Motion Prediction Methods for Surrogate Safety Analysis

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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 several 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. Three safety indicators, the TTC, an extended version of predicted post encroachment time pPET 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 four case studies of lateral road user interactions. The evidence suggests that the prediction method based on the use of a set of initial positions seems to be the most robust. The last contribution of this paper is to make all the data and 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.

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) (1). 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 (2). Safety manuals such as the manual of the World Road Association (3) 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 methods 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 (4)). 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 (5) 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 (6). This paper presents the following contributions:

1. 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;
2. an investigation of different motion prediction methods to evaluate whether two road users are on a collision course and to compute safety indicators;
3. probabilistic versions of two safety indicators, TTC and the gap time or predicted post-encroachment time (PET), and a measure of the probability of unsuccessful evasive action;

4. an open source software implementation (6) of the proposed methods and an accompanying website with 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 real cases, the discussion of the results and the conclusion.

RELATED WORK

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 (TCT), first proposed in the late 1960s in (7) (cited in (8)). TCTs are sets of 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 for such an extent that there is a risk of collision if their movements remain unchanged"* (4).

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 the next subsection).

For a proactive 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 (5). PET is another common indicator, defined only in cases where the road users' observed trajectories cross as the time difference between the instants at which the two vehicles pass the crossing zone. PET is very different in nature from TTC since it is based on the complete observed trajectories and only one value may be computed. The concept of PET was extended to be computed continuously at each instant as the PET for the trajectories predicted for the road users, given a motion prediction method. This indicator was proposed in (9) (cited in (10)) and is sometimes called gap time. Many other conflict indicators have been presented over the years and the readers are referred to (10), (11), (12), and (13) for more details.

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 goal of this subsection is therefore to give an overview of the state of the art of methods for motion prediction in the field of robotics and surrogate safety analysis.

The early work of Zhu (14) 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 (15):

- **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 (3) (8) (10) (13) (16).
- **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 (17), while the state and goals of the robot are known, the movement of other objects is usually modeled stochastically. There are several stochastic motion prediction methods, among which one can cite: vehicle motion model using Monte Carlo simulation (15) (18) (19) (20), reachable sets (21), Gaussian processes (22) and trajectory learning (5) (23) (24) (25).

Modeling vehicle motion depending on driver behaviour has been examined previously in the literature (15) (18) (19) (20) (26) (27). In a traffic scene, a general threat assessment using Monte Carlo simulation was first proposed in (18) and extended in (15). Broadhurst et al proposed a reasoning framework for the future motion of multiple objects in a scene (18). Vehicle motion is predicted by using the current positions and velocities of all objects as known variables and by modeling the future behaviour control inputs (e.g. acceleration and steering) as random variables. The random control inputs, which determine the future trajectories, are generated in a Monte Carlo Simulation. As a result, the probability of collision can be assessed for each path. Eidehall et al (15) refined the previous trajectory generation framework using an iterative sampling process which aimed at removing and replacing samples that cause collision at an early stage of simulation. In addition, visibility constraints were added to capture the fact that the driver is more attentive to the front of the vehicle than to other directions. Sorstedt et al (27) proposed a new vehicle motion model taking into account four components of a cost function to select a trajectory: longitudinal velocity, lateral positioning, comfort of trajectory, and vehicle interaction.

Althoff et al predicted the possible future behaviour of traffic participants using a probabilistic framework and stochastic reachable sets (21). The dynamics is modeled by a hybrid automaton combining discrete and continuous dynamics, which are modeled by four modes: acceleration, braking, standstill and speed limit. The reachable sets are computed using Markov chains. Similarly, Sekiyama et al decompose future behaviours into spatial regions (28), called Attainable Regions (AR). A collision is predicted if two ARs overlap each other.

Laugier et al used both hidden Markov models (HMM) and Gaussian processes (GP) to estimate the probability of collision for a given vehicle (22). The authors advocate the use of TTC as a common indicator to assess the collision risk. The architecture of their model is composed of three sub-modules: 1) a driving behaviour recognition module using HMM to estimate the probability distribution of driver behaviour, 2) a driving behaviour prediction module using GP, and 3) a risk estimation module. Lambert et al represented the movement of each robot and obstacle as a Gaussian distribution (29). The probability of collision is computed from the integral of the product of the distributions, taking into account the configuration and volume of the objects.

