

Road User Collision Prediction Using Motion Patterns Applied to Surrogate Safety Analysis

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ABSTRACT

Surrogate safety analysis is the process of diagnosing road safety indirectly from measures of ordinary (non-collision) road user behaviour, such as absolute speed and time-to-collision. While absolute speed has enjoyed much popularity in the literature, other measures such as time-to-collision are currently under developed. Before conflict measures such as time-to-collision can be adopted, several challenges need to be overcome, notably the problem of accurately modeling collision courses and collision probability from normal road user behaviour.

This paper describes and explores the feasibility of implementing discretized motion pattern maps for the purpose of predicting potential collisions between road users and their measures based on an empirical naturalistic behaviour model calibrated from site-specific data for use in surrogate safety analysis. The methodology is applied to a pre-existing framework which extracts road user trajectory data from video data of a traffic scene, and then predicts and estimates potential collisions.

To this end, this paper examines the motion pattern model discretization process, the probabilistic framework, the resulting indicators, and then compares the motion prediction methodology with that of the classical constant velocity motion prediction methodology. The methodology is explored using road user behaviour inside the weaving zone of a roundabout to illustrate the flawed use of constant velocity motion prediction.

INTRODUCTION

Traffic conflicts are classically understood to be traffic events in which two or more road users (motorists, cyclists, pedestrians, etc.) enter some collision course containing some meaningful potential for collision. The majority of these collision courses are benign as users are given the opportunity to correct their course and it is assumed that all road users will attempt to do so given the opportunity. However, when course correction fails, the collision course prediction is realised and a collision ensues. Course correction failure might be attributed to any number of causes; the broadest of these categories include: a) environmental causes, b) vehicular mechanical failures; or c) user control failures, i.e. a failure to detect and/or to avoid an obstacle. Furthermore, some of these factors might overlap, for example: a situation in which a mechanical failure causes a road user to lose control and a second vehicle fails to react in time. As these factors are complex and difficult to record (despite several attempts, notably (1)), methods for surrogate safety analysis aim to substitute these factors empirically in order to detect and characterize the potential for collisions among ordinary traffic events.

The core concept of a traffic conflict, and it can be argued any safety-related traffic event, is the collision course, i.e. a situation at some instant(s) where, if a road users fails to correct their current course, they are expected to collide in the future with either another road user or some other roadside obstacle. For example: a road user is distracted and fails to correct a collision course in time for a collision with a pedestrian to occur. The general hypothesis of the surrogate safety methodology is that surrogate safety measures can be designed with predictive power such that the expected number of collisions can be estimated from non-collision traffic observations. One of the best known surrogate safety measures (besides speed) is temporal proximity to a collision, namely time-to-collision (TTC). TTC is especially useful in the context of road user behavior as it shares the same dimension as distraction time, reaction time, breaking time, etc. This however leaves the problem of properly predicting uncorrected motion and detecting potential collision courses. This aspect will be the focus of the remainder of this paper.

The classical approach to this problem assumes that the natural motion of a vehicle which has no control input is one simply undergoing Newton's first law, that is, one undergoing zero significant net force (no acceleration and no change in heading) (2). In such a scenario, a collision would occur if both road users failed to correct their course vector in the time, i.e. TTC, it takes to arrive at a collision point defined by motion prediction at a constant velocity. However, outside of certain ideal situations, such as road users traveling in straight, isolated highway sections (3) and simultaneous loss of control/failure to initiate evasive action by both road users, collision courses predicted using constant velocity make some limiting assumptions about naturalistic motion paths of road users.

For example, in a curved road section, the distraction or the slow reaction time of a road user does not necessarily translate to a tangential exit path from the roadway. In fact, a distraction, for example, might even lead a road user to fail to exit an ongoing turning manoeuvre which otherwise might lead to some collision. Furthermore, even in the event that an operator is no longer in physical contact with the controls of a vehicle, road vehicles do not behave as frictionless particles. Finally, it can be simply argued that constant velocity does not account for natural variability in driving behaviour such as subtle lane drift.

