,t_0}(t) = A_i)\, P(\hat{T}_{j,t_0}(t) = A_j)\, (1 - Proximity_\epsilon(A_i, A_j))\, dA_j\, dA_i \tag{3}$$

The independence assumption relies on the definition of traffic conflicts as interactions in which a collision is imminent if the road users' movements remain unchanged, i.e. if the road users do not react to each other. If it is possible to draw from the distribution of possible future positions for road users, the probability of collision may be computed by simulation, counting the number of situations in which the proximity function is equal to 0.

Movement Extrapolation

Road users have particular dynamics that can be described by prior knowledge of their motion model and empirical knowledge learnt from observations. This work relies on learning the distribution of road users' trajectories from observations (*24*), which can be used to predict road users' future positions with associated probabilities. More precisely, an *extrapolation hypothesis* H is defined by a trajectory $I \subset \mathbb{R} \rightarrow \mathbb{R}^2 : t \mapsto H(t) = (x(t), y(t))$, derived from an observed prototype trajectory by translation and resampling, with a probability $P(H)$ of the road user following the extrapolation hypothesis. Each road user U_i can be assigned at t_0 a finite set of M_i extrapolation hypotheses $\{H_{i,1}, ..., H_{i,M_i}\}$, such that $\sum_{1 \leq m \leq M_i} P(H_{i,m}) = 1$. For N_U road users existing at time t_0, the sample space is the Cartesian product $\{H_{1,1}, ..., H_{1,M_1}\} \times ... \times \{H_{N_U,1}, ..., H_{N_U,M_{N_U}}\}$. Each road user is assumed to follow an extrapolation hypothesis independently from other road users.

It is then possible to enumerate the road users' predicted positions at each future instant $t \geq t_0$ for a limited time horizon (See t_1 in Equation (2)), and identify the instants at which the proximity function will be 1, called *collision points*. A collision point CP_n is defined for two extrapolation hypotheses H_{i,m_i} and H_{j,m_j} as the first instant $t_n \geq t_0$ at which $Proximity_\epsilon(H_{i,m_i}(t_n), H_{j,m_j}(t_n)) = 1$. Let f be the function that associates to each pair of extrapolation hypotheses a collision point if it exists, or the element $NoCollision$ (f is symmetric with respect to its inputs), and let g_1 and g_2 be the inverse functions defined over the collision points that return the extrapolation hypotheses that lead to the collision point. If $f(H_1, H_2) = CP$, then $g_1(CP) = H_1$ and $g_2(CP) = H_2$ (or vice-versa).

The Case of Two Isolated Road Users

The first simple case of two isolated road users U_i and U_j is considered (as if there are only two road users in the region of interest). They may collide at any of N_{CP} potential collision points. The event of their collision at collision point CP is denoted $Collision(U_i, U_j, CP)$, which can be written simply $Collision(CP)$ since CP is associated with the two given extrapolation hypotheses of the two road users that lead to it. The probability of $Collision(CP)$ is approximated by the product of the probabilities of following $g_1(CP)$ and $g_2(CP)$. This can be written as

$$P(Collision(U_i, U_j)) = \sum_{1 \leq n \leq N_{CP}} P(Collision(CP_n)) = \sum_{1 \leq n \leq N_{CP}} P(g_1(CP_n))P(g_2(CP_n)) \quad (4)$$

The formula presented previously in (*5*) as a collision probability is very close to Equation (4), but cannot be properly considered as a probability, and is referred in this paper as the severity index. The formula to compute the severity index for two road users U_i and U_j at t_0 is the following

$$SeverityIndex(U_i, U_j, t_0) = \sum_{1 \leq n \leq N_{CP}} P(g_1(CP_n))P(g_2(CP_n))\, e^{-\frac{(t_n - t_0)^2}{2\sigma^2}} \quad (5)$$

where σ is a normalizing constant, equal to an average user reaction time (chosen as 1.5 seconds in this paper).

Collision Probability and Other Indicators for any Number of Road Users

However, analyzing the situation is much more complex if taking into account all road users (and if there are three road users or more). The probability of collision at a collision point CP is the probability of the road users following the extrapolation hypotheses leading to the collision point and not having collided before with other road users. Similarly to the previous case, the N_{CP} collision points are enumerated for all road users and now ordered by their predicted instant of occurrence so that $t_n \leq t_{n+1} \; \forall \; 1 \leq n \leq N_{CP} - 1$.

The probability of collision at the collision point CP_n is the probability of the corresponding road users to follow $g_1(CP_n)$ and $g_2(CP_n)$ and that there is no collision point CP_m with another road user occurring prior to CP_n (i.e. with $m < n$) involving one of the previous extrapolation hypotheses (i.e. such that there exists another extrapolation hypothesis H and $f(g_1(CP_n), H) = CP_m$ or $f(g_2(CP_n), H) = CP_m$). This can be computed recursively as

$$
\begin{aligned}
P(Collision(CP_1)) =& P(g_1(CP_1))P(g_2(CP_1)) \\
\forall\, 1 \le n \le N_{CP}-1,\ P(Collision(CP_{n+1})) =& P(g_1(CP_{n+1}))P(g_2(CP_{n+1}))... \\
\prod_{\substack{1 \le m < n \text{ such that} \\ CP_m \text{ involves } g_1(CP_{n+1}) \text{ or } g_2(CP_{n+1})}} & (1 - P(Collision(CP_m)))
\end{aligned} \tag{6}
$$

