A Probabilistic Framework for Estimating the Risk of Pedestrian-Vehicle Conflicts at Intersections

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Abstract—Pedestrian safety has become a critical issue due to the increase in pedestrian crashes every year, while proactive traffic safety management based on surrogate safety measures (SSMs) has been considered one of the key approaches to improving pedestrian safety. However, existing SSMs are developed based on the assumption that road users will maintain constant speed and direction. Risk estimations based on this assumption are less stable and more likely to be exaggerated. Considering the limitations of existing SSMs, this study has proposed a probabilistic framework for estimating the risk of pedestrian-vehicle conflicts at intersections. The proposed framework works by predicting the trajectories of vehicles and pedestrians using Gaussian process regression models and incorporating these results with the probability of vehicles making different maneuvers. The proposed framework has been evaluated using both simulated and real-world data collected at an intersection. The simulation results validated an increased estimated risk given time-based pedestrian-vehicle conflicts, as well as a higher probability of the vehicle maneuver that led to such conflicts. This observation remained even when multiple conflicts arose from different directions. Moreover, experimental results using real-world data suggested that the proposed framework outperformed traditional time-to-collision (TTC) in terms of conflict prediction, quantification, and localization. For example, the proposed framework had a sensitivity of 0.92 in terms of conflict prediction, while TTC had a sensitivity of 0.62. Furthermore, the proposed framework required much less computation time compared to deep learning methods, which made it an optimal choice for proactive pedestrian safety solutions at intersections.

Index Terms—Pedestrian safety, traffic conflicts, surrogate safety measures, proactive traffic safety management.

I. INTRODUCTION

PEDESTRIAN safety is an important consideration in transportation management, due to the vulnerability of this group when involved in traffic crashes. However, streets in the United States are not becoming safer for pedestrians. There were 7,388 pedestrian fatalities that occurred on the roadways in 2021, a considerable 13% increase from the number in 2020 [1]. On average, a pedestrian was killed every 71 minutes in traffic crashes in 2021 [1], while this number was 81 minutes in 2020 [2]. Moreover, 15% of the pedestrian fatalities occurred at intersections [2]. Improving pedestrian safety at intersections has become an important topic for researchers, traffic practitioners, and policymakers.

Over the past decades, numerous studies have been conducted regarding pedestrian safety at intersections, which can be divided into crash- and conflict-based studies. Crash-based studies use historical crashes to predict future crashes, analyze crash severity, etc. [3], [4], [5], [6]. Differently, conflict-based studies predict, identify and quantify pedestrian-vehicle conflicts by analyzing road user behavior based on non-crash data (e.g., trajectory data) [7], [8], [9], [10]. Traffic conflicts are observable non-crash events, in which the interactions among multiple road users in space and time create a risk of crashes if they do not change their courses of movement [11]. The benefit of using conflicts over crashes is that they can proactively evaluate traffic safety status. Moreover, since pedestrian crashes are extremely rare events, it may take much more time to collect enough pedestrian crashes with necessary pre-crash information. Lastly, conflicts between pedestrians and vehicles do not necessarily lead to crashes, but still, need to be analyzed to better understand interactions between them.

Various surrogate safety measures (SSMs) have been used in existing studies, including time to collision (TTC) [12], [13], post encroachment time (PET) [14], gap time [15], deceleration to safety time (DST) [16], etc. Recently, due to the development of object detection techniques, it is much easier to collect trajectories of road users using sensors like cameras [8], [10], [17], LiDARs [9], [18], etc. Using trajectories obtained by these sensors, various SSMs can be estimated for measuring the risk of pedestrian-vehicle conflicts at intersections. However, most SSMs are developed based on the assumption of constant speed and direction. For example, the TTC and the gap time of a pedestrian-vehicle conflict are estimated while assuming each road user will remain at the current speed and on the same path [19]. However, the behavior of road users at intersections can be complicated. For example, drivers constantly adjust the speed of their vehicles while making turning maneuvers or reacting to the presence of other road users [8], [20]. The assumption of constant speed and direction does not hold true under these conditions, which will result in inaccurate estimations of risk. Moreover, due to this assumption, metrics like TTC and gap time are not able to capture the evasive behavior of vehicles and often overestimate the risk of conflicts [8]. Although SSMs (e.g., PET) estimated using historical trajectories do not suffer from this assumption, they can only be applied in post-analytical studies and thus cannot predict conflicts in advance.
Considering the aforementioned limitations of existing SSMs, this study proposes a probabilistic framework to estimate the risk of pedestrian-vehicle conflicts at intersections. First, the proposed framework does not assume constant speed and direction, rather it can accurately predict road users’ future trajectories. Second, the proposed framework incorporates the probability of vehicles making different maneuvers into the trajectory prediction results to enhance the accuracy of risk prediction, quantification, and localization. Lastly, the proposed framework uses simple observations of road users as inputs and does not require heavy computational resources compared to other deep learning methods. This makes it highly efficient as a real-time proactive pedestrian safety solution at intersections.