As such, a more naturalistic model is needed to meet the needs of motion prediction. However, because naturalistic motion paths are complicated and possibly unique to a given environment, an appropriate solution is needed to learn the site-specific motion patterns of road users. This is an active field of research in the field of robotics (see the review in (4)). Motion patterns are used to make automated choices adapted to a specific environment through learning, especially for spatial tasks such as path finding and classification from image data.

This paper explores the application of motion patterns by first attempting a basic learning process on a sample of 12-hours of traffic data (a full week day of typical, moderately heavy traffic flow) and then applying the motion pattern to collision prediction and computation of the surrogate safety measure time-

to-collision. The results are then compared with the naïve method of motion prediction at constant velocity.

BACKGROUND

Previous vehicle trajectory prediction used simplifying assumptions about naturalistic road user behaviour to model deterministic behaviour (prediction at constant velocity) or made use of objective-based prototypes. As mentioned before, constant velocity is a staple of the surrogate safety methodology for estimating time-to-collision, and traces its roots all the way back to the earliest implementation of the traffic conflict technique which measured traffic conflict events via trained observers (2) (5). Prototypes are frequently used to describe objective-based spatial tasks, often scene entrance and exit tasks. Examples of prototypes applied to traffic scenery include Baiget *et al.* who measured origin and destination points of outdoor pedestrians in a traffic scene (6) and Saunier *et al.* who used motion patterns to form prototypes for turning decisions inside of traffic intersections (7).

Mohamed and Saunier recently implemented more sophisticated methods stemming from the field of robotics and vision including normal adaptation which accounts for naturalistic variability between velocity vectors and evasive action, as well as variations on the collision detection algorithm (4), itself inspired from Broadhurst *et al.*'s modeling of control inputs (8).

Motion patterns have been relatively well developed in the field of Robotics as they describe naturalistic trajectory patterns from normal behaviour, including user trajectories. Motion patterns are frequently described in a number of ways, including prototypes, discrete maps, and probabilistic models such as hidden Markov models (HMM). A very popular approach to learning these motion patterns is by using the Expectation-Maximisation (EM) algorithm (9). Motion patterns are frequently implemented in traffic scenes, though typically in contexts outside of road safety, or frequently concerning image processing (trajectory extraction). For example, Gryn *et al.* use motion patterns and direction maps to construct turning ratios in a scene from traffic video data (10). Bennewitz *et al.* use motion patterns from laser-based detection to model motion of pedestrians inside of a building (11).

Morris and Trivedi have extensively reviewed motion patterns and trajectory path models and discussed the capability of trajectory prediction as well as collision prediction from learned behaviour (12). Paths are defined as one or a multiple of three type: i) centroid, ii) envelope, or iii) sub path models.

METHODOLOGY

Motion Pattern Learning

The objective of the model is to predict the destination probability of road user A at a given point x, y after Δt time from the time of origin t_o (event A_{x_i, y_i, t_i}), according to any set of additional initial conditions at the time of origin t_o (including speed, traveling lane, road type and spatial origin x_o, y_o). This is illustrated in **Figure 1a** and formally defined in **equation (1)**:

$$P(x_A = x_i, y_A = y_i, t_i = t_o + \Delta t) = P(A_{x_i, y_i, t_i}) = f(x_o, y_o, \text{other initial conditions at } t_o) \quad (1)$$

In order to calibrate this model numerically from the data set, discretized motion patterns are learned from the trajectory data of all road users at a given site with a first analysis. The motion patterns are multi-dimensional matrices of variable size, set according to the initial conditions being learned and the desired prediction precision and accuracy afforded by the sample data. Each dimension of the matrix represents the range of a single initial condition. A multi-dimensional initial condition, such as 2D Euclidean space, is represented by multiple discretized dimensions. The core dimensions are the destination probability for position at x and y , discretized over s_x and s_y steps, representing the learned

probability of the spatial position of vehicles, over the dimension of time flow Δt after the time of origin t_o , itself discretized over s_t steps, usually using a step size of $1/30^{\text{th}}$ to $1/15^{\text{th}}$ of a second, depending on the data sample rate. These represent the probability of a user arriving at a point at x, y , and in t .

