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Review

Motorcycle detection for ADAS through camera and V2V Communication, a comparative analysis of two modern technologies

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ABSTRACT

Motorcycles are one of the most dangerous means of transportation. Its death toll is higher than in others, due to the inherent vulnerability of motorcycle drivers. The latest strategies in Advanced Driving Assistance Systems (ADAS) are trying to mitigate this problem by applying the advances of modern technologies to the road transport. This paper presents two different approaches on motorcycle protection, based on two of the most modern available technologies in ADAS, i.e. Computer Vision and Vehicle to Vehicle Communication (V2V). The first approach is based on data fusion of Laser Scanner and Computer Vision, providing accurate obstacle detection and localization based on laser scanner, and obstacle classification using computer vision and laser. The second approach is based on ad-hoc V2V technology and provides detection in case of occlusion for visual sensors. Both technologies have been tested in the presented work, and a performance comparison is given. Tests performed in different driving situations allows to measure the performance of every algorithm and the limitations of each of them based on empirical and scientific foundations. The conclusions of the presented work help foster of expert systems in the automotive sector by providing further discussion of the viability and impact from each of these systems in real scenarios.

1. Introduction

Motorcycles are, by nature, one of the most dangerous transportation means. According to European Comission (2014, 2016), 15% of road driver deaths in 2014 were motorcyclists; this is a relevant figure, taking into account that motorcycles are a small percentage of the total vehicles. Although the figures are following the general decreasing trend for road accidents, motorcyclists' vulnerability in comparison with car drivers is evident. In 2014, 11 deaths per 100,000 motorcycles were registered (European Comission, 2014, 2016) compared to only 4 deaths for 100,000 cars. These numbers clearly justify the special attention given to motorcycle safety in the latest years, involving changes in infrastructures and safety policies to mitigate the dead toll for these vehicles.

In the latest years, advances in Information Technologies (IT) incorporated to the road environment have created novel ADAS applications able to identify hazardous situations and warn the driver accordingly. These systems take advantage of novel communication and computation technologies in order to obtain and process a wide variety of information to increase security in road environments by creating advanced expert systems for road safety applications. These applications are included in the Intelligent Transportation Systems (ITS), a research branch involved in the inclusion of the novel IT technologies in the transportation framework.

ITS has been a frequent topic in Expert Systems community, making use of state of the art technologies in the perception and computational fields to provide expert systems. These systems are able to provide intelligent applications, which make use of these novel advances in the IT field to provide advanced applications, thus, enhancing road safety. This paper presents two novel expert approaches for motorcycle detection, and provides a comparison of performances in real road situations, giving full report of the strengths and weaknesses of each of the approaches with an empirical basis, providing full information for each expert system and its capabilities.

The two approaches presented represent state of the art works, fostering the development of ADAS for vulnerable road users i.e. motorcycle drivers. The two technologies presented: data fusion of laser scanner and computer vision and the V2V communication, represent novel approaches in the use of their respective technologies.

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The rest of the paper is structured as follows: Section 2 provides a state of the art revision; Section 3 explains both detection approaches. In Section 4, algorithms tests are presented, and the comparative analysis of the results is given. Finally, Section 5 provides some conclusions extracted from the presented tests.

2. State of the art

The recent advances in computational technologies have allowed the creation of novel applications able to deal with great amounts of information. In this context, computer vision applications have been reached a point where information retrieval and processing are performed in real time. ADAS applications are taking advantage of these improvements, with the creation of powerful applications that are able to detect and identify the different users of the roads in real time. One of the first applications introduced in ADAS is related to vulnerable road users such as pedestrians (Dalal & Triggs, 2005; García, García, Ponz, de la Escalera, & Armingol, 2014) and vehicles (Sivaraman & Trivedi, 2013a,b). However, although motorcyclists represent a vulnerable road user, its difficulty of detection and variety of shapes lead to a minor appearance in the literature. Some of the works related to motorcycle detection rely on the detection of the helmet, prior or posterior to the detection of the motorcycle: Tai, Tseng, Lin, and Song (2004) and Tai and Song (2010) propose vision-based detection algorithms, relying in the helmet search and detection; in the former work, an automatic contour initialization method is used for vehicles and motorcycles tracking; in the latter, a further occlusion segmentation is presented. Chiverton (2012) presents a system for automatic classification and tracking of motorcycle riders, based on head detection (with or without helmet), relying in Support Vector Machines (SVM) algorithm, trained with histograms derived from head region image data. Background subtraction is later used for tracking. Chiu, Ku, and Chen (2007) also relying in helmet detection in the image, by means of vertical histogram projection of the silhouette in order to identify the region where the head is located; later, the presence of a circular object is used to identify the helmet.