The rest of the paper is organized as follows: Section II reviews the current SSMs and their applications in existing studies. Section III introduces the methods used in this paper, including the proposed framework and numerical experiments. Section IV introduces the data used in this paper to demonstrate the performance of the proposed framework. Section V presents the experimental results, as well as a comparison of the proposed framework to other methods. Section VI summarizes the conclusions and future research directions.

II. LITERATURE REVIEW

In general, two types of SSMs have been used in existing studies, proximity- and deceleration-based SSMs. Proximity-based SSMs, including TTC, PET, and gap time are defined as follows: TTC is the time that remains until a conflict between two road users occurs given that the conflict course and speed difference are maintained [12]. PET is the time difference between the moment an “offending” road user passes out of the area of a potential conflict and the moment of arrival at the potential conflict point by the “conflicted” road user possessing the right-of-way [14]. Lastly, gap time is a variation of PET, which is calculated at each time instant by projecting the movement of road users that have potential conflicts [15].

Ismail et al. [7] applied TTC, PET, and gap time to analyze pedestrian-vehicle conflicts using video data. Although these SSMs were able to identify most pedestrian-vehicle conflicts, the authors suggested that combining different SSMs could better capture pedestrian-vehicle conflicts. Some studies adopted this strategy and used multiple SSMs. For example, Wu et al. [21] combined PET with other SSMs to identify conflicts between pedestrians and vehicles, since PET could not reflect the change in driver behavior, such as a sudden deceleration before reaching the potential conflict point.

Deceleration-based SSMs, such as DST, deceleration rate (DR), and deceleration rate required to stop (DRS), identify pedestrian-vehicle conflicts based on vehicle deceleration and are defined as follows: DST is the deceleration a vehicle needed to reach a non-negative PET value if the movements of the conflicting road users remain unchanged [16]. DR is the highest rate at which a vehicle must decelerate to avoid a collision [22]. DRS is the constant deceleration rate required for the vehicle to stop and give the right-of-way to pedestrians [23].

Fig. 1 provides an example of potential pedestrian-vehicle conflicts. Fu et al. [23] used DRS to evaluate pedestrian safety at unsignalized intersections. Results suggested that stop sign-controlled intersections had lower DRS than unprotected intersections, indicating that stop signs provided better protection for pedestrians. Olszewski et al. [22] used the value of deceleration to identify pedestrian-vehicle conflicts at intersections. A threshold of 4 m/s^2 was used to detect the abrupt braking behavior of vehicles. Ismail et al. [8] conducted a before-and-after study to evaluate the impact of pedestrian scramble phasing on pedestrian safety. The number of medium and high values of DST had significantly decreased after the implementation of the pedestrian scramble phasing, indicating its positive impact on pedestrian safety.

Although various studies have effectively employed existing SSMs, there has been limited investigation into addressing the inherent deficiencies within them. First, SSMs such as TTC and gap time cannot accurately quantify conflicts due to the assumption of constant speed and direction. For example, TTC quantifies conflicts by using the instant speed and direction of road users at the current time and assumes that the potential conflict exists along the instant direction. However, the estimated conflict may not correspond to the actual conflict as road users would adjust their speed and direction while traveling. The lack of the ability to measure future speed and direction makes metrics like TTC less reliable and accurate. Second, existing SSMs usually overestimate the severity of conflicts and fail to capture the evasive actions of drivers. For example, given a potential conflict between a right-turning vehicle and a crossing pedestrian on its path, the vehicle’s speed may be constantly adjusted during turning. The driver may also make evasive behavior such as braking while approaching the pedestrian, which can not be captured by metrics like TTC [24]. Lastly, deceleration-based measures may falsely identify conflicts since they only focus on the magnitude of deceleration.

III. METHODS

A. Probabilistic Risk Estimation Framework

Fig. 1 provides an example of potential pedestrian-vehicle conflicts. Given a vehicle’s current position, the proposed
framework estimates its probability of turning left, turning right, and going straight and predicts the corresponding future trajectories for each maneuver. Moreover, the framework predicts pedestrians’ future trajectories based on their current positions. The risk is then estimated as a sum of individual Risk\(i\), the risk given the vehicle’s \(i^{th}\) maneuver, weighted by the probability of each maneuver. The estimation is given in Equation 1, where \(i = 1, 2, 3\) denotes left-turn, right-turn, and going straight, and \(\text{Prob}(\text{pos})\) represents the probability of the vehicle making the \(i^{th}\) maneuver given its current position \(\text{pos}\). Risk\(i\) is calculated using Equation 2, where \(\text{Tveh}_{ij}\) and \(\text{Tped}_{ij}\) represent the time the vehicle and the \(j^{th}\) pedestrian need to reach the conflict point \((c_{ij})\) if it exists. The estimation considers the most extreme situation if multiple pedestrian-vehicle conflicts exist by taking the minimum of the absolute difference between \(\text{Tveh}_{ij}\) and \(\text{Tped}_{ij}\). The use of the exponential function allows the risk to increase gracefully with a decreasing time difference so that a smaller time difference corresponds to a higher risk of conflict.

