Evaluation of a collaborative-based filter technique to proactively detect pedestrians at risk

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***Abstract*—Tragically, traffic accidents involving pedestrians or cyclists cause thousands of fatalities and serious injuries worldwide every year. Therefore, improving the safety of vulnerable road users is an international priority. One key challenge in designing an "ideal" protection system is to filter the endangered pedestrians out of potentially many. In this paper, we present a novel approach to proactively filter those pedestrians whose very next step would bring them (dangerously) closer to the street so as to provide an extra and crucial time advantage for a collision avoidance system. To predict a pedestrian's next step, we use the Collaborative Context Predictor. It takes advantage of collaborative behaviour patterns, in this case the movement patterns of the pedestrians. As well, a comparison with two state of the art context prediction approaches is carried out. The comparison is performed using real measured movement data, which is received from a smartphone the pedestrians carry in their trouser pocket.**

***Index Terms*—context prediction, context awareness, car2pedestrian, collaborative.**

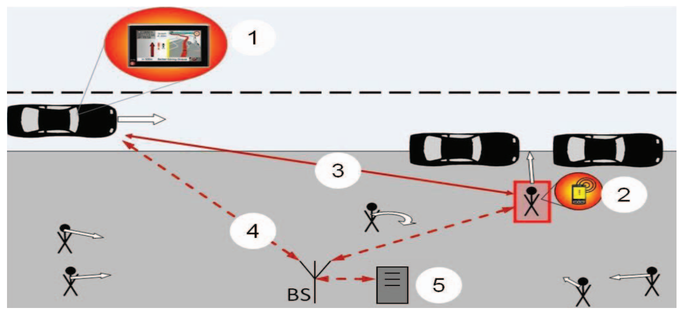

Fig. 1. Filtering pedestrians at risk.

I. Introduction

Road traffic crashes and injuries are a serious public health problem. Every year, more than one million people worldwide are killed as a result of traffic accidents [1]. 400,000 of them are pedestrians [2].

In order to reduce accidents between cars and pedestrians, several research groups use different technologies to develop passive and active pedestrian protection systems. The target of passive pedestrian protection is the reduction of the impact on a pedestrian when the accident is no longer avoidable. This is achieved by mechanisms like rising hoods or pedestrian airbags that are under investigation to prevent the pedestrian from hitting the engine block respectively the windshield [3]. First passive systems are also provided in products by car manufactures like BMW, Audi or Honda.

Passive pedestrian protection is a first step to improve pedestrian safety, however the better solution is to actively avoid a collision. Current approaches use vehicle-based sensors such as infrared, radar or laser to detect pedestrians that might collide with a vehicle. In [4], an automotive night vision system for pedestrian detection based on infrared sensors is illustrated. The authors presented a pre-processing technique based on a Support Vector Machine classifier that filters pedestrians out of a given picture. A complete overview of different methods using laser, video and infrared sensors to avoid pedestrian-vehicle collisions is given in [5]. First active systems, enabling a car "to see what is on the road", have already been introduced in products by e.g. Mercedes and Toyota to detect pedestrians. All these approaches are promising, but they need a direct line of sight and do not use any contextual information of the pedestrians they are trying to protect.

First approaches that try to prevent possible pedestrian-vehicle accidents using car systems and information from pedestrians are outlined in [6] and [7]. The proposed systems use a pedestrian's cellular phone and a car navigation system. GPS coordinates of the pedestrian and the car are sent to a server. Then, the collision risk is calculated and the driver will be alerted of the likelihood of an accident. Another method uses radio frequency tags to avert collisions between pedestrians and cars. [8] and [9] describe strategies based on RF-communication between a long power transponder that is attached to a pedestrian and a receiver placed in a vehicle. The above mentioned approaches show possibilities of detecting pedestrians that are walking on the pavement or even pedestrians obscured by objects, but they do not filter the pedestrians that may be at risk in advance. For this reason, these approaches may be inefficient in terms of needed calculation time and battery consumption.

