Autonomous Evasive Maneuvers Triggered by Infrastructure-Based Detection of Pedestrian Intentions

Sebastian Köhler, Brian Schreiner, Steffen Ronalter, Konrad Doll, Ulrich Brunsmann and Klaus Zindler

Abstract—We present an active pedestrian protection system that performs an autonomous lane-keeping evasive maneuver in urban traffic scenarios when collision avoidance by braking is no longer possible. The system focuses on pedestrians standing at the curb and intending to cross the street despite an approaching car. It is demonstrated that the evasive maneuver of the car can be initiated before the pedestrian’s foot hits the lane, by means of video-based motion contour histograms of oriented gradients and stationary detection. Using clothoid-based real-time trajectory planning and a lateral control of the car, combining feedforward and feedback control, the difference between the driven and the calculated trajectories is kept below 10 cm at maximum lateral accelerations of 4 ms\(^{-2}\) and -5 ms\(^{-2}\). We present the technical realization of the system and its precision with respect to intention recognition and driven trajectories. A case study showed that the system reacted faster than human drivers in five out of 11 cases, with an average time gain of 214 ms, even though the drivers were able to pay the utmost attention to the behavior of the crossing pedestrian.

I. INTRODUCTION

A. Motivation

The global status report on road safety from the World Health Organization revealed that over 20 million people were injured in road traffic in 2009. The majority of victims are Vulnerable Road Users (VRUs), such as pedestrians [1]. Particularly alarming is the fact that VRU accidents are typically associated with serious injuries. Pedestrians account for 65% of the fatalities out of the 1.17 million worldwide traffic-related deaths [2]. As a consequence, pedestrian protection is an important part of the current research in the field of Advanced Driver Assistance Systems (ADAS). Gandhi and Trivedi supply a comprehensive overview of this issue in [2].

An analysis of the German traffic crash statistics published in 2011 [3] reveals that 83.7% of the accidents with injuries in an urban traffic environment caused by a pedestrian error are attributable to misbehavior when crossing the street. The majority of them arise because the pedestrians involved do not pay enough attention to the traffic. This is followed by accidents where a pedestrian, while hidden by an obstacle, unexpectedly starts to cross the road. Typical urban hazard spots are streets with a large concentration of pedestrians such as streets near bus stops, schools, or homes for the elderly, as well as busy and dangerous intersections. Therefore, it is worth focusing research efforts on improving pedestrian safety in these traffic situations.

An important aim of the research presented in this paper is active prevention of accidents with pedestrian involvement in urban traffic. To illustrate this, Fig. 1 shows a dangerous situation. A pedestrian between parked cars is crossing the street without paying attention to the approaching white car. The parked vehicles restrict the driver’s view of the pedestrian, so that he cannot recognize the pedestrian at all or at least until very late.

B. Requirements and Related Research

This example illustrates two essential requirements for a preventive pedestrian protection system. The first requirement is the early and reliable detection of a dangerous pedestrian movement, which may be achieved by means of vehicle-mounted sensors [4], [5]. However, many dangerous situations arise from the fact that the driver’s view of the pedestrian is restricted. In these cases, it is difficult or even impossible to detect the pedestrian from the vehicle itself. Rather, infrastructural sensors in combination with roadside units may be used. These can be mounted at urban hazard spots and send the appropriate signals to the vehicle through wireless communication channels. Several research projects worldwide, e.g., the American IntelliDrive program [6], the European SAFESPOT [7] and INTERSAFE [8] projects, and the German Ko-PER project (part of the research initiative Ko-FAS [9]), focus on infrastructural pedestrian perception. Such systems use various types of sensors (e.g., video- or LIDAR-based sensors) and pattern recognition algorithms for the detection of pedestrians and for the prediction of collisions.
The second requirement is the proper reaction of the preventive pedestrian protection system when a dangerous situation is detected. In this context, the ability of pedestrians at the sidewalk to suddenly start a motion or to change the direction of their motion towards the lane is especially challenging. A dangerous situation may arise within some hundreds of milliseconds. Depending on the vehicle’s current speed and distance to the pedestrian, it may not be sufficient to warn the driver, because he is no longer able to react in time. Rather, the safety system has to perform an autonomous emergency braking or an evasive maneuver in order to prevent the collision.