\[
\text{Risk} = \sum_{i=1,2,3} \text{Risk}_i \cdot \text{Prob}(\text{pos})
\]

(1)

\[
\text{Risk}_i = \begin{cases} 
\exp(-|\Delta T|) = \exp(-\min(|\text{Tveh}_{ij} - \text{Tped}_{ij}|)), & \text{if } c_{ij} \text{ exists, } j \in [1, K] \\
0, & \text{otherwise}
\end{cases}
\]

(2)

\section{Gaussian Process Regression}

The Gaussian process regression (GPR) is used in this study for trajectory prediction. It is a non-parametric Bayesian approach [25] that has been widely used for modeling trajectory data [26], [27]. GPR balances functional complexity with capturing the underlying data and is thus both more general and more principled than other forms of regression [28]. A GPR model on an input \(X\) can be defined by its mean function \(m(X)\) and covariance function \(k(X, X')\) as shown in Equation 3.

\[
f \sim \text{gp}(m(X), k(X, X'))
\]

(3)

In our context, given a road user’s position \(\text{pos} = (x_t, y_t)\) and velocity \(v = (v_x, v_y)\) at time \(t\), a pair of GPR models are used to model \(v\) using \(\text{pos}\) as shown in Equation 4.

\[
v_{x_t} \sim \text{gp}_x(m(x_t, y_t), k((x_t, y_t), (x_t, y_t'))) \\
v_{y_t} \sim \text{gp}_y(m(x_t, y_t), k((x_t, y_t), (x_t, y_t')))
\]

(4)

To predict a road user’s future trajectories \(\{(x_{t_1}, y_{t_1}), \ldots, (x_{t_f}, y_{t_f})\}\) based on its initial position \(x_{t_0}, y_{t_0}\), Equation 4 is utilized to sample the speed \((v_{x_{t}}, v_{y_{t}})\) and the next position \((x_{t_1}, y_{t_1})\) is estimated as \((x_{t_0} + v_{x_{t}} * (t_1 - t_0), y_{t_0} + v_{y_{t}} * (t_1 - t_0))\). Then, \((x_{t_2}, y_{t_2})\) is calculated using the speed \((v_{x_{t_1}}, v_{y_{t_1}})\) estimated by Equation 4. This process is repeated until the prediction of \((x_{t_f}, y_{t_f})\) is achieved. The GPR model has several crucial components that affect its performance, which are introduced in the following sections:

1) 

\[
k_{\text{RBF}}(X, X') = \exp\left(\frac{(X - X')^2}{2\sigma^2}\right)
\]

(5)

\[
k_{\text{RQ}}(X, X') = (1 + \frac{(X - X')^2}{2a\sigma^2})^{-\alpha}
\]

(6)

2) Hyperparameters: The RBF kernel in Equation 5 has one hyperparameter \(\sigma\), which is its length scale. The RQ kernel in Equation 6 has two hyperparameters including \(a\) and \(\sigma\), which are the weighting parameter and length scale, respectively.

3) Loss Function: Hyperparameters are tuned in the training step by minimizing the loss function, which is the log-transformed marginal likelihood of the GPR model. The marginal likelihood can be calculated as in Equation 7 [29], where \(X\) and \(y\) each denote the inputs and targets of the model. An Adam optimizer [30] with a learning rate of 0.1 was used in this study to optimize the hyperparameters of a GPR model.

\[
\mathcal{L} = p(f|y|X) = \int p(y|f(X))p(f(X)|X)df
\]

(7)

\section{Numerical Experiments}

To facilitate the interpretation of the risk value defined in this paper, a computational simulation has been conducted. Five variables are necessary to estimate the risk of a conflict according to Equations 1 and 2: \(\text{Prob}(i = 1), \text{Prob}(i = 2), |\Delta T_1|, |\Delta T_2|, |\Delta T_3|\), where \(i = 1, 2, 3\) denotes the vehicle’s maneuvers of turning left, turning right, and going straight, and \(\text{Prob}(i = 3) = 1 - \text{Prob}(i = 1) - \text{Prob}(i = 2)\).

