

AUTOMATIC INCIDENT DETECTION AND CLASSIFICATION AT INTERSECTIONS

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Paper Number 09-0234

ABSTRACT

Collisions at intersections are common and their consequences are often severe. This paper addresses the need for information on accident causation; a knowledge that can be used to obtain more effective countermeasures. A novel method that can be applied to data recorded in a ground-based observation system or similar is proposed for classifying vehicle interactions into a set of predefined traffic scenarios. The classification is based on possible combinations of trajectories of two interacting vehicles that have passed through an intersection.

Additionally, the authors present an incident detection algorithm that uses the classified vehicle interactions. This algorithm constitutes the core of a video-based automatic incident detection at intersections (AIDI) system. The performance of the AIDI system was successfully verified both in a driving simulator and in real traffic conditions.

INTRODUCTION

In Sweden, collisions at intersections account for approximately 30% of all severe injuries and 20% of all fatalities [1]. Corresponding figures from European studies report 30% to 60% and 16% to 36% for crashes with injuries and fatalities respectively [2]. In USA, 21% of the fatalities on the roadways were related to intersections [3].

Traditionally, traffic safety research has been conducted on retrospective crash data, which has been used for continuous improvement of traffic safety [4], [5]. However, such accident data contain limited detailed information on driver behaviour; information that can be used to increase the performance of preventive safety systems and to perform needed changes in the infrastructure [6].

The concept of traffic conflicts as an alternative to crash data was first introduced in 1968 by Perkins and Harris [7]. Furthermore, the importance of describing traffic conflicts as

surrogates for collisions for safety analysis purposes has been described in the Swedish traffic conflict technique (TCT), established at the University of Lund and now generally accepted as standard [8].

Incident detection can be defined as the process of identifying the spatial and temporal coordinates of an incident. Several surrogate safety measures have been previously proposed for detecting incidents such as: Post-encroachment time (PET), Time to collision (TTC) [9] and Distance between vehicles (DBV) [10]. In spite of the many advantages related to the usage of safety measures, some fundamental issues have been identified, such as the lack of a consistent definition, their validity as a measure of traffic safety, and the reliability of their associated measurement technique [10]. An important alternative in dealing with those limitations includes the study of relationships between safety measures in order to have a better understanding of traffic conflicts and the safety effects of those measures [11].

Several "on road" studies have been conducted to learn more on, e.g., driver behaviour [12] and even larger studies are planned for the near future [13]. These studies equip vehicles with cameras and extra sensors and store data during both normal driving conditions and traffic conflict situations. Another way to increase knowledge on driver behaviour is to equip parts of the traffic environment, e.g. intersections, with a ground-based observation system that uses cameras to observe the traffic flow [14]. One of the main challenges with such systems is to assess the collected data and extract relevant information. The vast amount of data from the observation system needs to be processed before any conclusions can be drawn.

This paper presents basic and fundamental methods for processing data from ground based observation systems to classify vehicle interactions into typical traffic scenarios and detect incidents or accidents for later analysis. The present study was carried out within a larger Swedish project involving several

partners from the industry, government and academy [15]. Focusing on intersections, three different data collection methods were used. One of them consisted of a ground-based observation system.

OUTLINE

This study extends over five main steps, illustrated in Figure 1, for processing continuously recorded real world data with the purpose of extracting relevant information for traffic safety research. The first step comprises assessing and structuring the **input data**. Next, definitions of zones and trajectories considering the size and layout of the studied intersection form the basis of the **traffic situation classification method**. Here, the classification of vehicle interactions into predefined scenarios is one of the desired outputs. The **automatic incident detection at intersections (AIDI) method** calculates a number of established safety indicators and a combination of these is suggested to estimate the crash risk for every interaction of two vehicles. The **validation** of this incident detection method is performed by processing data from a driving simulator study. Both methods are applied to real world traffic data in a **case study**. These steps are described in detail in the following sections.

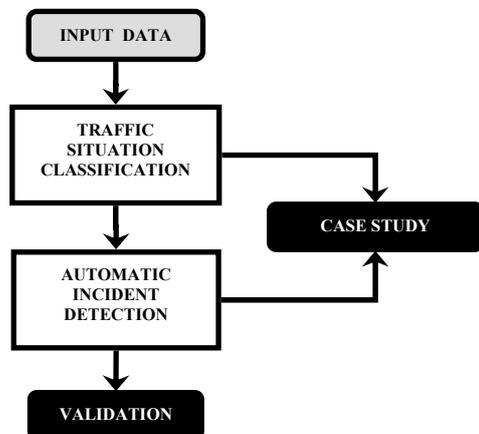


Figure 1. Process description.