The last approach relies on learning trajectories for prediction. The approach relies on the fact that motion is usually not random but structured and repetitive. The method comprises two phases: the learning and the estimation phases. The learning phase clusters a training dataset of observed trajectories into the main motion patterns. The estimation phase estimates the probability that a new observed trajectory will follow a learnt motion pattern. This approach has the advantage of representing the environment well and allowing long-term prediction. Bennewitz et al learnt the motion patterns of people in a scene which enables a robot to update its behaviour accordingly (23). The trajectories are clustered based on the Expectation Maximization (EM) algorithm. HMMs are used to estimate the persons' current and future movements. It was reported that the approach provided a good estimation of the persons' future movements and that it consequently improved the navigation process of mobile robots. Hu et al learnt vehicle activities with a fuzzy self-organizing neural network (24). This method predicts the future activity (motion) of a vehicle according to its past motion. In this way, the probability of collision between two road users can be approximated by a discrete sum when taking into account a finite number of the most probable predicted trajectories.

In the trajectory learning approach, predicting future motions is highly influenced by the learning phase. The training dataset must be selected carefully. A recent work focused on solving this issue automatically and in an unsupervised fashion (25). The authors proposed a 3-stages hierarchal learning framework to analyze object activities and to predict future activities, as well as to detect abnormal events. The 3 stages are: node level learning (e.g. points of interest POIs), spatial level learning (e.g. routes between POIs), and dynamic-temporal level learning (e.g. activity paths).

It can be concluded from this literature review that most approaches for motion prediction are probabilistic to take into account the intrinsic uncertainty of the task. There is a wide variety of methods and it should also be noted that there is a relationship between the prediction method and the representation of motion, e.g. a discrete trajectory, a mathematical function or probability distributions, which in turn conditions what can be done with the predicted motion and what indicators can be computed.

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 (30) and is freely available as open source software (6).
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 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. The following safety indicators are computed: the TTC for each collision point, the predicted PET (pPET) for each crossing zone, and the probability of unsuccessful evasive action P(UEA).

Motion Prediction Methods

The road users' predicted trajectories are determined by their current state and the chosen control input. Similarly to (18), 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:

$$\Delta\theta(t) = \frac{v(t)}{L}\sin(\phi(t))$$

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:

$$\begin{bmatrix} x(t+1) \\ y(t+1) \end{bmatrix} = \begin{bmatrix} x(t) \\ y(t) \end{bmatrix} + \begin{bmatrix} v_x(t+1) \\ v_y(t+1) \end{bmatrix}$$

$$\text{where } \begin{bmatrix} v_x(t+1) \\ v_y(t+1) \end{bmatrix} = \begin{bmatrix} (v(t)+a(t))\cos(\theta(t)+\Delta\theta(t)) \\ (v(t)+a(t))\sin(\theta(t)+\Delta\theta(t)) \end{bmatrix}$$

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 $t \geq t_0$. Three 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**: in this case, there is only one predicted trajectory with $I(t_0)=(0,0)$ for all $t \geq t_0$;
2. **normal adaptation**: 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**: 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.

Several other methods could be used, but it was found that these three methods provide a variety of realistic predictions that can serve as a basis for investigation. Finding the collision points and crossing zones 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. If there is no collision point, the algorithm searches for an intersection between the two predicted trajectories. If there is an intersection or crossing zone, the pPET is the difference between the predicted times at which the road users reach the point. One can see that TTC and pPET complement each other.

Assumptions are made for reasonable distributions of control input for normal adaptation. Information on this topic is limited in the literature. In (16) (cited in (12)), 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.

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 and crossing zones, with their associated TTC and pPET. Similarly to (5), the expected TTC and pPET are their expected value over respectively all collision points and crossing zones. Note that this could be weighted by probabilities for each predicted trajectory (this is implicitly taken into account for the normal adaptation method by the distribution of the control input).

A new indicator is proposed in this work 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 number of predicted trajectories of the two each road user). 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:

4. **evasive action sampling**: N_2 predicted trajectories are generated by randomly drawing a constant control input I that is applied at each future step $t \geq t_0$;
5. **set of initial positions**: 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 (18) 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. Samples of extrapolated trajectories are presented for two road users about to collide in FIGURE 1 (see study case 1 in the next section). An open source library has been developed to support these computations and to enable their replication by other researchers (6).