These probabilities of arrival are formed by evaluating the frequency of observed arrivals of all road users over x, y , and t corresponding to a set of initial conditions. The most basic initial conditions include speed, lane, spatial origin (using x, y , or curvilinear distance along the lane's center alignment), and road user type. More advanced initial conditions to use for learning could include vehicle type, lane drift, known route (scene destination or scene origin or both), vehicle following conditions, and presence of other constraining vehicles, among other factors. Initial conditions are discretized as well. Initial condition ranges used for these discretized motion patterns are given in **Table 1**. The curvilinear distance in this case is a spatial measurement along the center line of a given lane and is used to reduce the dimensionality of the model and the amount of superfluous learning which that would entail.

Table 1 – Discretization ranges used for the motion pattern learning for this case study.

| | <i>Lane Identifier</i> | <i>Curvilinear Distance</i> | <i>Speed</i> | <i>Time Horizon</i> | <i>Destination X</i> | <i>Destination Y</i> |
|----------------|------------------------|-----------------------------|--------------|---------------------|----------------------|----------------------|
| Discretization | Linear | Linear | Centile | Linear | Linear | Linear |
| Steps | no. of lanes | Variable | 10 | Maximum dwell time | 60 | 60 |
| Step Size | 1 lane | 3 m | Variable | 1 frame | 1 m | 1 m |

For continuous measures such as speed and spatial positioning, a sufficiently small step size is needed to obtain precise predictions. If, for example, the step size of the spatial initial condition is larger than the average distance between the centroid of two road users, and other initial conditions remain the same, then destination predictions will begin to artificially overlap, when in reality following behaviour is occurring. Given a fixed amount of data, however, increasing the prediction precision decreases the prediction accuracy as the sample size per bin for the initial conditions decreases. Because each prediction is made using a sample of observations with similar initial conditions, every additional dimension or increase in precision increases the size of the motion pattern matrix and decreases the sample size of each individual prediction, so a balance needs to be struck between desired prediction accuracy and prediction precision. Furthermore, prediction matrices become increasingly larger as initial condition complexity grows. Fortunately, this increase in matrix size can be managed to a certain degree using sparse matrices, particularly because as position prediction accuracy increases, the number of cells with non-zero spatial probability decreases.

Furthermore, sample sizes may be spread unevenly across dimensions that are not evenly distributed, leading to undersampling of some initial condition states (notably speed outliers). One strategy is to use centile discretization such that samples are evenly distributed according to a percentile. While this increases the prediction accuracy of outlier initial condition states, it tends to reduce precision as the similarity criteria between some initial condition states become stretched. Ultimately, collecting a sufficiently large data set is the solution to both problems simultaneously.