INPUT DATA

The input data used for developing the methods should contain information about the vehicles and the geometrical layout of the intersection. That kind of information can be collected using camera-based computer tracking of vehicles, driving simulators involving test persons, or fully generated by traffic simulators.

In the required structure of the input data, every object/vehicle is described with several attributes; from which the most relevant in the design and implementation of these methods are:

- Size (width, length and height)
- Time stamps
- Position (central point)
- Speed
- Acceleration
- Orientation (vehicle heading angle)

TRAFFIC SITUATION CLASSIFICATION

With regard to the actual size and layout of the studied intersection, a number of concepts that describe the traffic flow are defined. This step in the process describes how the intersection is first divided into **zones** according to its geometry, and then how these zones are used to identify vehicles' **trajectories**. Next, different types of interactions, classified into **scenarios**, can be found from different combinations of trajectories.

Trajectories - The trajectory classification is based on a *road segmentation process* which divides the layout of the intersection into zones, as shown in Figure 2.

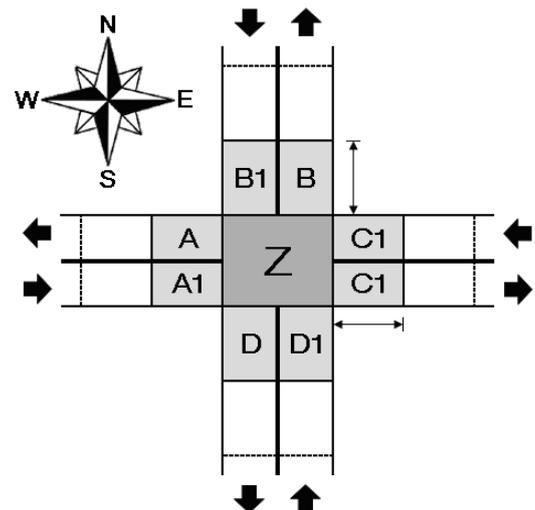


Figure 2. Definition of zones for a typical 4-way intersection. The shaded regions constitute the core of the intersection and the big arrows indicate the traffic flow directions.

In a typical intersection it is possible to identify and define *entry*, *exit* and *central* zones. Considering the dynamics of vehicles that pass through the intersection, the labels used to identify those zones are:

- Entry zones: A1, B1, C1 and D1
- Exit zones: A, B, C, and D
- Central zone: Z

The length of the entry zones can be altered and typically set to 5-10 m. The *intersection centre*

is the region where all four lanes merge together, starting where incoming vehicles begin to turn. In Figure 2, the centre is represented by the central square labelled with Z. This is the zone where most encroachment incidents and other conflicts are likely to happen and where it is possible to identify clusters of conflict locations and discover groups of events with similar driving patterns. The *intersection core* consists of the central zone and four entry and exit zones surrounding it.

Finally, a *trajectory type* is identified according to the sequence of zones that a vehicle visits. Table 1 lists all possible trajectories specifying a vehicle's transition *from an entry zone to an exit zone* (through the central zone). According to traffic rules, there are four correct possible ways to arrive at the central zone and four possible ways to exit it: turn right, go straight, turn left or make a U-turn. Thus, there are 16 different trajectories in a 4-way intersection.

Table 1.
Numbering scheme for traffic-permitted trajectories

| Trajectory ID | Entry Zone | Exit Zone |
|---------------|------------|-----------|
| 1 | A1 | D |
| 2 | A1 | C |
| 3 | A1 | B |
| 4 | A1 | A |
| 5 | B1 | A |
| 6 | B1 | D |
| 7 | B1 | C |
| 8 | B1 | B |
| 9 | C1 | B |
| 10 | C1 | A |
| 11 | C1 | D |
| 12 | C1 | C |
| 13 | D1 | C |
| 14 | D1 | B |
| 15 | D1 | A |
| 16 | D1 | D |

Interactions - The second step identifies fundamental concepts of the interactions between vehicles: the *number of vehicles* and the *scenario type*. Also, the identification process is restricted to interactions happening in the intersection core during a specific time window.

First, the *number of vehicles* is defined as the total number of vehicles present in the intersection core during a time-unit.

Then, according to the number of vehicles, the following three main cases of *interactions* are identified: the single-car case, the fundamental

two-car case, and the general multiple-car case. A single-car case refers to the situation in which only one vehicle passes through the intersection during a time-unit. Two-car cases are defined whenever two vehicles are observed in the intersection during the time unit. Multiple-car cases are treated as simultaneous combinations of two-car cases. When there is a multiple-vehicle interaction, the related number of cases is obtained by Equation (1).

$$N_{scenario} = \sum_{i=1}^{n-1} i = \frac{n(n-1)}{2}, \quad (1)$$

where n is the total number of vehicles in the intersection during the unit time.