EXPERIMENTAL CASE STUDIES

Dataset

To demonstrate, illustrate and evaluate the proposed approach and indicators, a small set of case studies extracted from video recordings was used. The dataset has been used in previous work (5). It contains a large number of collisions and conflicts, for which the vehicle trajectories are extracted using the algorithm presented in (30) and available as open source software (6). The accuracy of the extracted trajectories is sufficient for our purpose. FIGURE 2 shows an example of a video frame with the road user trajectories overlaid for the four cases presented in this paper. The four interactions are chosen to be representative of typical lateral conflicts and collisions, with different levels of safety or proximity to a potential collision, and to serve as a support for a detailed discussion of the methods and indicators.

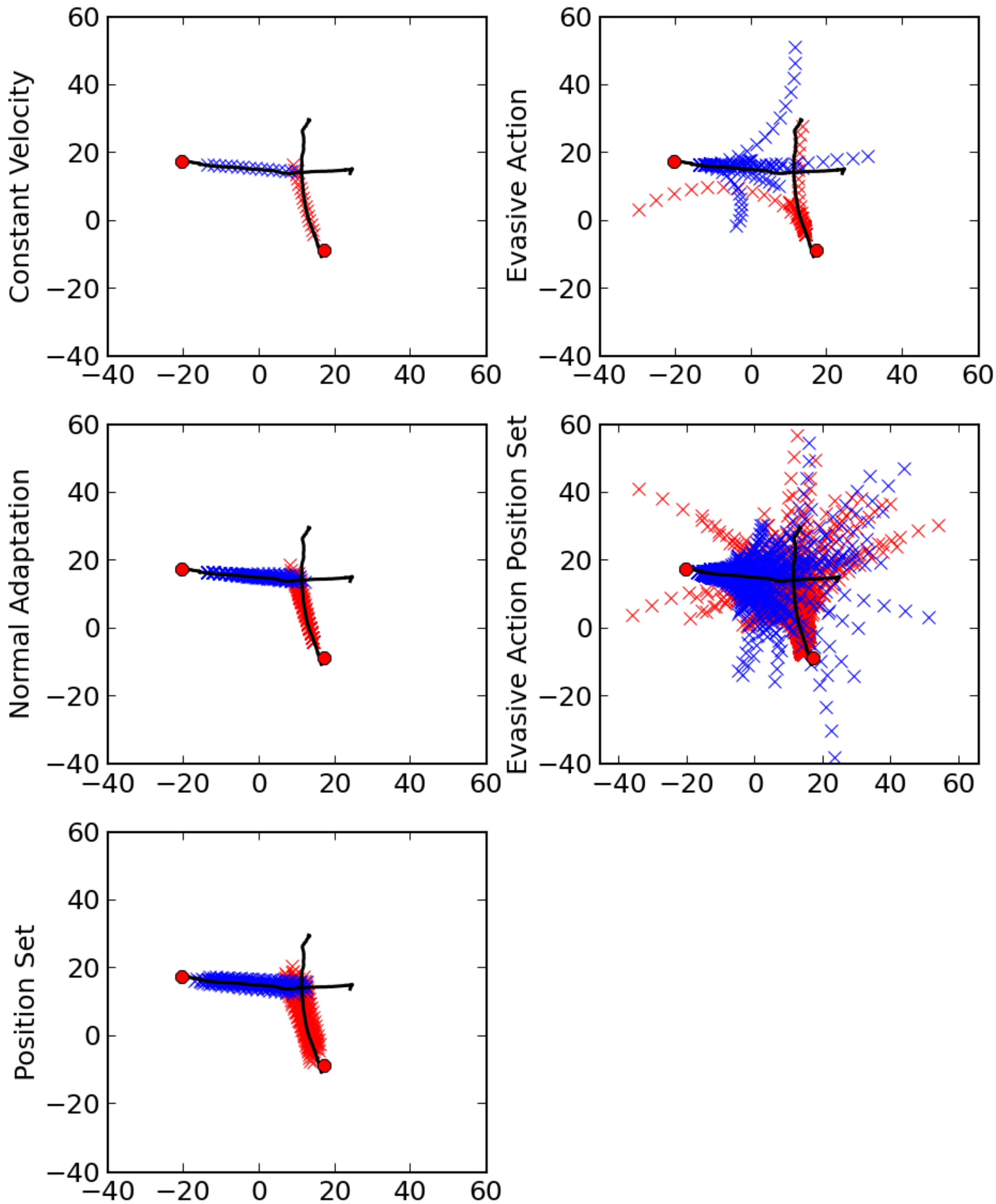

FIGURE 1 Sample predicted trajectories for the 5 methods (with N_1= N_2= N_3=10) for the two road users in case study 1 (collision) (their actual trajectories are overlaid in black with their origin as a red dot)

case study 1 (collision)

case study 2 (conflict)

case study 3 (conflict)

case study 4 ("normal" interaction)

FIGURE 2 Image of each case study, with trajectories overlaid

Results

For the four cases studies, the first three methods for motion prediction are applied to predict collision points and crossing zones, and to compute the associated TTC and pPET indicators. The other two motion prediction methods used to compute P(UEA) are also applied to each case. 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 (30), 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 along with the data of the four cases 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.