On the other hand, other works avoids the helmet or head detection algorithms; Hall and Birchfield (2010) focused on metrics of different vehicles types to provide traffic vigilance. Phatanasrirat and Phiphobmongkol (2009) used fixed-size vertical projection and neural network to provide motorcycle detection, and vertical and horizontal scanning was used for feature extraction. Finally, Kato, Ninomiya, and Masaki (2002) propose a classification method for vehicles, including motorcycles, based on visual features and a classifier which used “Multiclustered modified quadratic discriminant function” (MC-MQDF). Deformable Part Model (DPM) avoids the holistic description of the images, using segmented description and classification. This approach has been used in many fields, including pedestrian (Vázquez, López, Ponsa, & Marin, 2011) and bicycle detection (Cho, Rybski, & Zhang, 2010) .

The work presented in this paper focuses in two different algorithms. The former, based on computer vision and laser scanner, provides a novel approach using computer vision algorithms to identify and classify motorcycles, while laser scanner is used to provide accurate motorcycle localization and also classification. This sensor configuration is widely extended in literature, with different applications already presented, such as pedestrian detection (García et al., 2014), or vehicles (Garcia, Martin, de la Escalera, & Armingol, 2017). These kind of sensing technologies have the main drawback of being sensitive to occlusions. On the other hand, communication technologies can lead to reduce this risk, as presented in García et al. (2013), for distributed pedestrian detection, where the detection is relayed from the detected vehicle, to all the surrounding vehicles.

Vehicle cooperative systems are defined as those systems based on the exchange of information between vehicles and/or road infrastructure, through wireless communications, enhancing the driver’s visual horizon. These systems have a great potential in different fields of the automotive sector, e.g. safety and efficiency. Cooperative systems in the field of road safety can be differentiated among warning systems, assistance systems to reduce the cognitive load of the driver, collision avoidance systems, pre-crash systems, post-collision systems and vehicle automation systems.

All cooperative systems require a specific communication network between vehicles, or VANETs (Vehicular Ad-hoc NETtwork), which is an ad-hoc network where the nodes are elements of the road (vehicles and roadsides). The European Commission plans V2X communications to be mandatory equipment in new vehicles in the short term, according to the 2020 framework (Anaya, Talavera, Jimenez, Serradilla, & Naranjo, 2015) . Communications in cooperative systems in the automotive sector are established by Dedicated Short Range Communications systems (DSRC), which are divided into vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-Pedestrian (V2P) and vehicle-to-roadside stations (V2R) systems.

New communication technologies between vehicles, roadside and drivers will be used provide cooperative systems, which will support a new generation of ADAS. Vehicles will no longer be considered isolated from the road, but as an element of an intermodal network, which is travelling in a road infrastructure.

There are different technologies for VANET generation, such as Anaya et al. (2015) and Lee et al. (2006), where the infrastructure is built as a Wireless Sensor Network; this technology is limited by range and data transfer rate. Other approaches for VANETs generation exist, using exclusively mobile networks (2G, 2.5G, 3G, 4G, 4.5G and 5G). These networks require an existing infrastructure and suffer larger latency times than ad-hoc networks. Another option is the use of a specific technology developed for this kind of communications, based on the IEEE 802.11p standard; this technology has a high range of communication and data transfer rate. Hybrid solutions have also been created by integrating DSRC modules and mobile technology in order to fuse advantages from both technologies Benslimane, Taleb, and Sivaraj (2011) and Taleb and Benslimane (2010).

In order to provide communication abilities to DSRC modules, the creation of specific routing algorithms which take into account the casuistry of VANETs has been necessary: e.g. the links are constantly changing with no particular pattern. Therefore, specific georouting algorithms have been developed: In Sun, Feng, and Ten-Hwang (2000) and Durresi, Durresi, and Barolli (2005) specific algorithms for message broadcasting to all nodes in a network were presented. On the other hand, Johnson and Maltz (1996), Karp and Kung (2000), Namboodiri, Agarwal, and Gao (2004) and Perkins and Royer (1999) depict specific algorithms for message transmission from one node to another node using, if necessary, other nodes as relays (GeoUnicast). Finally, Bachir and Benslimane (2003), Briesemeister et al. (2000), Maihofer and Eberhardt (2004) and Maihöfer, Leinmüller, and Schoch (2005) specify algorithms where messages are disseminated over a controlled area (GeoBroadcast).