Finally, all the interactions between two vehicles are further classified into *scenarios* according to the combination of the vehicles' trajectories. 6 main categories of scenarios are defined:

- **Crossing** - scenarios with vehicles with intersecting paths.
- **Merging** - scenarios with vehicles moving from different into the same direction.
- **Splitting** - scenarios with vehicles moving from the same into the different directions.
- **Following** - scenario with one vehicle behind another vehicle that is moving ahead or waiting.
- **Oncoming** - scenario with oncoming traffic, none of the parties have the intention to turn and cross over the opposite lane.
- **General** - any other scenario.

Specific cases are defined and identified within each of the 6 main categories of scenarios. For example, there are four cases of crossing-path scenarios: Left Turn Across Path/Opposite Direction (LTAP/OD), Left Turn Across Path/Lateral Direction (LTAP/LD), Straight Crossing Paths (SCP), and Leaving by Left - Arriving by Right (LL-AR). These four cases, shown in **Figure 3**, are the focus of the analysis in the upcoming case study. Appendix 1 lists more specific cases identified within each of the other 5 main categories of scenarios.

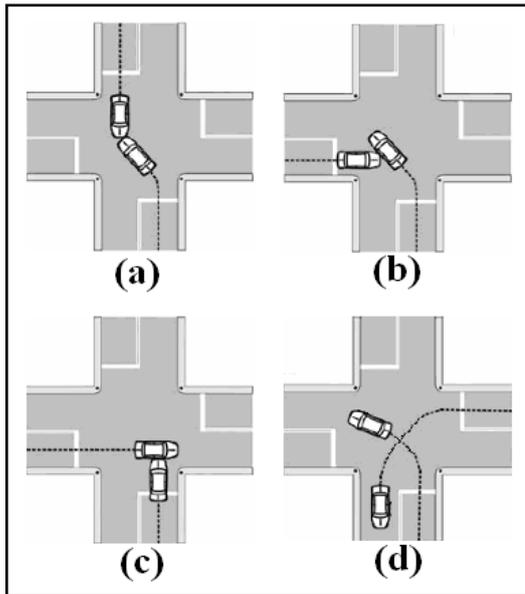


Figure 3. Scheme and graphical representation of crossing-path scenarios: (a) LTAP/OD, (b) LTAP/LD, (c) SCP and (d) LL/AR.

AUTOMATIC INCIDENT DETECTION AND CLASSIFICATION AT INTERSECTIONS

In this step, an algorithm is proposed for detecting and classifying incidents at intersections. The target cases of the present study are *2-vehicle interactions classified as crossing scenarios*; i.e., cases within the scenario type LTAP/OD, LTAP/LD, SCP or LL/AR.

First, several safety measures are computed for every interaction and are then used to build *crash risk indicators* (CRI). Secondly; since different sources of processed traffic flow data can have different levels of noise and usability, the proposed idea is to combine several CRIs to obtain a reliable and robust method for detecting and classifying incidents.

Crash Risk Indicators (CRIs)

For each 2-vehicle interaction, the following safety measures are computed:

1. Post encroachment time (PET), defined as the time measured from the moment in which the first road user leaves a potential collision zone, known as the encroachment zone, to the moment in which another road user enters this zone [16].
2. Time to collision (TTC), defined as the extrapolated time until a collision would occur keeping constant the heading and speed of both interacting vehicles [17].

TTC is a continuous measure computed during all the interaction and TTC_{min} is the minimum value of the TTC vector.

3. Distance between vehicles (DBV), defined as the estimated distance between the two closest points corresponding to each vehicle [18].
4. Acceleration rate (AR) of the first vehicle passing through the encroachment zone. The aim is to assess if any road user requires to accelerate in an unusual way in order to avoid a collision.
5. Deceleration rate (DR) of the second vehicle passing through the encroachment zone. The aim is to assess if any road user requires to brake unusually in order to avoid a collision.

The values of the above measures, together with related safety thresholds and guidelines proposed in the literature, are used to estimate CRIs normalised to the range [0,1]. The smaller the CRIs are, the less risky the corresponding interaction is assumed to be.

When referring to PET, van der Horst [9] states that an interaction can be considered as safe whenever this time measure is greater than 2 seconds. Thus, the PET-CRI, C_{PET} , is 0 for PET values bigger than or equal to 2 s., and is proposed to increase linearly as PET decreases (down to 0 seconds). The TTC_{min} -CRI, C_{TTC} , is computed similarly considering a safety threshold equal to 1.5 seconds [9].