The safety indicators, the collision points and crossing zones are plotted in FIGURE 3 to FIGURE 6 for the four case studies. The names of the motion prediction methods are abbreviated to avoid overlapping with the plots. The road users trajectories are overlaid over the collision points and crossing zones, with a dot indicating their origin or first instant of detection, to provide the context of the interaction.

Motion Prediction Methods

It is noteworthy that all motion prediction methods result in very similar measurements and that the main difference is the number of measurements for the TTC and pPET indicators (P(UEA) is different as its value is 0 if no collision point is predicted). Prediction at constant velocity provides the smallest number of measurements for TTC and pPET, followed by the sampling of trajectories with normal adaptation and finally the method based on a set of initial positions. The latter provides the largest number of measurements for all indicators and in particular for TTC for the most dangerous (lowest) values (see FIGURE 3). 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 (10). However, it was not anticipated that the method based on a set of initial positions would provide the largest number of measurements. It seems in fact that the indicators computed with the normal adaptation method are a smoother version of the indicators computed with the constant velocity method, with more measurements. 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.

The number of measurements seems to correspond to a larger number of collision points and crossing zones distributed over a larger region. As expected, the number of collision points and crossing zones predicted by the constant velocity method is small and very concentrated around the actual point of intersection of the trajectories, which is normal for mostly straight trajectories, but would be very different with significant turning movement. The points and zones predicted by the normal adaptation method are more concentrated than the ones predicted by the method based on a set of initial positions. This is also expected since normal adaptation simulate 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 (see FIGURE 1).

Another important topic is the computational cost of generating the predicted trajectories and computing the collision points and crossing zones. Identifying collision points requires a number of tests up to the time horizon, that is 75 steps in the presented results (time horizon of 5 s multiplied by a frame rate of 15 frames per second). Identifying crossing zones is more costly as it implies testing the intersection of all segments between two successive predicted positions: the number of computations can therefore reach the square of the time horizon, which is 75^2=5625 in this study. This number of computations is then multiplied by the product of the number of predicted trajectories for the two road users, e.g. N_1^2 for the normal adaptation method, which amounts to up 10000x5625 computations at each instant in this study. This is therefore very expensive as the maximum number of intersections tests (for crossing zones) grows with the product of the square of the time horizon and the square of the number of predicted trajectories (this is obviously variable for methods based on sets of positions). An advantage is that many operations can be done in parallel: for example, the computations at each instant are independent from one another. Further work is needed to speed up the process and find the right trade-off between computational cost and good coverage of the potential movements that may lead the road users to collide that yield valid and robust indicators.

Safety Indicators

A first comment is that TTC evolves as expected for the collision (case 1 in shown in FIGURE 3) and two conflicts (cases 2 and 3 shown respectively in FIGURE 4 and FIGURE 5). The value of 0 s is reached for the collision case, and values close to 0 s are reached for the conflict cases. The TTC values for the fourth case justify its labeling as a normal interaction since the only values computed by the third method based on a set of positions are above 3.5 s (see FIGURE 6).

The pPET should be complementary to the TTC by construction. However, its interpretation in our cases studies is not simple. It is constant or decreasing for the collision and the conflicts as the road users get closer to each other in cases 1 and 3, and increasing again after decreasing for case 2. It seems difficult to find distinct shapes or values from these examples. It may be possible to distinguish the collision from the two conflicts by the pPET value at the instant of smallest TTC: pPET is below 0.5 s for the collision, while it is increasing again for case 2 and above 1 s, and above 0.6 s for case 3. pPET also confirms that case 4 is normal with all values above 1.0 s. The small divergence in shape between the methods for case 3 should be further investigated.

The third safety indicator P(UEA), introduced in this paper, provides mixed results. The small values reached for the collision (case 1) are surprising, while higher values are reached for one conflict (case 2). Another surprise is that the highest value (the most dangerous) is not reached at the time the TTC is minimum, but up to a second before, depending on the case and the prediction method. 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. It should nevertheless be remembered that this indicator is designed to be complementary to the others and to the TTC in particular to measure the options the road users have to avoid each other. P(UEA) is flat around 0 for case 4 which confirms again that the interaction is “normal”.