Obtaining the individual collision probability for a single road user and a pair of road users at t_0, as well as the severity index for a pair of road users, is then just a matter of summing over the corresponding collision points:

$$
P(Collision(U_i, U_j)) = \sum_{\substack{1 \le n \le N_{CP} \text{ such that} \\ CP_n \text{ involves } U_i \text{ and } U_j}} P(Collision(CP_n)) \tag{7}
$$

$$
P(Collision(U)) = \sum_{\substack{1 \le n \le N_{CP} \text{ such that} \\ CP_n \text{ involves } U}} P(Collision(CP_n)) \tag{8}
$$

$$
SeverityIndex(U_i, U_j, t_0) = \sum_{\substack{1 \le n \le N_{CP} \text{ such that} \\ CP_n \text{ involves } U_i \text{ and } U_j}} P(Collision(CP_n))\, e^{-\frac{(t_n - t_0)^2}{2\sigma^2}} \tag{9}
$$

The expected time to collision (TTC) for two road users U_i and U_j, $TTC(U_i, U_j, t_0)$, can also be computed in this framework if $P(Collision(U_i, U_j)) > 0$, i.e. if there is at least one collision point:

$$
TTC(U_i, U_j, t_0) = \frac{\sum_{\substack{1 \le n \le N_{CP} \text{ such that} \\ CP_n \text{ involves } U_i \text{ and } U_j}} P(Collision(CP_n))\, t_n}{P(Collision(U_i, U_j))} \tag{10}
$$

In a simple example with three road users and four collision points presented in Figure 1, the resulting probabilities of collision at the collision points are:

$$
\begin{aligned}
P(Collision(CP_1)) =& P(H_{1,1})P(H_{3,1}) \\
P(Collision(CP_2)) =& P(H_{1,2})P(H_{3,1}) \\
P(Collision(CP_3)) =& P(H_{1,1})P(H_{2,1})(1 - P(Collision(CP_1))) \\
P(Collision(CP_4)) =& P(H_{1,1})P(H_{2,2})(1 - P(Collision(CP_1)))
\end{aligned}
$$

The probabilities of collision for the pairs of road users are the sum of the probabilities of collision at the corresponding collision points, CP_1 and CP_2 for U_1 and U_3, CP_3 and CP_4 for U_1 and U_2. These are also respectively the individual collision probabilities of U_3 and U_2 since they are each involved in a potential collision with only one other road user U_2. Finally, the individual probability of collision for U_1 is the sum of the probabilities of collision at all collision points.

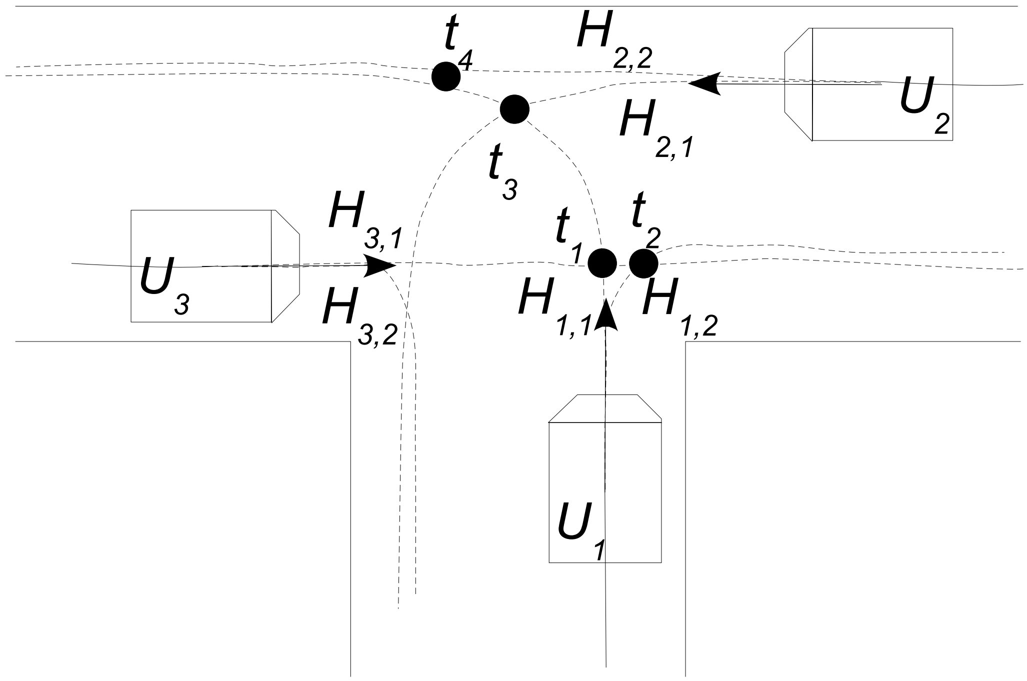

FIGURE 1 Simple example of three road users in interaction at a three leg intersection. There are four collision points, CP_1, CP_2, CP_3 and CP_4, at respective times t_1, t_2, t_3 and t_4, ordered temporally (U_3 is supposed to be too early at the point of intersection for hypotheses $H_{2,1}$ with $H_{3,1}$ and $H_{3,2}$ for a collision point to be considered).

