Identification of evasive action in traffic interactions and conflicts

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Abstract

The study presents a simple and easy to implement method for detection of the evasive action start in traffic interactions. The method is based on comparison of the studied trajectory with a reference set of 'unhindered' trajectories, interpreting the start of evasive action as the moment when no more similarities can be found. The suggested algorithm performs well for primary interactions when road users arrive in an unhindered state. It fails, however, in case of secondary interaction. Traffic conflicts occur more frequently in secondary interactions, probably, due to higher cognitive load of the involved road users. Despite the limitations, the method can be used both for the safety studies based on traffic conflicts and for more general quantification and visualisation of the road user behaviour.

Keywords: collision course, evasive action, motion prediction, near-misses, Surrogate Measures of Safety (SMoS), Time-to-Accident (TA), Time-to-Collision (TTC), traffic conflicts

1 Introduction

Surrogate measures of safety (SMoS) are meant to be an alternative/complement to crash-data in traffic safety analysis (*Saunier & Laureshyn, 2021; Chang et al., 2017; Tarko et al., 2009*). The main idea behind SMoS is that near-crash events in traffic can be used as surrogates for real crashes and by studying these events it is possible to learn about safety of a specific traffic system. The advantage of using SMoS is that near-crashes occur much more frequently compared to crashes which makes it possible to directly observe these events in traffic and to perform safety studies during a relatively short period of time.

Following this idea, many different indicators have been developed that attempt identify these near-crash events (or conflicts) in traffic. Some of these indicators are based on observations from human observers while others are specifically designed to be calculated from trajectory data gathered from either video analysis or simulations.

The most frequently used SMoS indicator is Time-to-Collision, TTC (*Laureshyn et al., 2016*), which is the time remaining before the two road users collide given they continue travelling as intended. Obviously, TTC is a continuous indicator and it provides a value as long as the road users are on a collision course. The concept of TTC was introduced by *Hayward (1971)* who also argued for using the lowest TTC value during the entire interaction (TTC_{min}) since it represents the moment of the maximal proximity to a collision.

Alternatively, *Hydén (1977)* suggested to use the TTC value at the moment of the onset of an evasive action taken by one of the road users, calling it Time-to-Accident, TA. Together with Conflicting Speed (road user speed at the start of the evasive action), TA forms the basis of the Swedish Traffic Conflict Technique (*Laureshyn & Varhelyi, 2020; Hydén, 1987*).

Since more and more SMoS studies utilise trajectory data from either video analysis tools or microscopic simulations, the use of TTC_{min} has become more or less exclusive compared to TA (*Johnsson et al., 2018*). The reasons for that, however, are purely pragmatic—while it is quite straightforward to choose the lowest value in a sequence of numbers, identification of the moment of evasive action requires understanding of the interaction development process and its operationalisation is not trivial.

From the theoretical perspective, however, there are many arguments that favour TA in front of TTC_{min}. *Güttinger (1982)* introduced the two models of reasoning when defining a traffic conflict, also showing how the choice of the conflict-defining indicators has a direct impact on which track will be followed (see Figure 1). In the first model (Figure 1*a*), a conflict is defined as a set of *initial conditions* that depending on the presence and effectiveness of an evasive action either result in a collision or resolve the situation without further consequences. Defined in this way, conflicts and collisions are steps within the same causal chain, conflict being a situation that

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might, but not necessarily will, develop into a collision. This model is expandable, for example one can further construct mathematical framework that quantify the probability of a given conflict to become a crash. The beginning of an evasive action (the moment for which TA is measured) is a good candidate to define the start of a conflict since it represents the qualitative change in the situation development from unawareness of the danger to active actions to avert it.

The alternative model (Figure 1*b*) defines the conflict as the *outcome* of the evasive actions. This track is followed if conflict is defined on the basis of TTC_{min}, but also many other outcome-based indicators, such as Post-Encroachment Time, PET (*Allen et al., 1978*), as well as indicators describing the evasive action itself (*Tageldin & Sayed, 2016*; *Bagdadi, 2013*; *Gettman et al., 2008*; *af Wåhlberg, 2004*). Being defined this way, conflicts land on a parallel track with collisions since by the moment the conflict is identified we can be sure that the collision has already been avoided (knowing that the lowest TTC value is TTC_{min}, we also know that it cannot go down to zero to become a crash). Thus the theoretical foundation for using conflicts belonging to one chain of events as a predictor for frequency of crashes belonging a parallel chain of events appears to be quite shaky.

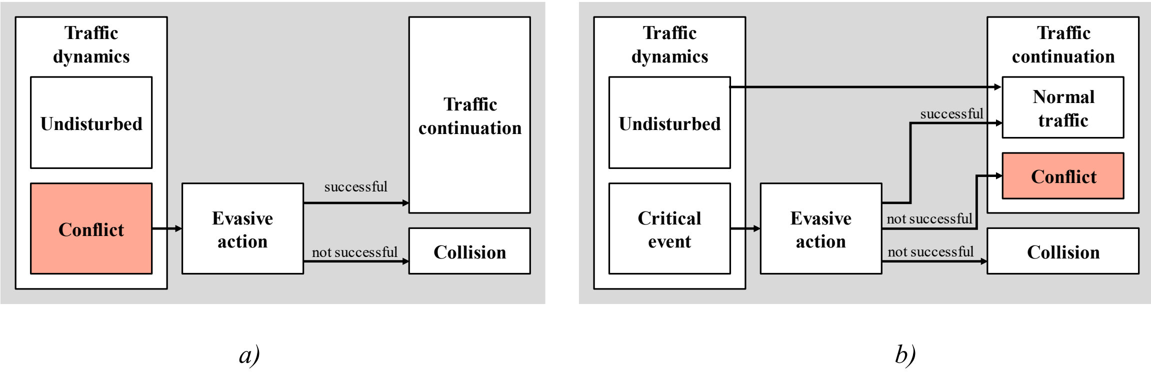

Figure 1. Two models of relation between traffic conflicts and crashes—adopted from *Güttinger (1982)*: a) conflict precedes a collision; b) conflict is mutually exclusive with a collision

