Autonomous Pedestrian Collision Avoidance Using a Fuzzy Steering Controller

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Abstract—Collision avoidance is one of the most difficult and challenging automatic driving operations in the domain of intelligent vehicles. In emergency situations, human drivers are more likely to brake than to steer, although the optimal maneuver would, more frequently, be steering alone. This statement suggests the use of automatic steering as a promising solution to avoid accidents in the future. The objective of this paper is to provide a collision avoidance system (CAS) for autonomous vehicles, focusing on pedestrian collision avoidance. The detection component involves a stereo-vision-based pedestrian detection system that provides suitable measurements of the time to collision. The collision avoidance maneuver is performed using fuzzy controllers for the actuators that mimic human behavior and reactions, along with a high-precision Global Positioning System (GPS), which provides the information needed for the autonomous navigation. The proposed system is evaluated in two steps. First, drivers' behavior and sensor accuracy are studied in experiments carried out by manual driving. This study will be used to define the parameters of the second step, in which automatic pedestrian collision avoidance is carried out at speeds of up to 30 km/h. The performed field tests provided encouraging results and proved the viability of the proposed approach.

Index Terms—Collision avoidance, fuzzy control, pedestrian protection, steering control, stereo vision.

I. INTRODUCTION

COLLISION avoidance is one of the most difficult and challenging automatic driving operations for autonomous vehicles. This maneuver is used as a last resort in a critical situation by braking and/or steering, as long as the accident is still avoidable. Collision avoidance can be applied to either vehicles (e.g., cars, trucks, motorbikes, and bicycles) or pedestrians. In both cases, this maneuver is considered a hazardous operation not only from the point of view of an autonomous system but from the perspective of a human driver as well.

A collision avoidance system (CAS) involves, at least, the following three main parts: 1) *object detection*; 2) *decision-making*; and 3) *actuation*. Object detection relates to perception tasks that analyze the environment information obtained by one or more sensors. Although object detection has been carried out through ranging sensors, e.g., lidar or radar, the computer vision community has developed an extensive amount of interest in solving this stage over the last few years. Many techniques have been proposed in terms of features, models, and general architectures to estimate the position and velocity of objects, e.g., vehicles, bicyclists, or pedestrians. A decision-making system interprets these estimates and makes a decision on when and how collisions can be avoided [1]. The complexity of this stage depends on the specific traffic situation. The huge set of possible maneuvers, their physical restrictions, and nonlinear properties makes decision making a multidimensional difficult problem. Finally, one actuation system adapts the target commands generated by the previous stage and transforms these commands to low-level control signals needed by the respective actuators: 1) *throttle*; *brake*; and 3) *steering*. The generated signals have to take the corresponding actions to avoid the collision, i.e., acceleration, breaking, or steering.

Autonomous collision avoidance comes down to overruling the driver. This case entails a considerable number of important concerns. The legislation referred to active systems is not yet fully developed. It is essential to identify new potential problems with regard to regulatory and liability law, particularly in situations where technical systems are designed to take over certain driving tasks in whole or in part from the driver [2]. The driver acceptance of active systems has to be investigated in detail. False alarms are extremely critical, because they may lead to unpredictable situations with serious consequences. In addition, the introduction of autonomous and active systems, which can be seen as autopilot systems, may cause misuse problems if the drivers reduce their attention, because they completely rely on the system [3]. This condition can be avoided by designing not fully automated systems to keep the driver concentration at all times, e.g., systems in which only a certain percentage of the required steering torque is applied. Another possible solution can be obtained by combining these systems with driver-monitoring methods [4].

The analysis of the human driver behavior is one of the main encouragements for proposing the avoidance maneuver by steering. Adams [5] suggests that, in emergency situations, drivers are more likely to brake than to steer, whereas the optimal maneuver would be more frequently steering alone. It is unclear why drivers tend not to use the optimal strategy in

emergency situations. It is possible that drivers' reluctance to steer is due to a tendency to maintain their own lanes of travel at all costs, their lack of knowledge about alternative maneuvers and the handling capability of their vehicles, or their preference to lessen the severity of the accident by applying the brakes rather than risking a different collision by executing a lateral maneuver [5]. Systems that take active control of the vehicle and automatically perform the optimal maneuver may be the solution to avoiding accidents in the future.

In this paper, we are concerned with autonomous pedestrian collision avoidance by steering. Pedestrian detection is carried out using a stereo-vision-based approach [6], [7], which provides pedestrians position and relative motion. Decision making is based on the computation of the time to collision (TTC) between the host vehicle and the pedestrian ahead. On the one hand, if the system considers the collision unavoidable, pedestrian protection systems (PPSs), e.g., active breaking, active hood, or pedestrian protection airbags, will be triggered [7]. On the other hand, if the collision is still avoidable, the collision avoidance maneuver is performed using fuzzy steering controllers for path tracking and lane change, which are defined as a function of the vehicle speed. Speed control is also autonomously managed, keeping the vehicle at the target speed (cruise control). Extra sensorial information is obtained from a high-precision Global Positioning System (GPS) and a wireless communication system.

From the experimental side, some conditions are out of the scope of this paper. For instance, complex traffic situations, which require a more complete sensor fusion scheme and complex decision making, e.g., situation and threat assessment [1], are not analyzed. Instead, a simple scenario is defined. The vehicle moves along a straight road. The pedestrian with whom the collision may take place is located in the same lane as the host vehicle. The left lane is free and long enough for the collision avoidance maneuver to be completed at the current speed. During the avoidance maneuver, the vehicle speed is considered constant, i.e., braking is not allowed. Pedestrian dynamics are considered negligible compared with the vehicle dynamics. Thus, only short-term collision estimations are determined, instead of long-term impact predictions that would require pedestrian behavior modeling [8].

The remainder of this paper is organized as follows. Section II briefly surveys computer-vision-based pedestrian detection and autonomous steering maneuvers. An overall description of the system is presented in Section III. The stereo-vision-based pedestrian detection system and the fuzzy steering controller for pedestrian collision avoidance are described in Sections IV and V, respectively. The preliminary results with regard to the analysis of the drivers' behavior and the accuracy of the sensor system, as well as the real collision avoidance experiments, are listed in Section VI. After discussing our results, we conclude in Section VII.

II. PREVIOUS WORK

Sensor systems onboard the vehicles are required to predict the car-to-pedestrian distance and the TTC. Cameras are the most commonly used sensors for that purpose. Over the last decade, a considerable number of vision-based pedestrian detection systems have been proposed. Several remarkable surveys have been presented [9]–[12], some of which have recently been published [13], [14]. Most of the work with regard to human motion have been summarized in [9]–[13], focusing on the pedestrian protection application in the intelligent vehicle domain, covering both passive and active safety techniques. An overview of the state of the art from both methodological and experimental perspectives is presented in [14], where a novel benchmark set has been made publicly available.