The creation of the VANETs provide a foundation for ADAS applications. The work (Anaya et al., 2015) presents an application based on cooperative security systems, focused on improving raiders’ safety on interurban roads and mountain roads.

ADAS applications are a common topic in the Expert System field. Applications such as an autonomous overtaking system (Milanés, Llorca, Villagrá, Pérez,Fernández, et al., 2012) or automatic stopping (Milanés, Llorca, Villagrá, Pérez, Parra, et al., 2012) are based on advanced vision together with control applications. Other classical applications are advanced localization

(a) (b)

Fig. 1. (a) Test platform: IVVI 2.0 including laser scanner and camera. MotoWarn GPS is mounted on the roof of the car. (b) Test platform: Motorcycle including MotoWarn GPS in the back.

(Gruyer, Belaroussi, & Revilloud, 2016), pedestrian detection (García et al., 2014), driver drowsiness detection (Jo, Lee, Park, Kim, & Kim, 2014), lane departure (Son, Yoo, Kim, & Sohn, 2015), rear obstacle detection (Kim, Choi, Yoo, Yang, & Sohn, 2015), and roundabout moving obstacle detection (Hassannejad, Medici, Cardarelli, & Cerri, 2015). Other advanced control applications use V2V information, such as cooperative control for highways (Pérez, Milanés, Godoy, Villagrá, & Onieva, 2013) and intersection management (Bi, Srinivasan, Lu, Sun, & Zeng, 2014).

The present work represents a step forward in the protection of motorcycle users, one of the most vulnerable road users. Moreover, it tries to overcome the limitations of the aforementioned works i.e. the lack of reliability of the visual based approaches, their sensitivity to occlusions. The first is overcome in the data fusion based algorithm, where laser scanner help to mitigate the reliability and accuracy limitations of the detections and localization of the computer vision approaches. On the other hand, occlusions do not represent a problem when dealing with the V2V communication approaches, where the communication can be performed even if the is no direct line of sight.

3. General description

This work is developed in the ADAS_ROAD project framework, funded by the Spanish Government for research in modern technologies for dangerous situations identification in interurban roads. Thus, the algorithms were developed to deal with real interurban environments, focusing in single carriageway roads. The purpose of the work presented in this paper is the development of different technologies for motorcycles detection and identification. The different technologies developed are later tested and compared, and the results are shown in this paper. All the tests are performed under real road conditions in the platform Intelligent Vehicle based on Visual Information 2.0 (IVVI 2.0) (Carmona, García, Martín, Escalera Ade, & Armingol, 2015; Martín et al., 2014), and the test motorcycle shown in Fig. 1. The different sensing and communication devices are installed in the vehicles.

3.1. Visual based motorcycle detection

Visual motorcycle detection is achieved using sensor fusion between a SICK LD-MRS 4 layer laser scanner and Point Grey XB3 Bumblebee stereo camera, as seen in Fig. 1. The laser scanner performs an initial obstacle detection, and obstacle classification as motorcycle/non-motorcycle is obtained from a fusion between SVM classification using Histogram of Oriented Gradients (HOG) descriptor for camera, and SVM for laser classification using the synthetic features shown in Table 1.

HOG is widely used in computer vision to describe the general shape of an image thanks to the orientation of its gradients. The HOG features extraction involves an initial step of gradient study.

Table 1
Features considered for cluster classification.

Concentration: Normalized mean distance (NMD) to the 3D centroid
Y-Z, X-Z, X-Y concentration: NMD to the centroid excluding x,y,z
Planicity: NMD to the most populated plane
Sphericity: NMD to the most populated sphere
Cubicity: Measures how far are the planes containing the mesh triangles from being the same plane or from being perpendicular.
Triangularity: Measures the triangles uniformity
Average deviation from the median in x,y,z

This step highlights the shape of the objects in the image, defined by the parts of the image where the changes in intensity are maximum, and by the orientation of the maximum variations. Once the gradient is obtained, the image is divided into a fixed number of cells and a calculation of the histogram of the orientations in each cell is performed. This histogram represents the general shape of the object, as seen in Fig. 2. The HOG features in the image also includes gradients present in the background of the image, so it is important for training to acquire a great variety of different backgrounds in order to ensure than only relevant obstacle characteristics are learned.