Another theoretical challenge is related to the motion prediction necessary for calculation of TTC. The classical definition of TTC suggested by *Hayward (1971)* assumed that both road users will keep the same speed and heading. It has been repeatedly shown that this assumption does not hold, particularly in situations when the road geometry, the nature of the manoeuvre performed or interaction with the traffic light actually require adjustments of both speed and travelling path (*Laureshyn et al., 2017*; *Lefèvre et al., 2014*; *Mohamed & Saunier, 2013*; *van der Horst, 1990*). The simplistic kinematic-based methods for addressing the issue, such adding constant acceleration or angular speed assumptions, rather make the predictions more unrealistic than solve the problem (*van der Horst, 1990*).

Context-based motion prediction which utilises the historical trajectories of other road users performing the same manoeuvres shows better performance (*Lefèvre et al., 2014*; *St-Aubin et al., 2014*; *Mohamed & Saunier, 2013*). It is reasonable to assume that in case of no conflict, the road users would continue travelling just as many others did before them. However, as soon as they realise the danger and initiate an evasive action, using the historical data becomes irrelevant, since it comes from the situations *without* a conflict. *Lefèvre et al. (2014)* theorise that in this occasion, special interaction-aware motion models should be used. To our knowledge, however, there are hardly any models available that can describe the functional road user behaviour in a safety-critical situation. Practically, this means that while TTC calculation until the start of evasive action (moment of TA) are relatively reliable with the context-based motion predictions, any calculations after that, including the moment of TTC_{min}, involve simplistic/unrealistic assumptions and cannot be trusted.

Finally, an additional argument in favour of TA can be drawn from the studies on the human perception of the traffic conflicts. Even though human judgements are often questioned for their subjectivity, there is also a solid bulk of evidence showing that humans generally agree both in identifying the traffic conflicts and in ranking the conflicts by their severity (*Yastremska-Kravchenko et al., 2022*; *Madsen, 2018*; *Kruysse & Wijlhuizen, 1992*; *Kruysse, 1991*; *Hydén, 1987*; *Grayson, 1984*; *Lightburn & Howarth, 1979*). Traffic conflict validation studies in which observer's judgements were the main conflict definition tool or at least had potentially significant influence on how the conflicts were coded through the objective measures, show much better correlations with crash counts compared to what is found in more recent studies utilising automated methods for conflict detection (*van der Horst et al., 2017*; *Svensson, 1992*; *Hydén, 1987*; *Migletz et al., 1985*). These results point in the direction of that while we cannot fully rely on human judgements as the absolute ground truth, they may provide valuable insights in what traffic conflict 'ingredients' are important, including which moments are the most relevant, in the holistic perception of a traffic situation dangerousness by a human observer.

In the study of *Kruysse (1991)*, the observers were shown videos containing traffic conflicts, interrupted in the beginning, culmination and the final resolution stages of the conflict. The results showed, both for traffic professionals and observers with no traffic background, that the initial phase of a conflict contained sufficient information to predict the final severity score of the situation, while the later stages (culmination and resolution) hardly contributed to the opinion already formed at the beginning. The recent study of *Yastremska-Kravchenko et al. (2022)* attempted to mimic human ranking of traffic situation dangerousness using objective indicators calculated, similarly to approach used in *Kruysse (1991)*, for the start of an evasive action ('beginning'), moments of indicators reaching their extremes ('culmination') and the latest moment of the road users still being on a crossing path ('resolution'). Both the fact of presence of an evasive action and the indicator values calculated for these moments came as the strongest explanatory variables in the built decision machine (for the situations with no evasive action, the 'culmination' variables came out as significant).

It can be concluded that the moment of evasive action initiation appears to have a special meaning within the SMoS discourse both from the theoretical perspective and supported by empirical evidence. This paper suggests and tests an automated method to identify the start of an evasive action from trajectory data, as well as provide some insights related to the differences and challenges in detection of evasive actions in normal and safety-critical situations.

2 Method

This section will present a general method for identifying the start of an evasive action from any road user based on trajectory data and how a simple manoeuvre-based motion model can then be used to make motion prediction from the moment before an evasive action is detected.

