Automated Learning of Pedestrian Walking Speed Profiles for Improved Movement Prediction

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Abstract: Every year, about 310,500 pedestrians still lose their lives in traffic accidents worldwide. Cooperative pedestrian collision avoidance represents a promising approach to reduce those accident numbers. This approach assumes that pedestrians are equipped with mobile devices to obtain and exchange their current movement information with nearby vehicles and use those to predict and prevent possible collisions. However, the ability to predict collisions between a pedestrian and a vehicle also depends on the assumptions about the pedestrian's future behavior. One important aspect of those assumptions is a pedestrian's individual walking pattern, like his common or maximum speed. Thus, learning and applying individual walking speed profiles of pedestrians to improve movement prediction may increase the accuracy of a collision detection algorithm and could, in turn, reduce the probability of missing or erroneously triggering an alarm. In this publication, we propose an approach to learn individual walking speed profiles of a pedestrian based on smartphone Global Navigation Satellite System (GNSS) data and evaluate the ability to predict collisions based on those profiles. Therefore, we first conducted experiments to estimate the error of walking speed obtained from smartphone GNSS. Second, using our Pedestrian Monitor application, we recorded real-world walking speed information from nine participants. Based on these data, we show that individually learned walking speed profiles are able to increase the accuracy of predicting an impending collision.

Keywords: collision avoidance; collision detection; pedestrian safety; Car2P; movement prediction; walking speed

1 Introduction

About 310,500 pedestrians have been killed in road traffic accidents in 2016, according to the WHO [Wo]. To reduce accident numbers, several solutions for active collision avoidance systems have already been introduced and are available in current vehicles in form of cameras, radars or LIDAR systems. While these solutions work well under clear weather conditions and direct line of sight between vehicle and pedestrian, they may struggle under bad weather or non-line of sight (NLOS) conditions. To overcome these limitations, cooperative collision avoidance assumes that pedestrians are equipped with mobile devices like smartphones or smart watches, which are able to obtain movement information and exchange it with nearby vehicles, even in NLOS conditions. Usually, pedestrian collision avoidance systems use this movement information, i.e. position, heading direction and speed from pedestrians and vehicles, and determine if their trajectories intersect in the near future.

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If such an intersection can be determined and the remaining time to collision is below a certain threshold, a warning is given. However, depending on how much time to collision is left, the pedestrian as well as the vehicle can change their movement at any time and, for example, slow down or speed up. Those possible movement changes are usually not anticipated in existing approaches, for instance due to the absence of personalized movement profiles. As an example, consider that a smartphone based safety application detects that the current walking speed is slower than his average speed, which was obtained from past movement data. Assuming that the pedestrian would collide with a vehicle if he speeds up, the collision detection algorithm could use this information to make the prediction more accurate, or even issue a warning, provided certain conditions are met. As another example, consider that an elderly person walks at a much higher walking speed than usual. The algorithm could assume in this case that the pedestrian will slow down eventually due to old age, and may not reach a potential collision point.

In this publication, our aim is to investigate whether it is possible to learn individual walking speed profiles of pedestrians using smartphones and to use those profiles to improve movement prediction. Obtaining more individual information about a pedestrian may not only improve the prediction of future movements, but may also increase the accuracy of predicting an impending collision. Therefore, we first conducted measurements to estimate the accuracy of smartphone GNSS when pedestrians walk at different speeds. After this, we wrote an Android-based application which was used on personal smartphones of nine participants and automatically recorded GNSS data during their everyday life. Based on those recorded data, we use a simulation environment to show the improvements of using personalized walking speed profiles for movement prediction of pedestrians.

The remainder of this paper is structured as follows. The next section gives an overview about related publications. In Section 3, we describe the experiments for evaluating the accuracy of smartphone GNSS. Section 4 presents details about our own application, which was used for our long-term experiments. Section 5 describes the methodology for our simulation setup for our evaluation, which is presented in Section 6. Finally, we conclude the paper in Section 7.

