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THE INFLUENCE OF MOTION PREDICTION METHODS ON SURROGATE SAFETY MEASURES

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Abstract: Despite the rise in interest for surrogate safety analysis, little work has been done to understand and test the impact of the methods for motion prediction which are needed to identify whether two road users are on a collision course and to compute many surrogate safety indicators such as the time to collision (TTC). The default, unjustified method used in much of the literature is prediction at constant velocity. In this paper, a generic framework is presented to predict road users' future positions depending on their current position and their choice of acceleration and direction. This results in the possibility of generating many predicted trajectories by sampling distributions of acceleration and direction. Two safety indicators, the TTC, and a new indicator measuring the probability that the road users attempting evasive actions fail to avoid the collision P(UAE), are computed over all predicted trajectories. These methods and indicators are illustrated on several video datasets containing safety critical interactions between road users. The evidence suggests that the prediction methods based on the use of a set of initial positions and on motion pattern matching seem to be the most robust. Another contribution is the integration of TTC values with P(UEA) to rank all interaction in a safety hierarchy. The last contribution of this work is to make all the code used for this paper available (the code as open source) to enable reproducibility and to start a collaborative effort to compare and improve the methods for surrogate safety analysis.

1 INTRODUCTION

Road safety is one of the most important social issues due to the multiple costs of accidents. The total social cost of road collision in Canada in 2004 was estimated at $62.7 billion yearly (about 4.9% of Canada's 2004 Gross Domestic Product) (Vodden, Smith, Eaton, & Mayhew, 2007). The World Health Organization (WHO) estimated in 2009 road accidents to be ranked in the ninth place of leading causes of death and disability and predicted it will rise to the fifth place by 2030 (WHO, 2009). Safety manuals such as the manual of the World Road Association (Road Safety Manual, 2003) depend mainly on historical collision data obtained from police and hospital reports and on different types of statistical analysis to identify and understand the failures of the road system, and to propose corrective actions. This type of data has several shortcomings, such as the underreporting of some types of accidents, the lack of information in the reports and the relatively small number of events. Besides, the record is done after the accident happens and the analyst and decision maker must wait till a sufficient number of accidents is collected to analyze the collisions and to devise countermeasures. Therefore, collision-based safety analysis is a reactive approach and the existing safety problem may only be remedied after the

materialization of the induced social cost. These limitations have lead researchers to search for new methods to perform road safety diagnosis with higher confidence and in a proactive manner.
One such promising approach relies on the observation of "unsafe" traffic events without a collision, often called near misses or conflicts. Such types of analyses have been developed in several countries since at least the late 1960s and are now better known as surrogate safety analysis. A key defining concept of conflicts and, it can be argued, of all safety relevant traffic events, is the collision course, i.e. a situation in which two road users would collide if their movements remain unchanged (taken from the conflict definition in (Hydén & Amundsen, 1977)). This requires specifying a method to predict road users' motions in order to evaluate if they are on a collision course, and to measure several surrogate safety indicators such as the time to collision (TTC). Most analyses rely on the rarely specified or justified method of extrapolation at constant velocity, while several possible paths may in general lead road users to collide. This uncertainty in motion prediction is the result of the following factors:

- unobserved variables, e.g. the characteristics of the driver and the vehicle (if any), including the driving skills and ability to perform an evasive action, the awareness of the road users of each other and their environment;
- the stochastic nature of predicting the future given the current state of the system, e.g. the variability of motion choices (small variations in speed and direction), the complexity of all the road users' interactions;
- measurement uncertainty, depending on the accuracy of the sensing technology.

This work builds on previous work (Saunier, Sayed, & Ismail, 2010) to develop a consistent and generic framework for motion prediction to measure the safety of road users' interactions. Road user trajectories are extracted using a custom open source video tracking tool from video data recorded with a fixed camera (Saunier, 2012). This paper presents the following contributions:

1. an investigation of different motion prediction methods to evaluate whether two road users are on a collision course and to compute several safety indicators;
2. a measure of the probability of unsuccessful evasive action P(UEA),
3. the study of the TTC and P(UEA) indicators and their distribution in a set of interactions with and without a collision;
4. an open source software implementation (Saunier, 2012) of the proposed methods and an accompanying website with a sample of the data and step by step instructions to encourage adoption and further development.