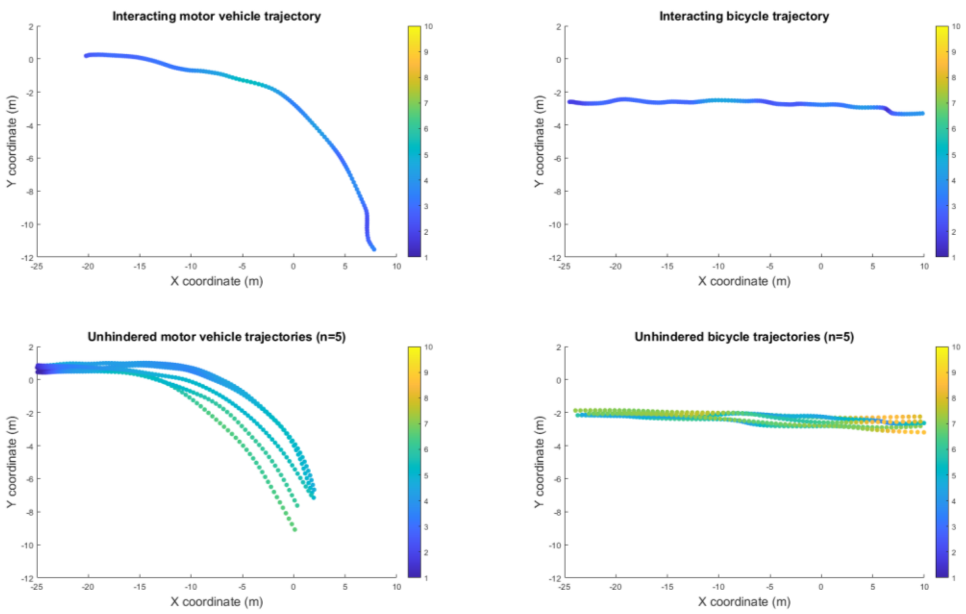

Figure 2. Trajectories from one interacting motor vehicle and bicycle (top) and a set of 5 unhindered motor vehicle and bicycle trajectories (bottom). The colour bar shows speed in m/s.

The method relies on comparing the trajectory under examination to a reference set of trajectories from unhindered road users and calculating its similarity to that set. The top two images in Figure 2 show the trajectory of a motor vehicle and a bicycle captured during their interaction. These two trajectories are then compared each with a set of trajectories from unhindered road users performing the same manoeuvre (bottom of Figure 2). If a trajectory is significantly different from the unhindered set at any point in time, this indicates that it has stopped being 'unhindered' and is therefore in an interaction (evasive action has begun).

Starting with unhindered traffic, the term refers to road users performing a certain manoeuvre without interacting with any other road user. The unhindered trajectories are meant to capture travel patterns at the studied location when the road users only negotiate the infrastructure geometry and interact with the traffic light.

The proposed method relies on two main definitions: i) what an unhindered motion is and ii) what is a proper measure of similarity between two different trajectories.

As for the similarity between trajectories, this paper proposes a simple method that relies on the average distance between two trajectories. The calculation of 'similarity' at a specific position (and time instance) of the trajectory under examination is made in two steps. First, the point in the unhindered trajectory closest the current position is identified. Second, using the closest point as a starting point for the unhindered trajectory, the distances between the points (Δs_i, see Figure 3) in the two trajectories can be calculated (of course, this assumes that the trajectory points in both trajectories have the same temporal resolution). The final 'similarity' at the timestep t is the average distance calculated from the current position and n steps backwards in time as shown in Equation (1):

$$Similarity_t = \frac{\sum_1^n \Delta s_i}{n}. \tag{1}$$

By calculating the number of similar trajectories for each time step it becomes possible to determine at what time step the evasive action starts. Figure 4 illustrates how the number of similar trajectories decreases over time during an interaction between a motor vehicle and a cyclist. Assuming that the evasive action starts when there are no more similar unhindered trajectories (i.e. no one would travel like that in an unhindered situation), it can be concluded that the motor vehicle starts interacting at the time step 49 and the cyclist at the time step 47 (see Figure 4).

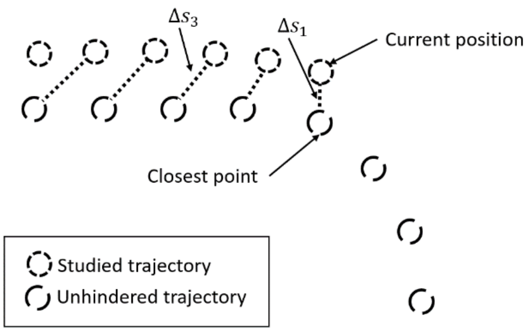

Figure 3. The calculation process for the similarity between two trajectories at a specific point in time

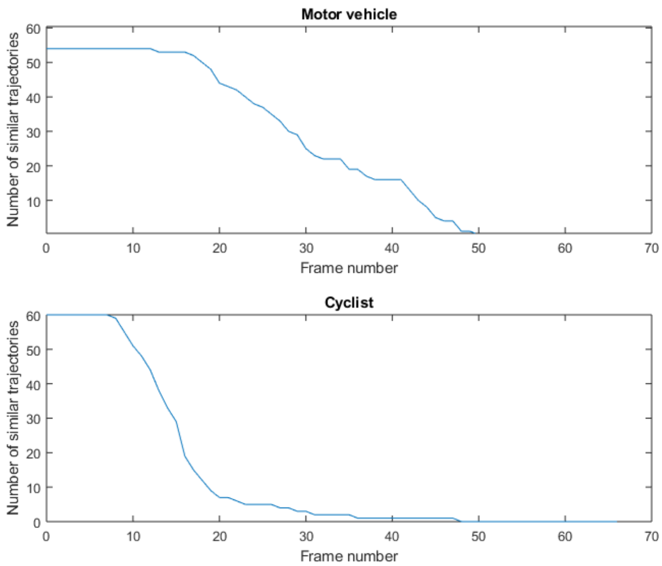

Figure 4. The number of similar trajectories for each time-step between two interacting trajectories and a set of unhindered trajectories (54 unhindered motor vehicles and 60 unhindered cyclists). The evasive action starts when there are no more similar trajectories left.