A technique to filter pedestrians that may be at risk from those without being at risk is proposed in [10] and [11]. The authors present various filters differing by input information like movement speed, movement directions and possible intersection points between cars and pedestrians. Figure 1 presents possible architectures to filter pedestrians. One uses ad hoc communication (3) between the pedestrian's mobile phone (2) and the navigation system of a car (1) and the second uses cellular communication (4) between the pedestrian's mobile phone a central server unit (5) and a car navigation system.

In this paper the following contributions are presented: (i) Extending the promising idea of filtering pedestrians by forecasting a pedestrian's next step using her context information (movement and orientation). Hence, it is possible to proactively filter pedestrians and provide a collision avoidance system with an additional time advantage. To proactively filter the pedestrians that might be at risk we apply the Collaborative Context Prediction (CCP) technique, first introduced in our previous work [12].

(ii) Using real movement data measured by a Samsung Galaxy S II smartphone the pedestrians have carried in their left trouser pocket to gather realistic input data. Further, we describe in detail how the movement behaviour of the pedestrians is derived from the measured data.

(iii) Comparing the results of the CCP approach predicting the pedestrian's next step to two state of the art context predictors, the Alignment [13] and Active LeZi [14] predictor.

The document is organised as follows: Section II provides an overview of the experimental settings used in this paper and gives a brief introduction to the CCP prediction approach. Section III presents how the movement data of the pedestrians have been collected from the smartphone and processed. Section IV outlines and discusses the gained prediction accuracy of CCP, Alignment and Active LeZi using the pedestrians' real movement data. In Section V the conclusions are given.

II. Description of the Selected Environment

In this section, we provide an overview of the scenario, a brief introduction of the used CCP predictor to proactively filter pedestrians at risk and a description of the used settings for the real world experiment.

A. Scenario

The scenario consists of a pavement beside a street that has been segmented into several parts (see Figure 2). The different parts are used to locate a pedestrian's current position on the pavement. The size of one part of the pavement is 0.75cm $\times$ 0.75cm and results from the average length of a step of pedestrians. Hence, with each step a pedestrian reaches a new part on the pavement. We use this segmentation because current GPS technologies do not offer sufficient accuracies that are needed to locate the current position of a pedestrian on a pavement precisely. Current standard implementations of GPS devices only achieve accuracies of 3 to 5 meters [15]. In our experiment the average speed of a pedestrian is determined as $1.34\frac{m}{s}$ [16]. Hence, a pedestrian takes approximately 0.56 seconds to move from one part to another.

In order to describe the pedestrian's current position on the pavement we labelled the different parts horizontally with numbers and vertically with letters. The pavement is divided into two areas. One area close to the street $A0$ till $A14$ is marked in red and indicates that a pedestrian might be at risk. The other area marked in black is further from the street and indicates that pedestrians inside this area are not at risk.

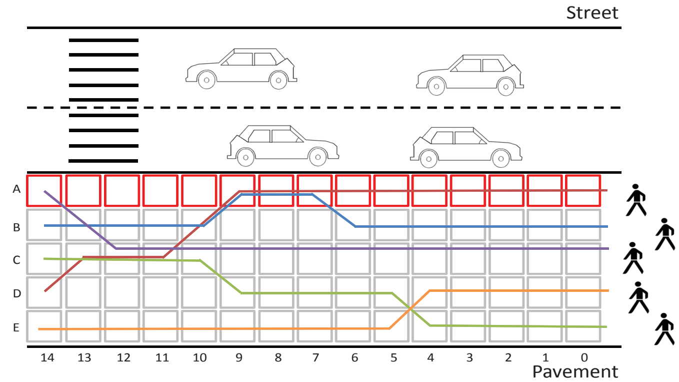

Fig. 2. The underlying scenario consists of a pavement aside a street divided in several labelled parts. Dangerous spots are marked in red.

In Figure 2 we further see paths in different colours. The position the pedestrian enters the pavement is known a priori and is not in the focus of the examination outlined in this paper. A technology for relative positioning of a pedestrian on a pavement that can be used to detect her entrance point on the pavement is already presented in the AMULETT project [8]. Each path belongs to a pedestrian and indicates her recorded movement sequence on the pavement using a smartphone. A set of different runs of a pedestrian represents her movement history, respectively her context history. Hence, the context history consists of the different parts that form the paths walked by the pedestrian. The context histories are used by the prediction algorithms to predict the pedestrian's next step.