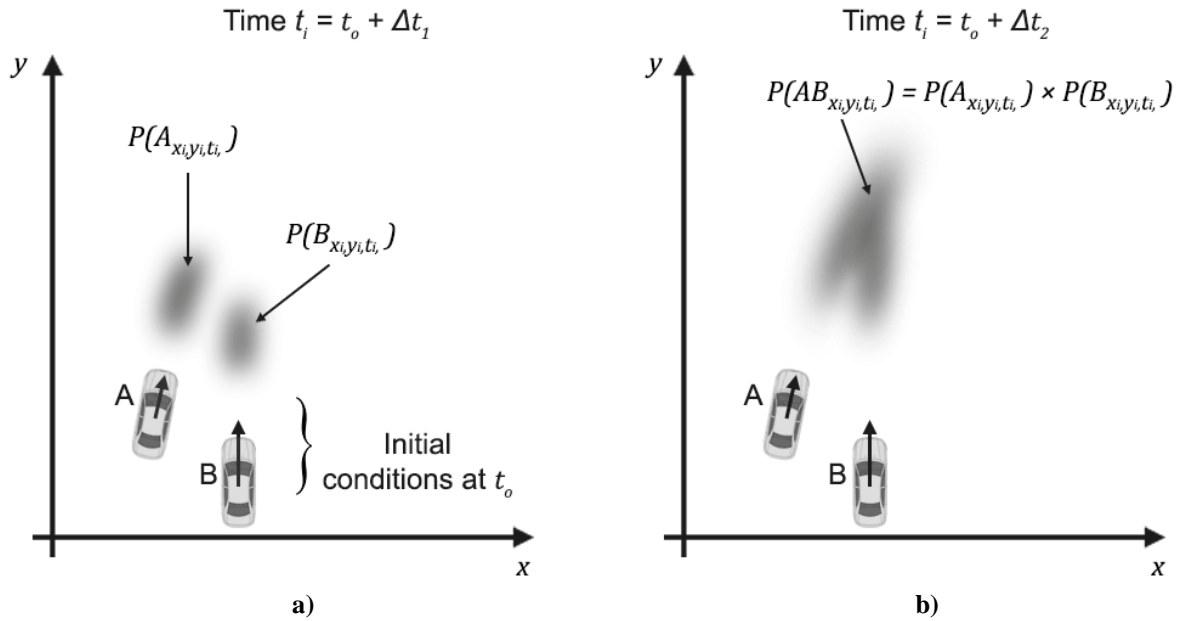


Figure 1 – Motion pattern maps for two road users demonstrating the probability of arrival for vehicles A and B in x y space for two successive timesteps: a) no arrival probability overlap, and b) arrival probability overlap with a collision (joint) probability of $P(A_{x_i, y_i, t_i}) \times P(B_{x_i, y_i, t_i})$.

Collision Detection

We denote the collision event between road user A and road user B, which coexist in the scene over a common time interval, as AB. The probability of collision at a given point x_i, y_i after Δt time from the time of origin t_o (illustrated in **Figure 1b**) is thus the joint probability of the individual destination events of either road user which are assumed to be either independent or already factored by the motion prediction (this independence should not be confused with road user interaction dependency, e.g. spatial awareness). That is, if the two events are independent, the joint probability is given by (2):

$$P(x_A = x_B = x_i, y_A = y_B = y_i, t_i = t_o + \Delta t) = P(AB_{x_i, y_i, t_i}) = P(A_{x_i, y_i, t_i}) \times P(B_{x_i, y_i, t_i}) \quad (2)$$

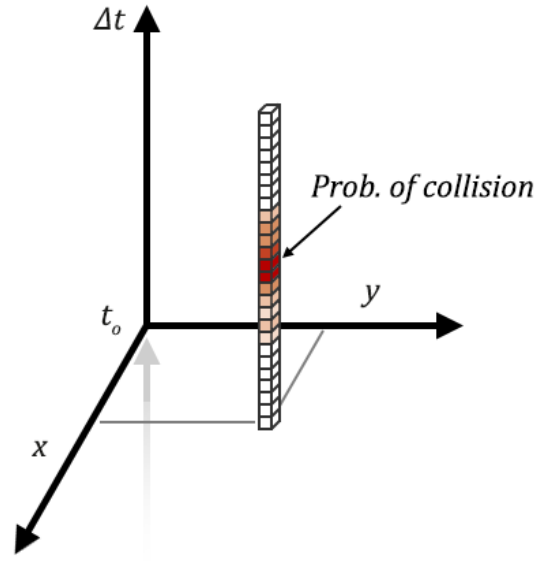


Figure 2 – Probability of collision at a given position x, y as a function of time.