Autonomous collision avoidance was first proposed for unmanned aerial vehicles (UAVs) [15], and it has been in place onboard domestic transport aircraft since the early 1990s [16]. Although autonomous aerial navigation considerably differs from autonomous navigation in the intelligent vehicle domain, several aspects can fruitfully be extended. For instance, in [17], an overtaking control method is proposed using the conflict probability, which has widely been used in the aviation community [18]. Other concepts, e.g., TTC, time-to-escape, and risk assessment, which have deeply been studied for UAVs, are also suitable for intelligent vehicles.

The next step carried out by the research community took place for autonomous-mobile-robot applications. In robotics, collision avoidance consists of modifying the trajectory of the mobile robot in real time such that the robot can avoid collisions with obstacles found on its path. This approach comprises the following two main layers: 1) obstacle avoidance and 2) path planning. Due to the idiosyncrasy of this field, a sizeable number of works have been developed during the past few decades. We refer to the review in [19] for a general background with regard to obstacle avoidance for autonomous mobile robots.

With regard to autonomous collision avoidance for intelligent vehicles, in particular, collision avoidance by steering, we can define, at least, the following four stages of development.

1) *Guidance or lane keeping*. Autonomous guidance or lane keeping refers to the technology that tries to prevent lane departure, usually by monitoring the lane markers using a vision-based system and controlling the steering wheel. The first work on lane guidance was built in Japan in 1977 [20]. Subsequently, works started to appear in the late 1980s [21], [22]. The Carnegie Mellon University (CMU) Navlab gained much experience in developing steering controllers for autonomous navigation for the Navlab vehicle series, which are equipped with artificial vision systems. The steering of the early versions was controlled by the template-based rapidly adapting lateral position handler (RALPH) [23]. Several lateral controllers and autonomous guidance systems have also been developed through the Partners for Advanced Transit and Highways (PATH) Program [24]–[27]. As part of the well-known ARGO Project [28], an automatic guidance system was developed with an onboard computer that manages the steering wheel of a mass-produced car. The guidance system was based on a classical proportional controller whose inputs signals were directly supplied by the lane-recognition vision system. Other real-vehicle applications have been developed, which can perform autonomous

lane keeping and navigation by automatic steering management [29], [30].

2) *Lane change*. In contrast to lane keeping, lane change concerns methods that allow the vehicle to target a different lane, estimate the lane-change trajectory, and track the new path. There is sufficient literature related to the lane-change issue. Most of the works have been proposed by the PATH Program. In [26], a classical analytical control system is proposed for performing lane-change to get an autonomous vehicle to automatically join or leave a platoon of unmanned vehicles that circulate in a different lane. The input variables are lateral and angular errors, which are provided by a magnetic marker sequence placed at the center of the lanes. A fuzzy controller, which consists of 24 rules, for managing the steering wheel of an autonomous vehicle in lane-change maneuvers is presented in [31]. A new longitudinal controller for lane-change tracking within platoon operations is proposed in [32]. The longitudinal controller is combined with lateral controllers to minimize the length of the maneuver. In [33], an autonomous navigation system that performs lane keeping and lane-change maneuvers following magnetic markers that are placed in each lane of the road has been developed. The lane-change maneuver is defined as the movement from one lane to the adjacent lane. During this process, the navigation is performed by dead reckoning until the vehicle locates the new lane magnetic sensor sequence. An exhaustive analysis for calculating the lane-change trajectory is conducted in [34].

3) *Overtaking*. An overtaking maneuver can be defined as a sequence of a lane-change maneuver, a path tracking along the new lane, and a return to the original lane. The optimal trajectory for executing this complex maneuver was first proposed in [35]. A fuzzy-control-based automatic lane-change system that mimics human behavior and reactions during overtaking is presented in [36]. The navigational information that is needed for the overtaking operation is supplied by a differential GPS (DGPS). Recently, a conflict-probability-estimation-based overtaking control method has been proposed to enhance safety during an overtaking maneuver [17]. The conflict probability is used as the safety indicator.

4) *Collision avoidance*. Most of the collision avoidance approaches have been defined to avoid collision between vehicles. Lane-change maneuvers are used as a response to an emergency situation, resulting in the so-called emergency lane change (ELC) [37] or emergency lane assist (ELA) [3] systems. The minimum distance or TTC beyond which an obstacle cannot be avoided at a given initial speed is determined as 1 s in [37]. The design of an ELC maneuver that enables the follower vehicle to track the lead vehicle's trajectory for a platoon of two vehicles is presented in [38]. The analysis of the kinematics of the vehicles involved in a lane-changing/merging maneuver and the study of the conditions under which lane-changing/merging crashes can be avoided are provided in [34]. In [3], a new type of lane guidance system (ELA) is proposed. The main goal is to prevent dangerous lane

Fig. 1.   Experimental vehicle and the onboard stereo sensor.

departure maneuvers by automatically applying a torque to the steering wheel.

In this paper, we will focus on autonomous pedestrian collision avoidance by steering. According to the literature, we can conclude that this issue is one of the less well-researched topics in the autonomous vehicle domain, because it has been somewhat neglected.

III. SYSTEM DESCRIPTION

A. Experimental Vehicle

The experimental vehicle used in this paper is a Citröen C3 Pluriel, which has been automated by the Spanish National Research Council (CSIC; see Fig. 1). It is a dual-mode vehicle that offers an automatic mode in specific situations (e.g., platooning) and specific locations (e.g., automated parking lots) and a manual-assisted mode in regular situations [39]. It has an onboard computer that houses the control system. The GPS is connected through an RS232 serial port, the cameras provide the images through the FireWire port, and the speed signal is read through the controller area network (CAN) bus interface. Finally, a wireless networking infrastructure is used to transmit the differential correction from a GPS base station to the vehicle [40].

B. Collision Avoidance Overview

Pedestrian collision avoidance is defined as a three-stage process. As soon as the stereo vision sensor detects a potential pedestrian collision that can be avoided, a lane change to the adjacent left lane is performed. Path tracking is then applied until the pedestrian has been passed. Finally, a second lane change is carried out to go back to the right lane (see Fig. 2). We do not consider oncoming traffic along the left lane, because it would require a vehicle detection system and complex decision making, which are out of the scope of this paper.