The remainder of this paper is organized as follows: the review of related work, the presentation of the proposed method, the experimental results on a large number of real cases, the discussion of the results and the conclusion.

2 RELATED WORK

2.1 Surrogate Safety Analysis

There is a large and growing body of literature on methods for surrogate safety analysis. The best known approaches are the Traffic Conflict Techniques (TCTs), first proposed in the late 1960s in (Perkins & Harris, 1967). TCTs are methods to collect traffic conflicts, to evaluate their proximity to a potential collision, and to interpret this data for a safety diagnosis. The widely accepted definition of a conflict is *"an observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged"* (Hydén & Amundsen, 1977).
As argued in the introduction, a traffic conflict thus implies that road users are on a collision course, which depends itself on a method for motion prediction. Although prediction at constant velocity is the most common, often implicit, method in the literature, various methods may be applied to represent uncertainty in future motion. This topic is discussed at length in the robotics literature for path planning, with applications to assisted or autonomous vehicles (see (Mohamed & Saunier, 2013)).
For surrogate safety analysis to be objective, a number of quantitative safety indicators have been proposed in the literature to measure the proximity to a potential collision, or probability of collision, and the severity of the potential collision. The general term safety indicator is used in this paper to avoid confusion. Further work is required to validate how the indicators may be interpreted. TTC is the best

known of these indicators. It is defined for a given motion prediction method as the time required for two vehicles to collide following the predicted trajectories. If several predicted trajectories are available, with corresponding probabilities, the expected TTC can be computed (Saunier, Sayed, & Ismail, 2010). Many other conflict indicators have been presented over the years and the readers are referred to (Laureshyn, 2010), (Tarko, Davis, Saunier, Sayed, & Washington, 2009), (Archer, 2005), and (Ismail, 2010) for more details.

2.2 Motion Prediction and Collision Avoidance

The choice of a method for motion prediction is essential to evaluate whether road users are on a collision course and to compute several safety indicators. Such methods are very similar to navigation and path planning in robotics, where collisions should be predicted and avoided. The difference is that robots know their goals, in particular places to reach, and can plan accordingly, while the analysis of road user interactions based on exterior observations does generally not have access to their internal state and goals. Nevertheless, path planning requires taking into account all obstacles and the movement of all other moving objects, i.e. it relies on motion prediction methods for the assessment of the safety of planned movements, just as surrogate safety analysis.
The early work of (Zhu, 1990) describes three types of motion prediction models:

1. the constant velocity model: it assumes that the object moves with no change in speed nor direction;
2. the random motion model: it assumes that acceleration changes according to probability distribution functions such as a Gaussian or a uniform distribution;
3. the intentional motion model: the objects move in a scheduled way (e.g. an object moves towards a specific goal and/or seek to avoid collision).

These models fall into two categories, the deterministic and stochastic motion prediction approaches (Eidehall & Petersson, 2008):

- **Deterministic** motion prediction consists in predicting a single future trajectory for each object. The constant velocity model is one such method, choosing the most probable trajectory among several alternatives is another. The former approach has been the default, sometimes implicit, method used to compute several safety indicators such as the TTC (Road Safety Manual, 2003), (Cunto, 2008), (Laureshyn, 2010), (Ismail, 2010), (Hydén, 1996))
- **Stochastic** motion prediction relies on taking many different scenarios into account. With the rise of computer power, this approach is becoming more manageable and therefore more popular. In robotics, while the state and goals of the robot are known, the movement of other objects is usually modeled stochastically (Thrun, Burgard, & Fox, 2005). There are several stochastic motion prediction methods, among which one can cite: vehicle motion model using Monte Carlo simulation (Eidehall & Petersson, 2008), (Broadhurst, Baker, & Kanade, 2005), (Danielsson, Petersson, & Eidehall, 2007), reachable sets (Althoff, Stursberg, & Buss, 2008), Gaussian processes (Laugier, et al., 2011), and trajectory learning (Saunier, Sayed, & Ismail, 2010), (Bennewitz, Burgard, Cielniak, & Thrun, 2005), (Hu, Xiao, Xie, & Tan, 2004), and (Morris & Trivedi, 2011)

A literature review of the research on motion prediction, in particular from the field of robotics where motion prediction for collision avoidance is an important and well-researched topic; was summed up in previous work (Mohamed & Saunier, 2013).