Fig. 1 illustrates a fundamental limitation concerning the range of operation of autonomous emergency braking systems. They are able to avoid accidents provided there is sufficient distance between the vehicle and the pedestrian. But as mentioned above, dangerous traffic situations involving a pedestrian can arise suddenly. As a consequence, at the time of pedestrian detection, the vehicle may have already passed the point called “Last Point to Brake” (LPB) as shown in Fig. 1. In this case it isn’t possible to avoid the collision by means of emergency braking. Provided that the vehicle has not yet crossed the “Last Point to Steer” (LPS), it is more appropriate to perform an evasive maneuver. These points describe the last possibility for the vehicle control either to brake (LPB) or to steer (LPS) in order to avoid a collision. The exact positions of the LPB and LPS depend on the vehicle’s speed. A detailed description of this dependency and a comprehensive overview of the optimal strategies for collision avoidance and pedestrian protection can be found in [10], [11]. Roth et al. have shown in [11] that under the assumption of an initial vehicle speed $v_{initial} > 30$ km/h, the LPS lies in direction of motion behind the LPB. This result is valid under the assumptions of an agile pedestrian movement and the steering capacity of a normal driver. It is expected that the use of an autonomous evasive system is useful even at lower vehicle speeds due to higher dynamic capability of the steering actuator compared to a human driver.

In [12] a system for infrastructure-based pedestrian detection for collision avoidance in industrial environments is demonstrated although currently there is no infrastructure-based system that is able to detect the pedestrian and its intention and to initiate dynamic autonomous evasive maneuvering for collision avoidance when the driver might not have sufficient time to react.

For vehicle-based safety systems, the situation is similar. Several car manufacturers are working on solutions to prevent pedestrian accidents by emergency braking. But most of the emergency brake assist systems offered in the current series of production vehicles are still limited to the avoidance or mitigation of rear-end collisions with other vehicles [13]. The braking assistant of Volvo called “Collision Warning with Full Auto Brake and Pedestrian Detection (CWAB-PD)” [4] is an example of an automatic emergency braking system including pedestrian detection. It combines monocular vision and radar.

Recent research projects are addressing the task of autonomous evasive steering with the aim of preventing rear-end accidents [14], [15], [16]. However, pedestrian collision avoidance by evasive steering has not been covered in depth in the literature. The first results on this topic are described in [5], but as already mentioned above, the investigations are based on vehicle-mounted sensors for pedestrian detection.

C. Main Contributions and Outline of This Paper

The main contribution of this paper is the implementation of an autonomous evasive maneuver for collision avoidance, triggered by an infrastructure-based very early detection of the pedestrian’s intention to cross the street. A novel method for real-time calculation of a suitable evasive trajectory is proposed. The implementation of a lane-keeping evasive maneuver represents the central idea of the method. I.e., the trajectory has to be planned so that the vehicle does not leave its own lane during the evasive maneuver. In this way, we avoid a collision with traffic on the other lanes. Since the safety system is dedicated to pedestrians who are located a short distance from the vehicle, the proposed evasive movement is sufficient for collision avoidance.

Section II gives an overview of the technical components used for detecting the pedestrian’s intention and for the autonomous evasive maneuvering. The algorithms for detecting pedestrians and their intentions are discussed in Section III; trajectory planning and the appropriate algorithms for lateral vehicle control are introduced in Section IV. Experimental results are presented in Section V, including a case study of the response time of the developed safety system and of its drivers. Finally, in Section VI, the main conclusions and open issues are discussed.

II. SYSTEM OVERVIEW

Our system consists of two components, a mobile Road Side Unit (RSU), which can be placed at typical urban hazard spots to observe the sidewalk and the parking lane (see Fig. 1), and an On Board Unit (OBU). Both units are illustrated in Fig. 2.
pavement is observed using a mobile TYZX embedded stereo vision subsystem mounted on a tripod. The stereo system features a baseline of 33 cm, two monochrome cameras with a resolution of 752 × 480 px, a frame rate of 35 Hz, and a horizontal FOV of 83°. Based on the 3D data provided via Ethernet, the algorithms for detecting the pedestrian and his intention run on a standard PC equipped with a 2.27 GHz CPU and an NVIDIA GeForce® GTX 680 GPU.