Interactions and Categories

The elementary traffic events that are considered in the analysis are road user *interactions*. An interaction is defined as a situation in which two or more road users are close enough in space and time, and their distance is decreasing. This is a necessary condition for road users to collide, i.e. some form of exposure to the risk of collision following the definition of (*10*) of "an elementary unit of exposure [...] as any clearly defined and countable event that generates an opportunity for an accident to occur". This is implemented as a test over the distance between road users, and over the cosine of the angle θ between the relative velocity, i.e. the difference of the road users' velocities, and the vector that links the vehicle positions (See Figure 2). The actual condition is $cos(\theta) \geq 0$, and a value close to 1 means that vehicles are heading almost straight towards each other. Simple measurements are made for all interactions at all instants, namely the distance, cosine of the velocities, and speed differential (norm of the difference of the velocities). The collision probability, severity index and TTC are also computed at each time instant: if there is no collision point between the interaction road users, the collision probability and severity index are 0, and TTC is undefined.

Interactions are classified according to the relative trajectories of the road users. Four

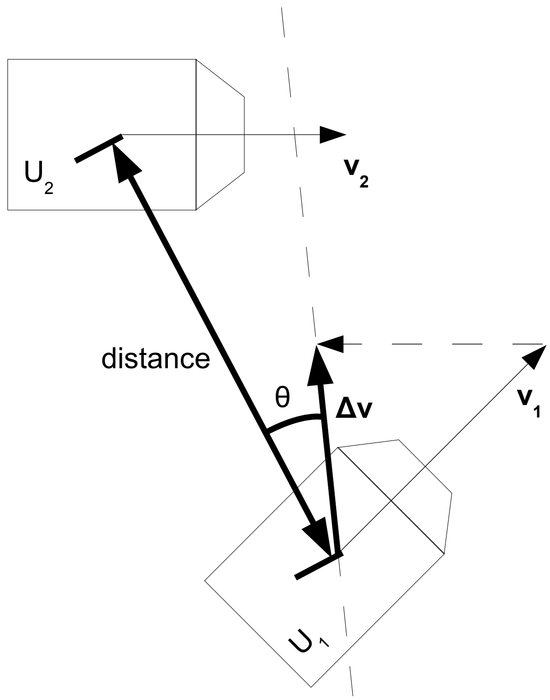

FIGURE 2 Interaction measurements at each instant. Two road users are defined to be in an interaction if $distance$ is below a given threshold and $cos(\theta) \geq 0$ (θ is the angle between the relative velocity $\Delta\vec{v} = \vec{v_1} - \vec{v_2}$ and the vector that links the road users' positions).

categories are proposed similarly to (*10*):

- head-on: road users moving in opposite direction,
- rear-end: road users following each other, potentially on different lanes,
- side: road users originating from potentially conflicting direction, e.g. at intersections,
- parallel: road users travelling in parallel in the same direction on different lanes.

Categories are identified by counting the number of instants at which the angle $\phi(t)$ between the road users' velocities is within some intervals:

- if $\phi(t) \in [-30°, 30°]$, the instant t counts for rear-end or parallel interactions,
- if $\phi(t) \in [-180°, -150°]$ or $\phi(t) \in [150°, 180°]$, the instant t counts for head-on interactions,
- if $\phi(t) \in [30°, 150°]$ or $\phi(t) \in [-150°, -30°]$, the instant t counts for side interactions.

Rear-end and parallel interactions are further differentiated by looking that the relative position of the road users with respect to their common direction of movement. These rules may be crude and arbitrary, especially because interactions may last some time and really belong to different categories at different intervals. But they help to broadly categorize interactions. All the conditions and measures used to characterize interactions are symmetric with respect to the two road users, as they should be.

EXPERIMENTAL STUDY OF COLLISIONS AND CONFLICTS

Dataset and System description

The framework proposed in this paper is used to explore a large dataset of video recordings of traffic conflicts and collisions in Kentucky. The dataset was first mentioned in (*20*) where it was used to test the video-based tracking system. All the analysis reported here was carried out with the video recordings as the only source of information. A report providing more details about the origin of the data was lately found (*25*). There are two subsets of video recordings, one labeled as "miss" and the other as "incident", corresponding respectively to traffic conflicts of mild to high severity and collisions. It is not clear from (*25*) how the severity was estimated to identify the subset of traffic conflicts. Each short video recording is composed of two sub-sequences with opposite viewpoints taken from two different cameras, each less than ten seconds long. For this study, only one of these is used. Each recording contains, or should contain, one clear interaction, i.e. a traffic conflict or a collision. From the original set of 238 traffic conflicts, 9 were removed because of the dire quality of the video or because no obvious relevant traffic event was recorded. For similar reasons, 15 collisions were not considered from the original set of 116 collisions. In some cases, it appears that the recording started after the event of interest. It is not always clear if a collision actually occurred for interactions in the collision subset. Although the framework proposed in this paper is generic and can deal with all road users, the interactions contained in this dataset involved only motorized vehicles.