Besides the identification of an evasive action, the presented similarity concept can be used for motion prediction assuming that the studied road user would continue to travel in the same way as the trajectories found to be similar. As long as there is more than one similar trajectory, several potential future paths are possible. Figure 5 shows an example of what the predications would look for both the cyclist and the motor vehicle at a given time instance. However, this prediction is only possible while there are similar trajectories, meaning that the prediction cannot be made once an evasive action has been identified. The latest prediction can be done just one time step before the start of evasive action.

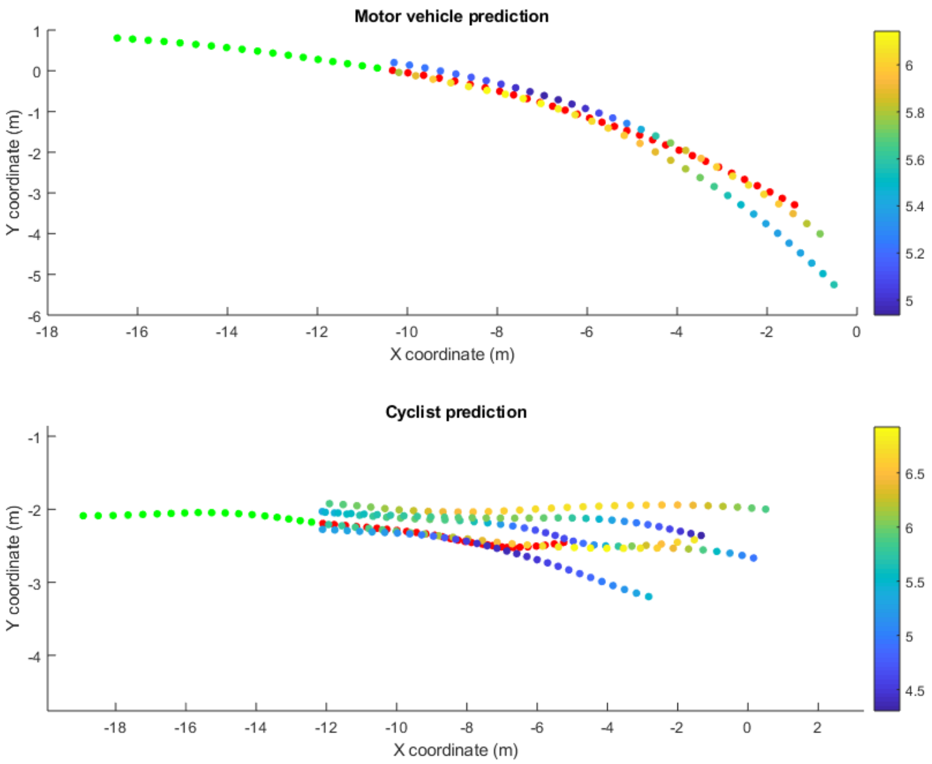

Figure 5. A visualisation of a predication made one second before the first evasive action was detected. The green trajectory shows the historic path of the road user, and the red trajectory shows the actual future path of the road user. The other trajectories ranging from blue to yellow show the predicted motion patterns from unhindered traffic with their corresponding speeds shown by the colour (m/s).

Multiple possible future paths for both the motor vehicle and the cyclists results in several possible combinations, some with a collision course and a corresponding TTC value, and some without. The probability of a collision course (PCC) can be calculated then as the share of the trajectory pairs with a collision course in the total number of trajectory combinations. As for the TTC, *Saunier et al. (2010)* provide the calculation procedure for a 'probabilistic TTC' that aggregates the individual values into one indicator:

$$TTC = \frac{\sum_{i=1}^{n}(p_i \cdot TTC_i)}{\sum_{i=1}^{n} p_i}, \quad \textbf{(2)}$$

where p_i is the probability of the road users to collide at collision point *i* and TTC_i is the predicted time at which they will reach it.

The 'probabilistic TA', accordingly, equals the TTC value at the moment of onset of the evasive action.

For the following experiments, all trajectories were produced using the T-Analyst software (*T-Analyst, 2020*). The software allows a human to browse the video frame by frame, marking positions of the road user and thus producing their trajectories (in world-co-ordinate system) and speed profiles. The screenshot of the program is shown in Figure 6.

The code for detection of evasive action, the presence of a collision course as well for calculating collision course probability was implemented in the *MATLAB* software (*MathWorks, 2022*). The collision was defined as the proximity of the two trajectory points below *0.8* meter (the trajectory point represent the middle of the road user ground projection). The trajectory data had a time resolution of *15* frames per second.