The future collision at a single point for a single interaction at t_o is thus the union of future collision events AB throughout the dimension of predicted time Δt as illustrated in **Figure 2** and demonstrated in **equation (3)**. It should be noted that individual collisions are not temporally independent events. As such, the approximation, which is the summation over all predicted time of all collision probabilities estimated at that point, is an upper bound on the collision probability at this point, and might yield a probability greater than 1 or otherwise overestimate the probability in situation where the intersection of two or more collision events for the same pair of users is significant.

$$P(AB_{x_i, y_i, t_o}) = P\left(\bigcup_{t_i=t_o}^{timehorizon} AB_{x_i, y_i, t_i}\right) \approx \sum_{t_i=t_o}^{timehorizon} P(AB_{x_i, y_i, t_i}) \quad (3)$$

The total probability of the event at t_o is similarly given by **equation (3)** :

$$P(AB_{t_o}) = P\left(\bigcup_{x=0}^{x_n} \bigcup_{y=0}^{y_n} AB_{x_i, y_i, t_o}\right) \approx \sum_{x=0}^{x_n} \sum_{y=0}^{y_n} P(AB_{x_i, y_i, t_o}) \quad (4)$$

Δt is the time-to-collision (TTC) value for any collision event at that point in time, i.e. if the probability of collision is non-zero at that future time t_i . However, it is also useful to compute the expected TTC over all predicted times. As such, the expected TTC at a given point is given by **equation (5)** while the weighted TTC for the entire interaction at t_o is given by **equation (6)**.

$$TTC_{(x_i, y_i, t_o)} = \frac{\sum_{t_i=t_o}^{timehorizon} (P(AB_{x_i, y_i, t_i}) \times (t_i - t_o))}{\sum_{t_i=t_o}^{timehorizon} P(AB_{x_i, y_i, t_i})} \quad (5)$$

$$TTC_{(t_o)} = \frac{\sum_x \sum_y P(AB_{x_i, y_i, t_o}) \times TTC_{(x_i, y_i, t_o)}}{\sum_x \sum_y P(AB_{x_i, y_i, t_o})} \quad (6)$$

This model works reasonably well for collisions between particles, or if at least each road user can be contained within a bin in the destination space, but in general vehicles and other road users are

Figure 4 presents a slice of the motion pattern. The figure plots the sample space for the learned arrival probabilities across x, y (1.5 m by 1.5 m) after a Δt of 60 frames (4 s) associated with road users matching a particular set of initial conditions including a speed of between 16.2 km/h and 21.6 km/h, a curvilinear origin of between 5.94 and 8.9 m and located on align_1. The probabilities of this figure are exhaustive; in other words, there is a 100 % calculated chance that the future position will be located in this graph after Δt time. The full motion pattern consists of a sample space for each Δt timestep and each combination of initial condition. There are thousands of these combinations. The sample for this particular set of initial conditions is composed of 292 observations of road users matching the initial conditions and the highest cell density is 15 observations. The distribution of these sample sizes is generally logarithmic. A small number of sample spaces have over a thousand observations, while a larger number sample spaces have a few dozen. Fortunately, sample spaces with a low number of observations are composed primarily of outliers. The variability in the distribution of sample spaces (prediction accuracy) can be mitigated by choosing centile discretization at the expense of introducing variability in prediction precision.