The information that the pedestrian will cross the street is communicated to the car via IEEE 802.11g (WLAN). Triggered by this message, in the second stage the OBU has to perform the autonomous evasive maneuver. The OBU consists of several technical components. The algorithms for evasive trajectory planning and lateral vehicle control are implemented on a real-time PC (dSpace PC plug-in card DS1103). The current vehicle position required for both tasks is provided via a Differential Global Navigation Satellite System (DGNSS) consisting of a GNSS-Receiver with antenna and a GSM reception unit for receiving correction data of a satellite reference service (e.g. [17]). The receiver includes algorithms for multipath reduction avoiding inaccuracy in position measurement caused by objects in the environment of the vehicle such as other road users or parking cars. Furthermore, the OBU includes a steering actuator with an associated servo controller.

III. DETECTION OF THE PEDESTRIAN’S INTENTION

We use our Motion Contour image based HOG-like (MCHOG) descriptor in combination with Support Vector Machine (SVM) classification for recognizing the pedestrian’s gait initiation. The MCHOG descriptor is calculated by overlaying a sequence of pedestrian contour images, e.g., from a motion history image of contours. Its details and performance have been described in [18]. In this paper, we present the technical innovations which we apply to the RSU. At first, we generate pedestrian hypotheses by analyzing the 3D data provided by our stereo vision system.

III-A. Hypothesis Generation and Verification

To generate hypotheses, we compute the following illumination invariant representations. Computing the cardinality of the projection yields counts

\[ S_i(k, l) = |P(k, l)|. \]

A. Hypothesis Generation and Verification

The stereo system delivers a set of 3D points \( P \) with Cartesian coordinates \((x_i, y_i, z_i)\). The \((x, y)\)-plane is divided into quadratic cells of size \(a \times a\). For each cell we define coordinates \((k, l)\) ∈ \( \mathbb{N} \times \mathbb{N} \). We project the 3D points onto these cells. The set of 3D points assigned to cell \((k, l)\) is given by

\[ P(k, l) = \{P_i | (k - 1) \cdot a < x_i \leq k \cdot a \land (l - 1) \cdot a < y_i \leq l \cdot a\}. \]

To generate hypotheses, we compute the following illumination invariant representations. Computing the cardinality of the projection yields counts

\[ S_i(k, l) = |P(k, l)|. \]
For hypothesis verification, we construct pedestrian candidate Regions Of Interest (ROIs) in the image of the left camera by reprojecting the footpoints and adding 2 m above and 20 cm below the footpoint for the ROI height and 65 cm to the left and right for the ROI width.

The OpenCV GPU-implementation of multi-scale HOG- and linear SVM-algorithms is used to verify the pedestrian candidates.

B. Recognition of the Pedestrian’s Intention

1) Feature Extraction: Our feature extraction approach is based on the MCHOG descriptor [18]. Taking advantage of the stereo-vision based depth information, we compute a depth-based foreground image for each positively verified pedestrian candidate ROI: Each pixel is labeled foreground (white) if the distance between the pixel’s \((ξ, η)\)-coordinate and the pedestrian’s footpoint is less than 50 cm, to ensure that the whole pedestrian, even with spread legs, is labeled foreground. Otherwise, the pixel is labeled as background (black). A Motion History Image (MHI) is composed of ten consecutive foreground images. MHI images are scaled to \(72 \times 128\) px. Fig. 4 shows the grayscale image with a pedestrian candidate ROI, the foreground image, and an MHI. Building on this MHI representation, normalized cell histograms of oriented gradients are calculated. We use a cell size of \(8 \times 8\) px and 12 bins for orientation discretization. Eventually, the cell histograms are normalized and concatenated to form the feature descriptor.

2) Classification: To classify the gait initiation, we employ a two-class soft-margin linear SVM with class probability estimation based on Platt’s probabilistic outputs for SVMs [20], which was improved by Lin et al. [21]. The SVM output probability is interpreted as the pedestrian’s starting probability. In order to train the classifier, we generated a video database comprising 63 videos of nine adults standing upright at the pavement near a curb and starting to walk at some point in time while performing typical scenarios, e.g., standing still before crossing, approaching and crossing with a short intermediate stop, or freestyle scenarios, where the test person can perform any kind of action. The base scenarios which we use for training are described in detail in [18]. Here we added two more freestyle scenarios, including stretching the upper body or shaking the legs before starting. The test persons then cross the road at a distance from the stereo camera of approx. 8 m while the camera is looking nearly perpendicular to their trajectory.