According to this scheme, two controllers have to be designed: one controller for the speed and another controller for the steering wheel. Although both controllers are considered partially decoupled and, thus, they can independently be

(a)

(b)

(c)
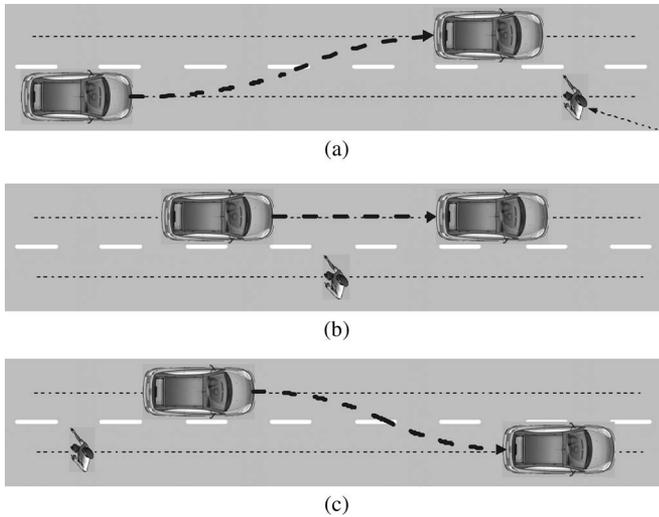
Fig. 2. Pedestrian collision avoidance stages. (a) First lane change to the contiguous lane, (b) path tracking in the left lane, and (c) second lane change to the right lane.
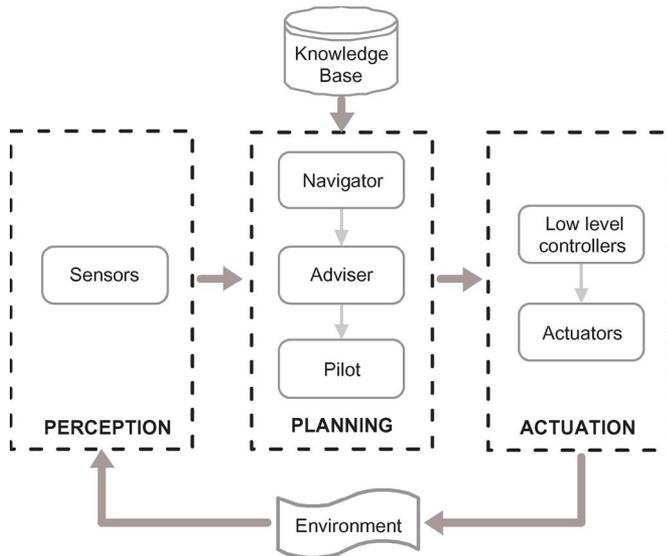
Fig. 3. Stages of the control architecture.

designed, they share the input information and decision-making layers and work in a coordinated way. The speed control [39] works as an adaptive cruise control (ACC), maintaining a target speed for obstacle-free circulation, platooning, overtaking, and collision avoidance. Several fuzzy steering controllers have previously been designed to manage obstacle-free circulation and platooning [41] and overtaking [36]. In this paper, a fuzzy control system is specifically designed to control the steering in pedestrian collision avoidance maneuvers.

C. Architecture Description

The control architecture is divided into three different stages, as shown in Fig. 3. This architecture can deal with different vehicle models, actuators, and control methods. It is open and distributed, allowing scalability without substantial changes to its configuration, even with the inclusion of different elements
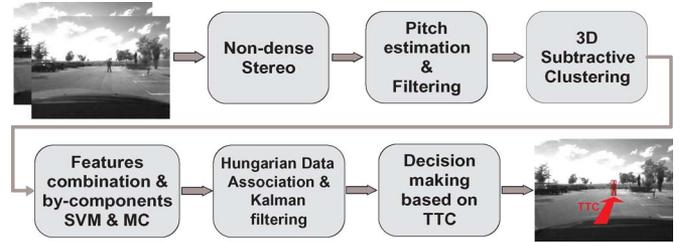
Fig. 4. Overview of the stereo-vision-based pedestrian detection architecture.

in each car and irrespective of the vehicle model. The stages are listed as follows.

1) *Perception*. In this stage, the acquisition of the environment information is carried out. The main sensorial inputs include a real-time kinematic DGPS (RTK-DGPS), an inertial measurement unit (IMU), and a stereo-vision-based system. These systems are combined [40] to obtain a good vehicle position that is used as the input to the next stage.

2) *Planning*. This phase is subdivided in three subphases. The first subphase is a navigator that, in this case, will be defined as a set of GPS waypoints used as the reference route. The second subphase is the adviser, whose mission is to select among all the different controllers. These controllers—all based on fuzzy logic—have been designed to take into account any traffic condition, i.e., straight-road tracking, bend tracking, overtaking, or ACC. Finally, the pilot decides the best controller for each traffic situation and generates the corresponding output for the actuators.

3) *Actuation*. The latter stage is in charge of the execution of the targets that come from the planning stage. Its function is to adapt the output value generated by the pilot to values that can be applied to the actuators, i.e., the throttle, the brake, and the steering wheel. The actuators have been modified to permit autonomous driving. In particular, an analog output card carries out the control of the throttle, and an added electrohydraulic pump acts on the brake. For the steering wheel, a parallel system to the electrical assisted power steering has been installed. A pulsewidth modulation (PWM) signal is sent to act over the steering wheel, and a power stage manages the motor.

IV. STEREO-VISION-BASED PEDESTRIAN DETECTION

Pedestrian detection is carried out using the system described in [6] and [7] (see Fig. 4). Nondense 3-D maps are computed using a robust correlation process that reduces the number of matching errors [42]. The camera pitch angle is dynamically estimated using the so-called virtual disparity map, which provides a better performance compared with other representations, e.g., the v-disparity map or the yOz plane [7]. Two main advantages are achieved through pitch compensation. First, the accuracy of the TTC estimation in car-to-pedestrian accidents is increased. Second, the separation between road points and obstacle points is improved, resulting in lower false-positive and false-negative detection rates [7].
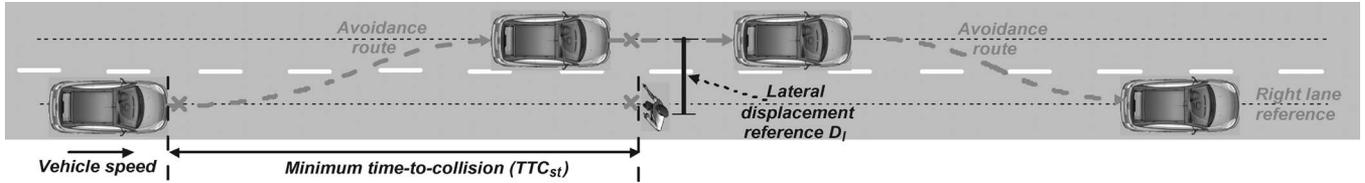
Fig. 5.   Representation of the pedestrian collision avoidance maneuver variables.