B. Collaborative Context Predictor

The idea of the Collaborative Context Predictor is not only to be limited to the information of the pedestrian's history whose next step has to be predicted, but also to take advantage of information stored in histories of other pedestrians. The usage of additional information increases the information space and therefore gives an advantage to provide predictions even if the pedestrian's own context history does not provide suitable information. Instead of only concatenating additional history information to the user's history, CCP utilises existing direct and indirect relations between the pedestrians' movement actions. Regarding to our scenario presented in Figure 2 CCP utilises the set of pedestrians $P \in \mathcal{P}$. Their recorded movement behaviours $B \in \mathcal{B}$. A movement behaviour of a pedestrians represents a subset of his recorded movement paths. In our experiments we generated the subsets using a sliding window approach that segmented the pedestrians' movement paths. Each subset consists of three contexts (parts of the pavement). Finally CCP utilises all possible future steps $F \in \mathcal{F}$, whereby a future step is the part of the pavement that follows after a movement behaviour $B \in \mathcal{B}$ of a pedestrian.

For the storage of the existing direct and indirect relations between the movement behaviours of the pedestrians we use a 3-order tensor structure $\underline{\mathbf{A}} \in \Re^{|P|\times|B|\times|F|}$. A direct relation $P_i \oplus P_j$ between two pedestrians $P_i \in \mathcal{P}$ and $P_j \in \mathcal{P}$ exists if $P_i \oplus P_j \Leftarrow \exists B_n \in \mathcal{B} \vee \exists F_m \in \mathcal{F} : \underline{\mathbf{A}}\left(P_i, B_n, F_m\right) \neq 0 \vee$

$\underline{\mathcal{A}}(P_j, B_n, F_m) \neq 0$. An indirect relation between two pedestrians P_i and P_j exists if $\neg P_i \oplus P_j \vee (P_i \oplus P_k \vee P_j \oplus P_k)$.

To find new latent relations between the movement behaviours of the pedestrians, CCP downsizes the dimensionality of the 3-order tensor structure $\underline{\mathbf{A}}$ using the Higher-order Singular Value Decompostion (HOSVD) and the n-mode product. As a result we receive a 3-order tensor $\underline{\mathbf{\Sigma}} \in \Re^{c_1 \times c_2 \times c_3}$ whose three dimensions are reduced to the information that spans the space that contains the most relevant and less noisy information. Subsequently the tensor $\underline{\mathbf{A}}$ is recalculated using the approximated information contained by $\underline{\mathbf{\Sigma}}$. The resulting tensor $\underline{\mathbf{A}'} \in \Re^{|P| \times |B| \times |F|}$ finally includes all previously existing direct and indirect relations between the movement behaviours of the pedestrians plus additional new latent relations.

C. Experimental Test Setting

For our real world experiment outlined in Section IV we recorded movement data from eight pedestrians. Each pedestrian performed four different runs across the pavement. The recorded movement data has been saved to the context history of the respective pedestrian.

Three randomly chosen context histories represent the test dataset, the remaining five the training dataset. For the evaluation process we use the leave-one-out strategy. Therefore, a new prediction model was built for each test instance. All occurrences of the current movement patterns in the test dataset which has to be classified are deleted in the test dataset and the "cleaned" test dataset is added to the training data set afterwards. This step has been repeated for every test instance.

To further elaborate the prediction accuracy of the CCP approach using different number of pedestrians we distinguish between six different training datasets. The first training dataset is represented, by only using the histories of the three pedestrians the test dataset has been generated from. The remaining five training datasets are generated by subsequently enhancing the first training set with the datasets of the remaining five pedestrians.

III. Receiving real movement data from a smartphone

In this section, we describe how the movement data of the pedestrian is recorded using a smartphone, pre-processed and finally mapped to the pavement segmentation presented in Figure 2.