2 Related Work

Within the last decade, considerable attention has been paid towards the development of cooperative pedestrian collision avoidance. The earliest publications like [DF10; SNH08] assumed the usage of mobile phones on the pedestrian side to send information to nearby vehicles to estimate a collision risk. However, in these publications, this risk estimation is based on current movement information and does not consider pedestrians' past movement data for prediction. Nevertheless, [DF10; Ta17] discussed the theoretical benefits of using a pedestrian's movement history for movement prediction. An actual investigation about those benefits, to the best of our knowledge, has not been conducted so far. However, there are publications which have made certain assumptions about pedestrian movement speed. In [An14], Anaya et al. proposed an approach for smartphone based pedestrian protection, in which the collision risk level between pedestrian and vehicle is dependent on vehicle dimensions, speed, yaw rate as well as the pedestrian's current position and maximum speed. More specifically, the collision risk is estimated based on the fact whether the pedestrian is able to reach the intersection point between the pedestrian's and the vehicle's trajectories, while the pedestrian's speed is assumed to be the highest possible pedestrian speed. Compared to our approach, the authors always use a fixed value for maximum pedestrian speed and do not consider individually learned walking speed profiles. In [Mu18], Murphey et al. proposed an approach for pedestrian path prediction based on neural networks. For training the neural networks, the authors used prerecorded trip data from pedestrians, which contain position, velocity, yaw rate and heading information. However, past pedestrian speed information is only used implicitly for improved movement prediction, so its actual impact remains unclear.

In conclusion, no other publication has investigated how to automatically learn individual walking speed profiles of pedestrians and how those profiles can be used to improve movement prediction to detect and avoid collisions.

3 Evaluation of smartphone GNSS speed accuracy

In order to estimate how accurate smartphones are able to measure a pedestrian's walking speed, we conducted a measurement campaign using five participants and two different smartphones. We also investigate if it is possible to recognize different walking speed profiles in smartphone GNSS data when participants walk with varying speeds, i.e., slow, normal and fast. Walking at a slow speed simulate situations like strolling through a city while walking fast could represent a situation in which a pedestrian is in a hurry.

3.1 Measurement Setup

Our measurements were conducted in an urban area, where participants walked along a straight line with a length of 50 m, while maintaining a constant speed. This measurement track was divided into segments of 10 m. We recorded a timestamp every time a participant passed a 10 m mark. The ground truth speed for one segment is then estimated by dividing the distance, i.e., 10 m, by the time the participant took to walk along the segment. We used two smartphones, a Google Nexus 5X and a Nokia 7.1 and captured GNSS speed data at the maximum sampling frequency, which was about 1 Hz. During each measurement, the participant holds a smartphone in the hand, which was pointing towards walking direction. Every participant walked at a slow, normal or fast but constant walking speed for 5-10 minutes, respectively. The actual walking speed for different speed classes was dependent on each individual participant, i.e. the participants were free to decide which walking speed they consider as slow, normal or fast.

3.2 Evaluation of GNSS Speed Accuracy

For our first evaluation, we considered all recorded values for walking speed, as reported by the Android Location Provider. No outliers were removed. The evaluation results for speed accuracy are shown in Tab. 1. The Root Mean Square Error (RMSE) values for speed range between 0.19 $\frac{m}{s}$ and 0.25 $\frac{m}{s}$ for the Nexus 5X and between 0.17 $\frac{m}{s}$ and 0.27 $\frac{m}{s}$ for the Nokia 7.1. The mean RMSE for both smartphones differs by 0.02 $\frac{m}{s}$.

participant	RMSE for speed [$\frac{m}{s}$]	
	Nexus 5X	Nokia 7.1
1	0.25	0.17
2	0.25	0.27
3	0.19	0.24
4	0.25	0.15
5	0.22	0.24
mean	0.23	0.21