3 METHODOLOGY

The main objective of this work is to investigate different methods for motion prediction to predict potential collision points and compute several safety indicators. This is tested on real cases of vehicle interactions: conflicts and collisions. A choice was made to focus in the present work on trajectories to represent motions, since road user data is provided in the same format by the video analysis tool. The general approach follows four steps:

1. The trajectories of each road users are extracted from video recordings. The video analysis tool relies on feature-based tracking (Saunier & Sayed, 2006) and is freely available as open source software (Saunier, 2012).
2. For each **interaction**, defined as an event in which two road users are close enough, different motion prediction methods are used to predict the road users' trajectories.
3. At each instant, two predicted trajectories for the two road users may have three outcomes: no intersection or an intersection that can be either a crossing zone or a collision point. A **crossing zone** is a location in which two trajectories intersect each other. A **collision point** is a crossing zone that the road users are predicted to reach at the same time.
4. Two safety indicators are computed: the TTC for each collision point and the probability of unsuccessful evasive action P(UEA) (the predicted PET (pPET) for each crossing zone can also be computed, see (Mohamed & Saunier, 2013)).

3.1 Motion Prediction Methods

The road users' predicted trajectories are determined by their current state and the chosen control input. Similarly to (Broadhurst, Baker, & Kanade, 2005), the current state at t_0 is represented by the state $S(t_0)=(x(t_0),y(t_0),v(t_0),\theta(t_0))$ where $(x(t_0),y(t_0))$ represents the position vector (if an object is simply represented by its centroid) and $(v(t_0),\theta(t_0))$ are the norm and angle of the velocity vector $(v_x(t_0), v_y(t_0))$. The control input $I(t_0)$ reflects the action undertaken by the road user behaviour at t_0, such as acceleration, steering, etc. The $I(t_0)$ vector can be written as $(a(t_0),\Delta\theta(t_0))$ with $a(t_0)$ the acceleration or braking and $\Delta\theta(t_0)$ the change in the road user orientation both chosen by the road user at t_0. $\Delta\theta(t)$ can be computed as a function of the steering angle $\varphi(t)$, the wheelbase L and the speed $v(t)$ in case of a vehicle as follows:

[1] $$\Delta\theta(t) = \frac{v(t)}{L}\sin(\varphi(t))$$

The general formula used to compute iteratively the future positions at each time step $t \geq t_0$, where t is discretized at regular intervals Δt, is:

[2] $$\begin{bmatrix} x(t+1) \\ y(t+1) \end{bmatrix} = \begin{bmatrix} x(t) \\ y(t) \end{bmatrix} + \begin{bmatrix} v_x(t+1) \\ v_y(t+1) \end{bmatrix} \text{ ; where } \begin{bmatrix} v_x(t+1) \\ v_y(t+1) \end{bmatrix} = \begin{bmatrix} (v(t)+a(t))\cos(\theta(t)+\Delta\theta(t)) \\ (v(t)+a(t))\sin(\theta(t)+\Delta\theta(t)) \end{bmatrix}$$

For realistic results, the speed is bounded by 0 and a maximum value v_{max} (i.e. $v(t+1)$ is the minimum of v_{max} and $v(t)+a(t)$). This model is generic and can represent complex motions, by having varying control inputs $I(t)$ at future time steps $t \geq t_0$. Four methods are considered in this work to predict possible trajectories to evaluate whether road users are on a collision course or not at t_0:

1. **constant velocity (CV)**: only one predicted trajectory with $I(t)=(0,0)$ for all $t \geq t_0$;
2. **normal adaptation (NAS)**: in reality, road users make, consciously or not, small speed and steering adaptation, even when following a straight traffic lane. Such a trajectory can be predicted by drawing the acceleration and orientation change $a(t)$ and $\Delta\theta(t)$ randomly and independently at each step $t \geq t_0$;
3. **set of initial positions (SP)**: if the road user position is represented by a set of positions instead of only its centroid, these can be used as initial position for predicted trajectories. For simplicity and faster computation, prediction is done at constant velocity for each initial position.
4. **motion pattern matching (MPM):** current road user motion is matched to prototype trajectories representing the main motion patterns at a location. The predicted trajectories are the matched prototypes resampled based on the current road user speed (see previous work (Saunier, Sayed, & Ismail, 2010)). The advantage is that context, such as the road geometry is thus taken into account (most road users will not continue straight into a curb or a wall).