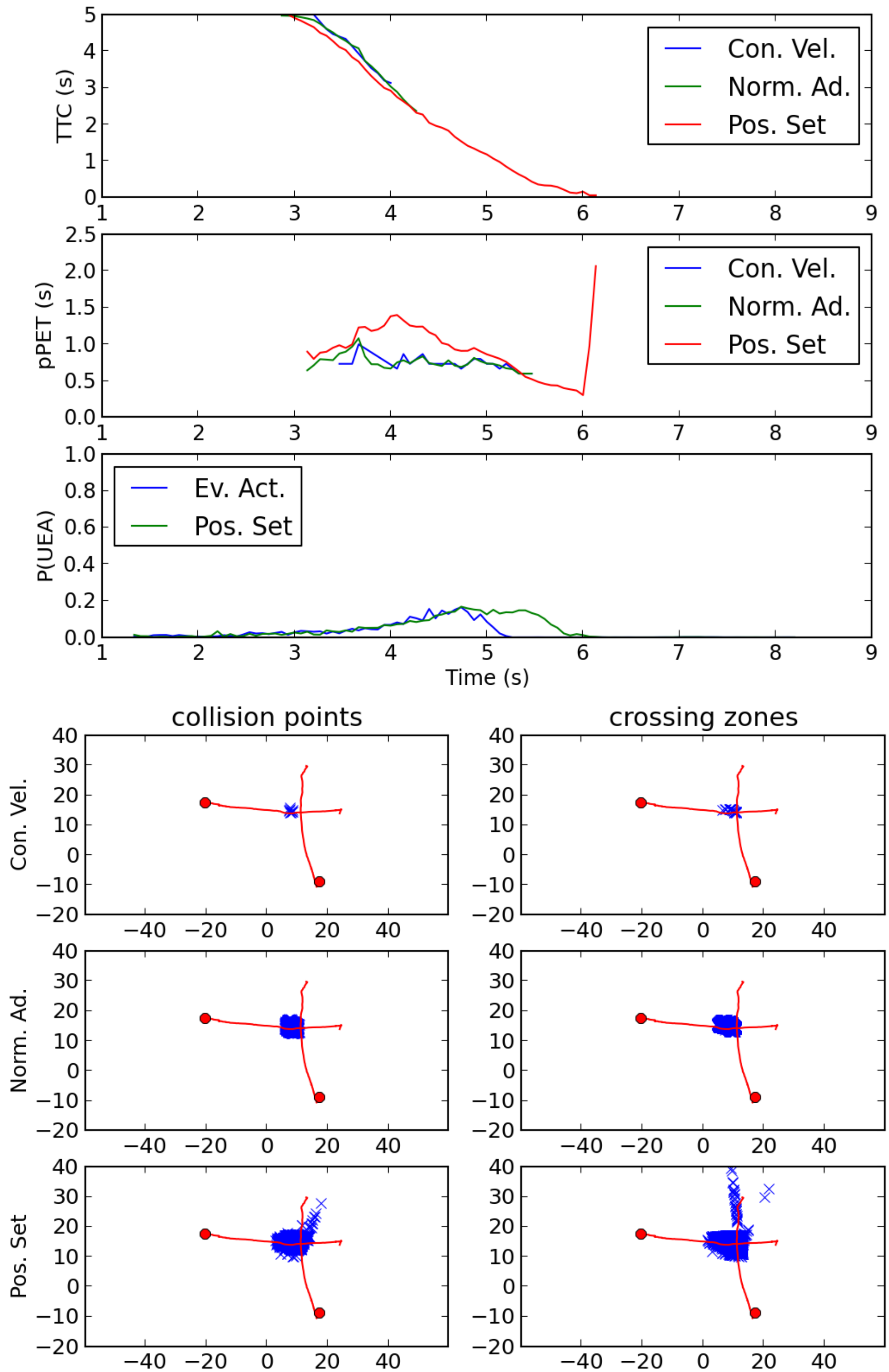

FIGURE 3 Plots of the 3 safety indicators (top), the collision points and crossing zones for the various motion prediction methods for case study 1 (collision)