For better figure readability and a more straightforward interpretation, we provided an example by varying two of the five variables related to left-turn. The probability of a vehicle turning left \(\text{Prob}(i = 1)\) was manipulated between 0 and 1, and the minimum absolute time difference \(|\Delta T_1|\) between the vehicle and any pedestrians reaching the conflict points was set between 0 and 55 s based on real-world data. More details of the data will be given in Section IV.

Two sets of values were used for the rest three variables, i.e., \(\text{Prob}(i = 2), |\Delta T_2|, \text{and } |\Delta T_3|\). The first set of values illustrated how risk changed as a function of the probability of a vehicle moving in a certain direction and the minimum absolute time difference associated with potential pedestrian-vehicle conflicts in that direction. This first example set \(|\Delta T_2| = \infty\) and \(|\Delta T_3| = \infty\) denoting a simplified situation where there were pedestrian-vehicle conflicts in only one moving direction (i.e., left-turning direction). \(\text{Prob}(i = 2)\) did not need to be explicitly specified given \(\text{Risk}(i = 2) = \exp(-|\Delta T_2|) = 0\). The simplified situation sufficed to encompass the entire range of risk levels. More specifically, one may consider the magnitude of \(|\Delta T_1|\) a measure of the severity of potential pedestrian-vehicle conflicts in one direction. That is, the smaller the \(|\Delta T_1|\), the more severe the potential pedestrian-vehicle conflict will be. Under the proposed framework, one
would further consider the probability of a vehicle going in a certain direction to encounter the conflict. Thus, given an arbitrary set of $|\Delta T_1|, |\Delta T_2|, |\Delta T_3|$, the highest possible risk is achieved at $\text{Prob}(i = 1, i = \text{argmin}(|\Delta T(i)|))$ and the lowest possible risk at $\text{Prob}(i = 1, i = \text{argmax}(|\Delta T(i)|))$.

In our example, with $\text{Prob}(i = 1) \in [0, 1]$ and $|\Delta T_1| \in [0, 55]$, the highest risk (i.e., 1) can be achieved at $\text{Prob}(i = 1) = 1$ and $|\Delta T_1| = 0$, while the lowest risk (i.e., 0) can be achieved at $\text{Prob}(i = 1) = 0$ with $|\Delta T_2| = \infty$ and $|\Delta T_3| = \infty$.

The second set of values of $\text{Prob}(i = 2), |\Delta T_2|, |\Delta T_3|$ aimed to illustrate the influence of potential pedestrian-vehicle conflicts from multiple directions on risk estimation. More specifically, $\text{Prob}(i = 3)$ was set to three values (i.e., 0.1, 0.5, and 0.9) representing a low, medium, or high probability of going straight. Although the probability of turning left $\text{Prob}(i = 1)$ was manipulated from 0 to 1, the range of this variable would depend on the selected probability of going straight. The minimum absolute time difference associated with a straight-going vehicle and any pedestrians ($|\Delta T_3|$) was set to 1 s, representing a higher risk from the potential pedestrian-vehicle conflict in this direction. The minimum absolute time difference associated with pedestrian-vehicle conflicts in the right-turning direction ($|\Delta T_2|$) was fixed at the median value for right-turning vehicles in the observed dataset, i.e., 16 s. The probability of turning right was calculated as $\text{Prob}(i = 2) = 1 - \text{Prob}(i = 1) - \text{Prob}(i = 3)$.

The simulation results are presented in Fig. 2, where Fig. 2 (a) is with the first set of values ($|\Delta T_2| = \infty, |\Delta T_3| = \infty$) and Fig. 2 (b) is with the second set of values ($|\Delta T_2| = 16$ s, $|\Delta T_3| = 1$ s). The risk value is bounded by 0 and 1, where a higher risk corresponds to a smaller absolute time difference value (e.g., $< 5$ s) and a higher probability of the vehicle moving in the direction of potential conflicts. When there are potential conflicts from multiple directions, the minimum absolute time difference in the moving direction with a higher probability dominates the risk estimation, such as the case of $\text{Prob}(i = 3) = 0.9$ in Fig. 2 (b).

Table I further summarizes from Fig. 2 (a) the total risk at seven minimum absolute time difference values under three left-turning probabilities. A threshold can be specified on the risk value to identify critical pedestrian-vehicle interactions at an intersection. We recommend choosing the threshold by considering the distribution of risk values in a single conflict situation where the probability of vehicle maneuver in the conflicting direction is 1 (as in Fig. 2 (a)). For example, existing studies have suggested TTCs of less than 1.5 to 3 s to define pedestrian-vehicle conflicts [8], [31], [32]. Accordingly, we may select a threshold value of 0.05, corresponding to a $|\Delta T_1|$ of 3 s. Any pedestrian-vehicle interactions with an estimated risk larger than 0.05 will be considered under a critical situation.