Several other methods could be used, but it was found that these four methods provide a variety of realistic predictions that can serve as a basis for investigation. Finding the collision points at each t_0 consists in predicting the trajectories for each pair of interacting road users over a fixed time horizon. A collision is identified if the distance between their predicted positions is below a threshold (1.8 m is used in this work as this represents the typical width of a car). The time step at which this condition is met is the TTC. Assumptions are made for reasonable distributions of control input for normal adaptation method. Information on this topic is limited in the literature. In (Hydén, 1996), threshold on the deceleration-to-safety safety indicator are proposed to measure the conflict severity. Since braking in the range [0,-1m/s^2] and [-1m/s^2,-2m/s^2] was considered to require respectively only "normal adaptation" and a "reaction", the range of [-2 m/s^2,2 m/s^2] was chosen for acceleration in this work. The range [-0.2 rad/s, 0.2 rad/s] was chosen for $\Delta\theta(t)$ after some trial and error. The triangular distribution was selected to represent lower probabilities of choosing the most extreme values, with 0 for the mode. These choices could easily be adjusted if better information becomes available. For each road user, N_1 predicted trajectories are generated for the normal adaptation method.

3.2 Safety Indicators

At each time instant t_0, a set of predicted trajectories for the two road users may generate a set of collision points with their associated TTC. Similarly to (Saunier, Sayed, & Ismail, 2010), the expected TTC is its expected value over all collision points. Note that this could be weighted by probabilities for each predicted trajectory; this is done in case of the MPM method and is implicitly taken into account for the normal adaptation method by the distribution of the control input.
A new indicator was proposed in (Mohamed & Saunier, 2013) to distinguish between interactions where the TTC may be the same but the spaces of possible evasive actions that can be attempted by the road users are different. This can be characterized by sampling through the space of possible evasive action and computing the probability of collision as the number of predicted collisions divided by the total number of predicted situations (i.e. the product of the numbers of predicted trajectories of the two road users). This is the probability of unsuccessful evasive action P(UEA) and can be computed based on various motion prediction methods. Two methods are used in this work:

5. **evasive action sampling (EAS)**: N_2 predicted trajectories are generated by randomly drawing a constant control input that is applied at each future step $t \geq t_0$;
6. **set of initial positions (EASP)**: the first method of evasive action sampling is applied to a set of initial positions for each road user (N_3 trajectories are predicted for each initial position with a constant control input drawn randomly).

The distribution for the control input is also triangular with 0 for the mode. The range is taken from (Broadhurst, Baker, & Kanade, 2005) which reports that for a Lexus LS430 at below 60 mph, steering angle varied from -0.5 rad to 0.5 rad and the acceleration varied from -9.1 m/sec^2 to 4.3 m/sec^2. An open source library has been developed to support these computations and to enable their replication by other researchers (Saunier, 2012).