Tab. 1: Mean root mean square error (RMSE) of GNSS speed

3.3 Evaluation of different speed classes

In Tab. 2, we show the results for five participants for the three considered speed classes, and their corresponding values for mean ground truth speed (μ_{GT}), mean relative speed error (μ_{error}) and standard deviation for speed error (σ_{error}).

participant	speed class	$\mu_{GT}[\frac{m}{s}]$	μ_{error} [$\frac{m}{s}$]	$\sigma_{error}[\frac{m}{s}]$
1	slow	1.10	0.01	0.17
	normal	1.54	-0.02	0.19
	fast	1.90	0.01	0.16
2	slow	1.33	-0.11	0.25
	normal	1.58	-0.07	0.20
	fast	1.85	-0.03	0.35
3	slow	1.24	-0.16	0.23
	normal	1.63	-0.04	0.27
	fast	1.94	-0.02	0.23
4	slow	1.10	-0.02	0.12
	normal	1.51	-0.01	0.14
	fast	1.74	-0.04	0.19
5	slow	0.90	-0.05	0.18
	normal	1.47	0.06	0.20
	fast	1.93	-0.09	0.33

Tab. 2: Mean ground truth speed (μ_{GT}), mean relative speed error (μ_{error}), and mean standard deviation for speed (σ_{error}) for the Nokia 7.1 smartphone and five participants

Despite a few outliers, e.g. participant 2 and 3 for slow walking speed, the mean relative error is around 0 $\frac{m}{s}$, but with varying values for σ_{error}.

In Fig. 1, we plotted a histogram including speed values of all speed classes of participant 1. This histogram shows three speed distributions which correspond to considered speed classes slow, normal and fast.

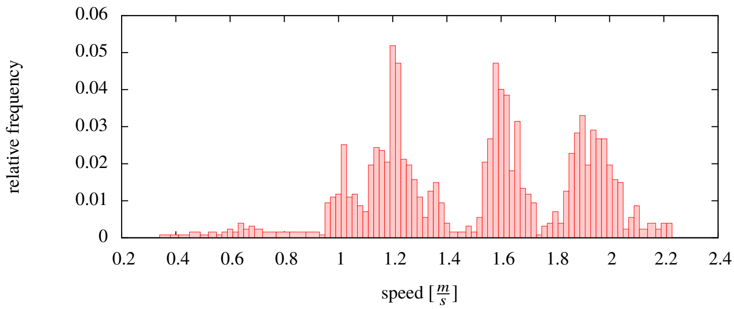

Fig. 1: Histogram for participant 1 with bin size 0.02 $\frac{m}{s}$, showing three different walking speed classes (slow=1.10 $\frac{m}{s}$, normal=1.54 $\frac{m}{s}$, fast=1.90 $\frac{m}{s}$), using a Nokia 7.1

Considering the obtained results and the ability to discriminate individual walking speed classes shows that speed values obtained from smartphone GNSS are sufficient for learning individual speed profiles. Approaches to improve the GNSS accuracy, like the usage of sensor fusion techniques or upcoming advancements in GNSS technology may be able to provide even more accurate results. However, the main focus in this publication is on the methodology of learning individual walking speed profiles from pedestrians in order to improve the prediction accuracy, independent of the actual data source.

4 Pedestrian Monitor

In order to capture the walking speeds from participants during their everyday life, we implemented an Android-based smartphone app, which was used on their personal smartphones. During one measurement, we obtained a pedestrian's current movement (latitude, longitude, speed, bearing, accuracy), the current activity (type, confidence) as well as a list of satellites available. To obtain these data, we used the Android Fused Location Provider API and the Google Activity Recognition API. Using the Activity Recognition API, the app can automatically detect whether the pedestrian is walking or, for example, standing still. We consider a measurement (or walking speed profile) as valid, if the pedestrian's activity is *walking/on foot* with confidence of ≥ 90%, the walking speed is $\geq 0\ \frac{m}{s}$ and $< 4\frac{m}{s}$, and the reported GNSS error $\leqslant 7$ m. Since the error also influences the accuracy of the speed estimation, the maximum allowed GNSS error was set to 7 m to avoid learning based on data with insufficient accuracy.