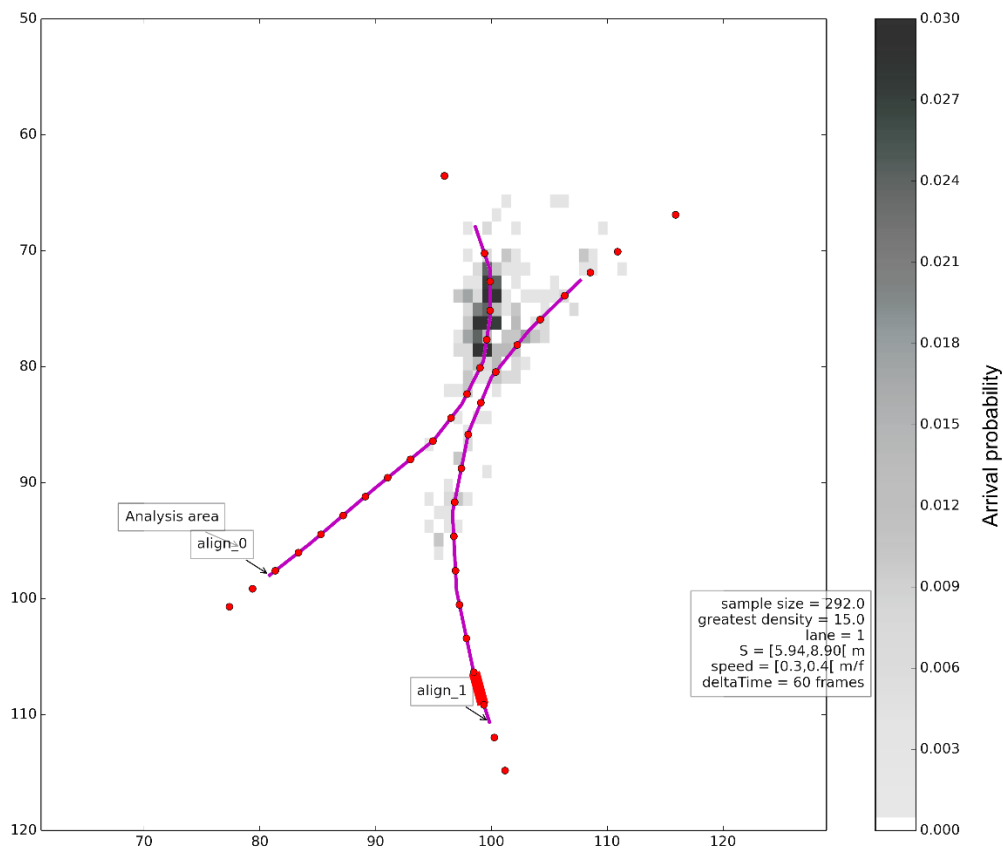


Figure 4 – Arrival probability in x, y for a Δt of 60 frames (4 seconds) for a single road user according to a set of initial conditions.

For this exercise, the constant velocity motion prediction methodology (reusing the computing function formulated and used in (4)) is compared to the motion prediction methodology based on learned motion pattern. **Figure 5** illustrates the spatial distribution and density of collision points predicted with both methodologies. As expected, collision points have shifted away from the point of intersection of constant velocity collision courses of road users entering the scene (which actually appears to be positioned before the weaving zone). The collision points using the motion pattern methodology are now clustered near the approach yield line, where road users must stop to allow passage of other road users

already engaged inside the roundabout, and a little bit after the weaving zone. The distribution also appears less artificial and concentrations of smaller TTC's (below 1.5) seem more meaningful.

Of special note is the large density of expected collision points near both exiting branches of the roundabout (top half of the motion pattern graphs). This is explained by the choice to not use a posteriori knowledge of the intended destination of each road user in the motion pattern learning function. If motion patterns predict exclusively according to known intended destination, they may not be able to simulate situations in which the destination is unknown or hypothetical. However, if the destination is not modeled, there may be oversampling of unrealistic motion. This parameter will therefore have to be calibrated.

Finally, it should be noted that conflicts can only be detected within camera space as the motion pattern cannot learn and predict movements outside of the study area, as opposed to constant velocity that can predict conflicts to infinity. While temporally distant conflicts tend to be of little predictive value, this can cause oversampling of interaction probability according to sampling exposure. As such, a per-vehicle pair approach to aggregating data is generally preferred.