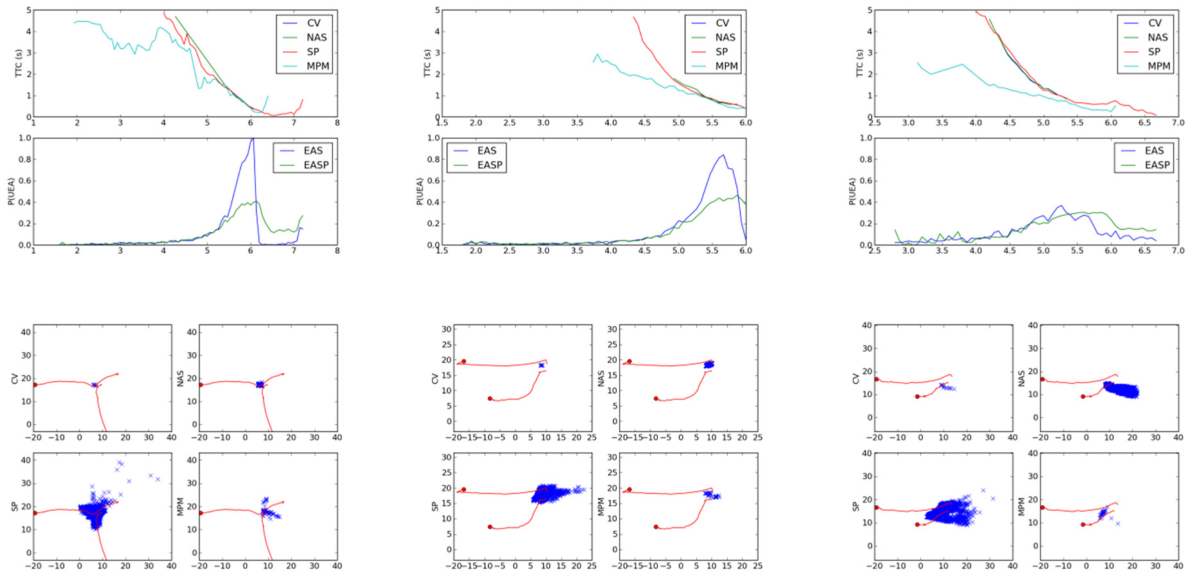
4 EXPERIMENTAL STUDY OF COLLISIONS AND CONFLICTS

4.1 Dataset

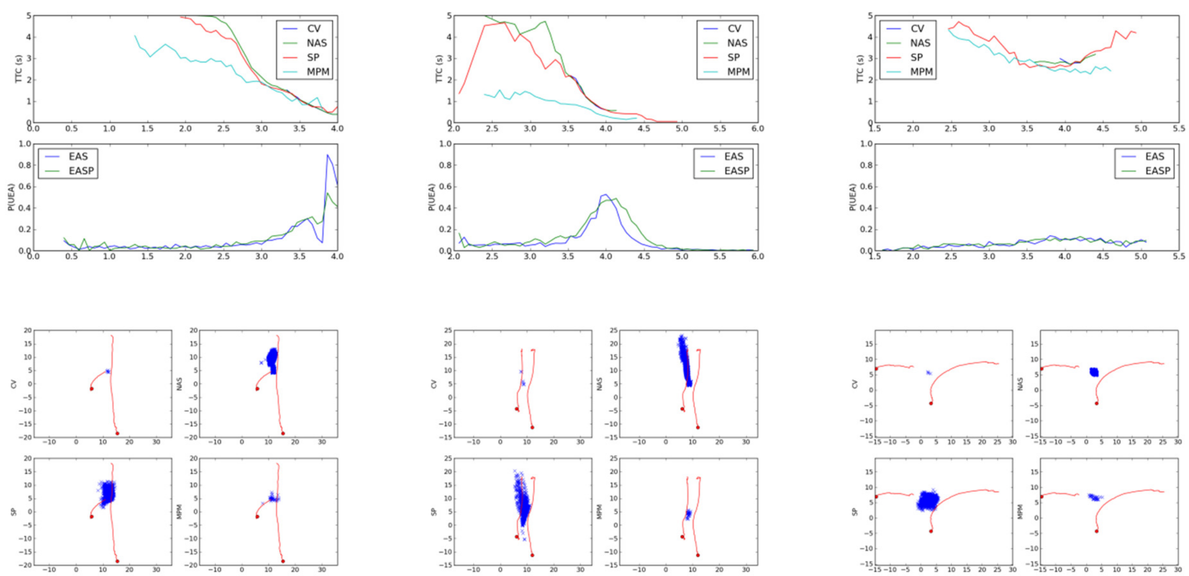
To demonstrate, illustrate and evaluate the proposed approach and indicators, a large set of case studies extracted from video recordings was used. The dataset has been used in previous work (Saunier, Sayed, & Ismail, 2010). It contains a large number of interactions: 295 cases: 82 collision cases and 213 conflict cases, for which the vehicle trajectories are extracted using the algorithm presented in (Saunier & Sayed, 2006). The accuracy of the extracted trajectories is sufficient for our purpose.