The computation of the DBV-CRI, C_{DBV} , takes also into account the mutual approaching speed (AS) of two interacting vehicles. C_{DBV} is basically the result of the integration over time of a function that combines DBV and AS. It is small when DBV is big and AS is small, and it increases linearly as DBV decreases and AS increases.

Consider Figure 4 for the computation of the CRIs related to the AR and DR measures, C_{AR} and C_{DR} . There are three regions with different shading levels. It is assumed that the inner region (light shading) contains most of the combinations of speed and acceleration in normal traffic, and thus the corresponding CRI is 0. The immediate outer region (medium shading) represents the transition from normal to anomalous traffic [19]. Here, the CRI increases linearly as the combination of speed and acceleration gets closer to the outmost

region (dark shading), where it reaches its maximum value (i.e., 1). All five CRIs are gathered in an **incident vector** (I_V), as shown in Equation (2)(3):

$$I_V = [C_{PET} C_{TTC} C_{DBV} C_{AR} C_{DR}]^T \quad (2)$$

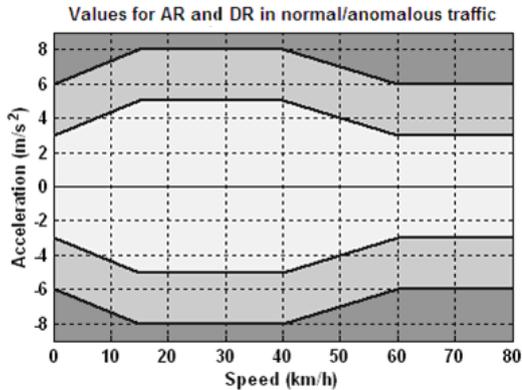


Figure 4. Definitions of the boundaries used for detecting anomalous accelerations and decelerations of a vehicle according to its actual speed (adapted from [19] and [20]). The definitions of boundaries remain constant for speeds greater than 60 km/h.

For each interaction, the **incident number** (I_N) is a global estimation of the quantified combination of the 5 contributions to risk. It is normalized to the range [0,1] and it is equal to the weighted average of the elements of the incident vector as shown in Equation (3):

$$I_N = \frac{\sum_{i=1}^5 W_i I_{V_i}}{\sum_{i=1}^5 W_i} \quad (3)$$

The higher the value of I_N is, the riskier the corresponding interaction is assumed to be. The elements of the weight vector $\mathbf{W} = [W_{PET} W_{TTC} W_{DBV} W_{AR} W_{DR}]^T$ can be used as calibration parameters in order to deal with different quality levels of the input data that should be processed. Considering the characteristics of the data described in the Case Study and Validation sections—which were continuously used during the implementation—an appropriate choice for the weight vector is: $\mathbf{W} = [1,1,1,1,1]^T$, since it has proved to generate representative values for I_N .

Incident Classification

In general, qualitative definitions of traffic events have been identified by Hydén [8], such as:

- **Undisturbed passage** - A road user is passing through an intersection without

being influenced by the presence of any other road user at all.

- **Potential conflict** - Two road users are approaching each other in such a manner that the occurrence of a conflict is imminent unless some avoidance action is undertaken by either one of the road users involved. Ample reaction time is at hand, offering margins to compensate for a mistake.
- **Slight conflict** - Two road users are approaching each other in such a manner that the risk of a serious conflict is obvious. Time margins are fairly small, thus demanding a rather precise and alert action to avoid an accident.
- **Serious conflict** - Two road users appear in a situation that demands sudden and severe action to avoid an accident. A small number of serious conflicts lead to accidents because the available margins are not large enough. Therefore, the outcome of a serious conflict may be a near-accident or an accident when a physical collision happens.

By observing interactions (animations and/or video files) and by considering the definition of the above four types of incidents, it is possible to subjectively estimate three **incident thresholds** for I_N that classify an interaction as whether an undisturbed passage (U), a slight conflict (S), a serious conflict (also near-accident, N) or as an accident (A).

Thresholds are named in the following way: I_{us} to distinguish between U and S, I_{sn} to distinguish between S and N, and I_{na} to distinguish between N and A. Then, interactions are classified according to the value of I_N as shown in Equation (4):

$$\text{Interaction} = \begin{cases} \text{Undist. Passage} & \text{if } 0 \leq I_N < I_{us} \\ \text{Slight conflict} & \text{if } I_{us} \leq I_N < I_{sn} \\ \text{Near-accident} & \text{if } I_{sn} \leq I_N < I_{na} \\ \text{Accident} & \text{if } I_{na} \leq I_N \leq 1 \end{cases} \quad (4)$$

Where the proposed values for the thresholds are: $I_{us} = 0.15$, $I_{sn} = 0.20$ and $I_{na} = 0.35$.