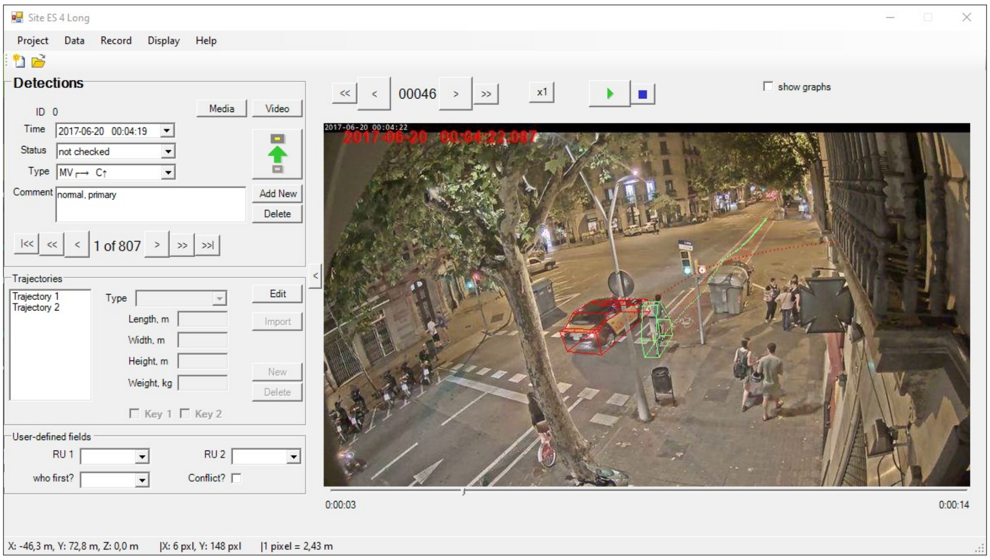

Figure 6. Screenshot of T-Analyst software

3 Dataset

3.1 Data origins

To test the proposed method, this study uses trajectories from 7 signalized intersections in Spain (1), the Netherlands (3) and Denmark (3). The data was originally gathered in the Horizon 2020 project InDeV, 'In-depth Understanding of accident causation for Vulnerable road users' (*InDeV, 2015-2018*).

Figure 7. The camera view at the seven intersections and the studied interaction (note that a thermal camera was used in Denmark and the Netherlands)

More specifically, the dataset includes trajectories from interactions between right-turning motor vehicles approaching from the intersection leg closest to the camera and straight-moving cyclists arriving from the same direction (both have green at the same time). Figure 7 shows the camera views at the seven sites.

3.2 Calibration and validation dataset

The calibration/validation dataset contained two types of data:

- **A set of unhindered trajectories for both motor vehicles and cyclists.** A human observer selected *50* trajectories of each road user type based the reasoning presented in the Method section (free passage with no interactions involved; presence of other road users on non-conflicting course was allowed). Since the speed profiles are highly affected by the traffic light, the instruction was to include both road users arriving during the green or the red traffic light phases in approximately equal proportion. The procedure was then repeated for each of the studied locations.
- **A set of events with an observable evasive action.** *48* interactions were manually selected based on the criteria that there must be a clearly observable evasive action present. *29* of these interactions come from the Spanish site and the remaining *19* were uniformly spread among the other locations. Four human observers with significant experience in traffic conflict analysis were then asked to produce the ground truth by identifying the moment of the evasive action onset in each situation. The observers had an opportunity to re-watch and examine the videos frame-by-frame if needed. The videos had a resolution of *15* frames per second (*66.7ms* per frame).

3.3 Exploration dataset

The calibrated algorithm was then applied on a large set of interactions coming from the Spanish site. This included:

- **All encounters between a motor vehicle and a cyclist within a *24*-hour period.** The encounters (n=*417*) were manually selected using the following definition—two road users must be heading towards the common conflict area in a way that: i) both road users are in motion, and the latest one should have crossed the stop line before the first one leaves the conflict area (i.e. a collision at least hypothetically should be possible); ii) if the encounter involved queueing motor vehicles or/and a group of cyclists, trajectories were only made for the pair of cyclist/motor vehicle that were closest to each other (the elaborated reasoning behind this definition can be found in *Johnsson et al. (2020)*).
- **A dataset of safety critical events (conflicts).** The conflicts (n=*142*) were manually detected from ca 6 weeks of continuous video recording. The definition of a conflict used was somewhat loose and formulated as any breakdown in otherwise smooth traffic flowing that might indicate that the safety margins were compromised. Despite the inclusiveness of this definition, the dataset has a relatively high share of serious conflicts and even actual collisions (collisions were excluded from the tests in this paper).

4 Results

4.1 Calibration

The proposed method relies on two parameters to identify similarity between the trajectories: i) a threshold for the average distance between the trajectories—the similarity value in Equation (2), and ii) a limit on how far into the past the calculation should be made— n in the same equation.

The aim of the calibration test is to find a set of parameters that provide the best agreement with the ground truth produced by the human observers. The Intraclass Correlation Coefficient (ICC) can be used to measure the reliability among several observers (or raters) (*Fisher, 1932*). The ICC produces a reliability index between *0* and *1* when comparing the result from different raters. Values less than *0.5*, between *0.5* and *0.75*, between *0.75* and *0.9*, and greater than *0.9* are indicative of poor, moderate, good, and excellent reliability respectively (*Koo & Li, 2016*). There are many different forms of the ICC index. Following the guideline by *Koo & Li (2016)*, a Two-Way Mixed-Effects Model focused on absolute agreement was chosen for the following test.

The ICC value represents the inter-rater reliability among the raters. The optimisation problem then is to find the parameter values which produces the highest ICC value between the algorithm result with human observations. For the calibration, this comparison was made using the *19* events selected from the Danish and Dutch sites. The tested combinations included distance values from *0.05* to *5* meters (*0.05m* step) and the time parameter from *1/15s* to *4s* (*1/15s* step).