Three-dimensional maps are filtered, assuming that the road surface is planar (which can be acceptable in most cases), i.e., points under the actual road profile and over the actual road profile plus the maximum pedestrian height are removed, because they do not correspond to obstacles (possible pedestrians). The resulting filtered 3-D maps are used to obtain the regions of interest. A subtractive clustering method, which is adapted to the accuracy provided by the stereo sensor, is applied to detect generic obstacles with a 3-D shape that is similar to the pedestrians. The 2-D candidates are then obtained by projecting the 3-D points of each resulting cluster and computing their bounding boxes. A support-vector-machine-based (SVM) classifier is then applied using an optimal combination of feature extraction methods and a by-components approach [6]. Nonetheless, the 2-D bounding box that corresponds to a 3-D candidate might not perfectly match the actual pedestrian appearance in the image plane. Multiple candidates are generated around each original candidate. The so-called multicandidate (MC) approach proves to increase the detection rate, the accuracy of depth measurements, and the detection range. The tracking stage is carried out using a Kalman filter, including both pedestrian position and relative velocity in the state vector and assuming a constant velocity motion model.

The pedestrian detection system runs in real time with 320×240 images and a baseline of 30 cm. The stereo-vision-based pedestrian detection system has been tested in real collision–mitigation experiments by active hood triggering and collision avoidance tests by breaking or decelerating [7]. These two actions are now combined with collision avoidance by steering resulting in a complete PPS.

V. Pedestrian Collision Avoidance

Some preliminary considerations must be done to define the condition to activate the autonomous pedestrian CAS. First, the vehicle has to be moving along a straight road and in the right lane. Second, the pedestrian has to be located in the same lane. Third, the left lane has to be free and long enough for the pedestrian collision avoidance maneuver to be completed at the current speed. Because we have developed a fuzzy steering controller, we consider a constant speed that is autonomously fixed.

A. Collision Avoidance Maneuver

If the previous conditions are satisfied, the collision avoidance maneuver is carried out. To perform a good maneuver, we must guarantee the safety of both the pedestrian and the vehicle occupants. Accordingly, the trajectory of the vehicle must be as soft as possible to avoid a car accident, e.g., lateral overturning of the vehicle. Once the car-to-pedestrian TTC is

under a specific threshold, the following two main parameters have to be considered: 1) the actual speed of the car and 2) the lateral displacement, which is needed to avoid running over the pedestrian. The actual speed of the vehicle is used to restrict the torque applied to the steering wheel. The lateral displacement is used to define the new reference during the avoidance maneuver (see Fig. 5).

The planning stage in our architecture allows the following of a predefined route. The target reference is located in the right lane until an unexpected traffic situation takes place. Once the system triggers the collision avoidance maneuver, a projection of the predefined route is computed with the reference located in the right lane plus the lateral displacement. Virtually, some kind of a triangle, whose vertices are the vehicle position, the pedestrian position, and the future safety vehicle position in parallel with the pedestrian, is traced.

This movement consists of a soft action over the steering wheel that the implemented fuzzy controllers cannot carry out. The straight-road fuzzy controller permits a minimum movement to avoid unexpected turns of the steering wheel in a straight stretch [41]. In a parallel line, the bend fuzzy controller permits a complete freedom in the action over the steering wheel [41]. Other fuzzy controllers implemented act over the longitudinal control [39]. A lane-change fuzzy controller has been developed to perform the overtaking maneuver [36]. In this case, we obtained a function that depends on the speed of the vehicle to determine the distance necessary to safely perform the lane-change maneuver.

In our case, we want to deal with an unexpected traffic situation, i.e., when a pedestrian suddenly appears in front of the vehicle. The goal is to avoid the car-to-pedestrian collision without causing an accident. A new fuzzy controller is developed to achieve that goal.

B. Fuzzy Steering Controller

There are several approaches for performing the control of the actuators in a vehicle. The conventional methods of control produce good results but with a high computational and design cost due to the nonlinear characteristic of a vehicle. Indeed, its mathematical representation becomes extremely costly. Another way of coming closer to the human behavior for the steering control is the use of technologies based on artificial intelligence, e.g., neural networks [43], but fuzzy logic gives a good approximation to the human reasoning and is an intuitive control technique.

The fuzzy controller developed will be responsible for managing the steering wheel (i.e., the lateral control) in making a decision about modifying the autonomous vehicle's steering. This controller consists of a rule base that contains expert
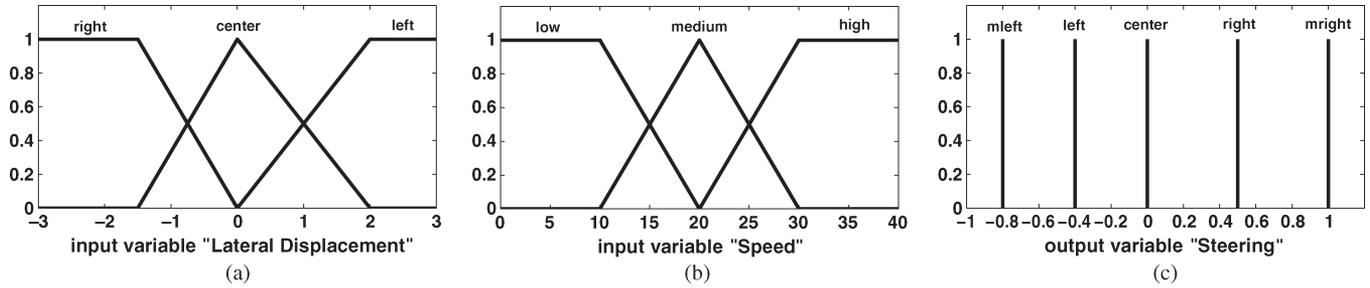
Fig. 6. Membership function definition for the input variables. (a) *Lateral displacement*, (b) *speed*, and (c) output variable *steering*.

knowledge and a set of variables that represent the linguistic values considered. Functionally, the fuzzy reasoning process can be divided into the following three stages.

Fuzzyfication receives the stage in which a crisp input value is converted to a fuzzy value. The following two inputs have been used in the definition of this controller: 1) the lateral displacement, which is measured as the difference between the actual position of the vehicle and the desired safety position, and 2) the speed of the vehicle, which is obtained from the CAN bus.

Inference engine simulates the human reasoning process by making fuzzy inference on the inputs and *if–then* rules. We use Mamdani's inference method [44] (min–min–max) to solve the implication. The application of the inference engine yields the values of the output fuzzy variables.