4.2 Results

For this analysis, the first four methods for motion prediction are applied to compute the TTC indicator. The other two motion prediction methods are used to compute P(UEA). For the methods relying on a set of initial positions, the initial positions are the positions of features that are detected and tracked on a road user by the computer vision algorithm (Saunier & Sayed, 2006), which can be seen as a distribution over the actual position of the road user, or as a proxy for its actual volume. For all the methods that require to set a number of trajectories (for sampling the control inputs), the following values were chosen: N_1=100 for normal adaptation, N_2=100 for evasive action sampling and N_3=10 for evasive action sampling with a set of initial positions. The scripts that generated all the presented results (except the MPM method) along with a sample of the data are available on the website http://nicolas.saunier.confins.net/data/mohamed13trb.html to enable other researchers to replicate and build on the proposed approach.



(a) Collisions case studies



(b) Conflicts case studies

Figure 1 Plots of the two safety indicators and the collision points for the various motion prediction methods for samples of collisions (top) and conflicts (bottom)

The safety indicators and the collision point distributions are plotted for a sample of interactions in Figure 1 **Error! Reference source not found.**. The road user trajectories are overlaid over the collision points with a dot indicating their origin or first instant of detection, to provide the context of the interaction.

4.2.1 Motion Prediction Methods

It is noteworthy that all motion prediction methods result in similar measurements and that the main difference is the number of measurements for the TTC indicator (P(UEA) is different as its value is 0 if no collision point is predicted, while TTC is undefined in that case). Prediction at constant velocity (CV method) provides the smallest number of measurements for TTC, followed by the NAS method. Moreover, both of the MPM and SP methods provide the largest number of measurements in most cases and also provide the most dangerous (lowest) values for TTC indicator (see for example Figure 1). It was expected that motion prediction at constant velocity would provide the smallest number of measurements, which is a well-known shortcoming of that method (Laureshyn, 2010). This important characteristic is associated with robustness as measurements over longer periods of time should help better characterize the interactions over time and in terms of their overall safety, while a small number of data points provides a limited picture and are more subject to noise.

A larger number of measurements seems to correspond to a larger number of collision points distributed over a larger region. As expected, the number of collision points predicted by the CV method is small and very concentrated around the actual point of intersection of the trajectories, specifically for straight trajectories. The collision points predicted by NAS method are more concentrated than the ones predicted by the SP method. This is also expected since normal adaptation simulates small deviations around a trajectory at constant velocity that are compensating each other since positive and negative values of control inputs can be drawn with equal probabilities. The MPM method predicts a number of collision points between the numbers respectively predicted by the CV and NAS methods.

4.2.2 Safety Indicators

This section discusses the most extreme values reached by the safety indicators, although the whole time series can and should also be studied and interpreted. Regarding the TTC indicator, the values should theoretically reach zero for the collision cases. As shown in

Table 1, the minimum TTC (TTC_{min}) values of most collision cases (82 % in SP method and 62 % in MPM method of the cases) are between 0 and 0.5 s. The fact that 0 s is not always measured is related to video tracking (colliding road users are more difficult to track) and simplifications of the vehicle volume. Conversely, minimum TTC values are between 0 to 2.5 s for the conflict cases, with about 69 % (MPM method) and 68 % (SP method) between 0 and 1.5 s. Surprisingly, the highest share of TTC_{min} values computed using the SP method is between 0 to 0.5 s for the conflict cases (37 % of all cases), while it is between 0.5 to 1.0 s. when using the MPM method (34 %). The SP method provides lower TTC_{min} values than the MPM method, as well as fewer cases without any measurement at all (see the last column in Table 1).

Table 1 : The distributions of TTC_{min} for all interactions for the SP and MPM prediction methods.

		TTC(sec)						
		0 -0.5	0.5-1	1-1.5	1.5-2	2-2.5	>2.5	None
SP	collision	82%	15%	1%	0%	0%	0%	2%
	conflict	37%	13%	18%	14%	7%	8%	3%
MPM	collision	62%	23%	4%	1%	0%	2%	7%
	conflict	12%	34%	23%	10%	4%	2%	14%

The second and new safety indicator P(UEA) provides mixed results (see Table 2 for the EAS method (EASP provides similar results that are not included in the paper)). For the collision cases, 41 % of the cases have maximum P(UEA) reach the highest values (from 0.8 to 1.0), while several cases have maximum P(UEA) inferior to 0.2, in which cases the driver has the opportunity to avoid the collision. For the conflict cases, most (60%) of the maximum P(UEA) values are less than 0.2, followed by the 0.2 to 0.4 range (24 %). The remaining values are distributed in the other intervals with only 3 % reaching the highest maximum P(UEA). This is expected as road users would have more possibilities to avoid a collision all along their interaction without a collision.