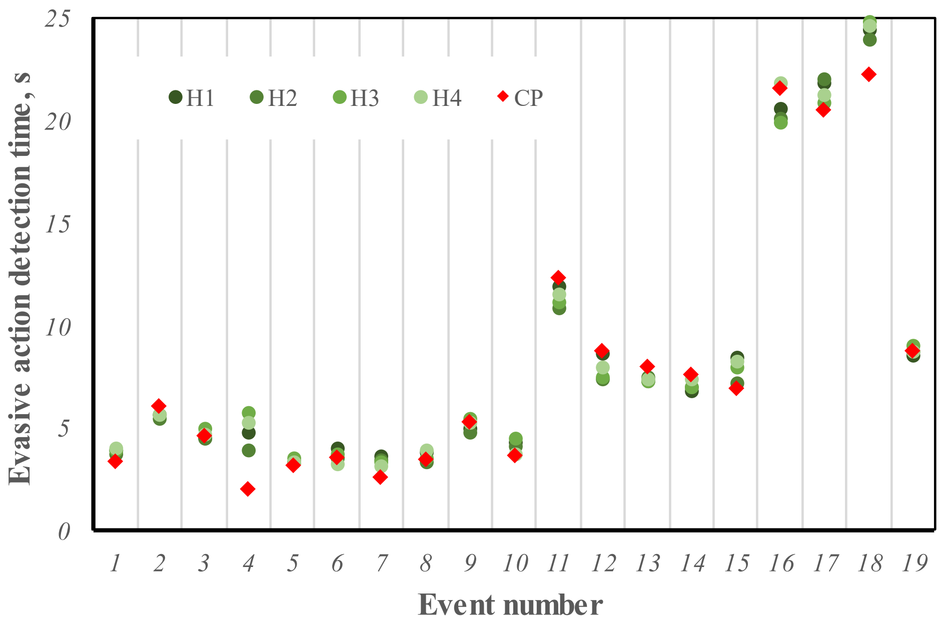

Figure 8. Time into an event when the human observers (H1–4, green) and the algorithm (CP, red) detected an evasive action.

The best result was found using an average distance value of *0.75m* and a time parameter of *1.67s* (*25* frames). Figure 8 shows the results of the human observers and the algorithm using these parameters. The Y-axis shows at what time from the start of an event the human observers (green) and the algorithm (red) have detected an evasive action. The ICC value shows an excellent reliability between the human and the algorithm results with all values above *0.99*.

While the ICC values indicates that the proposed approach shows an excellent reliability with the human observers, it is still a bit difficult to discern what this means in practice. Looking at the difference between the individual raters and the mean result reveal some further information (Table 1). Compared with the mean result, the result from the algorithm is generally somewhat early and there also seems to be a higher variation in the computer result when compared to the result from the human observers.

Table 1. The difference between the individual and the mean result from observers and the algorithm (all values in seconds)

	Mean errors	Standard deviation of error	Earliest detection compared to mean	Latest detection compared to mean
P1	*0.1*	*0.3*	*-0.3*	*0.8*
P2	*-0.2*	*0.3*	*-1.1*	*0.6*
P3	*0.0*	*0.4*	*-0.7*	*0.8*
P4	*0.1*	*0.3*	*-0.4*	*1.2*
CP	***-0.3***	***1.0***	***-3.0***	***0.9***

4.2 Validation

The aim of the validation is to test whether the proposed parameter values are suitable at another location with different design (in our case, whether the parameters calibrated on Danish and Dutch sites will still work at the Spanish site). The same algorithm parameters were applied on the remaining *29* interactions from the Spanish intersection. Figure 9 shows the algorithm results compared to the human observers. The ICC value indicate an excellent reliability between with the lowest value being *0.95*.

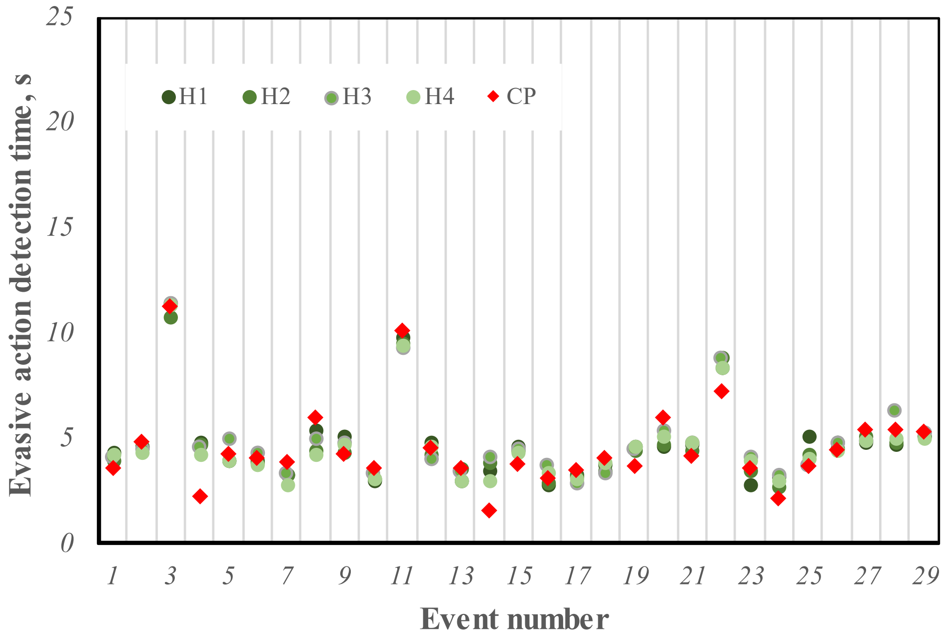

Figure 9. Time into an event when the humans (H1–4, green) and the algorithm (red) detected an evasive action.

Table 2 shows the difference between the mean human result and the individual raters. Similarly, to in the calibration, the computer result shows a larger standard deviation when compared to the humans and the computer is once again a bit early in its detections.

Table 2. The difference between the individual result and the mean result from the observers and the best computer result (all values in seconds).