A. Used sensors to detect the pedestrians' movements

To collect the pedestrians' movements and direction changes on a pavement we used a Samsung Galaxy S II smartphone with Android 2.3.3 operating system that the pedestrians were wearing in their left trouser pocket. Three ground truth annotations (W = walk straight ahead, L = turns left and then continues walking, R = turns right and then continues walking) were made with a Nokia N800 Tablet during the measurement of sensor data. The annotated movement data has been saved to the respective context history of the pedestrian called $CH_{annotated}$. We have selected the following software sensors available on the Samsung Galaxy S II smartphone: gravity, accelerometer, magnetic field, gyroscope, rotation and orientation. These sensors are derived from available hardware sensors built-in on the smartphone, such as accelerometer, magnetometer and gyroscope sensors. The sensors deliver values in x, y, and z axis, which are relative to the screen of the phone in its default orientation. The gravity sensor provides a three dimensional vector that indicates the direction and magnitude of gravity. The accelerometer sensor measures the acceleration of the pedestrian. If the pedestrian is not moving, the accelerometer delivers only the value of $9.81\frac{m}{s^2}$, which is the influence of gravity. Therefore, if the smartphone is stationary, the output of the accelerometer sensor should be identical to the output of the gravity sensor.

The magnetic field sensor measures the ambient magnetic field of each axis, while the gyroscope provides the angular speed around each axis respectively. The rotation sensors provides a vector $x * sin(\frac{\theta}{2})$, $y * sin(\frac{\theta}{2})$, $z * sin(\frac{\theta}{2})$, where θ is the rotation angle and x, y, z are the axes relative to the device. The orientation sensor delivers three types of values, which are Yaw, Pitch and Roll. Yaw represents the compass heading in degrees. Pitch represents the tilt of the top of the smartphone while Roll represents the side-way tilt of the smartphone. The sensor values for each sensor were measured at a sampling rate of 32 Hz. The gravity and accelerometer sensors were expected to capture the motion of the pedestrian. The other sensors were used to detect possible change of direction as the pedestrian continued to walk. The measured sensor data and the corresponding movement patterns are shown in Figure 3. To reduce the dimension of the sensor data and to allow classification of the movement patterns, features were extracted from the obtained sensor data. Mean and standard deviation values were computed for each axis of every sensor and the magnitude of all three axes. The sliding window technique was used to compute features. Each window consisted of one second of measurements, which was equivalent to 32 instances of sensor values. No overlapping of windows was used for the computation of features. As a result, there were a total of 48 features.

B. Movement pattern recognition using decision tree classifier

To derive movement paths of the pedestrians from the recorded sensor information we used a Java implementation of the C4.5 decision tree learning algorithm. The produced decision tree classifier automatically recognises the movement patterns based on the computed features. As input for the learning algorithm, the computed features were combined with the ground truth annotations. The generated decision tree produced a recognition accuracy of 96.64%, where the training data was used as the test data. The output (W, L, R) was saved to the respective context history of the pedestrian called $CH_{recognised}$. If the classifier performs perfectly, the $CH_{recognised}$ from a pedestrian should be the same as the corresponding $CH_{annotated}$.