VALIDATION OF THE INCIDENT DETECTION METHOD

Within incident management systems, most of the subsequent incident management actions are commenced only after the existence of an

incident has been confirmed, therefore the verification step is a fundamental and required part of a complete incident detection system [14]. Data from an experimental study in a driving simulator was used for validating this incident detection method. In total, 105 participants completed a simulator drive with different road environments including events such as intersection scenarios. The simulator provides all the required data to apply this method; such as time stamps, size of vehicles, position, heading, speed and acceleration. Video files of the front view were recorded by the simulator system and videos of the driver's face were recorded by a faceLAB system [21]. During the driving test, the subject estimates the collision risk and tells it out directly after the event. After the experiment was over, trained technicians conducted a subjective off-line assessment of the crash risk present in each interaction.

The AIDI method was applied to a data subset that corresponds to moments in which the simulated vehicle driven by the participants was involved in an LTAP/OD scenario. Table 2 shows examples of the direct relation found between the quantitative crash-risk assessment provided by the computed I_N 's and the qualitative evaluations provided by the technicians. This comparison shows effectively that the estimated crash risk given by I_N constitutes a reliable quantification of what actually happened in the analysed L ATP/OD interactions.

Table 2.
Comparison of different criteria to assess the crash-risk present in some interactions of the simulator study

| I_N | Comments |
|-------|-------------------------------------|
| 0.05 | Smooth braking, normal passage |
| 0.19 | Sudden braking, interrupted passage |
| 0.25 | Hard braking, near accident |
| 0.79 | Accident |

CASE STUDY

The traffic situation classification and incident detection systems developed in the present study are applied to video-processed data from an intersection that has been filmed. The main outcomes of the automatic analysis provide basic information about traffic flow patterns (such as trajectories and scenarios) and estimations of the crash risk present in crossing-path interactions.

Input Data

The data was collected during day time from a non-signalized, low speed priority (50 km/h

posted speed) intersection (yield sign regulation) near the city centre of Gothenburg, Sweden. The traffic at the intersection was video recorded with two cameras placed on adjacent buildings. The cameras had 90° and 50° field of view (FOV) and were placed 18 m above the ground as depicted in Figure 5. The total video-recorded area of the intersection was approximately a 40 m radius circular area. A video processing and tracking system was applied to extract data of objects passing through the intersection and provide estimates of, e.g., the objects' position and size in real world coordinates.

More details about the locations, the video analysis procedure and the like can be found in [22].

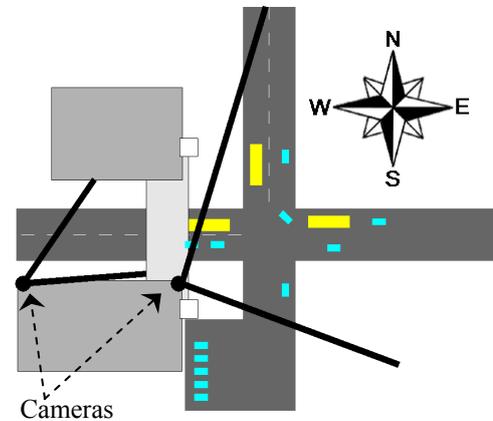


Figure 5. Intersection overview and camera locations.

The sampling frequency of the processed data is equal to 20 Hz. The definition of the intersection's layout is provided in the input data and a bird's eye view of it is sketched in Figure 5. The total amount of input data used in this case study was obtained after processing approximately 470 hours of video.

Before using the objects' data for further analysis, they were subjected to certain quality requirements. In general, the so called *appropriate objects* should have been observed during at least 2.5 s, have speeds below 200 km/h, make a single pass through the intersection only once, have an acceptable percentage of position points located inside the intersection road section and long enough trajectories.

The quality-checking procedure was designed in such a way that the greatest possible number of objects would be classified as appropriate. The criteria used are not rigid, but they proved to be an effective way to find objects with good enough trajectories in this case study data.

Traffic Situation Classification

Trajectories - Figure 6 illustrates the numbering scheme used for classifying trajectories passing through the studied intersection and also the distribution of the 6 most commonly used trajectories. Notice that the other 10 permitted trajectories (the ones that are not shown in Figure 6) involve U-turns and traffic to or from a rarely used minor road.

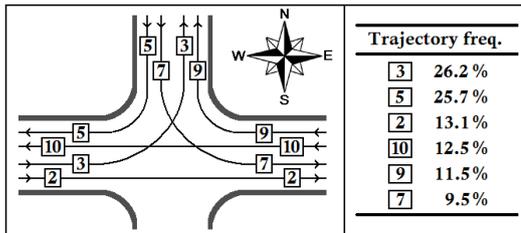


Figure 6. The most common trajectories occurring at the studied intersection and their corresponding relative frequencies.