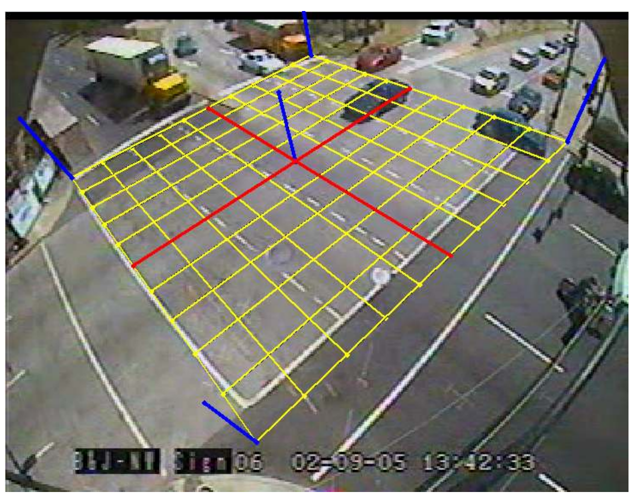

FIGURE 3 Reference grid in world coordinates projected in the image space and overlaid over a video frame. The grid spacing is 2.0 m and the height of the displayed vertical line segment (in blue) is 4.0 m.

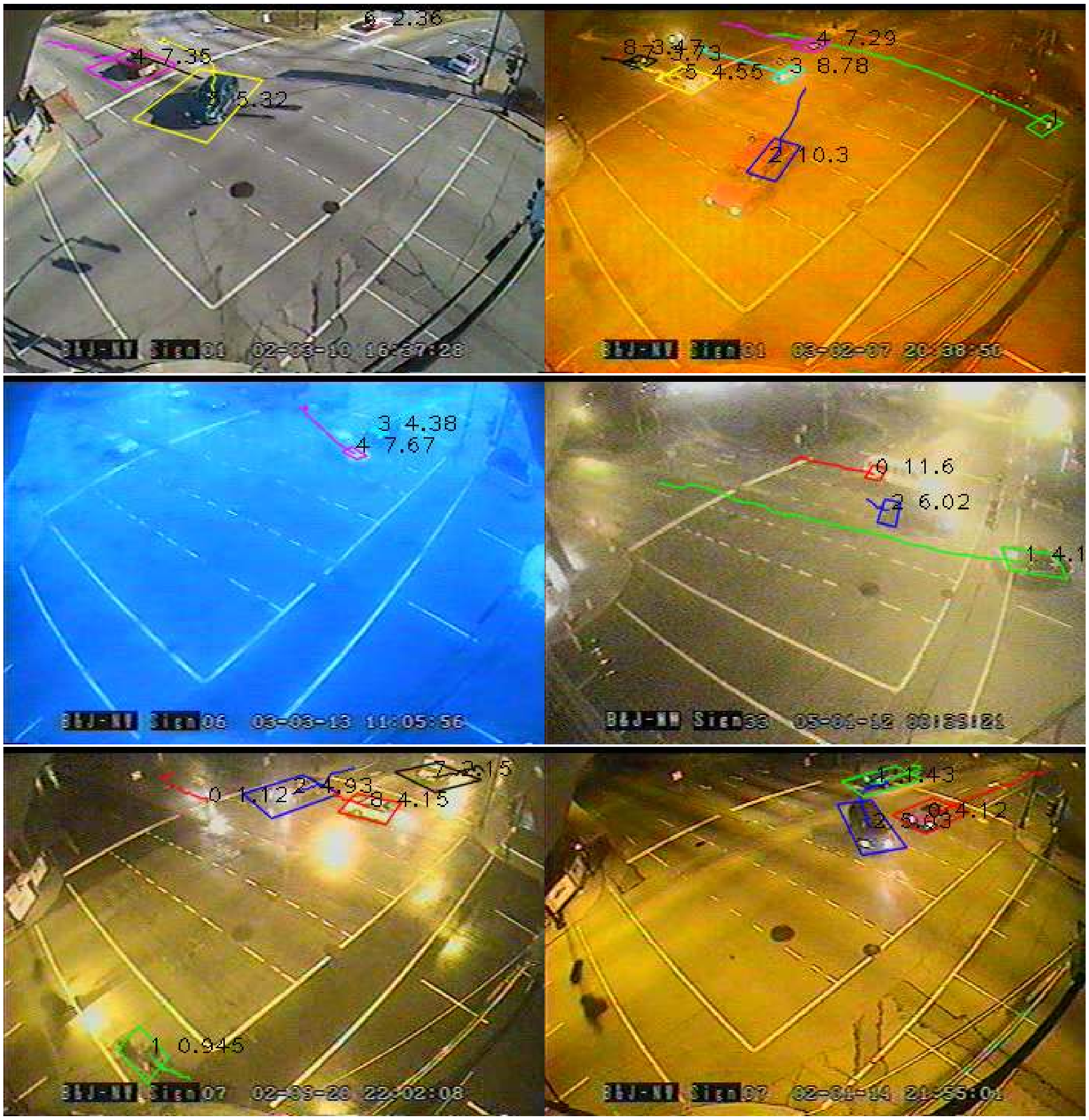

FIGURE 4 Example of video recording conditions, with road users tracks, id number and speed overlaid.