The descriptors of the frames between the initial frame (defined by heel-off) and the heel-down of the first step are taken as positive training samples and the descriptors between 30 frames and five frames before the initial frame are taken as negative samples. The descriptors between four frames before the initial frame and the initial frame are ignored. To determine the best SVM penalty multiplier \(C\), we performed a controlled cross-validation procedure, taking the MCHOG descriptors of four out of the nine test persons for training and the remaining for testing. With these resulting 126 combinations, we employed a parameter search of the penalty multiplier \(C\) using the average instance count weighted \(F\)-score

\[
F_α = \left(1 + \alpha \right) \frac{\text{precision} \times \text{recall}}{\alpha \times \text{precision} + \text{recall}},
\]

where

\[
\alpha = \frac{\text{Number of positive samples}}{\text{Number of negative samples}}.
\]

of the 126 corresponding SVMs as the criterion for test sets with an unequal number of positive and negative samples. The highest \(F\)-Score reached was with \(C = 2^{-8}\) at 84.8%.

IV. LATERAL VEHICLE CONTROL

We now assume that the intention of a pedestrian to cross the street has just been transmitted to the OBU. The vehicle is approaching the pedestrian with the velocity \(v\) and has already passed the LPB (Fig. 1). In order to avoid a collision, the OBU has to perform an evasive maneuver. This task consists of two parts, which are described in the following subsections.

A. Evasive Trajectory Planning

First an evasive trajectory has to be generated in real time, that meets the following requirements:

- The coordinates of the trajectory should be specified in the fixed Cartesian \((x, y)\)-coordinate system shown in Fig. 5. Its origin lies at the vehicle’s position at the moment of detecting the pedestrian’s intention to cross the street.
- The calculated data set must include further information that is important for lateral control, such as the curvature \(\frac{d^2 y(x)}{dx^2}\) of the trajectory.
- The trajectory should be chosen so that the vehicle remains within its own lane. Taking this constraint into account, the lateral distance \(d\) to the current pedestrian position has to be maximized.
- In order to ensure the feasibility of the trajectory for the vehicle’s current speed, several constraints have to be considered. For example, the maximum velocity of the steering actuator (700°/s) and the maximum steering wheel angle (620°) of the car must not be exceeded during the evasive maneuver. Moreover, the trajectory planning has to guarantee a stable vehicle guidance with minimal side slipping.

The methods of evasive trajectory planning described in the literature (e.g. [5], [14]) assume that the steering...
maneuver does not start until the vehicle has reached the LPS (Fig. 1). The resulting severe evasive maneuvers require big steering wheel angles as well as high velocities of the steering actuator, and possess high lateral accelerations.

The method proposed in this paper aims at optimally exploiting the available distance to the pedestrian in order to achieve a relatively smooth evasive maneuver. Therefore, the maneuver is started immediately at the moment of detecting the pedestrian’s intention and is terminated at the longitudinal distance $x_P$. I.e., the starting point of the trajectory is located at the origin of the Cartesian $(x, y)$-coordinate system and the trajectory is calculated as a function of the pedestrian distance $x_P$. This approach should help comply with the constraints mentioned above, so that the feasibility of the planned trajectory is ensured. In particular, the required stable lateral vehicle guidance should be achieved in this way.

In order to calculate the trajectory according to the previously described requirements, the data set transmitted from the RSU to the OBU must include the following information:

- the absolute position of the pedestrian (geodetical coordinates $Long_P$ and $Lat_P$)
- the geodetical coordinates $Long_R$ and $Lat_R$ of a reference point at the curbside
- the angle $\varphi$, which describes the orientation of the road with respect to the north axis
- the lane width $w$.

Moreover, the real-time data of the absolute vehicle position (geodetical coordinates $Long_V$ and $Lat_V$) are available.