Interactions - Table 3 shows the distribution of the number of interacting vehicles (NoV) from which the single-car situation was the most frequent. Cases that involved 6 or more vehicles could not be identified due to limitations in the extraction of data from the video files. Then, Table 4 illustrates the distribution of the scenario categories.

Table 3. The distribution of interactions as a function of the number of vehicles (NoV)

| NoV | Rel. freq. (%) |
|-----|----------------|
| 1 | 53.0 |
| 2 | 33.1 |
| 3 | 11.2 |
| 4 | 2.4 |
| 5 | 0.3 |
| 6 | 0.0 |

Table 4. The distribution of scenario categories with NoV ≥ 2 observed at the intersection

| Category | Rel. freq. (%) |
|-----------|----------------|
| Crossing | 13.09 |
| Merging | 13.10 |
| Splitting | 16.72 |
| Following | 26.07 |
| Oncoming | 16.39 |
| General | 14.63 |

Table 5 shows the distribution of crossing-path scenarios. Since trajectories going from north to south and vice-versa are very rare in this

intersection (refer to Figure 6), it is natural to expect a minimal occurrence of SCP scenarios.

Table 5. Distribution of interactions classified within crossing-path scenarios based on interactions with NoV ≥ 2 . The trajectory pairs presented are the most representative combinations occurring in each scenario

| Crossing scenario | Rel. freq. (%) | Trajectories |
|-------------------|----------------|--------------|
| LTAP/OD | 34.22 | 3, 10 |
| LTAP/LD | 20.20 | 7, 10 |
| SCP | 0.82 | Varies |
| LL/AR | 44.76 | 3, 7 |

Automatic Incident Detection at Intersections

The automatic incident detection system is based on the computation of I_N 's. Figure 7 shows a histogram of the incident numbers for all crossing-path interactions, the cumulative distribution of I_N and also sketches the location of the identified incident thresholds.

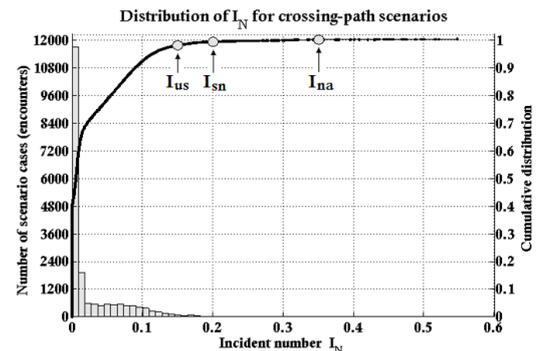


Figure 7. Histogram and cumulative distribution of incident numbers. The distribution of traffic events is: undisturbed passages (U) 93.6%, slight conflicts (S) 4.0%, serious conflicts (near-accidents, N) 1.8%, and accidents (A) 0.6%.

As stated before, there are limitations in the extraction of traffic flow data which directly influence the global performance of this incident detection system.

When viewing the corresponding video files, no incidents or accidents were encountered. The main reason for this is that the estimated shape and size of the vehicles in the case study data do not always correspond to the actual extension of the vehicles. Since the aim of the proposed method is to automatically find specific types of events for further studies, it is necessary to find a way to decrease the reality gap between the extracted data and the corresponding video files.

Representing vehicles in the same dataset with particles constitutes a good alternative to deal with the limitations in the data.

If vehicle interactions are approximated by interactions between particles (i.e., all vehicles' shapes are set to squares of 1 cm on each side), the observation and subjective classification of these interactions provide the following new values for the incident thresholds: $I_{us} = 0.007$, $I_{sn} = 0.019$ and $I_{na} = 0.071$. The corresponding new distribution of incident types is: undisturbed passages (U) 94.99%, slight conflicts (S) 2.50%, serious conflicts (near-accidents, N) 2.40% and accidents (A) 0.11%.

DISCUSSION

The formulation of these methods provides an opportunity to assess continuously recorded data and extract relevant information for driving behavior studies.

In this study, the proposed classification method is used to classify typical intersection scenarios. However, the method can also, in a logical and straight forward way, be further developed to meet the requirements of other analysis purposes. For example, will there be a difference in the distribution of classified incidents in Straight Crossing Path scenarios with both a passenger car and a truck involved compared to the same scenario where vehicles of only one type interact? Other descriptors of the involved vehicles such as "vehicle arrives at the incident area as first vs. second car" and "left turning vehicles arriving from west vs. east" are examples of information that can be added to the traffic situation classification method presented here—and hence form the basis for further behavioral studies.