The calibration of the scene is necessary to recover the real-world positions of the road users from their coordinates in image space. A robust method was developed to integrate various pieces of geometric information found in urban traffic scenes and address situations where little is known about the location, which is common when data is obtained from traffic cameras installed previously (*26*) (See Figure 3). The quality of the video data makes road user detection and tracking challenging. The video recordings have a resolution of 352 pixels in width by 240 pixels in height, and varying levels of compression, color aberrations..., affecting the image quality. All the challenging conditions are covered, with various times of recording (day and night) and weather conditions: sunny days cause strong shadows, there are many cases of snow, fog and rain (some-times at night, in which case the reflection of vehicle headlights causes particular glare). Although these issues made some recordings impossible to analyze, road users' detection and tracking was possible in most recordings (See Figure 4), using a video-based system developed previously (*4*). The parameters for tracking were taken from a previous validation study done on a separate dataset in which an automated search for the best parameters was conducted (*27*).

The distribution of road user trajectories, in the form of prototype trajectories, was learnt using a distance of 4 m (*24*). All pairs of road users existing simultaneously are considered. If they satisfy the conditions of interaction, their positions are extrapolated using the prototypes, the collision points are identified and the severity indicators computed automatically. The distance threshold for the proximity function is set to 1.7 m, which corresponds to a typical minimum width of current cars. Assuming that road users' estimated positions are close to their centers, being at a distance less than this threshold means a collision occurred or was barely avoided.

Example of Interactions

Most interactions of interest in the dataset are either categorized as side or parallel interactions, on which the rest of this study will focus. The collision probability and TTC as a function of time are represented for a few interactions of the two subsets in Figure 5. It was found that the severity index did not carry much additional information (it basically combines the collision probability and TTC) and is therefore not displayed. A very distinctive feature is that overall, the TTC exhibits a decreasing trend as time goes by for collisions, as one would expect. On the contrary, the TTC reaches a minimum then increases again for the traffic conflicts, as the road users manage to avoid the collision. It may be surprising that extrema for the two indicators may be reached at different instants. Yet the gap is typically limited and is related to difficult tracking and movement extrapolation when the road users get very close.

Distribution of Indicators and Collision Points

To plot the distributions of indicators for all interactions, we need an aggregated measure to characterize each interaction. A method similar to the one adopted in (*5*) is used, namely to average the n maximum (respectively minimum) values for the collision probability (respectively for the TTC). The distributions are drawn for interactions with an aggregated collision probability above a given threshold, set to 0.1 in these results. The distributions are plotted for the two subsets of traffic conflicts and collisions in Figure 6. It would be expected that collisions would exhibit more severe indicator values. This is not completely obvious on the plots, although collisions reach higher collision probabilities and there is a high proportion of them with TTC around 0.5 and 1 second. The two-sample Kolmogorov-Smirnov test was used to compare the sample distributions of each of the two indicators for the two subsets: the distributions were found to differ significantly at 4 % and 1 % respectively for the collision probability and the TTC.

It is also possible to study the spatial distribution of the interactions and in particular their potential collision points. For the same interactions as previously, the maps of all the collision points are plotted in Figure 7. It can be seen that the distribution is quite different, although conclusion are difficult to draw since the conditions of the data collection are unclear. This type of visualization should be useful to explore large amounts of microscopic road safety data.