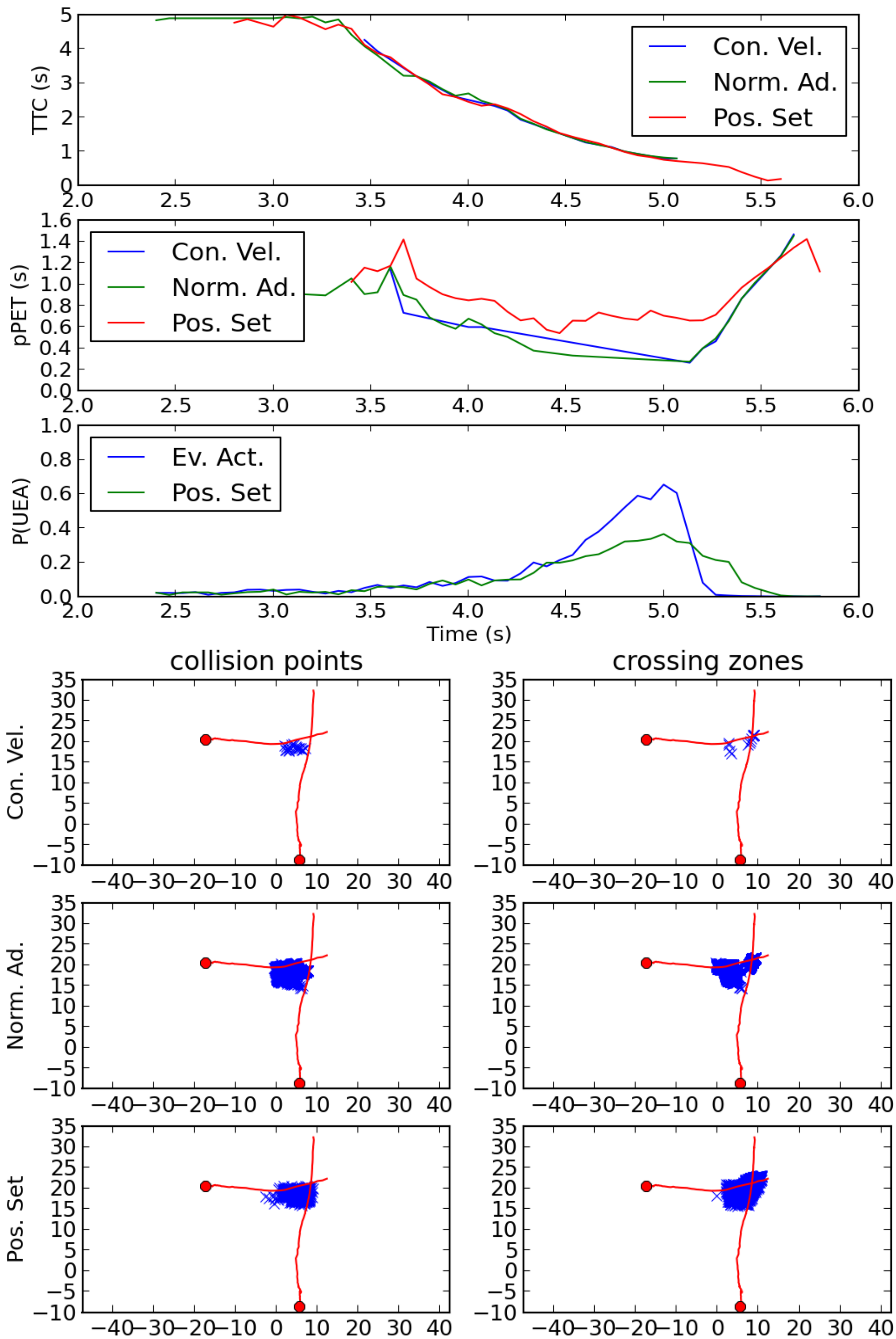

FIGURE 4 Plots of the 3 safety indicators (top), the collision points and crossing zones for the various motion prediction methods for case study 2 (conflict)