In the following sections, we considered the data obtained in this measurement campaign to represent the pedestrian's real walking speed profile. However, it should be noted that deviations within the captured pedestrian's walking speed profiles are not only caused by pedestrian movement changes, but also GNSS errors, as shown in Section 3.

5 Simulator Setup

After capturing measurement data of walking speed from nine participants, we use those individually learned walking speed profiles to predict collisions between vehicles and pedestrians. In detail, we determine the distribution of future position probabilities which is based on individually learned speed distributions. For the evaluation, we use our own Java-based simulator which we already used in prior publications [Ba18; BMD17].

5.1 Scenario

The scenario which we chose for our evaluation is a Euro New Car Assessment Programme (NCAP) scenario which is depicted in Fig. 2. For our evaluation the vehicle is assumed to be a car. This scenario was chosen since it represents approximately 80% of all accident scenarios between pedestrians and vehicles, according to the German In-Depth Accident Study (GIDAS) database [EKD13]. The scenario is modeled in a 2-dimensional Cartesian coordinate system. For the car's geometry, we use a rectangle with a length of 4 m and a width of 2 m. The pedestrian is modeled as a point. In the given scenario the car and the pedestrian are moving perpendicular to each other which is modeled by setting the vehicle's motion parallel to the x-axis and the motion of the pedestrian parallel to the y-axis. For convenience, but without loss of any generality, we assume the collision point to be at $(0, 0)$.

5.2 Motion modeling and Collision Detection

For both, the pedestrian and the car, we assume constant, linear motion. Let $\overrightarrow{r}_{\{p,c\}} = (x, y)$ be the current position of the pedestrian (p) and car (c), respectively. Since we consider linear movements along the coordinate system's axes, the motion for the car can be expressed as

$$\overrightarrow{r}_c(t) = (v_c \cdot t, 0) + (x, 0) \tag{1}$$

where v_c is the speed and x is the starting position of the car. Likewise, the motion of the pedestrian is expressed as

$$\overrightarrow{r}_p(t) = \left(0, v_p \cdot t\right) + (0, y) \tag{2}$$

with v_p being the speed and y being the starting position of the pedestrian. Concerning the car, which has a rectangular geometry, $\overrightarrow{r}_c(t)$ represents the center of the car's geometry at time t. Based on Equation (1) and Equation (2), a collision can be detected by evaluating if there is a t for which the current position of the pedestrian $\overrightarrow{r}_p(t)$ intersects the rectangle of the car which is at position $\overrightarrow{r}_c(t)$. If such a t exists, then the time-to-collision (TTC) is $TTC = t$. The movement equations $\overrightarrow{r}(t)$ only depend on two parameters: The speed v and the starting position (x, y). For better readability we will use a vector notation $\overrightarrow{m}_i = (v_i, (x_i, y_i))\ i \in \{p, c\}$ to refer to a specific motion equation for the car (c) and the pedestrian (p). Using the vector notation, we define a binary function $col\left(\overrightarrow{m}_c, \overrightarrow{m}_p\right)$ which evaluates a collision as follows:

$$col\left(\overrightarrow{m}_c, \overrightarrow{m}_p\right) = \begin{cases} 1 & \text{, if } TTC \geq 0 \\ 0 & \text{, else} \end{cases} \tag{3}$$