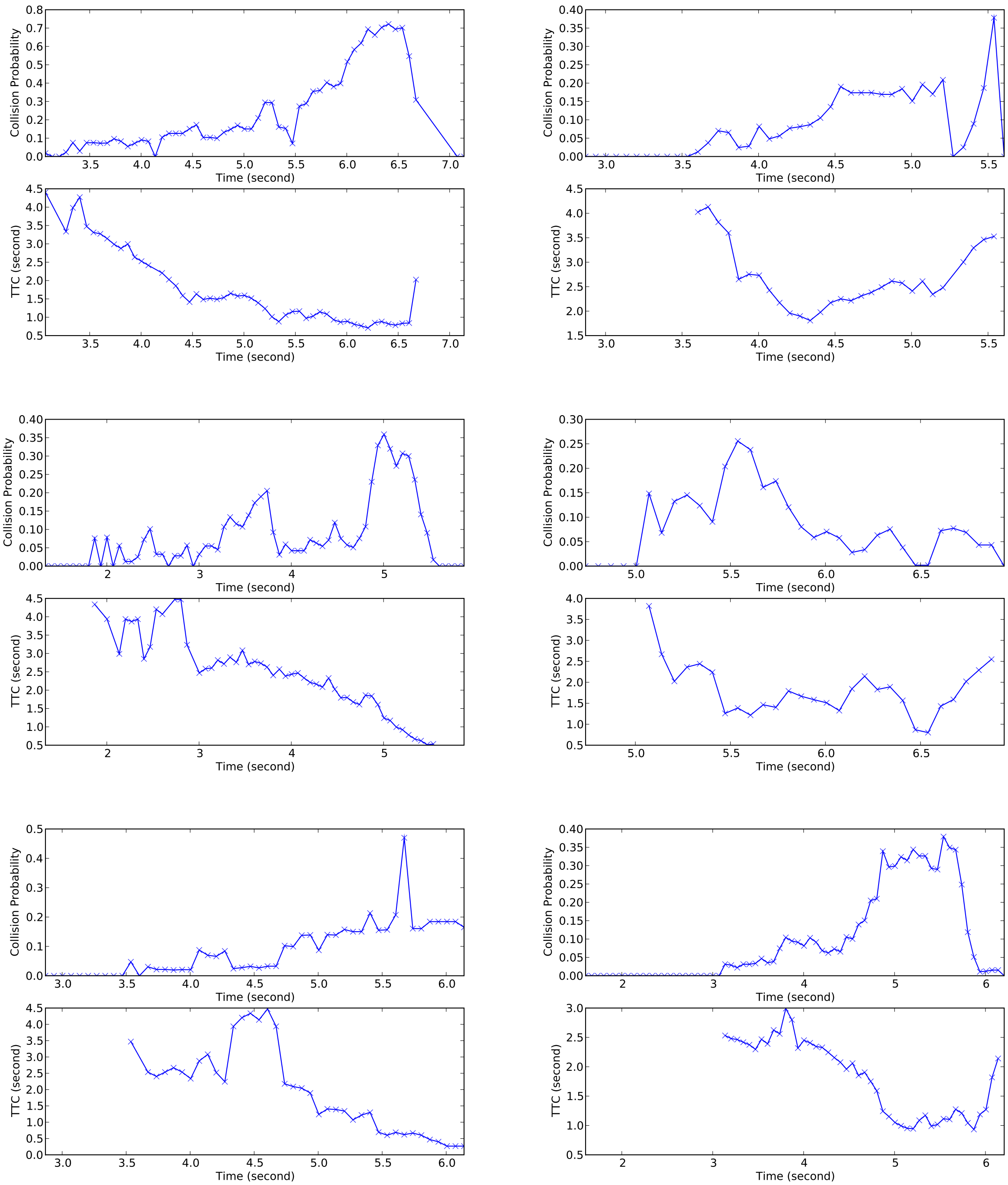

FIGURE 5 Plots of the collision probability and TTC at each instant for a small sample of interactions (without any post-processing), from the two subsets of collisions and traffic conflicts (respectively on the left and right columns). The interactions plotted on the first two rows are categorized as side interactions, the ones on the last are categorized as parallel interactions.

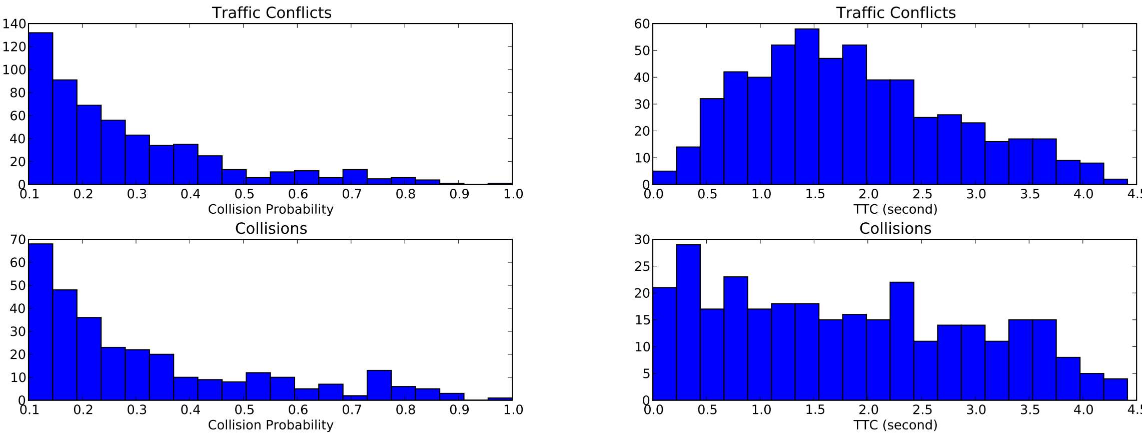

FIGURE 6 Distribution of the maximum collision probability and TTC for interactions in the subsets of traffic conflicts and collisions (respectively top and bottom histograms).

Discussion

One important aspect of this work is the level of automation of the data processing. Apart from the sample of manually chosen interactions, all the processing can be done automatically. Yet, it would be difficult to rely on the tool without verifying its output. Only the side and parallel interactions were studied in details, as the dataset contains very little actual rear-end interactions and no head-on interaction. The interactions detected by the system as rear-end or head-on cover a lot of "normal" interactions, or at least not as severe as some computed indicators could imply. These limits are first and foremost the limits of the current video-based systems for road user detection and tracking in urban intersections. The second source of errors in this analysis was the challenging data quality and the lack of information.

However, it is the authors' belief that this system can be useful in the exploration of road safety data. A particular focus is the development of methods robust to errors and noise characteristic of real data, to produce aggregated results such as distributions that can be used for road safety diagnosis.

Another limitation of this study is the particular dataset available, with such a high proportion of severe interactions. It is difficult to draw any conclusion, as could be done for example in studies of data collected before and after a counter-measure is implemented. The lack of "normal" traffic makes comparisons difficult, and has an influence on the distribution of the prototype trajectories used for the prediction of road users' positions. Evasive actions may therefore have been picked up as prototype trajectories. It is believed that the impact is limited as these trajectories should not be very common and have therefore low probabilities.