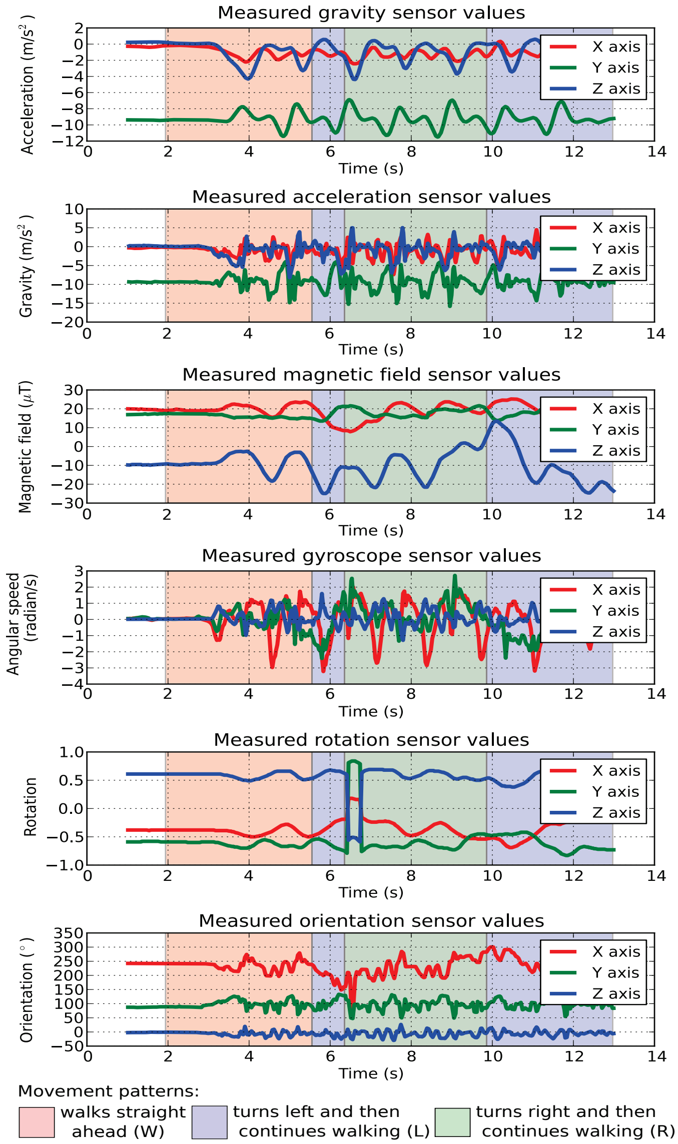

Fig. 3. Different measured sensor values provided by a smartphone.

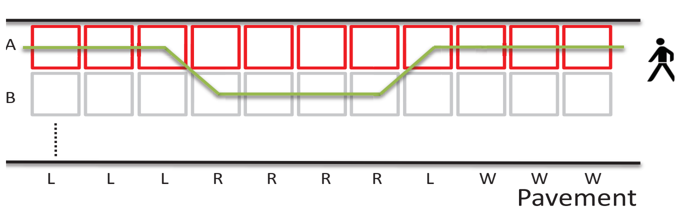

Fig. 4. Example of the movement pattern recognition output.

C. Movement pattern mapping

In order to use the recognised movement patterns to proactively filter pedestrians at risk, we have to transfer the recognised pattern to the coordinate system outlined in Section II. The mapping is needed to assign the recorded and annotated movement patterns to the locations on the pavement where the movement really took place. We used a parser that converts the context history $CH_{annotated}$ and $CH_{recognised}$ of a pedestrians into the coordinate representation. In relation to the movement path depicted in Figure 4 the mapping results in "A0, A1, A2, A3, B4, B5, B6, B7, A8, A9, A10". Afterwards, the resulted movement path is segmented using a sliding window approach.

IV. Evaluation and Discussion

Next, we will present the evaluation of our proposed proactive filtering technique. This evaluation uses real movement patterns of pedestrians recorded by a smartphone. We discuss the results of CCP and compare it with the results gained by Active LeZi and Alignment. To receive representative results, we randomly picked three different $CH_{annotated}$ out of the eight available. These data have been used to represent the test instances (movement patterns) whose next step has to be predicted.

Then, we used $CH_{annotated}$ and $CH_{recognised}$ to classify the test instances. The results have been obtained using the test method outlined in Section II-C. The first result outlined in Figure 5 presents the maximum prediction baseline of the three approaches used $CH_{annotated}$ to train the models. The second result presented in Figure 6 shows the prediction accuracy of the algorithms using the real recognised movement data in $CH_{recognised}$.

The results presented in Figure 5 using the annotated movement data and the results in Figure 6 using recognised movement data show that CCP clearly outperforms Active LeZi and Alignment. In both cases, the gained accuracy of CCP is 30% higher than the accuracy gained by the other approaches. The accuracy achieved by Active LeZi and Alignment is almost the same. Compared to Alignment and Active LeZi, which only try to find the best possible match for a given movement sequence, the usage in CCP of existing relations between movement behaviours of different pedestrians leads to better prediction results for the pedestrian's next step.