3.1.1. Obstacle detection system

Obstacle detection is performed through the laser scanner located under the front bumper of the IVVI 2.0. This is the most effective location for the laser, as it provides the widest detection range in most road shapes.

The laser scanner used in this work is configured for a four horizontal layer operation with variable angular resolution in the horizontal layers. As seen in Fig. 3, (a.1), vertical divergence between horizontal layers is 0.8°. (a.2) represents one of the four scan planes, (a.3) is the Sick LD-MRS laser scanner. Maximum resolution is obtained in front of the sensor and minimum resolution is obtained in the right and left regions of the 110° aperture, as seen in Fig. 3. (b.1) is the central area of 0.125° angular resolution in front of the laser, (b.2) represents the area of 0.25° angular resolution, and (b.3) is the lateral area of 0.5° angular resolution, being (b.4) the Sick LD-MRS laser scanner.

The four layer laser scanner obtains a set of points in (x,y,z) coordinates called PointCloud (PCD), representing the readings from the laser beams in each of the scans, as seen in Fig. 4. Laser scanner and camera are shown in Fig. 1.

The PCD is computed and searched for obstacles in the road, which will be treated later by the classification system. Obstacles in the road will be represented as local concentrations of points in the PCD called clusters, that can be mathematically categorized (see Fig. 4).

3.1.1.1. PCD clustering. PCD clustering is performed using an adapted Euclidean distance and geometrically constrained cluster

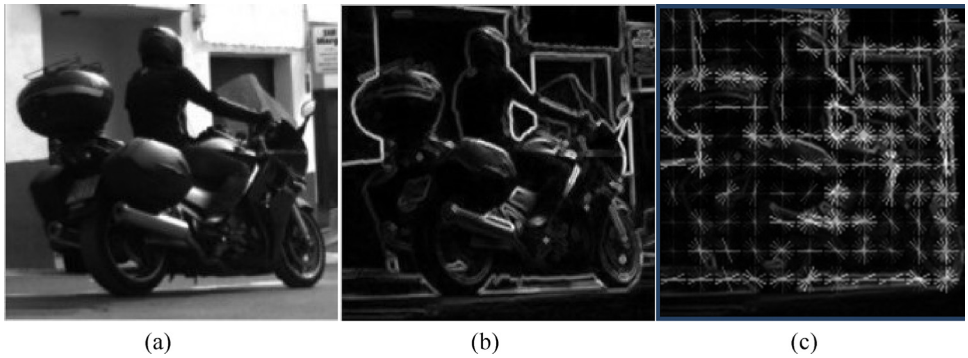

Fig. 2. (a) Original Image. (b) Gradients extracted, outlining the general shape of the image. (c) Graphical representation of the HOG features.

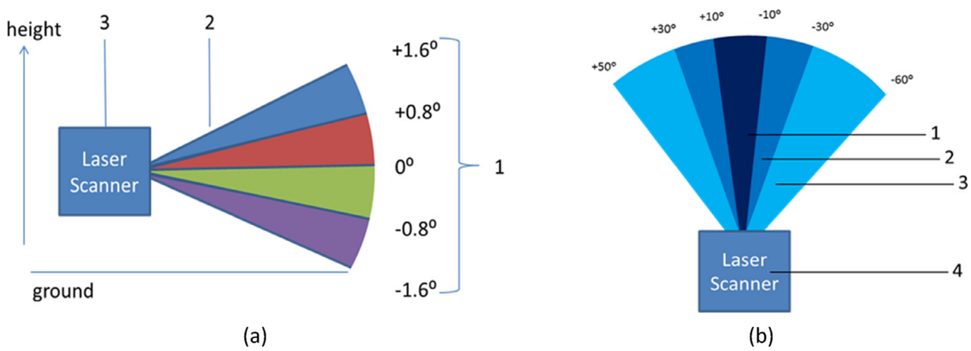

Fig. 3. Laser scanner configuration. (a) Four horizontal layers with 0.8° divergence. (b) Different horizontal angular resolution by sector.