	Mean error	Standard deviation of error	Earliest detection compared to mean	Latest detection compared to mean
P1	*0.0*	*0.3*	*-0.8*	*0.8*
P2	*-0.1*	*0.2*	*-0.4*	*0.3*
P3	*0.1*	*0.3*	*-0.5*	*1.1*
P4	*-0.1*	*0.2*	*-0.6*	*0.4*
CP	***-0.1***	***0.8***	***-2.3***	***1.2***

4.3 Exploration

The previous section established that the best parameter values is an average distance *0.75* meters as a similarity threshold while looking *25* frames (*1.67s*) into the past. Using these values *417* encounters and *142* conflicts (exploration dataset) between right-turning motor vehicles and cyclists observed at the Spanish intersection were analysed.

Following the structure of the proposed method, each interaction can be classified into four main categories:

1. events with no detected evasive action,
2. events with a detected evasive action with zero probability of collision course (PCC),
3. events with a detected evasive action and a non-zero PCC,
4. Abnormal and secondary events.

The first three categories follow from the method description in the method section; however, the fourth type of events were identified when analysing the explorstion dataset. These abnormal events are immediately detected as evasive actions the moment a road user enters the scene. In these cases, the algorithm is unable to make any motion predictions since no similar trajectories were ever detected. Looking at these situations in more detail, they can be further divided into two main types:

- **Type A.** In these events one or both road users show uncommon behaviour which is too different from the behaviour of the unhindered trajectories that are used by the algorithm. Some examples of such behaviours include motor vehicles turning right from the wrong lane and cyclists entering the intersection from irregular locations.
- **Type B.** The second type of abnormal events are secondary interactions in which one of the road users have already interacted with another road user before the second road user have entered the scene. The algorithm correctly identifies that an evasive action has occurred the moment in which the second road user enters the camera view but cannot make any motion predictions from that point.

Table 3 shows how the events from both exploration datasets are split between the four categories. As expected, the traffic conflicts contain significantly fewer events without any evasive actions and also contain a higher percentage of events with a non-zero PCC. There is also a higher percentage of abnormal events within the safety critical dataset.

Table 3. The result from the two datasets divided into four separate categories showing the number of events with no detectable evasive action, how many events with a zero and non-zero probability of collision course and the number of abnormal events.

Category	Encounter Events	Conflict Events
1. No evasive action	*26 (6%)*	*3 (2%)*
2. Evasive action detected, PCC=0	*286 (69%)*	*68 (48%)*
3. Evasive action detected, PCC>0	*62 (15%)*	*48 (34%)*
4. Evasive action detected immediately (abnormal/secondary events)	*43 (10%)*	*23 (16%)*
Total	*417 (100%)*	*142 (100%)*

For the events with a detected evasive action and a non-zero PCC, it is possible to further investigate the distribution of both the PCC values and the estimated probabilistic TA. The cumulative frequency distributions are shown in Figure 10. The results show a clear difference between the encounters and conflicts in both probability of a collision course and in the TA-values. This suggests that when the algorithm is able to proceed and produces the indicators values, the results are consistent with what human observers would consider to be more severe events.

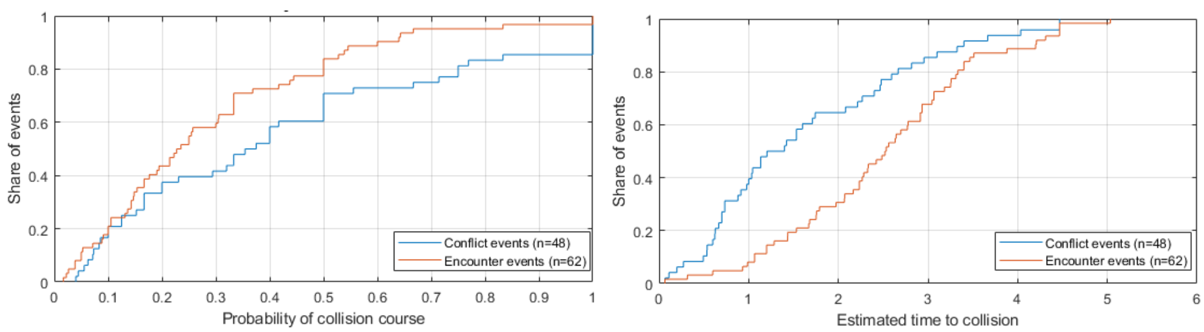

Figure 10. The cumulative frequency distribution of the probability of collision course (PCC) and the probabilistic TA average time to accident the Category 3 events.

It has been pointed out already that the share of abnormal/secondary events (category 4) is higher in the conflict dataset compared to the encounters. Further visual examination of these events indicates that out of the *43* 'normal' encounters *24* (*56%*) are caused by abnormal situations, like motor vehicles arriving from the wrong lane or the bicyclist coming from the wrong direction. In the conflict dataset, however, only *3* (*13%*) of events are explained by such abnormalities, the rest being multi-step interactions.

Such situation is illustrated in Figure 11. The studied interaction is between the car and the bicycle marked red and green respectively. However, at the moment shown in the left image, the car start braking for the cyclist ahead of the 'green' one, an evasive action being correctly detected. However, from that moment on, the car I no longer 'unhindered, which makes it impossible to detect the second evasive action that takes place at the moment shown in the right image, now for the studied 'green' bicycle.