**IV. Data**

A case study based on real-world data at an intersection was used to demonstrate the performance of the proposed framework. This section introduces the data and the data preparation strategies before applying the framework.

**A. Data Description**

Data used in this study was collected by three Ouster OS1-128 LiDAR sensors and cameras installed at the intersection of E. MLK Blvd. and Georgia Ave. in Chattanooga,
Tennessee (Fig. 3) from approximately 11 AM to 12 PM on Oct 8, 2021. The west approach on E. MLK Blvd. has three lanes with a designated left-turn lane to the leftmost; the east approach on E. MLK Blvd. has two lanes with a right-turn/straight lane on the right and a left-turn/straight lane on the left. The south approach on Georgia Ave. has one lane; the north approach on Georgia Ave. has two lanes with a designated right-turn lane on the right. LiDAR and camera data were processed by Seoul Robotics and trajectory data including labels, corresponding size, velocity, etc., were released as part of the Transportation Research Board (TRB) Transportation Forecasting Competition 2022 [33].

B. Data Preprocessing

The goal of preprocessing data is to retain a set of clean and complete vehicle and pedestrian trajectories to demonstrate the proposed framework and to compare its performance with existing methods. A heuristic approach was applied where data filtering criteria and thresholds were determined through an iterative process based on data at the studied intersection. One can refer to the used criteria for other scenarios but may not want to apply the threshold values directly given the potential differences between scenarios. We describe the steps taken to identify data issues, clean data anomalies, and transform the data into a readily usable format below:

1) Labeling Tracked Objects: A unique label (i.e., vehicle, pedestrian, cyclist, or misc) was assigned for every trajectory based on a majority vote, where each trajectory was given the label with the highest proportion of assignments.

2) Estimating Roadway and Non-Roadway Areas: This study focuses on encountering events defined as pedestrian-vehicle interactions in which their trajectories intersect. To identify encountering events, the pedestrian’s relative position to the roadway needs to be determined. Unfortunately, due to the absence of GPS coordinates in the data, roadways, and non-roadways in the studied area cannot be precisely identified. Thus, our approach involves initially identifying the crosswalk location and then using the crosswalk boundary as a reference to estimate the roadway and non-roadway areas at or near this intersection.
roadways were defined by extending the four crosswalk boundaries. A specific point was considered “in the roadway” when within the rectangular area bounded by the four dashed lines or between the pair of blue or green dashed lines; otherwise, the point was “outside the roadway”. An exception was the northwest corner (leftmost circle in Fig. 5), where all points near this location were considered “in the roadway” per its sidewalk location. The relative position of a pedestrian trajectory to a roadway was determined by the majority vote of all the trajectory points involved.

3) Classifying Entering and Moving Direction for Vehicles: The two pairs of central points of crosswalk corners in the diagonal direction were used to divide the intersection into four quadrants. The entering direction of a specific vehicle trajectory was then determined based on which quadrant the first point of the trajectory belonged to. For example, if the first point was located in the bottom right quadrant, the trajectory was labeled as entering from the South of the intersection. Additionally, the sequence of unique quadrants a trajectory has traveled through was extracted and used to label its moving direction. This paper has focused on going straight, left-turn, and right-turn maneuvers since they accounted for most vehicle maneuvers at the intersection.

4) Merging Pedestrian Trajectories: Pedestrian trajectories contained in the initially processed data were oftentimes short and suspected to be incomplete. These trajectories may not be directly used by the framework. In order to obtain as many pedestrian trajectories as possible to demonstrate and evaluate the proposed framework, an effort was taken to identify trajectories that were potentially from the same pedestrian and to combine them into a single longer trajectory. The assumption was that a pedestrian would not appear or disappear suddenly while walking at or near the intersection. Thus, two trajectories were considered partial trajectories from a single longer trajectory if one followed the other in a coherent manner. More specifically, a trajectory $T_B$ is considered an immediately next trajectory of trajectory $T_A$ if $T_A$’s endpoint and $T_B$’s start point satisfy the following four criteria:

- Difference in time is no more than 0.2 s.
- Difference in distance (based on X and Y coordinates) is no more than 1 m.
- Difference in heading is no more than 90°.
- Difference in the angle of a trajectory, pointing from the position of the first data point to the last data points, is no more than 120°.

All thresholds were determined heuristically through an interactive process. A threshold value was chosen and checked against the resulting combinations until a reasonable set of combined trajectories was achieved. It was aware that the heuristic approach had limitations in precisely concatenating and verifying the combined trajectories. For example, partial trajectories from two pedestrians overlapped during rush hours could be combined and considered as from the same pedestrian. That being said, this approach serves the goal of the current study. Our framework considers the most extreme situation of a pedestrian-vehicle conflict by utilizing the smallest absolute time difference between a vehicle and any pedestrians at a given time. Thus, two or more pedestrians with overlapped trajectories will share a similar risk value under the framework even when identified individually.