Fig. 4. Point cloud representation, with points detection (small red points) including the measured distance highlighted in green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

algorithm. Clusters are defined as groups of points in the PCD meeting some geometrical constraints, and distance requirements between them.

The process for clustering extraction from the PCD is as follows: The first point in the PCD is taken as the first point in the alleged cluster, and the distance from that first point to each of the remaining points in the PCD is checked against a variable threshold. If (distance(p1,p2) < threshold), then the new point is added to the cluster. The threshold depends on the distance from the laser scanner to the obstacle, represented as the x coordinate of the point in the PCD, as seen in Eq. (1). As the angle between two consecutive beams from the laser is known, we can compute DistCorr(x) as the minimum possible distance between two consecutive reads. This physical limitation must be taken into account, especially in long distances, where the cloud is sparse and obstacles are represented by small amounts of points. α_Z Represents the angle between two consecutive laser beams in the z axis (vertical), and α_y is the angle between two consecutive laser beams in the y axis (horizontal).

$$ClusterTh = BaseTh + DistCorr(x) \tag{1}$$

$$DistCorr(x) = \sqrt{(xtan(\alpha_y))^2 + (xtan(\alpha_z))^2} \tag{2}$$

$$if\left|arctan\left(\frac{y}{x}\right)\right| < 2\pi\frac{10}{360}\ then\ \alpha_y = 2\pi\frac{0.125}{360} \tag{3}$$

$$if 2\pi\frac{10}{360} \le \left|arctan\left(\frac{y}{x}\right)\right| < 2\pi\frac{30}{360}\ then\ \alpha_y = 2\pi\frac{0.25}{360} \tag{4}$$

$$if 2\pi\frac{30}{360} \le \left|arctan\left(\frac{y}{x}\right)\right| < 2\pi\frac{60}{360}\ then\ \alpha_y = 2\pi\frac{0.5}{360} \tag{5}$$

where x,y,z are point's coordinates. Due to laser scanner restrictions, α_z is always 0.8°

When the process is completed for the first point in the PCD, the same iteration is executed for each of the remaining points, until all the points in the PCD are checked for inclusion in each of the clusters discovered. Restrictions on maximum and minimum number of points in cluster and physical cluster size also apply. In a later stage, points initially discarded and not belonging to any cluster can be added to the nearest cluster as a result of some geometrical constraints related to the kind of obstacle considered, in order to maximize the amount of information extracted from the PCD.

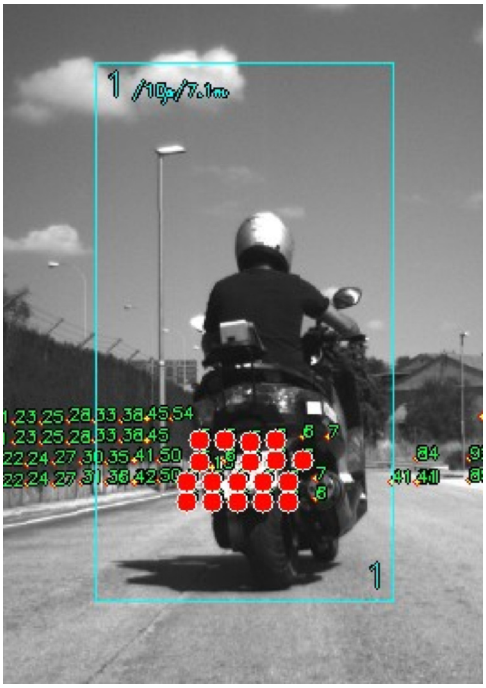

Fig. 5. Fusion between camera and laser. Red dots are the cluster representing an obstacle, blue square is the ROI extracted for image classification. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Each of the clusters detected in the scene will determine a region of interest (ROI) in the image where the obstacle associated to the cluster is supposed to be located, as shown in Fig. 5. These ROIs and the PCDs associated to the clusters are then passed to the classification system for obstacle classification. The dimension of the ROI is determined by the type of obstacle we are interested in. In the present case, ROI is generated from the elevation zero in the bottom of the ROI, up to two meters in the top at the position of the obstacle, then some padding in top, bottom, right and left of the position of the cluster in the image. Elevation zero and the two meter limits of the ROI are computed using the distance to the obstacle and the pin-hole model for the camera. The additional padding is big enough and distance-dependent so it is guaranteed that the obstacle represented by the cluster will be included in the ROI.