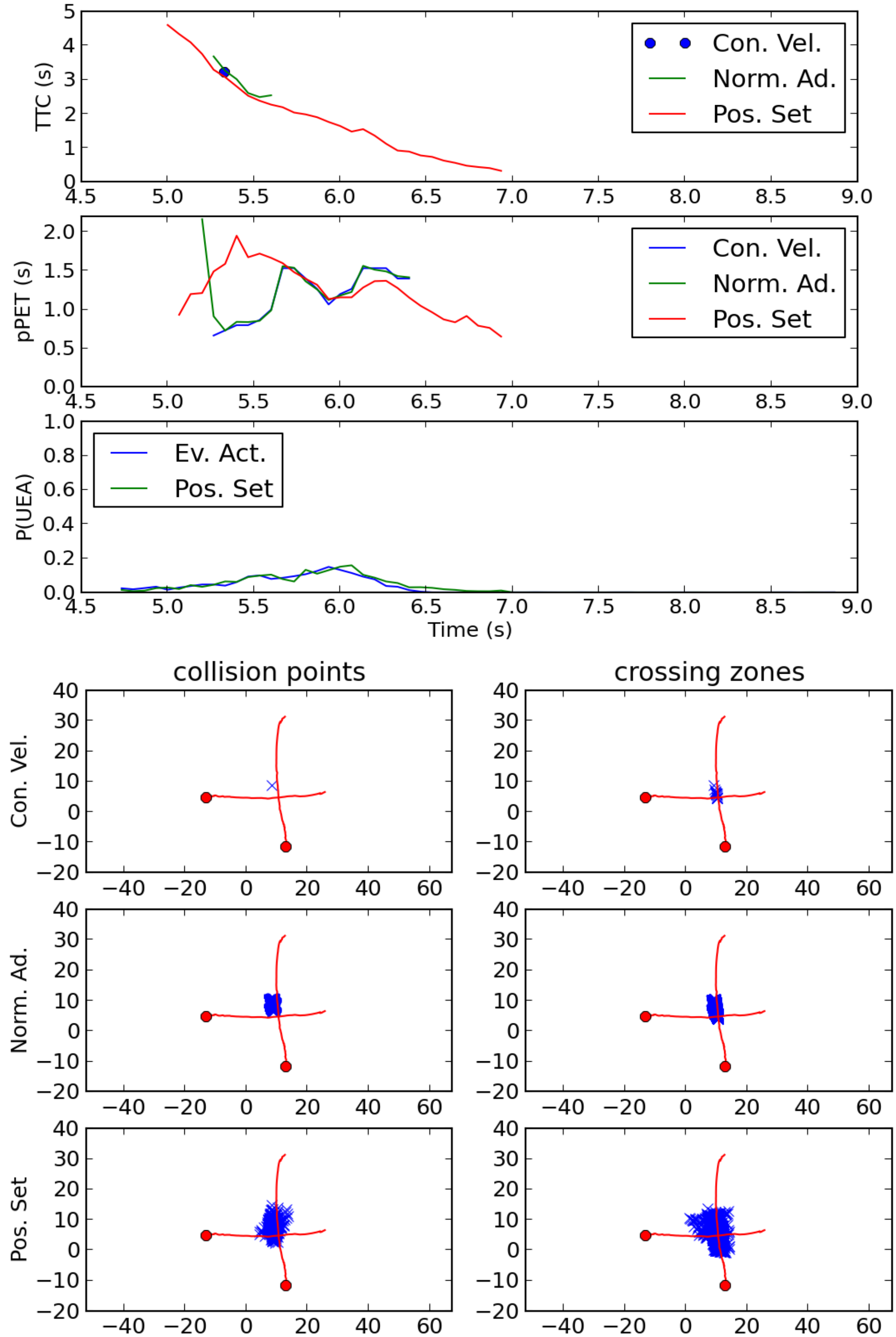

FIGURE 5 Plots of the 3 safety indicators (top), the collision points and crossing zones for the various motion prediction methods for case study 3 (conflict)