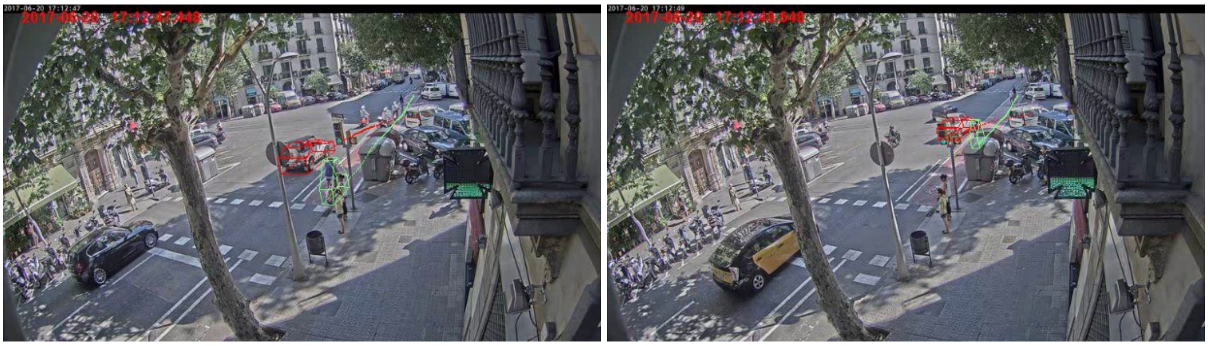

Figure 11. A secondary interaction in which the car (marked red) first brakes for one bicyclist (marked with an arrow) and then again brakes for the second bicyclist (marked green)

Visual examination of the entire dataset reveals that encounters contain *81%* of primary events (only one interaction involved) while only *60%* primary events are found among the conflicts.

5 Discussion

The calibration and validation of the proposed algorithm showed a good to excellent reliability between the human observers and the results from the algorithm. Here, some caution should be taken in interpreting the results, since the situations used both for training and validation were 'exemplary' and contained very clear and easily identifiable evasive actions. Have the evasive actions been less pronounced, a higher degree of disagreement between the human observers as well as between the observers and the algorithm could be expected.

The method performs well for primary interactions, i.e. in situations when the road users arrive from an unhindered state. It fails, however, in case a several interactions follow each other since, after the first adjustment, the road user is no longer unhindered and thus there is no data available to suggest what would be a 'normal' course of action from such starting conditions. Another problem discovered is that the evasive action is sometimes erroneously assigned to the studied interaction even though it actually belongs to an earlier interaction (as illustrated in Figure 11). This might lead to the situation being scored lower on the dangerousness scale, since the algorithm interprets it as having an early evasive action while the real evasive action is still to come later. Visual examination of the studied situations might help to identify and filter out such erroneous decisions.

The choice of the studied manoeuvre favours the algorithm performance since the right-turning vehicle and the cyclist come directly in contact with each other. This is not the case, for example, for the left-turning vehicles interacting with the same cycle flow, since before reaching the cyclists they must first negotiate the on-coming traffic.

The abnormal situations (like turning from a wrong lane) contributed to more frequent algorithm failures. However, this issue can probably be addressed by increasing the reference set of the unhindered passages so that even such unusual manoeuvres get represented. Otherwise, detection of odd situations, particularly if they are relatively frequent, might also provide valuable insights in the functioning of the studied location and what additional safety problems to anticipate that, otherwise, might not be easily identifiable without seeing the actual—not simply assumed based on the drawing or the rules—behaviour.

It has been found that secondary interactions are much more common in the traffic conflicts dataset. This finding makes sense, since one could expect that it is easier to make a mistake leading to a conflict or potentially a crash in a complex situation involving several road users to be negotiated simultaneously or closely one after another. It is thus quite unfortunate that the method is least fit for situations which have the most relevance for traffic safety. On the other hand, the majority of the conflicts in the dataset are still primary interactions for which the method can be applied. Also, at least for some crash scenarios, it is also more common for 'free vehicles' to be involved in severe crashes compared to those moving in platoons or hindered in some other way (*Pasanen, 1993*).

This study utilised PCC and TA as two measures describing a situation severity. However, one can imagine many other additional indicators to be introduced, for example those reflecting the potential consequences in case the conflict develops into a crash, such as speed, kinetic energy, or Delta-V *(Yastremska-Kravchenko et al., 2022)*. Alternatively, more general analysis of the road user behaviour can be performed, for example by counting the frequencies of evasive actions being necessary or by mapping the locations of the evasive action initiations. Such data might provide insights into how well the current infrastructure design functions and whether it encourages smooth and early adjustments rather than last-minute emergency reactions.

6 Conclusions

The paper suggests a relatively simple and easy to implement method for detection of the first evasive action in a traffic interaction, as well as for quantifying its dangerousness through the probability of collision course (PCC) and Time-to-Accident (TA) measures. The following conclusions can be drawn:

- The method works well for primary interactions, but frequently fails in case of secondary interactions.
- Secondary interactions are more common in traffic conflict situations, which limits applicability of the method
- The method could be used both for studying traffic conflict situations (using PCC, TA and other indictors), but also for quantifying and visualising the general behaviour at the studied locations.
- Expanding the reference dataset may help the algorithm performance, but will not solve some problems of the more fundamental nature.

CRediT contribution statement

Carl Johnsson: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing—original draft. **Aliaksei Laureshyn**: Conceptualization, Funding acquisition, Project administration, Resources, Software, Supervision, Writing—review & editing.

Declaration of competing interests

The authors report no competing interests.

Acknowledgement

This work received funding from Horizon 2020 project *InDeV (2015-2018)*, grant agreement 635895, and Vinnova Swedish innovation agency project Third Eye. The authors would like to thank all the international project partners contributed to the original data collection that made this work possible.

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