Defuzzification is the reverse process to the fuzzification. In this stage, the fuzzy output values are converted to crisp values. We defined the output fuzzy variable membership function shapes using Sugeno's singleton [45]. Thus, control decisions can be taken in a short period of time, with very good precision and quality for a real-time system. A modification of the center-of-area (CoA) method is applied as

$$y_{CoA}' = \frac{\sum \omega_i B_i}{\sum \omega_i} \qquad (1)$$

where ω_i represents the membership degree that results from the inference of the ith rule, and B_i is the membership function for the different values of the output variables of the ith rule.

Fig. 6(a) and (b) shows the membership functions for the input variables. Without unexpected traffic situations, the input variables for the control are the lateral error and the angular error [36]. We assume that the vehicle is driven on a straight-road stretch and that the main goal is to avoid the pedestrian collision. Therefore, the variation in the angular error is negligible. Taking this condition into account, an angular error can be removed from the rules, and a new variable can be included, i.e., the actual speed of the vehicle.

The fuzzy input variable *lateral displacement* contains three membership functions for each of its three associated linguistic labels. The right linguistic label is used to determine how far deviated to the right the vehicle is from its target route. In the same way, the left linguistic label is used to calculate how far deviated to the left the vehicle is from its target route. The center linguistic label detects when to stop the movement of the steering wheel when the reference route and the actual position

TABLE I
RULE BASE FOR STEERING CONTROL

Lateral Displacement	Speed		
	Low	Medium	High
Right	mright	mright	right
Center	right	center	center
Left	mleft	left	left

of the vehicle are coincident. When a variation from this point to the left or the right occurs, the steering-wheel action is then permitted. Note that this fuzzy membership function has been defined asymmetric. The reason for this approach is that we previously assumed that the vehicle was driven on the right lane and that the pedestrian is located on the same lane. Therefore, the first movement of the steering wheel must be as hard as possible to ensure that collision with the pedestrian is avoided. A lateral displacement around 2.5 m is considered maximum security. Due to this asymmetry, we carry out a hard movement in the avoidance maneuver and a softer movement when the vehicle returns to the right lane.

The second fuzzy input variable used to perform the steering for the pedestrian collision avoidance maneuver is the *speed* of the vehicle. This fuzzy input also has three membership function definitions for each of its three associated linguistic labels. The low linguistic label is used when the vehicle is driven at very low speeds, and the medium and high linguistic labels are defined to consider the moments when the vehicle is driven at medium and high speeds, respectively. As intuition commands, the higher the speed of the vehicle, the lower the movement of the steering wheel. In this case, the fuzzy membership function has been defined as symmetric.

The output variable is *steering*, which determines the steering-wheel position. As previously stated, the fuzzy output variable membership function shape is defined using Sugeno's singletons, which are based on monotonic functions [see Fig. 6(c)]. In the straight-road fuzzy controller, two singletons are defined with values of −1 and 1 to move the steering to the left or right, respectively. In this controller, we have defined five different singletons, as observed in Fig. 6(c). The movement to the left is limited to 80% of the maximum steering-wheel movement, because this maneuver occurs while the vehicle returns to the right lane. On the other hand, the movement to the right is completely allowed to avoid collisions with pedestrians. The rule base implementation is shown in Table I. One can appreciate how the fuzzy rules have been also selected as asymmetric. It is motivated by the consideration that the left lane is free during the maneuver. Accordingly, the softer the action, the higher the comfort of the occupants.
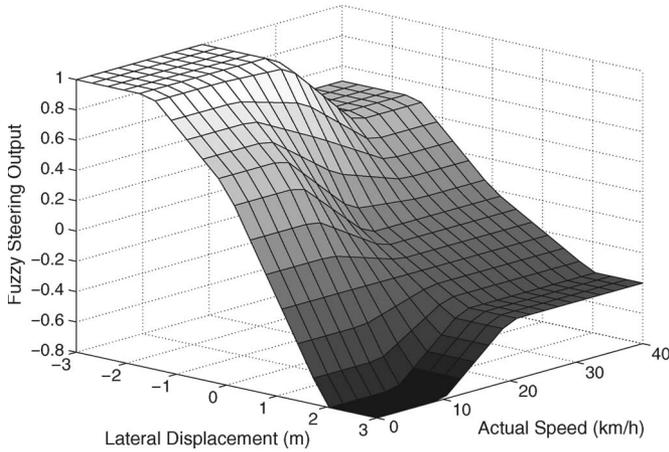
Fig. 7. Control surface of the fuzzy steering controller for pedestrian collision avoidance.

Fig. 8. Pedestrian collision avoidance maneuvers that correspond to driver 1 at different speeds.

Fig. 7 shows the control surface for the output variable—steering—as a function of the fuzzy input variables, i.e., lateral displacement and actual speed according to the fuzzy rules in Table I. The smoothness in the variation of the surface indicates that the rules selected are convenient.

VI. EXPERIMENTS

The proposed pedestrian CAS using a fuzzy steering controller is evaluated in two steps. First, several manually driven avoidance maneuvers are performed, with the aim of studying the sensor accuracy and determining the drivers' behavior. This study will be used to define the parameters of the second step, in which automatic pedestrian collision avoidance field tests have been carried out to demonstrate the viability of the proposed approach.

A. Drivers' Behavior and Sensor Accuracy

To evaluate the drivers' behavior, we have recorded a set of sequences in which five different drivers have been requested to perform pedestrian collision avoidance maneuvers by steering at different speeds: 10, 15, 20, 25, and 30 km/h. In addition to the stereo vision sensor, two DGPSs are used. The first DGPS is placed at the pedestrian position, and the second DGPS is installed onboard the vehicle. The measurements supplied by the DGPS (after linear interpolation due to its low sample frequency, i.e., -5 Hz) are considered the ground truth. Thus, we can compare the results provided by the stereo vision sensor and determine its suitability to carry out automatic pedestrian collision avoidance maneuvers.