5.3 Collision Prediction Probability

Let $V_{gt} = \{v_0, v_1, ..., v_N\}$ be the set of N measured pedestrian speeds. We derive an empirical distribution V_b from the measured speed values using a bin size of $b = 0.05\ \frac{m}{s}$. We chose $0.05\ \frac{m}{s}$ as bin size to avoid empty bins in the empirical distributions, which can occur if the smartphone's GNSS speed resolution is lower than the chosen bin size. Assuming σ_V to be the standard deviation of V_b we define

$$M_b = \{\overrightarrow{m}_b = (v_b, (x, y))| - 3\sigma_V \leq v_b \leq 3\sigma_V\} \tag{4}$$

as the set of 99.7% of all possible movement vectors based on walking speed distributions. Using Eq. (3) we can define the set $M_{col} \subset M_b$ of all movement vectors that lead to a collision as

$$M_{col} = \{\overrightarrow{m}_b | \overrightarrow{m}_b \in M_b \wedge col(\overrightarrow{m}_c, \overrightarrow{m}_b) = 1\} \tag{5}$$

Let $B = (v, v + b]$ the bin containing the value v_b. The probability that the pedestrian will move with a speed of $v_b \pm \frac{b}{2}$ is then determined by

$$P(\overrightarrow{m}_b) = P(v_b) = P(B) = \frac{|B|}{N} \tag{6}$$

We define P_C as the probability for a collision based on individual speed profiles as the sum of all probabilities $P(\overrightarrow{m}_b)$ over all $\overrightarrow{m}_b$ which lead to a collision:

$$P_C = \sum_{\overrightarrow{m_b} \in M_{col}} P(\overrightarrow{m}_b) \tag{7}$$

6 Evaluation

After defining the simulator setup in the last section, we now evaluate whether using individually learned pedestrian walking speed profiles (Section 4) are able to improve collision prediction.

6.1 Scenario

The scenario we considered is shown in Fig. 2. For sending and receiving movement information, we assume that there is no delay and the current movement vector of the vehicle and the pedestrian can be determined without errors. In this scenario, the pedestrian walks with speed v_{gt}, while the vehicles moves with a speed of $v_c = 50 \frac{km}{h} \approx 13.9 \frac{m}{s}$. The initial position of the vehicle is $\overrightarrow{r}_c(t) = (-(v_c \cdot TTC + 2)\,,\ 0)$, while the pedestrian's initial position is varied depending on the assumed ground truth walking speed. In detail, we set $\overrightarrow{r}_p(t) = (0\,,\ -(v_{gt} \cdot TTC))$ to assure that the collision point is always at the same position. We investigate scenarios in which the TTC is varied between 1 - 4 s.

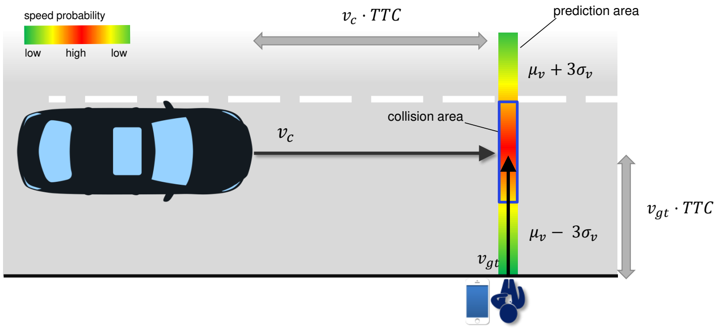

Fig. 2: NCAP scenario for our evaluation

6.2 Usage of individual walking speed profiles for movement prediction

In this section, our aim is to investigate whether personalized walking speed profiles can improve the probability of detecting an impending collision (P_C). Therefore, we consider scenarios in which pedestrians walk with their preferred walking speed, which was determined as the 68%-confidence interval $[\mu - \sigma, \mu + \sigma]$, calculated over all walking speed data of a pedestrian. As a baseline for our evaluation, we consider a generalized profile, which comprises walking speed data from all nine participants. This profile may be used to estimate the collision risk if no individual information about the pedestrian is available. The generalized profile has a mean value of 1.3 $\frac{m}{s}$ with a standard deviation of 0.34 $\frac{m}{s}$. For the personalized walking speed profile, we first assume for all scenarios that the pedestrian's current speed is known. Then, by comparing the mean of all recorded profiles with the pedestrian's current speed, the profile with the smallest absolute difference is selected for prediction. Finally, we determine P_C for scenarios in which all of the pedestrian's preferred walking speeds (in steps of 0.01 $\frac{m}{s}$) are used as ground truth, while applying a personalized and a generalized profile, respectively. We repeated these simulations for different values for TTC and then averaged the results.