Using this information, the evasive trajectory $y(x)$ can be calculated as follows. As the evasive trajectory depends on the longitudinal distance $x_P$, i.e., the position of the pedestrian relative to the vehicle, $x_P$ should be determined in the first step. For this purpose, the coordinates $E_P$ and $N_P$ (i.e., the coordinates in a fixed Cartesian East-North-up coordinate system with its origin at the vehicle’s position) of the pedestrian are calculated by means of the geodetical coordinates of the pedestrian and the vehicle using

$$E_P = (Long_P - Long_V) \cdot R_E \cdot \frac{\pi}{180^\circ} \cdot \cos(Lat_V)$$

$$N_P = (Lat_P - Lat_V) \cdot R_N \cdot \frac{\pi}{180^\circ} \cdot ,$$

where $R_E$ and $R_N$ are the radii of curvature in the eastern and northern directions at the latitude $Lat_V$ with respect to WGS84 [22]. Based on $E_P$ and $N_P$, the required distance $x_P$ can now be determined by a coordinate transformation (counterclockwise rotation by the angle $90^\circ - \varphi$).

The lateral offset $b$ at the end of the maneuver (Fig. 5) is the second variable which has a fundamental influence on selecting the evasive trajectory $y(x)$. It depends on the lane width $w$, the vehicle width $b_{\text{vehicle}}$, and the lateral distance $y_R$ of the curbside as follows: $b = w - |y_R| - b_{\text{vehicle}}/2$, where $y_R$ can be determined by means of the geodetical coordinates $Long_R$ and $Lat_R$ of the reference point and those of the vehicle.

In the next step, the shape of the trajectory has to be defined. In the literature, several methods for trajectory planning have been proposed, such as the choice of a sigmoidal trajectory [14] or a polynomial approach [5]. We follow an approach in which the evasive path is composed of three clothoids. A clothoid is a function with a linearly rising or falling curvature $\frac{dy}{dx}$. This feature has the advantage that it leads to harmonic steering wheel angles which is optimal concerning the limited actuator dynamics. As can be seen in Eqn. 12, the curvature of the three clothoids has a constant slope, either $m$ or $-m$.

$$\frac{d^2 y(x)}{dx^2} = \begin{cases} 
- m x, & 0 < x \leq \frac{1}{4} x_P \\
- m(x - \frac{1}{4} x_P), & \frac{1}{4} x_P < x \leq \frac{3}{4} x_P \\
(\frac{1}{4} m x_P)^2, & \frac{3}{4} x_P < x \leq x_P. 
\end{cases}$$

The required trajectory $y(x)$ can now be determined via twofold integration leading to:

$$y(x) = \begin{cases} 
\frac{1}{2} m x^2, & 0 < x \leq \frac{1}{4} x_P \\
-\frac{1}{8} m (x - \frac{1}{4} x_P)^3 + \frac{1}{8} m x_P^2 (x - \frac{x_P}{4}), & \frac{1}{4} x_P < x \leq \frac{3}{4} x_P \\
\frac{1}{4} m (x - x_P)^3 + \frac{1}{4} m x_P^3, & \frac{3}{4} x_P < x \leq x_P. 
\end{cases}$$

The slope $m$ can be determined using the boundary condition $y(x_P) = b$. As for the feasibility of the trajectory, it must be verified that the required velocity of the steering actuator depending on the slope $m$ and the vehicle speed $v$ as well as the steering wheel angle do not exceed their maximum values during the planned maneuver. If the trajectory is not feasible, the vehicle has already passed the LPS and hence the collision cannot be avoided completely by means of an evasive maneuver.

**B. Lateral Control**

In order to avoid the collision, the vehicle has to follow the desired evasive trajectory (Eqn. 13) as closely as possible. This objective should be achieved by means of an appropriate lateral control system used for performing the autonomous evasive maneuver. Fig. 6 demonstrates the proposed lateral control system. It is based on a two degree-of-freedom structure combining feedforward control (FFC) and feedback control (FBC). The command signal $u$ of the control system, i.e., the input of the steering actuator, is formed by superposing the outputs $u_{\text{FFC}}$ and $u_{\text{FBC}}$.