Fig. 8 shows the DGPS trajectories that correspond to driver 1, where the x-axis represents the Universal Transverse Mercator (UTM) East coordinates, and the y-axis represents the UTM North coordinates in meters. To compare these trajectories with the trajectories provided by the stereo sensor, the relative car-to-pedestrian positions with respect to the left camera have to be computed. This transformation is carried out by applying two translations: one translation from the UTM global reference to the DGPS onboard the vehicle and another
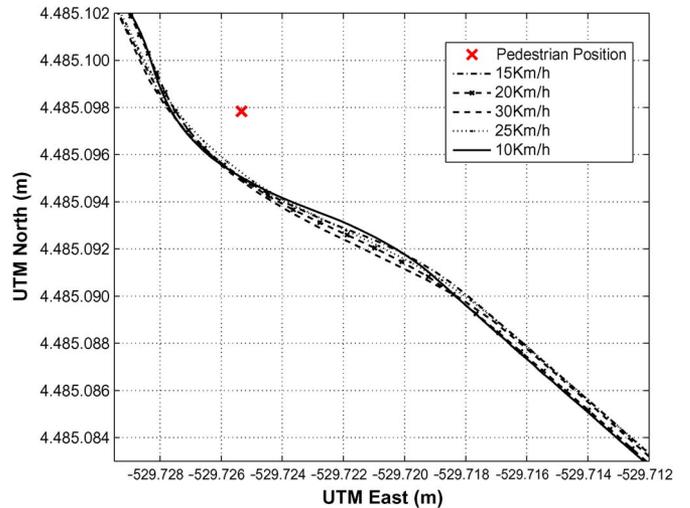
translation from the DGPS to the left camera. The orientation of both axes is computed using the longitudinal movement of the vehicle.

Fig. 9(a)–(c) depicts the trajectories supplied by the DGPS, with the reference located on the moving vehicle (left camera) and the trajectories provided by the stereo sensor, as well as their uncertainties (which are drawn with dotted ellipses), corresponding to driver 1 performing the avoidance maneuver at 10, 20, and 30 km/h, respectively. Some remarkable conclusions can be deduced from these figures. The maximum range (25–30 m) and the inverse proportion between the depth and the stereo accuracy can easily be appreciated. The DGPS trajectories are always inside the limits of the stereo measurements plus their corresponding uncertainties, which proves that the stereo sensor provides information that is accurate enough, despite its inner accuracy constraints. In addition, although stereo depth measurements are not reliable at long distances, their accuracy improves in proportion to the collision risk, i.e., as the car-to-pedestrian distance decreases. For example, at 15 m, the depth error is about ± 1.5 m; at 10 m, the depth error is about ± 0.7 m; and at 5 m, the depth error is lower than ± 0.2 m. These statements can be extended from driver 1 to driver 5.

However, as suggested in [46] for braking maneuvers, we deduce that the decision to start the avoidance maneuver and the control of steering may well be based on TTC information as directly available to the driver from the optic flow field. This TTC information is an important cue for the driver in detecting potentially dangerous situations. The problem is then to define an adequate criterion for activating the CAS. Fig. 10 shows the TTC computed through the DGPS and the stereo sensor, as well as the corresponding absolute error in the experiment performed by driver 1 at 10 km/h.[1] The error is clearly unacceptable for TTC values above 8 s. However, the accuracy of the measurements increases as long as the TTC decreases. The shape of the picture is highly similar in all tests (from driver 1 to 5 at all speeds).

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[1]The target speed has been used to compute the TTC. Actual speeds are unknown, because they have not been measured.
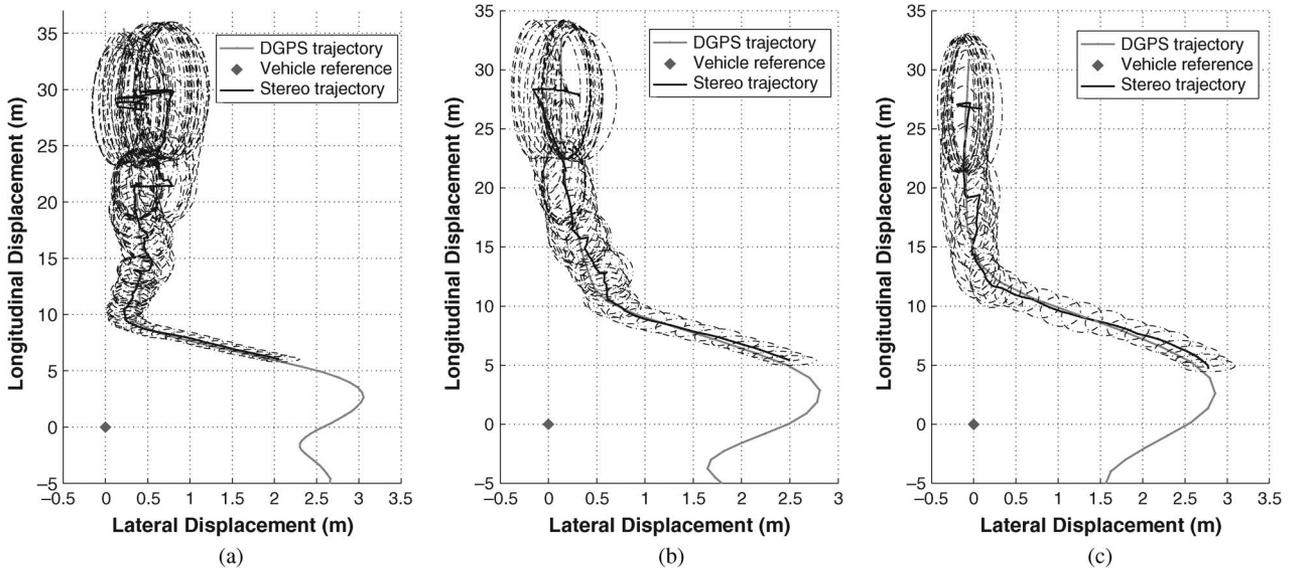
Fig. 9.   Vehicle-to-pedestrian trajectories from DGPS (ground truth) and stereo (including covariances of the given stereo uncertainty at one time step) that correspond to driver 1 at different speeds. (a) 10 km/h, (b) 20 km/h, and (c) 30 km/h. Note that the scales of the x- and y-axes are not equivalent.
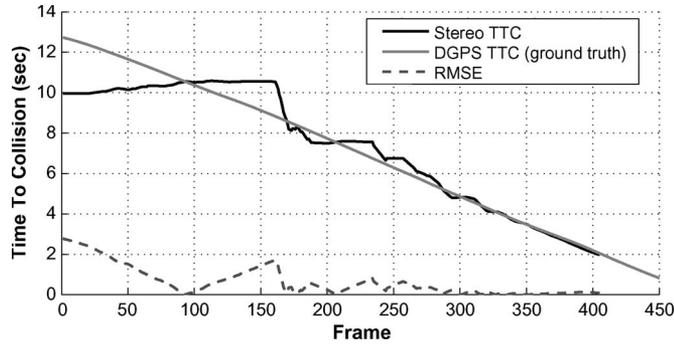
Fig. 10.   DGPS and stereo TTC and RMSE that correspond to driver 1 at 10 km/h.