Tab. 3 shows individual speed intervals, the pedestrians' age classes, the number of valid profiles (cf. Section 4) as well as the results for P_C. Our evaluation shows that using personalized profiles results in higher values for P_C when compared to using a generalized profile, regardless of the pedestrian considered. On average, the usage of personalized walking speed profiles improves P_C by 10%, 18%, and 21% for 2 s, 3 s, and 4 s TTC, respectively. Due to an increased number of possible future trajectories, the benefits of personalized walking speed profiles become especially present for higher TTCs. Moreover, these improvements are particularly noticeable for participants who walk at a lower speed than the generalized profile, like participant 1, whose mean walking speed is 1.04 $\frac{m}{s}$. For TTC=1 s, we obtained $P_C > 97\%$ for both personalized and generalized profiles and excluded it from the table, since it represents a scenario in which a collision is almost unavoidable.

#	age	speed interval [$\frac{m}{s}$]	# profiles	P_C(TTC=2s) pers	P_C(TTC=2s) gen	P_C(TTC=3s) pers	P_C(TTC=3s) gen	P_C(TTC=4s) pers	P_C(TTC=4s) gen
1	50-59	[0.76-1.33]	6	0.95	0.74	0.88	0.55	0.82	0.46
2	30-39	[0.95-1.73]	23	0.97	0.91	0.90	0.81	0.82	0.74
3	40-49	[0.66-1.37]	43	0.95	0.70	0.88	0.52	0.80	0.44
4	20-29	[1.11-1.39]	21	0.99	0.92	0.99	0.80	0.97	0.72
5	30-39	[0.84-1.35]	12	0.96	0.80	0.89	0.61	0.81	0.52
6	20-29	[1.23-1.51]	39	0.98	0.95	0.98	0.89	0.98	0.83
7	20-29	[1.11-1.65]	50	0.98	0.94	0.97	0.87	0.94	0.81
8	20-29	[1.18-1.69]	13	0.97	0.95	0.95	0.90	0.90	0.85
9	20-29	[1.06-1.45]	3	0.97	0.92	0.97	0.80	0.93	0.71
mean				0.97	0.87	0.93	0.75	0.89	0.68

Tab. 3: P_C for nine participants and varying TTCs, using their respective walking speed profiles (pers) and a generalized profile (gen)

However, for this evaluation, we only considered scenarios, in which the pedestrian ground truth speed actually matches typical learned pedestrian profiles. As a result, the outcome for P_C may be misleading in scenarios where the pedestrians' current speed exceeds or falls below the individual interval boundaries. In those cases, our approach might fail to recognize an impending collision. Therefore, it is important to additionally incorporate the current walking speed and find an appropriate weighting between the current and the predicted collision risk.

7 Conclusion

In this article, we showed how cooperative VRU collision avoidance can benefit from learning individual pedestrian walking speed profiles using smartphone GNSS. We first showed that it is possible to distinguish between different walking speed distributions, even in noisy smartphone GNSS measurements. We also conducted long-term experiments to capture walking speed information from nine participants. Those individually learned profiles were used to evaluate the benefits towards collision prediction. Using personalized profiles, our results show an average increase of 10%-21% collision detection accuracy compared to a generalized profile. These results indicate that the usage of additional personalized speed information, obtained from smartphones, is suitable to improve the prediction accuracy of a pedestrian collision avoidance system.

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