5) Selecting Pedestrian Trajectories: Since a large proportion of short and incomplete trajectories still exist even after merging, additional steps were taken to remove pedestrian trajectories that were:

- Too short in time ($\leq$ 1 s) or distance ($\leq$ 5 m)
- With a higher proportion ($\geq$ 50%) of invalid data points
- Moving too fast to be considered a pedestrian, i.e., velocity is no less than 3m/s for at least 10 data points (approximately 1 s)
- Either outside the roadway or in the roadway but leaving the intersection

Again, thresholds were determined heuristically based on an examination of the data.

V. RESULTS

A. Data Summary

The data contains trajectories of 935 vehicles and 229 pedestrians after data preparation. Table II gives the descriptive statistics of features related to vehicles and pedestrians. The number of vehicles turning left, turning right, and going straight are 145, 199, and 591, respectively. The number of vehicles entering the intersection from the North, East, South, and West directions are 197, 351, 93, and 294, respectively. Moreover, the number of pedestrians crossing the intersection starting from the bottom, left, right, and top of the intersection are 66, 60, 40, and 63, respectively. In total, the data has 51,073 pedestrian-vehicle encountering events, in which trajectories of pedestrians and vehicles intersect. To depict the characteristics of these events, the PET of each event was estimated as it was a post-processing metric estimated using empirical trajectories. A threshold of 30 s was used for filtering events as events that had PETs larger than 30 s could not possibly be conflicts. Fig. 6 presents the distribution of PETs. In general, the going straight maneuvers had larger PETs compared to turning maneuvers. The reason was that drivers might have better lines of sight while driving straight and thus had more time to react to the presence of pedestrians. The left-turn and right-turn maneuvers had a relatively uniform distribution of PETs, while the going-straight maneuvers had a left-skewed distribution of PETs.

B. Experimental Results

1) Vehicle Maneuver Identification: Random forest was used to identify the probability of vehicles making different maneuvers. The vehicle’s position, velocity, yaw rate, and entering direction were used as the inputs for the model.
Precision, recall, and F1-Score were averaged over the maneuvers. The data contained more going straight maneuvers than turning techniques, was applied to balance the training data since parameters, then it was evaluated on the test data. Moreover, the data were randomly divided into training, validation, and test data in a ratio of 80%:10%:10% and the division was repeated 10 times. The model was trained on the training data, and the validation data were used to tune the model’s hyperparameters, then it was evaluated on the test data. In total, the data contained 51,073 pedestrian-vehicle encountering events. A PET of 4 s was utilized for identifying pedestrian-vehicle conflicts as it was an empirical metric estimated using historical data. In total, this study has identified 13 conflicts and 51,060 non-conflicts. The evaluation included all 13 conflicts and 26,000 randomly selected non-conflicts.

C. Framework Evaluation

The proposed framework has been evaluated from four aspects, the accuracy of predicting, quantifying, and locating conflicts and the computation cost. The data were randomly divided into training, validation, and test data in a ratio of 80%:10%:10% and the division was repeated 10 times. The model was trained on the training data, and the validation data were used to tune the model’s hyperparameters, then it was evaluated on the test data. Moreover, the increase in accuracy and stability by using the GPR model was more significant in predicting vehicle trajectories than predicting pedestrian trajectories. The reason could be that pedestrians were less likely to have significant changes in speed within several seconds.

Additionally, to evaluate the impact of the prediction horizon on a model’s performance, the 10th trajectory point of a road user was used to predict the future trajectory points. Table IV gives the results of GPR and dynamic models on different prediction horizons. The performance of both models was related to the choice of prediction horizons, while the GPR model achieved a more stable performance. Table IV suggested that the GPR model was more robust towards the change of prediction horizons as it has smaller values of the standard deviation of distance.

\[ d = \sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2} \]  

where \( d \) represents the distance between the predicted and the actual conflict, \( T_{veh_{ij}} - T_{ped_{ij}} \) with \( \hat{x}_i, \hat{y}_i \) represents the position of the road user at time \( t \).

\[ x_{t+\Delta t} = \frac{1}{2} a_x \Delta t^2 + v_{x_i} \Delta t + x_i \]  

\[ y_{t+\Delta t} = \frac{1}{2} a_y \Delta t^2 + v_{y_i} \Delta t + y_i \]  