Table 2 : The distribution of maximum P(UEA) for all interactions for the EAS prediction method.

		P(UEA)					
		0.8-1.0	0.6-0.8	0.4-0.6	0.2-0.4	0-0.2	None
EAS	collision	41%	15%	7%	20%	17%	0%
	conflict	3%	3%	9%	24%	60%	0%

Analyzing the TTC and P(UEA) curves together shows that the highest value of P(UEA) is reached usually at the time the TTC is minimum in most cases (in the range of ± 0.5 s.) for MPM and EAS methods (186 cases (63 % of cases)), while in only 127 cases (43 % of cases) for SP and EAS methods (see Figure 2). In some cases, the highest value of P(UEA) is reached up to a second (tolerance ± 0.5 s) before TTC reaches its minimum value. A possible explanation is that it is related to the point approximation of the road user actual volumes: that the predicted trajectories may “miss” each other when very close, all the more as the position of one road user is often past the intersection of the two trajectories.

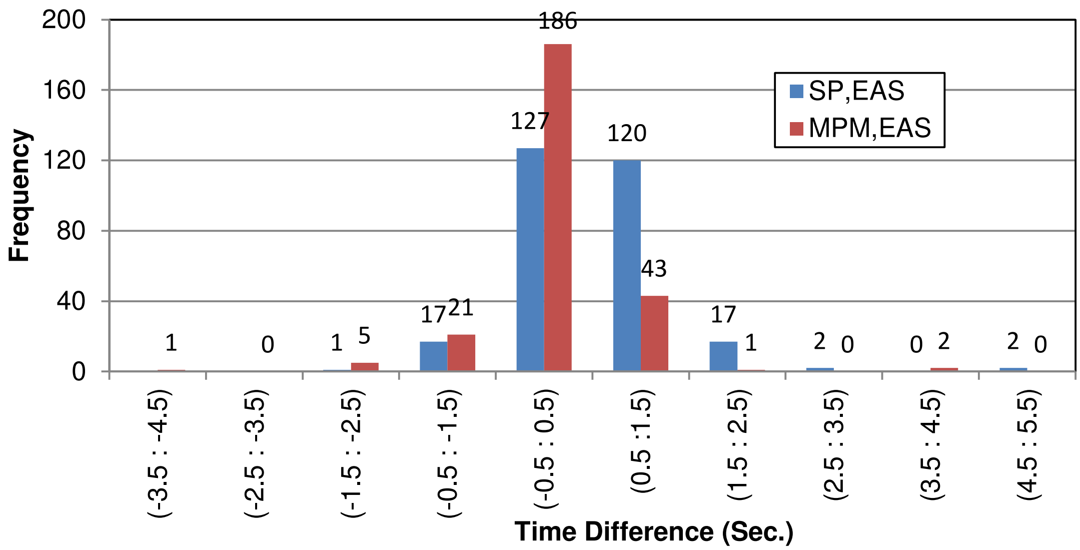


Figure 2 : The time difference between the instants at which respectively maximum P(UEA) and TTC_{min} are reached (positive sign means TTC_{min} occurred later).