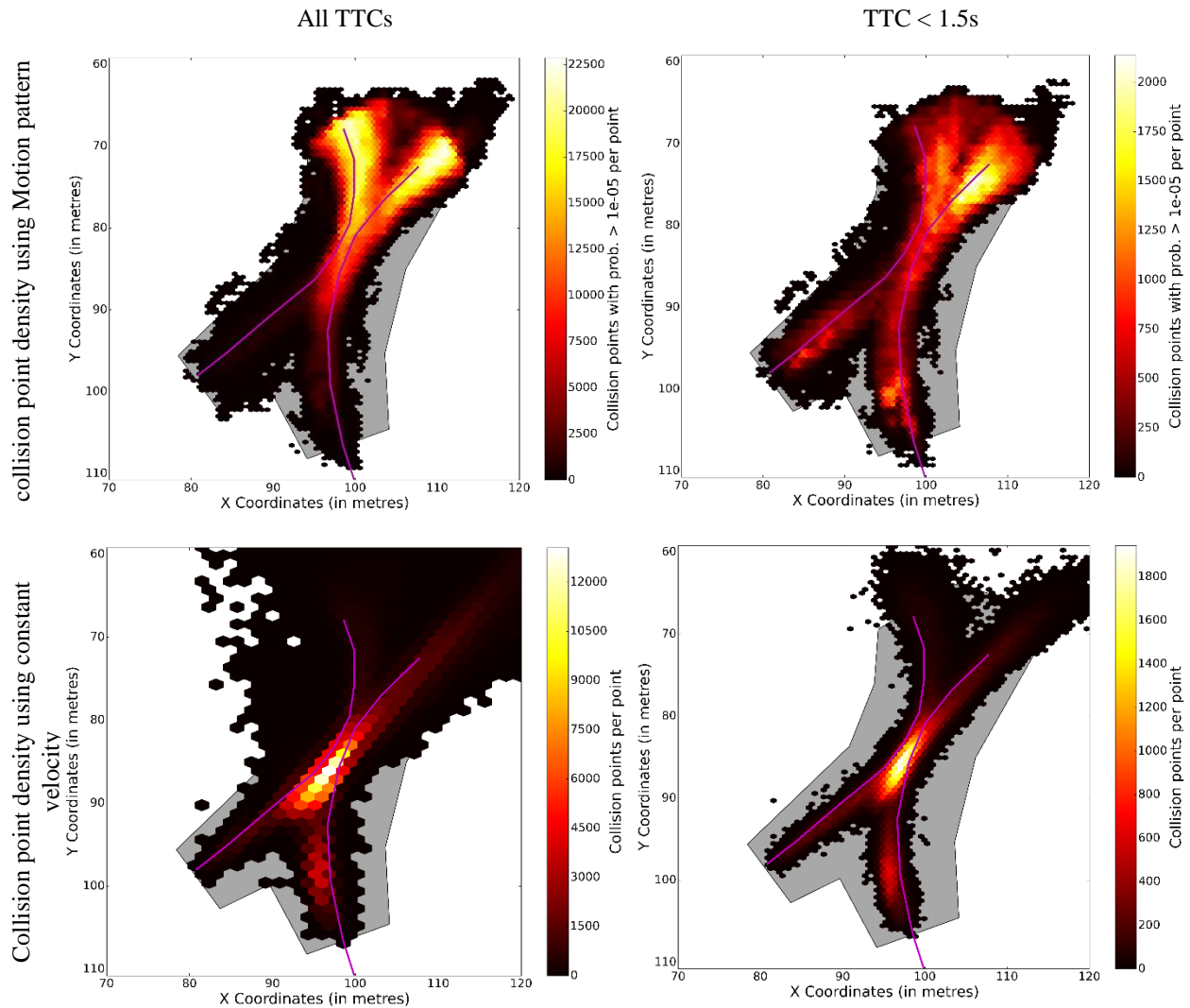


Figure 5 – Collision point density maps for the sample site according to the value of TTC at those points and the motion prediction method used. In all plots, the roundabout lane starts from the bottom left leg, while the approach starts from the bottom right leg. Vehicles leaving the weaving zone continue inside the roundabout

from the top-left leg, while vehicles exiting the roundabout leave using the top-right leg. Overall, the flow of vehicles is from bottom to top.

Figure 6 compares the distribution of TTC observations for both methodologies according to three aggregation methods: i) all instantaneous measures, ii) 15th percentile per unique pair of road users (i.e. set of interactions), and iii) minimum value per unique pair of road users. The principle behind aggregating by unique pair of road users is to account for biasing effects of the limited sample space and exposure from variable dwell time and location, as well as to keep the link between events without a collision and collisions (one pair or road user may lead to only one collision). Using the minimum value seems theoretically preferable as this samples the most dangerous interactions. However, as illustrated in **Figure 6**, minimum interaction values are oversampled with unrealistic low measures (up to 15 % of TTC measures below 0.25 seconds), likely biased from outliers and errors. Instead, a centile can be used to capture TTC measures which are unusually low, but not so low that outliers become oversampled. This generally yields results more consistent with previous research. Finally, the method of aggregation can be decided when it comes time to validate the model and correlate TTC measures with accident probability.