To quantify the performance of a model on trajectory prediction, the distance between the predicted trajectory point \((\hat{x}_i, \hat{y}_i)\) and the actual trajectory point \((x_i, y_i)\) was utilized as shown in Equation 9. Table IV shows the performance of GPR and dynamic models on different starting points and prediction horizons, respectively. First, these two models were used to predict the future 30 points (three seconds) of road users’ trajectories using different starting points. The mean and standard deviation of the distance were aggregated over each vehicle maneuver and each pedestrian location, respectively. Table IV indicated that the GPR model had achieved much better results than the dynamic model. First, the GPR model had higher accuracy than the dynamic model as it had smaller values of the mean distance. Second, the GPR model had a more stable performance compared with the dynamic model, which was suggested by smaller values of the standard deviation of distance. Lastly, the GPR model was not sensitive to the choice of starting points since it remained a consistent performance among different starting points. Moreover, the accuracy of estimating \( Prob(\text{pos}) \) and \( |T_{veh_{ij}} - T_{ped_{ij}}| \) according to Equation 1. Earlier, we showed in Table III that the proposed framework estimated \( Prob(\text{pos}) \) with an average F1-score of 0.949. This section evaluated the accuracy of estimating \( |T_{veh_{ij}} - T_{ped_{ij}}| \) through the mean squared error (MSE) and mean absolute error (MAE). Next, the accuracy regarding locating conflicts was measured by the distance between the predicted and the actual conflict locations. Moreover, the traditional TTC has been used as the baseline method. Lastly, this paper has developed two deep learning models (i.e., long short-term memory neural network (LSTM) and convolutional neural network (CNN)) and have compared their computation time with the proposed framework. The LSTM model contained one LSTM layer,

Fig. 6. The distribution of PETs.

### TABLE III

| Maneuvers     | Precision | Recall | F1-score |
|---------------|-----------|--------|----------|
| Left-turn     | 0.938     | 0.961  | 0.950    |
| Right-turn    | 0.916     | 0.946  | 0.931    |
| Going straight| 0.973     | 0.957  | 0.965    |
TABLE IV
| Trajectory Prediction Results of GPR and Dynamic Models on Different Starting Points and Prediction Horizons |
|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| Road Users                                      | Starting Points or Prediction Horizons          | Maneuvers or Locations                           | Results on Different Starting Points               | Results on Different Prediction Horizons          |
|                                                 | or Points                                       |                                                  | GPR Models                                        | Dynamic Models                                    |
|                                                 |                                                 |                                                  | Mean  | SD     | Mean  | SD     | Mean  | SD     | Mean  | SD     |
| Vehilces                                        | 15                                              |                                                 | 1.307  | 1.611  | 6.741  | 6.316  | 0.635  | 0.645  | 2.384  | 2.261  |
|                                                 |                                                 | Left-turn                                       | 2.169  | 2.076  | 7.863  | 6.443  | 0.676  | 0.582  | 2.765  | 2.212  |
|                                                 |                                                 | Right-turn                                     | 2.535  | 2.022  | 6.890  | 5.326  | 0.702  | 0.539  | 2.424  | 1.860  |
|                                                 |                                                 | Going Straight                                 | 1.869  | 2.069  | 6.087  | 5.051  | 0.803  | 0.898  | 3.490  | 3.344  |
|                                                 |                                                 | Left-turn                                       | 2.201  | 2.151  | 7.120  | 6.347  | 1.008  | 0.959  | 4.066  | 3.297  |
|                                                 |                                                 | Right-turn                                     | 2.141  | 2.196  | 6.056  | 4.921  | 1.021  | 0.848  | 3.566  | 2.751  |
|                                                 |                                                 | Going Straight                                 | 2.020  | 2.008  | 6.247  | 5.915  | 1.387  | 1.367  | 5.348  | 4.366  |
| Pedestrians                                     | 15                                              |                                                 | 2.526  | 2.375  | 4.933  | 4.344  | 1.332  | 1.184  | 4.685  | 3.622  |
|                                                 |                                                 | Bottom                                         | 1.243  | 1.377  | 1.521  | 1.625  | 0.395  | 0.432  | 0.494  | 0.552  |
|                                                 |                                                 | Left                                           | 1.156  | 1.352  | 1.570  | 1.689  | 0.366  | 0.441  | 0.532  | 0.570  |
|                                                 |                                                 | Right                                          | 0.785  | 1.024  | 1.764  | 1.787  | 0.249  | 0.288  | 0.559  | 0.575  |
|                                                 |                                                 | Top                                            | 1.231  | 1.377  | 2.763  | 1.956  | 0.360  | 0.423  | 0.940  | 0.652  |
|                                                 |                                                 | Bottom                                         | 1.222  | 1.568  | 1.554  | 1.715  | 0.606  | 0.664  | 0.744  | 0.821  |
|                                                 |                                                 | Left                                           | 1.143  | 1.358  | 1.538  | 1.689  | 0.564  | 0.674  | 0.793  | 0.858  |
|                                                 |                                                 | Right                                          | 0.564  | 0.788  | 1.826  | 1.832  | 0.363  | 0.464  | 0.855  | 0.869  |
|                                                 |                                                 | Top                                            | 1.154  | 1.341  | 2.731  | 1.901  | 0.562  | 0.652  | 1.395  | 0.982  |
|                                                 |                                                 | Bottom                                         | 1.261  | 1.381  | 1.525  | 1.732  | 0.817  | 0.900  | 0.998  | 1.088  |
|                                                 |                                                 | Left                                           | 1.119  | 1.349  | 1.478  | 1.628  | 0.760  | 0.900  | 1.053  | 1.137  |
|                                                 |                                                 | Right                                          | 0.600  | 0.804  | 1.891  | 1.940  | 0.495  | 0.646  | 1.157  | 1.174  |
|                                                 |                                                 | Top                                            | 1.238  | 1.392  | 2.779  | 1.935  | 0.776  | 0.864  | 1.851  | 1.309  |