[23] contains a detailed description of the design of the FFC. Its central idea can be described as follows. Without control, the varying curvature of the desired trajectory would
lead to a significant lateral deviation of the vehicle. Therefore, the FFC uses the curvature information of the desired evasive trajectory (Eqn. 12), which is known from the generation of the trajectory, in order to achieve a precise vehicle guidance. The command signal $u_{FFC}$ is calculated by means of the following transfer function: ($s = \text{complex Laplace variable}$)

$$G_{FFC}(s) = \frac{v^2}{K} \cdot \frac{(s + \frac{1}{A_1})(s + \frac{1}{A_2})(s^2 + a_1 s + a_0)}{(T_F s + 1)^2 (s^2 + b_1 s + b_0)} \quad (14)$$

which was derived in [23] based on a simplified and linearized model describing the dynamic behavior of the plant consisting of the vehicle and the steering actuator. As a consequence, the coefficients $a_0, a_1, b_0, \text{and } b_1$ and the constant $K$ depend on the model parameters of the plant, such as the vehicle weight, the wheelbase, the center of gravity, and the cornering stiffness of the tires. Moreover, $T_{A_1}$ and $T_{A_2}$ are time constants which describe the delay time of the steering actuator and $T_F$ is the time constant of a second-order low-pass filter used for noise reduction.

Due to the limited accuracy of the plant model used for determining $G_{FFC}(s)$, the FFC is not able to guarantee a precise vehicle guidance. Therefore, the FBC is used to compensate for the remaining lateral deviations of the vehicle. It helps to increase the robustness of the controlled system with respect to varying model parameters. Another important purpose of the FBC is the stabilization of the plant. The transfer function of the FBC is

$$G_{FBC}(s) = K_{FBC} \cdot \frac{T_D s + 1}{T_S + 1} \cdot \frac{1}{T_{F_2} s + 1} \quad (15)$$

$G_{FBC}(s)$ consists of a $PDT_1$-controller (gain $K_{FBC}$, derivative time $T_D$, delay time $T$) which is important for the stability of the control loop and of a first-order low-pass filter (time constant $T_{F_2}$) used for noise reduction of the DGNNS measurement signal.

As is commonly known, the lateral dynamic behavior of a vehicle is strongly dependent on the velocity $v$. Therefore, $G_{FFC}(s)$ and $G_{FBC}(s)$ are adapted at the current velocity $v$ via gain scheduling, in order to ensure a satisfying control result for a wide range of velocities [23]. Moreover, it is necessary to employ a preview concept, to ensure the stability of the control loop even for high vehicle speeds. I.e., the controller output is calculated with respect to a preview point, which lies at a particular distance in front of the vehicle’s current position [24].

V. EXPERIMENTAL RESULTS AND CASE STUDY

In this section we present the experimental results for the recognition of the pedestrian’s intention and for vehicle control. Furthermore, we compare the response time of the proposed system to the reaction time of a human driver.

A. Recognition of the Pedestrian’s Intention

Since the evasive steering maneuver is triggered by a single positive detection, we performed a per-sequence based evaluation by treating a single positive detection as a non-reversible trigger. We also measured the relation between the starting probability and the average classifier precision, as the relation between the starting probability and the frame number after the initial frame (heel-off, Frame 0 in Fig. 7) in which the pedestrian’s intention was recognized. The results for all scenarios (including the freestyle scenarios) and for only those scenarios in which pedestrians stand still before crossing the street are shown in Fig. 7. If a decision threshold of 0.8 for the starting probability is chosen (see arrows in Fig. 7) the system needs seven frames corresponding to 200 ms at a frame rate of 35 Hz on average in order to recognize the initiation of gait for all scenarios (solid green line in Fig. 7). For the same starting probability, a precision of slightly more than 80% can be obtained (dashed blue line in Fig. 7).

The precision increases to 96% and the response time decreases slightly if the pedestrian stands still before starting, i.e., if the freestyle scenarios are excluded (dotted green line and double dashed blue line in Fig. 7). This corresponds fairly well to human observation: the more the pedestrian moves before walking, the more difficult it becomes to determine when he starts to walk.