CONCLUSION AND FUTURE WORK

This paper has presented a refined probabilistic framework for the analysis of road user interactions. In particular, the identification of potential collision points was used to estimate collision probabilities and their spatial distribution can be visualized. The framework was applied to a large dataset of more than 300 severe interactions and collisions collected in Kentucky. Despite the lim-

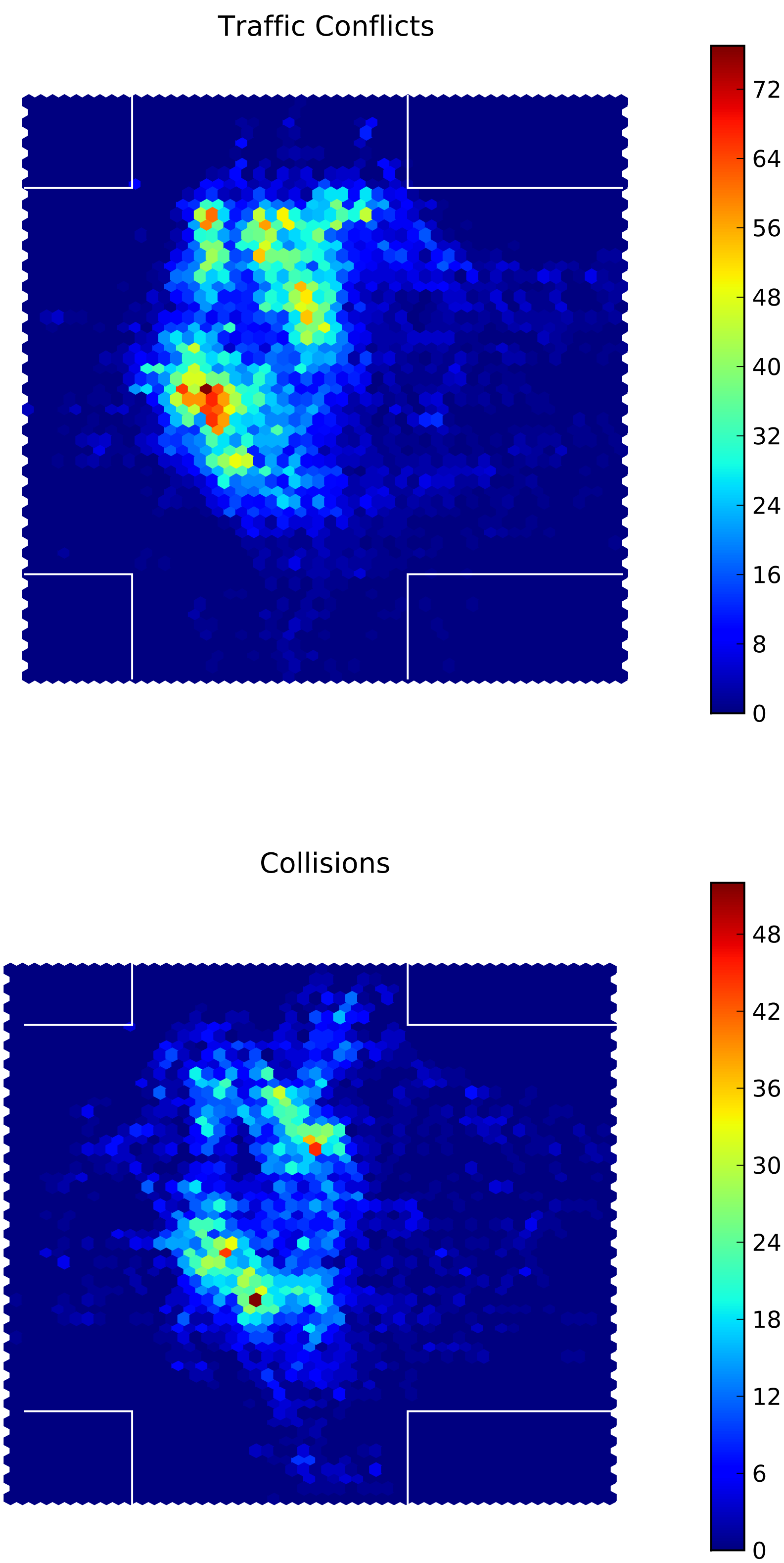

FIGURE 7 Maps of the distributions of the collision points (2D hexagonal binning plot) for the two subsets of sequences, the traffic conflicts (top) and the collisions (bottom).

ited quality of the data, the road users could be tracked and their interactions studied, including the computation of the proposed severity indicators. It demonstrates the usefulness of the approach in studying road user behavior and mechanisms that may lead to collisions.

Future work will explore the possibility of simulating the future positions to generate more varied outcomes and improve the robustness of the computation of the probability of collision. It will also focus on the validation of the proposed measurements and severity indicators with respect to other methods for road safety analysis, in particular based on historical collision data.

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REFERENCES

[1] Archer, J., *Methods for the Assessment and Prediction of Traffic Safety at Urban Intersections and their Application in Micro-simulation Modelling*. Academic thesis, Royal Institute of Technology, Stockholm, Sweden, 2004.