TABLE II
RMSE OF THE TTC

Speed	RMSE (sec)	RMSE (TTC<8s)	RMSE (TTC<4s)
10 km/h	0.9625	0.2164	0.0341
15 km/h	0.8775	0.3419	0.0360
20 km/h	0.5430	0.2200	0.0919
25 km/h	0.5997	0.2870	0.1281
30 km/h	0.7110	0.3731	0.1436
Average	0.7387	0.2877	0.0867

In Table II, we show the root mean square error (RMSE) of the TTC for all drivers at all speeds, specifying the error for TTC lower than 8 and 4 s. On the average, the error for TTC < 8 s is lower than 0.3 s, and for TTC < 4 s, it is lower than 0.1 s. In addition, we can see that the larger the speed, the larger the error, although this relationship is not linear.

As previously stated, the parameters needed to perform automatic pedestrian collision avoidance include the TTC at the beginning of steering, which will correspond to different distances, depending on the speed, and the minimum car-to-pedestrian lateral distance to safely avoid the collision. These values are obtained by computing the average for all drivers. Fig. 11 depicts the stereo TTC and the stereo car-to-pedestrian distance at the beginning of the steering and the DGPS car-
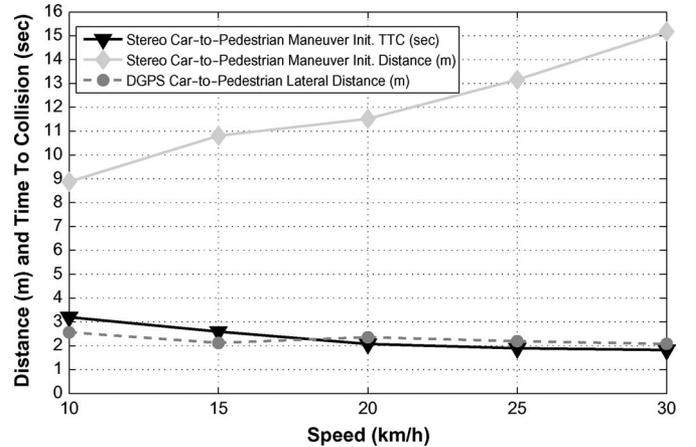
Fig. 11.   Average stereo TTC (in seconds) and stereo longitudinal distance (in meters) before starting the avoidance maneuver and maximum DGPS car-to-pedestrian lateral distance.

to-pedestrian lateral distance when the car exceeds the pedestrian position for all the speeds. On the one hand, the car-to-pedestrian distance before starting the maneuver almost linearly increases with the speed. On the other hand, the TTC at the beginning of steering and the lateral distance at the moment of passing the pedestrian remain almost constant. In particular, the average TTC is 2.3 s, and the average lateral distance is 2.2 m.[2] These parameters are slightly oversized up to 2.5 s and 2.5 m, respectively, to increase the safety of the automatic field tests.

B. Automatic Pedestrian Collision Avoidance

To try to mimic the human behavior, the results obtained with human drivers in Section VI-A were used as reference for the automatic trials. The trigger used to change the straight-road fuzzy controller to the fuzzy steering controller for pedestrian collision avoidance is the TTC. Therefore, a value equal to or

[2]Note that the TTC at the beginning of steering obtained in our experiments almost matches the TTC suggested in [46] (2.5 s) at the onset of braking.
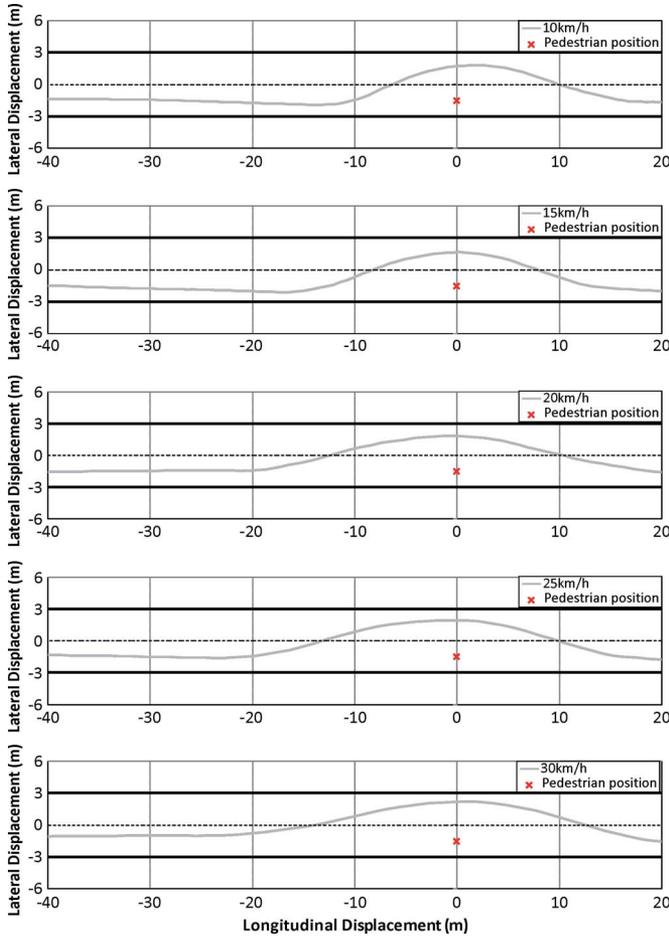
Fig. 12. Automatic steering wheel maneuvers at different speeds for pedestrian collision avoidance.

Fig. 13. Steering reference generated by the fuzzy controller at different speeds.

less than 2.5 s was used as the threshold for the activation of the automatic pedestrian CAS that has been developed. A set of trials for performing the avoidance maneuver at different speeds—10, 15, 20, 25, and 30 km/h—were done.

The trials were developed at the CAR–CSIC facilities in a real environment. A 6-m-wide road is used, where two lanes of 3 m are defined. The vehicle was driven across the right lane, and the left lane was used to perform the avoidance maneuver. A 150-m straight stretch of the circuit was selected to perform the experiments. One RTK-DGPS onboard the vehicle is used to define the reference of the lateral controller. The stereo-vision-based pedestrian detection system provides the TTC measurements. In this case, a lightweight dummy made of cardboard was used.

The automatic system behavior shown in Fig. 12 allows us to evaluate the steering response at different speeds and to compare it with the steering response of a human driver. The upper part of the figure shows the avoidance maneuver at a lower speed, i.e., 10 km/h. This case is the more difficult control because of the physical limitations of the automatic steering system. However, the vehicle can avoid the pedestrian with enough safety. The other plots in the figure show the avoidance maneuver at different speeds, i.e., 15, 20, 25, and 30 km/h. In all the cases, the automatic system carried out the maneuver without problems.