If we compare the two results gained by CCP using $CH_{annotated}$ and $CH_{recognised}$ as training data, we see that the prediction accuracy only slightly decreases by about five to seven percent using $CH_{recognised}$. The highest accuracy gained by CCP using $CH_{annotated}$ is 82% and 77% using $CH_{recognised}$. The small loss of prediction accuracy indicates that the reliability of the used movement recognition approach (see Section III-B) is promising.

Altogether we could show the feasibility of recognising pedestrians' movements using sensor information provided by smartphones. Here, we achieved a recognition rate of 96.64%, utilising a C4.5 classifier. Further, we showed that CCP can utilise the automatically recognised movement patterns to proactively filter pedestrians at risk with an accuracy close to 80%. With regard to our experiments, the time CCP needs to predict a pedestrian's next step is on average approximately 0.01 seconds. If we subtract the prediction time from the time a pedestrian needs to make his next step (cf. Section II) we get a significant time advantage of 0.55 seconds. This time advantage can be used by a collision avoidance system to detect a possible collision between a pedestrian and an

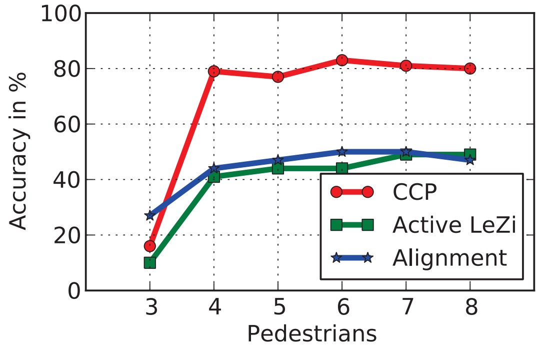

Fig. 5. Prediction results using $CH_{annotated}$.

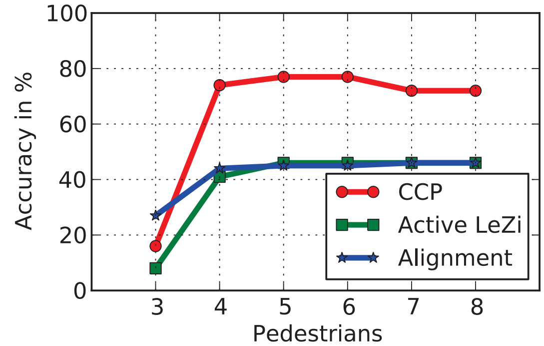

Fig. 6. Prediction results using $CH_{recognised}$.

approaching vehicle in advance. Supposing the nearby car has a speed of 50 $\frac{km}{h}$ and the driver could have been alerted 0.55 seconds earlier by a collision avoidance system the driver may react 6.21 meters earlier under ideal circumstances to prevent a collision with a pedestrian.

V. Conclusions

We have presented a novel approach for pedestrian safety. It is based on proactively filtering pedestrians at risk by predicting their next step on the pavement in advance. As input for the prediction, we utilise pedestrians' contextual information, such as their acceleration and orientation. The contexts have been extracted from various sensor information provided by a smartphone the pedestrians were carrying in their left trouser pocket. To proactively filter pedestrians at risk, we proposed the Collaborative Context Predictor (CCP) that utilises existing direct and indirect relations between the pedestrians' movements. The evaluation using the recognised movement data of the pedestrian's to predict their next step showed that CCP achieves prediction accuracy close to 80%. In contrast, the prediction accuracy of Alignment and Active LeZi only came up close to 50%. With regard to our performed evaluation the correct forecast of a pedestrian's next step offers a collision avoidance system a time advantage of approximately 0.55 seconds.

Acknowledgment

The authors are involved in the VENUS research project. VENUS is a research cluster at the interdisciplinary Research Center for Information System Design (ITeG) at Kassel University. We thank Hesse's Ministry of Higher Education, Research, and the Arts for funding the project as part of the research funding program "LOEWE - Landes-Offensive zur Entwicklung Wissenschaftlich-ökonomischer Exzellenz".

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