Many descriptive definitions of incidents are presented in the literature (see, e.g., [8], [9], [10] and [16]), but finding arithmetical classifications is difficult. One of the closest attempts is completed in the Lund Conflict method [8], but it requires manual coding and interpretation on the scene. The proposed incident detection algorithm can be used to automatically detect potential incidents in large traffic flow data sets. The algorithm combines several measures; such as PET, TTC and DBV, to automatically detect traffic incidents. In the validation and case study sections it is indicated that the algorithm is effective. However, it shall be noted that it has not been proven that the algorithm is able to detect *all* incidents or if it does not make any false detections. Further development and verification is needed.

The incident thresholds can be verified (and tuned) by using input data from other intersections. In that case, the input data should

follow the structure of the dataset used in this project and the zone segmentation should be adjusted according to the characteristics of some specific intersection. The method can be extended to include the analysis of swerving as a type of evasive action usually present in incidents. Moreover, the vehicles' momentum can be calculated when appropriate parameters are provided in order to have a better estimation of the severity present in some incidents.

For the Automatic Incident Detection, the quality and accuracy of the data applied are significantly influencing the outcome. As an example, the estimated shape and size of the vehicles in the case study input data do not always correspond to the actual extension of the vehicles. A comparison of the outcome when representing the vehicles in the same dataset with particles shows that that is a good alternative to cope with the reality gap between the extracted data and the corresponding video files.

In the case study with real world traffic data from an intersection, adjustments according to the limitations in the extraction of data from video files were made. These can be classified into two main groups:

- *Primary limitations*; identified by the criteria of the quality-checking procedure described before (long enough trajectories in time and space, speeds below 200 km/h, single pass through the intersection and a minimal percentage of position points located within the road boundaries). All data related to objects classified as appropriate are free of primary limitations.
- *Secondary limitations*; still present in the data related to appropriate objects. The most relevant cases include trajectories that are closer to each other than in reality and incorrect estimations of the size and heading angles of vehicles.

The global quantification of the risk present in every interaction of the recorded data is based on a robust combination of five independently crash risk indicators. That combination represents an important alternative for dealing with secondary limitations present in the data.

Even though the global performance of the proposed video-based incident detection system is influenced by limitations in the extraction of data, this methodology constitutes an important approach to automatically perform several analyses of vehicle interactions and point out

interesting situations according to predefined criteria. Thus, a large amount of manual work previously used to identify certain events could now be redirected to carry out more focused investigations and provide a better understanding of those events' dynamics.

The proposed methods use data without any driver information and their outcomes do not provide descriptions of the drivers' state. There can be interactions classified as incidents in which the driver is totally aware of his/her actions and thus feeling safe all the time. For these reasons, it would be good to also consider data from other sources (such as on-road studies and follow-up interviews) in order to build a system that takes into account the drivers' states in addition to the kinematics of the interacting vehicles.

CONCLUSIONS

The proposed Traffic Situation Classification and Incident Detection methods consider basic and fundamental procedures to be used in the initial stage of the analysis process of data collected at intersections.

After considering certain quality issues, it has been shown that it is possible to analyze extracted data in order to identify and classify essential traffic flow patterns occurring at intersections; such as trajectories and scenarios.

For all vehicle interactions found in the data, several safety measures were computed and used to obtain crash risk indicators (CRIs) which are then combined to get an incident number I_N (per interaction). The interpretation of the I_N values constitutes the basis of the proposed incident detection system and should provide a more robust way to automatically detect and classify incidents. The validation of this detection system used data from a driving simulator study and showed a promising relationship between the quantitative and qualitative assessments of the crash risk provided by the I_N 's and the perceptions of the observers (trained technicians) respectively.

When applying these methods to a real world case study, it has been found that limitations in the data are significantly influencing the outcome. However, the results obtained are approximately reflecting the tendencies found in real-world-traffic statistics.

Finally, when using automatic analysis tools like the one proposed here, large amounts of manual work used to identify or isolate certain traffic events could be redirected to carry out more focused investigations and provide a better understanding of the dynamics of those events.