B. Vehicle Control

Fig. 8 illustrates the test scenario and a testing ground which we used to simulate the dangerous traffic situation discussed in Section I (Fig. 1). On the left hand side, one can see the mobile RSU (blue rectangle in Fig. 8) installed for monitoring the roadside. The red and white pylons are used to mark the lane width. The red framed pedestrian standing at a simulated curb is approached by our
Fig. 8. Picture sequence of an autonomous evasive maneuver test vehicle at $v = 35$ km/h which is even higher than the typical speed limit in German residential areas. Suddenly, the pedestrian starts to cross the street. Note that the scenario should only simulate a real-world traffic situation. Therefore, the lateral distance of the proband is chosen in such a manner that a risk can be excluded even in the case of a malfunction of the developed system. The picture sequence demonstrates that the pedestrian’s intention to cross the street is detected at such an early stage that the evasive maneuver of the car is already initiated during the pedestrian’s first step: including the latencies of detection, transmission, and reaction. As requested, the vehicle remained within its own lane during the autonomous steering maneuver. Fig. 9 shows the corresponding measurement results. The top diagram illustrates the high accuracy of the lateral control system. The difference between the driven trajectory (green curve) and the generated evasive trajectory (blue curve) is kept below 10 cm at maximum lateral accelerations of $4 \text{ ms}^{-2}$ and $-5 \text{ ms}^{-2}$ (bottom diagram). The middle diagram demonstrates that the maximum available steering actuator velocity of $700^\circ/\text{s}$ is exploited almost completely (blue curve) whereas the steering wheel angle (green curve) remains significantly below its maximum possible value of $620^\circ$.

C. Human Driver vs. Test System

In order to compare the response time of the system with the reaction time of a human driver, we performed a case study by letting 11 test persons drive down a road parallel to the curbside at a safe distance and at about 35 km/h. A pedestrian was standing at the curbside and then would start to cross the street. The pedestrian’s initiation of gait was detected and transmitted to the test vehicle. The vehicle features a hand-held trigger button that should be pressed by the driver upon observing the initiation of gait. The drivers were told that the pedestrian would cross the street, but they did not know exactly when. Nevertheless, they had the chance to pay maximal attention to the pedestrian. The pedestrians were instructed to start walking at a distance of 15 m - 5 m to the approaching car. We captured the time difference $\Delta t$ between the driver’s trigger signal and the system’s signal arrival at the OBU using a decision threshold of 0.8 for the starting probability of the pedestrian. Table I shows the results. We observe that in five out of 11 test cases, our system reacts faster than the human driver, with an average time gain of 214 ms.

Although the drivers were able to pay a maximum of attention to the pedestrians, the system responded faster than the drivers in about 50% of the cases. In real world applications, the drivers would not be able to focus their attention on the pedestrians to such an extent. Thus, it can be assumed that the system will respond faster than the drivers in many real world scenarios.
<table>
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<th>1</th>
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<th>3</th>
<th>4</th>
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<td>-168</td>
<td>-204</td>
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</tr>
</tbody>
</table>

TABLE I
RESPONSE TIMES: TIME DIFFERENCE ∆t; NEGATIVE VALUES INDICATE THAT THE SYSTEM RECOGNIZES THE SITUATION EARLIER THAN THE DRIVER.

VI. CONCLUSION AND FUTURE WORK

In this paper, we presented an active pedestrian protection system that combines infrastructure-based detection of pedestrians' intentions with an autonomous lane keeping evasive maneuver at a time when collision avoidance by braking is no longer possible. Stereo-based hypotheses together with HOG-based SVM-classification and linear Kalman filters were used to recognize and track pedestrians standing at the curb. Their intention to cross the street was detected within the first step, using motion contour histograms of oriented gradients. These components were implemented as a mobile RSU that can be placed at different test fields and that overcomes the limits of occluded traffic participants.

The information of the RSU was transmitted via WLAN to the OBU of a test vehicle which performs clothoid-based real-time trajectory planning and lateral control using a two degree-of-freedom structure which combines feedforward and feedback control to perform the autonomous evasive maneuver. Lane keeping within ±10 cm from the calculated trajectory avoids endangering any other traffic without needing to monitor the opposite lane. The car autonomously reacts within the first step of the pedestrian at the curb. In a case study on the reaction speed of human drivers, the system responded faster in five out of 11 test cases, although the drivers were able to pay the utmost attention to the behavior of the crossing pedestrian.

Future research will concentrate on extending the system to scenarios with multiple pedestrians (e.g. trigger if anybody will cross), transferring the methods to other traffic participants and on pavement scenarios beyond the initiation of gait. Furthermore, studies on test fields are planned that allow for the application of maximum urban velocities even under different road surface conditions. Another objective is the development of control algorithms for collision avoidance by means of simultaneous autonomous braking and steering.

VII. ACKNOWLEDGMENT

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