Table V
The Comparison Between the Proposed Framework and TTC

| Types                 | Metrics      | Proposed Framework | TTC   |
|-----------------------|--------------|--------------------|-------|
| Conflict Prediction   | Sensitivity  | 0.92               | 0.62  |
|                       | AUC          | 0.96               | 0.81  |
| Conflict Quantification| MSE (s)    | 1.16               | 2 x 10^7 |
|                       | MAE (s)      | 0.37               | 196.72 |
| Conflict Localization | Mean Distance (m) | 1.64             | 87.78 |
|                       | Standard Deviation of Distance (m) | 4.73 | 2.339.71 |

Fig. 7. The computation time of different methods regarding various prediction horizons.

followed by one dropout layer to prevent overfitting, and one dense layer to generate the results. Similarly, the CNN model contained one CNN layer, one dropout layer, and one dense layer. The Adam optimizer [30] was used as the optimization function. All three models have been trained on the same data.

Table V shows the results of the framework evaluation. The proposed framework outperformed TTC in terms of various evaluation metrics. First, the proposed framework was able to accurately predict conflicts with a sensitivity of 0.92, while TTC only had a sensitivity of 0.62. Second, the proposed framework achieved an MSE of 1.16 s for quantifying conflicts, which was significantly better than the result of TTC. It also accurately predicted the locations of conflict points, with a mean distance of 1.64 m, while TTC had a mean distance of 87.78 m. Lastly, Fig. 7 presents the average computation time of different methods under the same computation resource. The proposed framework required much less computation time than LSTM and CNN for all prediction horizons. Moreover, the standard deviation of the computation time of the proposed framework, LSTM, and CNN were 0.019 s, 0.917 s, and 0.703 s, respectively, indicating that the performance of the proposed framework was much more robust than other models toward the change of prediction horizons.

VI. Conclusion
Extensive studies have utilized various SSMs as parts of proactive traffic safety management solutions that aimed to improve pedestrian safety at intersections. However, existing SSMs are limited by the assumption that road users would maintain a constant speed and direction, which could lead to inaccurate estimation of the risk associated with pedestrian-vehicle conflicts.

This paper proposes a probabilistic framework to estimate the risk of pedestrian-vehicle conflicts at intersections.
A probabilistic approach has been developed to incorporate the results from road user trajectory prediction and vehicle maneuver identification. The proposed framework demonstrates remarkable accuracy in predicting, quantifying, and localizing conflicts while maintaining minimal computation time. These qualities position it as an optimal selection for real-time proactive traffic safety management solutions that require prompt responsiveness.

The proposed framework has been evaluated using both simulated and real-world data. The simulation results validated that time-critical pedestrian-vehicle conflicts were associated with a higher estimated risk when given a higher probability of a vehicle maneuver leading to such conflicts. This observation remained consistent, even in scenarios where there were potential conflicts from multiple directions. Moreover, real-world trajectory data collected at an intersection was used to evaluate the proposed framework. A detailed data preprocessing procedure has been implemented to prepare the data. Experimental results have suggested that the proposed framework was able to accurately predict both pedestrian and vehicle trajectories and could keep a consistent performance over different starting points and prediction horizons. Moreover, the proposed framework outperformed the TTC method in terms of conflict prediction, quantification, and localization. For example, the proposed framework was able to capture 92% of all conflicts, while TTC was only able to capture 62% of them. Lastly, the proposed framework required much less computation time compared to deep learning methods such as LSTM and CNN and was robust to the change of prediction horizons.

In the future, additional studies could be conducted to further improve the accuracy of the trajectory prediction model, as the errors may be accumulated over longer prediction horizons. Moreover, the transferability of the proposed framework should be investigated using data from other intersections.

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