It should nevertheless be remembered that this indicator is designed to be complementary to the TTC, in particular to measure the options the road users have to avoid each other. Therefore, the distribution of TTC and P(UEA) values are studied and summarized in Figure 3, presenting only the most promising methods, SP and MPM with EAS. The results seem logical. For collision cases, most cases are concentrated primarily around the most severe indicator values, i.e. the lowest values of TTC_{min} and the highest values of maximum P(UEA), followed by a smaller cluster around the lowest TTC_{min} values with smaller maximum P(UEA) values (between 0.0 and 0.4). On the other hand, the distributions of the extreme indicators values are different for conflicts. For the SP method, the majority of conflict cases have TTC_{min} values in the 0.0 - 0.5 s range, and followed by the 1.5 - 2.0 s range with most maximum P(UEA) values below 0.2 for both ranges. For the MPM method, the largest group of conflicts has TTC_{min} values between 0.5 and 1.5 s. with maximum P(UEA) values below 0.2, followed by a smaller group with TTC_{min} values between 0.5 and 1.0 s and maximum P(UEA) values in the 0.2 - 0.4 range. In addition, it is notable that the upper right triangle in Figure 3 is essentially empty. This is expected as there is a relationship between TTC_{min} and maximum P(UEA): when TTC_{min} is large, road users have a large number of choices of evasive actions to avoid a collision, which corresponds to small maximum P(UEA) values. Overall, considering both TTC_{min} and maximum P(UEA) provides a promising method to rank all interactions with respect to their proximity to a potential collision, i.e. in a safety hierarchy.

TTC(S) / P(UEA)	0-0.5	0.5-1	1-1.5	1.5-2	2-2.5	>2.5	None
0.8-1.0	31	3	0	0	0	0	0
0.6-0.8	9	3	0	0	0	0	0
0.4-0.6	5	1	0	0	0	0	0
0.2-0.4	12	4	0	0	0	0	0
0-0.2	10	1	1	0	0	0	2

(a) collisions cases (SP & EAS prediction methods)

TTC(S) / P(UEA)	0 -0.5	0.5-1	1-1.5	1.5-2	2-2.5	>2.5	None
0.8-1.0	29	2	0	0	0	0	3
0.6-0.8	12	0	0	0	0	0	0
0.4-0.6	3	3	0	0	0	0	0
0.2-0.4	5	10	0	0	0	0	1
0-0.2	2	4	3	1	0	2	2

(b) collisions cases (MPM & EAS prediction methods)

TTC(S) / P(UEA)	0 -0.5	0.5-1	1-1.5	1.5-2	2-2.5	>2.5	None
0.8-1.0	6	1	0	0	0	0	0
0.6-0.8	5	2	0	0	0	0	0
0.4-0.6	9	9	2	0	0	0	0
0.2-0.4	20	5	18	5	3	0	0
0-0.2	38	11	19	24	12	17	7

(c) conflicts cases (SP & EAS prediction methods)

TTC(S) / P(UEA)	0 -0.5	0.5-1	1-1.5	1.5-2	2-2.5	>2.5	None
0.8-1.0	4	2	0	0	0	0	1
0.6-0.8	4	2	0	0	0	0	1
0.4-0.6	8	11	0	0	0	0	1
0.2-0.4	3	25	13	1	0	0	9
0-0.2	7	33	36	21	8	5	18

(d) conflicts cases (MPM & EAS prediction methods)

Figure 3 : Joint distribution of TTC and P(UEA) values for all interactions (collisions and conflicts)

5 CONCLUSION

This research is to the authors' knowledge the first to deal with various motion prediction methods for surrogate safety analysis. Following a previous paper that reviewed relevant methods from other fields (Mohamed & Saunier, 2013) in particular robotics, it describes a generic framework for motion prediction using sets of predicted trajectories. Six motion prediction methods are used to simulate future trajectories, whether the road users attempt evasive actions or not. This paper has tested a new indicator on several real world cases that measures the probability that the road users attempting evasive actions fail to avoid the collision. The methods are applied to a large number of real world case studies and the indicators are discussed in detail. An important criterion is the ability of the computed indicators to represent their intended measurements robustly. The motion prediction method based on a set of initial positions and motion pattern matching produce the most robust indicator computations since they provide the largest number of measurements. The new indicator P(UEA) shows some complementary features to the well-known TTC. The results seem to indicate that their integration may be used to rank all interactions according to their proximity to a potential collision.

Motion prediction methods depend on several parameters, which should be better estimated from large datasets of observations (e.g. evasive action for various categories of interactions). This will allow modelling more closely road user behaviour, for example by using better distributions of control inputs selected by road users. More work needs also to be done to continue validating the indicators.

Finally, this work is unique in the field of road safety analysis in sharing data and methods (the software code is released as open source) to enable scientific reproducibility and encourage more collaboration in this area. It is believed that these tools can benefit other researchers and that the area of surrogate safety analysis, with its many methods and indicators, can only progress if they can be compared by building upon each other's work.

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