ACKNOWLEDGEMENTS

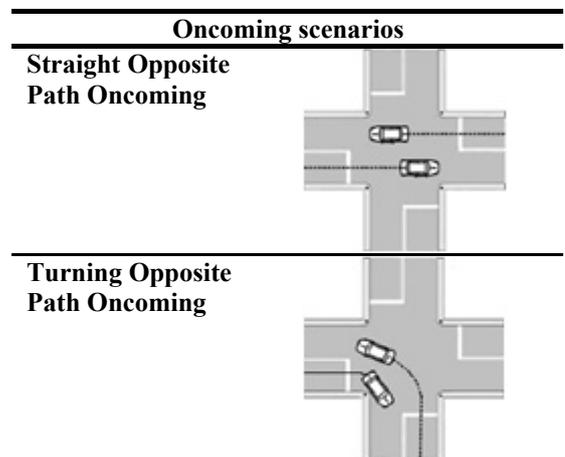
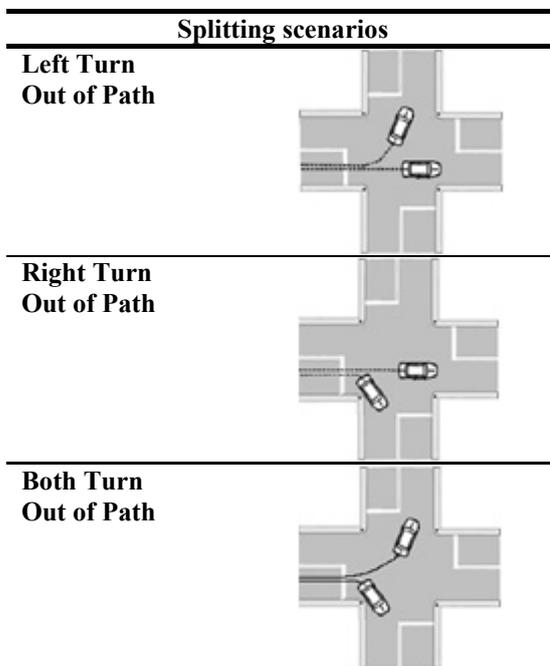
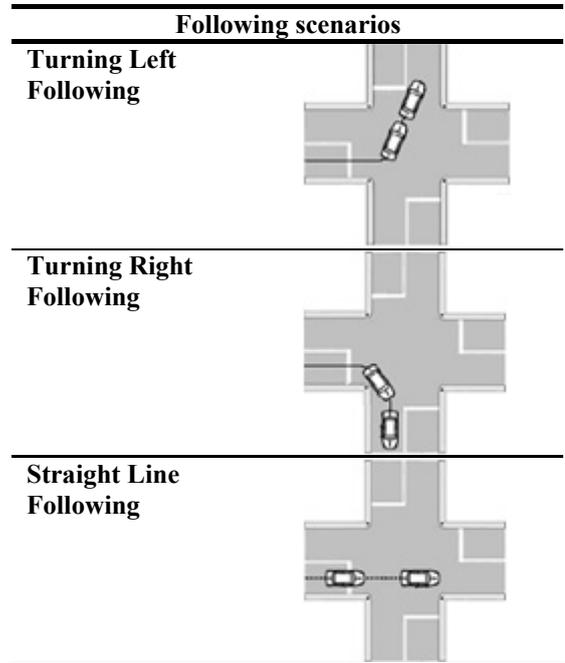
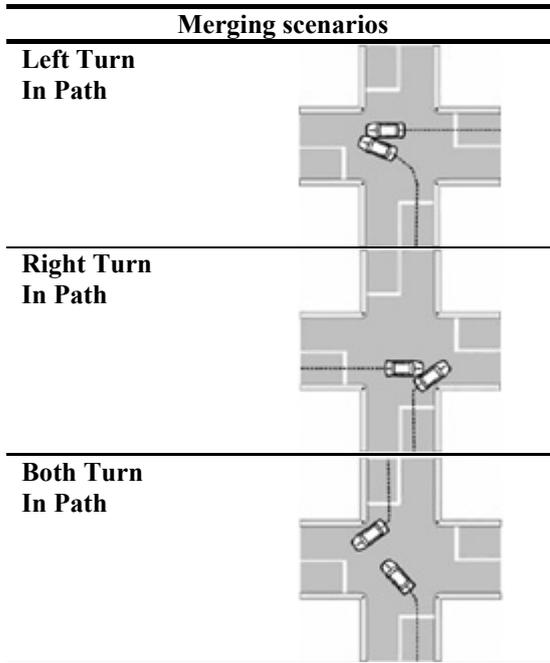
The authors would like to express their gratitude to the Intelligent Vehicle Safety Systems (IVSS) Project – Intersection Accidents: Analysis and Prevention, and especially to Jonas Bårgman.

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APPENDIX 1: SCENARIOS



General scenarios

**Missed Straight
Opposite Path
Oncoming by Right**



**Missed Straight
Crossing Path Both
by Right**



**Missed Straight
Crossing Path by
Both Sides**



**Missed Straight
Opposite Path
Oncoming Both
by Left**



**Missed Straight
Opposite Path
Oncoming Both
by Right**



**Missed Straight
Crossing Path
by Right**



Single Car