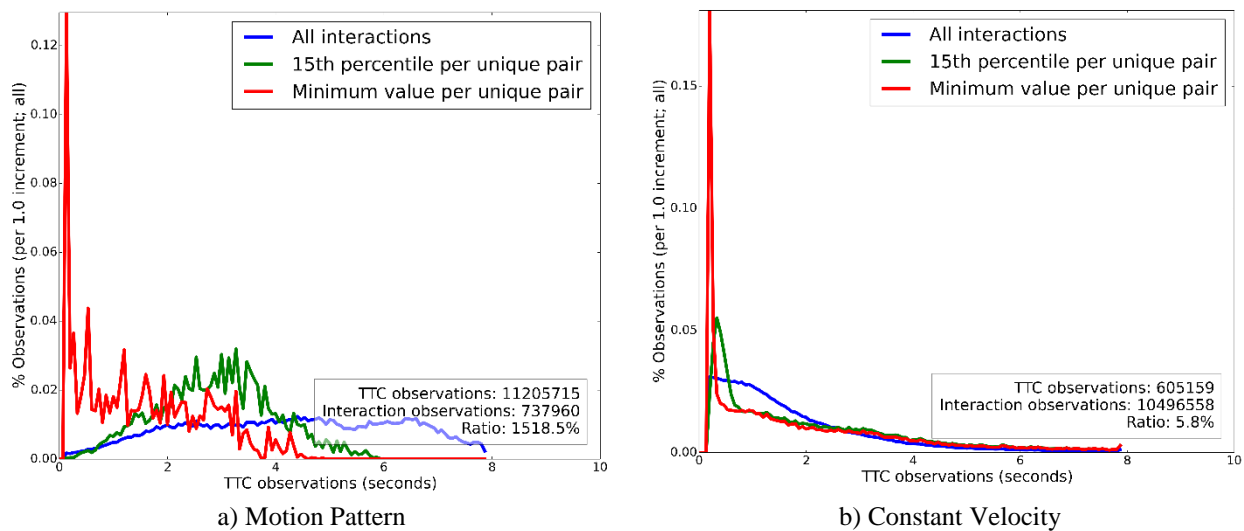


Figure 6 – Distribution of TTC observations by collision prediction method.

CONCLUSION

This paper reviews and demonstrates the feasibility of the motion pattern motion prediction methodology and compares it with the classical constant velocity motion prediction methodology. While validation with accident probability (observed accident rate) remains a long-term goal for surrogate safety measures, this paper does demonstrate the usefulness, applicability and feasibility of a more naturalistic and empirical approach to road user motion prediction learned from scene behaviour data. The expected location of collision points predicted using motion prediction based on motion pattern were satisfactory for vehicles, given the sample size used for the motion pattern learning, though additional testing will be required to verify if the methodology can be expanded to predict pedestrian trajectories. The model was not perfect however. Some issues were uncovered with processing time which diminishes the practical usefulness of the methodology at this time, and prediction accuracy remains a trade-off with prediction precision, or otherwise, the method requires a significant amount of data. However, it might be interesting to investigate this method using data collected over several days or weeks.

It was found that the precision provided by the discretization ranges constitutes the bare minimum for satisfactory driving behaviour modeling. Yet the model will need to be expanded with additional parameters (and potential collision factors) such as lane drift, short term acceleration trends, and

proximity to other drivers which may be of particular interest. Such an endeavour will likely require more calibration data. It would also be very interesting to compare motion patterns across different sites to see if patterns are comparable across different geometric or regional factors. This will be applied in particular to a large sample of roundabout sites built in the province of Quebec in order to identify the impact of their different attributes on behaviour and safety.

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