[2] Cunto, F., *Assessing Safety Performance of Transportation Systems using Microscopic Simulation*. Ph.D. thesis, University of Waterloo, 2008.

[3] Gettman, D. and L. Head, *Surrogate Safety Measures From Traffic Simulation Models, Final Report*. Federal Highway Administration, 2003.

[4] Saunier, N. and T. Sayed, A feature-based tracking algorithm for vehicles in intersections. In *Third Canadian Conference on Computer and Robot Vision*, IEEE, Québec, 2006.

[5] Saunier, N. and T. Sayed, A Probabilistic Framework for Automated Analysis of Exposure to Road Collisions. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2083, 2008, pp. 96–104.

[6] Svensson, A. and C. Hydén, Estimating the severity of safety related behaviour. *Accident Analysis & Prevention*, Vol. 38, No. 2, 2006, pp. 379–385.

[7] Amundsen, F. and C. Hydén (eds.), *Proceedings of the first workshop on traffic conflicts*, Institute of Transport Economics, Oslo, Norway, 1977.

[8] Davis, G. A. and P. Morris, Statistical versus Simulation Models in Safety: Steps Toward a Synthesis Using Median Crossing Crashes. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2102, 2009, pp. 93–100, 09-1989.

[9] Hakkert, A. and L. Braimaister, *The uses of exposure and risk in road safety studies*. SWOV, Leidschendam, 2002.

[10] Elvik, R., A. Erke, and P. Christensen, Elementary units of exposure. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2103, 2009, pp. 25–31.

[11] Sayed, T., G. R. Brown, and F. Navin, Simulation of Traffic Conflicts at Unsignalised Intersections with TSC-Sim. *Accident Analysis & Prevention*, Vol. 26, No. 5, 1994, pp. 593–607.

[12] Sayed, T. and S. Zein, Traffic conflict standards for intersections. *Transportation Planning and Technology*, Vol. 22, 1999, pp. 309–323.

[13] van der Horst, R., *A time-based analysis of road user behavior in normal and critical encounter*. Ph.D. thesis, Delft University of Technology, 1990.

[14] Tarko, A., G. A. Davis, N. Saunier, T. Sayed, and S. Washington, *Surrogate Measures of Safety*. White paper, ANB20(3) Subcommittee on Surrogate Measures of Safety, 2009.

[15] Songchitruksa, P. and A. P. Tarko, The extreme value theory approach to safety estimation. *Accident Analysis & Prevention*, Vol. 38, No. 4, 2006, pp. 811–822.

[16] Davis, G. A., J. Hourdos, and H. Xiong, Outline of Causal Theory of Traffic Conflicts and Collisions. In *Transportation Research Board Annual Meeting Compendium of Papers*, 2008, 08-2431.

[17] Atev, S., H. Arumugam, O. Masoud, R. Janardan, and N. P. Papanikolopoulos, A vision-based approach to collision prediction at traffic intersections. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 6, No. 4, 2005, pp. 416– 423.

[18] Hu, W., X. Xiao, D. Xie, T. Tan, and S. Maybank, Traffic Accident Prediction using 3D Model Based Vehicle Tracking. *IEEE Transactions on Vehicular Technology*, Vol. 53, No. 3, 2004, pp. 677–694.

[19] Kamijo, S., Y. Matsushita, K. Ikeuchi, and M. Sakauchi, Traffic Monitoring and Accident Detection at Intersections. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 1, No. 2, 2000, pp. 108–118.

[20] Kim, Z., Real time object tracking based on dynamic feature grouping with background subtraction. In *Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, 2008, pp. 1–8.

[21] Laureshyn, A. and H. Ardö, Automated Video Analysis as a Tool for Analysing Road Safety Behaviour. In *ITS World Congress*, London, 2006.

[22] Messelodi, S. and C. M. Modena, *A Computer Vision System for Traffic Accident Risk Measurement: A Case Study*. ITC, 2005.

[23] Macedo, J., C. Vangenot, W. Othman, N. Pelekis, E. Frentzos, B. Kuijpers, I. Ntoutsi, S. Spaccapietra, and Y. Theodoridis, Trajectory Data Models. In *Mobility, Data Mining and Privacy* (F. Giannotti and D. Pedreschi, eds.), Springer Berlin Heidelberg, 2008, pp. 123–150.

[24] Saunier, N., T. Sayed, and C. Lim, Probabilistic Collision Prediction for Vision-Based Automated Road Safety Analysis. In *The 10^{th} International IEEE Conference on Intelligent Transportation Systems*, IEEE, Seattle, 2007, pp. 872–878.

[25] Green, E. R., K. R. Agent, and J. G. Pigman, *Evaluation of Auto Incident Recording System*. Kentucky Transportation Cabinet, 2005.

[26] Ismail, K., T. Sayed, and N. Saunier, Camera Calibration for Urban Traffic Scenes: Practical Issues and a Robust Approach. In *Transportation Research Board Annual Meeting Compendium of Papers*, Washington, D.C., 2010.

[27] Saunier, N., T. Sayed, and K. Ismail, An Object Assignment Algorithm for Tracking Performance Evaluation. In *Eleventh IEEE International Workshop on Performance Evaluation of Tracking and Surveillance (PETS 2009)*, 2009, pp. 9–16.