Fig. 13 shows the steering reference generated by the fuzzy controller. Because the vehicle is driving along a straight stretch, the steering output is close to zero to maintain the lane before the automatic avoidance pedestrian controller is triggered. In all the cases, the trigger causes a sudden steering output change. The lower the speed, the higher the steering reference change. The higher the speed becomes, the longer the reference is maintained to avoid hard steering movements. One can appreciate how the fuzzy output takes negative values before reaching the pedestrian position. The goal is to straighten the trajectory, maintaining the vehicle in the road, to be in parallel to the reference lane when the pedestrian position is reached. Once the avoidance has been achieved, the vehicle comes back to the reference lane, taking a longer time as rules were designed to command.

Two main conclusions are obtained in these experiments. First, we have achieved the development of an autonomous system that can avoid pedestrian collisions. Second, hard steering-wheel movements have been avoided when the lane change to the left is done. The variation of the steering is softer when the speed is higher. Note that the return to the right lane is carried out with soft steering changes, because we assume that the left lane is free as a preliminary consideration. One can appreciate how the response of the autonomous system (see Fig. 12) is similar to the human drivers' behavior (see Fig. 8).

To compare the results, in a parallel line with the manually driven experiments, the stereo TTC and the stereo car-to-pedestrian distance at the beginning of the steering and the
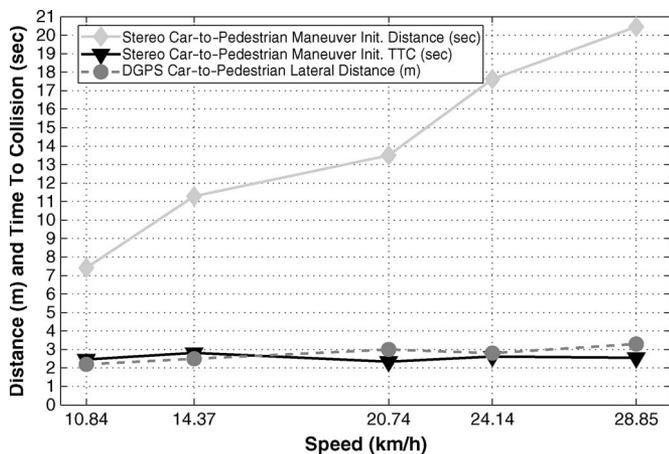
Fig. 14. Average stereo TTC (in seconds) and stereo longitudinal distance (in meters) before starting the avoidance maneuver and maximum DGPS car-to-pedestrian lateral distance obtained in the automatic experiments.

TABLE III
SUMMARY OF THE EXPERIMENTAL RESULTS IN
MANUALLY AND AUTOMATICALLY DRIVEN MODES

Average Speed (km/h)		TTC (sec)		Longitudinal distance (m)		Lateral displacement (m)	
M	A	M	A	M	A	M	A
10	10.84	3.2	2.46	8.88	7.42	2.6	2.2
15	16.07	2.59	2.49	10.82	11.29	2.2	2.5
20	20.78	2.07	2.33	11.52	13.5	2.4	3
25	25.38	1.89	2.49	13.16	17.62	2.2	2.8
30	30.85	1.82	2.38	15.17	20.45	2.1	3.2

DGPS car-to-pedestrian lateral displacement when the vehicle exceeds the pedestrian position for all speeds are shown in Fig. 14. In all cases, the car-to-pedestrian distance is enough to guarantee the pedestrian safety. One can observe how the values for the lateral displacement between the vehicle and the pedestrian when they are in parallel lanes are similar to the values depicted in Fig. 11.

Finally, a summary of the results obtained with the autonomous system (A) and the manual one (M) at different speeds are shown in Table III.[3,4] The relative TTC and lateral offset errors of the automatic system are 2.8% and 14.4%, respectively, with regard to the oversized parameters. In all cases, these values are greater than the values obtained from the manual experiments. We can conclude that the automatic pedestrian CAS clearly mimics the human drivers' behavior, which satisfies our design requirements. The question whether the human drivers' behavior is the best choice or if there are more sophisticated solutions remains open.

VII. CONCLUSION

This paper has described an automatic driving system that can carry out autonomous pedestrian collision avoidance by steering. The detection component involved a stereo-vision-based system that provides suitable measurements, despite its

inner accuracy constraints. Both car-to-pedestrian trajectory and TTC are satisfactorily supplied to cope with autonomous pedestrian collision avoidance maneuvers at speeds of up to 30 km/h. The risks associated with performing collision avoidance maneuvers at higher speeds are not acceptable with our experimental setup. However, some conclusions can be extrapolated from our results. The distance needed to safely perform the avoidance maneuver would approximately increase by 3 m per 5 km/h. For example, for a target speed of 50 km/h, the distance would be greater than 30 m. In addition, higher speeds will endure higher errors in the estimated TTC. To increase the accuracy of the measurements provided by the stereo system, higher resolution images can be used. However, that approach would increase the computational cost.

The proposed system implements a fuzzy-control-based automatic collision maneuver by steering. The lateral displacement and the actual speed of the vehicle are used as fuzzy inputs. The output of the fuzzy steering controller is the steering-wheel position. The navigational information that is needed to perform the collision avoidance operation is supplied by an RTK-DGPS that governs the navigation of the vehicle. No specific reference trajectory needs to be defined, because the lane-change system can perform the collision avoidance maneuver by just specifying the right-lane reference plus the lateral displacement. The parameters of the automatic pedestrian collision system are defined after studying the drivers' behavior, as well as the sensor accuracy.

This paper has demonstrated that the proposed approach can perform humanlike pedestrian collision avoidance maneuvers by steering under certain conditions that have to be fulfilled: The vehicle has to be moving along the right lane, the pedestrian has to be located in the same lane, and the left lane has to be free and long enough for the collision avoidance maneuver to be completed. Although the proposed approach provides very encouraging results, from a real-world application perspective, where the traffic conditions are certainly more complex, significant effort is further necessary to solve this important problem.

Our future work includes new experiments at higher speeds in more challenging scenarios with moving pedestrians, including emergency maneuvers with lower TTC values (e.g., at $1.0 \text{ s} < \text{TTC} < 2 \text{ s}$). Free-space computation [47] will be necessary to define the maximum lateral and frontal distance available to safely perform the avoidance maneuver. Other sensors, including V2V and V2I communications, will be included to better understand the specific traffic situation. Finally, more sophisticated decision-making schemes [48] will be included to deal with real urban traffic scenarios.

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[3]Note that the automatic parameters were oversized to increase the safety of the automatic field tests.

[4]The speed that corresponds to manual experiments is the target speed, because it has not been measured.

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