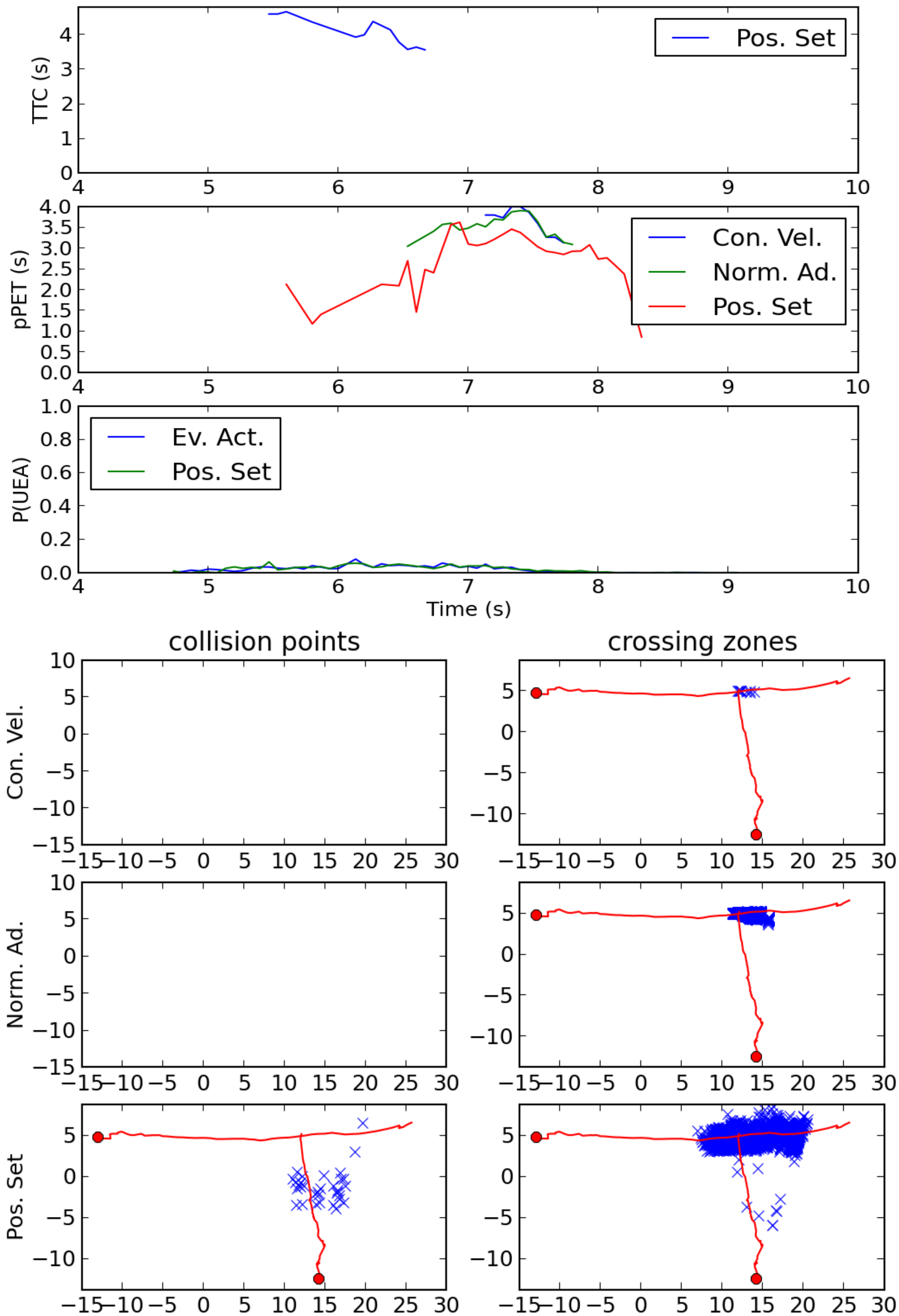

FIGURE 6 Plots of the 3 safety indicators (top), the collision points and crossing zones for the various motion prediction methods for case study 4 ("normal" interaction)

CONCLUSION

This paper presents to the authors' knowledge the first detailed discussion of various motion prediction methods for surrogate safety analysis. After reviewing relevant methods from other fields, in particular robotics, it describes a generic framework for motion prediction using sets of predicted trajectories. Five motion prediction methods are proposed to simulate future trajectories, whether the road users attempt evasive actions or not. This paper has introduced a probabilistic version of the PET, the pPET, and a new indicator that measures the probability that the road users attempting evasive actions fail to avoid the collision. The methods are applied to four 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. It follows that the motion prediction method based on a set of initial positions produces the most robust indicators, in particular for TTC, since the most dangerous values were predicted with this method and it provides the largest number of measurements for all indicators.

The two other indicators, pPET and P(UEA) must be tested on a larger dataset with different parameter settings and using other motion prediction methods. In particular, the prediction method based on pattern motions learnt from observation presented in previous work (5) will be compared to the methods presented in this paper. The advantage of motion patterns is that they take the context into account, such as the road geometry (most road users will not continue straight into a curb or a wall). Other methods should be designed to take into account other road users. A difficulty of such methods is the estimation of the parameters that will require 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. This paper has only dealt with pairs of road users in isolation, but will build upon the method presented in (5) to deal with all interactions and their dependencies, although the added computational cost is again an issue.

Finally, this work is unique in the field of road safety analysis in sharing all the 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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