3.1.2. Obstacle classification system

Obstacle classification is performed using SVM for images in the ROI extracted from the scene and for clusters representing the obstacle.

SVM is a machine learning algorithm for classification, first introduced in Cortes and Vapnik (1995) and widely used in Computer Vision. The goal for SVM is to find a boundary between two types of objects, in our case motorcycles vs non-motorcycles. In the current work, classification is performed using both the PCD from the laser scanner and images from the camera, fusing the results of both classifications in a final stage. The reason for the information fusion from laser scanner and camera for classification is to improve reliability in cases when any of the sensors is not available or the information it provides can not be trusted.

SVM classification depends on an initial stage of supervised learning, when examples of positive obstacles (motorcycle) and negatives (objects different from a motorcycle, commonly found in road scenarios) are provided to the SVM learning procedure, in order to extract the common features that characterizes a motorcycle, both in images and clusters.

Several thousands of images are labeled as motorcycle or non-motorcycle and then processed as depicted in Fig. 2, for HOG features extraction. Finally, the extracted HOG features are fed to the SVM training algorithm. An alternative for classification is Deformable Part Model (DPM). DPM is a classification algorithm in which the image is segmented into several parts, and each of them is classified using specialized classifiers. Our experience with Deformable part model shows better results with pedestrians, but in the case presented in the paper, results for DPM are about the same than for holistic descriptors, and performance drops for DPM.

In this work, classification is performed fusing the results from SVM for image, and PCD classification. SVM training and classification requires fixed length features, but PCD representation of the obstacles size is inherently variable. To overcome this problem, PCDs representing the obstacles are computed and some features are extracted, as seen in Table 1. This process is similar to the HOG features extraction for images. After the training stage, a SVM to classify the obstacles as (motorcycle/no motorcycle) is obtained for PCDs and another one for images. In the classification stage, information fusion of the results of both classifiers, applied to the ROI and the associated cluster, determines the probability of the presence of a motorcycle in the scene. The classification as motorcycle/non-motorcycle is made by weighting the final results from image and PCD classification.

3.1.3. Motorcycle location in the space

The purpose of this work is the location of the motorcycle with respect to the IVVI 2.0 vehicle using vision and vehicle to vehicle communication with GPS information, and compare the results. The vision and laser system can locate precisely the motorbike using the PCD representing the obstacle. After completing the obstacle detection and positive classification as a motorcycle, a spatial localization of the detected motorcycle is possible, as the distance from the laser scanner to the obstacle is represented as the x coordinate of the points in the associated cluster, and the angles referred to vehicle's direction are also known from the coordinates of the points in the cluster.

3.2. Vehicle to vehicle Communication: motowarn (Motorcycle warning)

The warning system has been developed using DSRC technology, specifically implemented to be mounted in vehicles and motorcycles. DSRC modules allow the build of a VANET Network, providing high speed V2V communications for ADAS applications. In this case, the technology ITS-INSIA (Anaya et al., 2015) is used for DSRC communication modules; these communication modules have been designed to support collaborative systems and safety applications. DSRC ITS-INSIA modules have been implemented following the IEEE 802.11p communication technology operating in the 5 GHz frequency band and following European standards for vehicle communications. The standard is based on the protocol ETSI EN 302 636 to provide X2X communication, where X can be any road user (V – Vehicle, I – Infrastructure, P - Pedestrian). These DSRC ITS-INSIA modules include different services and networking capabilities to increase their applicability. Specifically, these modules allow V2X, BLE, WiFi, LAN, CAN-BUS and GPS inputs.

The DSRC ITS-INSIA modules support V2X communications for information exchange between different vehicles on the road. However, this information exchange is useless by itself, since it lacks high-level functionality. That is why it is necessary to develop a high level application in order to provide the functionality for safety application.

The DSRC ITS-INSIA module has strong communication capabilities but lacks a proper technology for driver communication.

Table 2
Main data retrieved by the MotoWarn App from the ITS-INSIA module for each vehicle in the geonetworking net.

Name	Description
ID	Unique identification of each vehicle
ITS-S type	Kind of vehicle
ITS-S Country Code	ID of the vehicle's country of origin
GPS Position	Coordinates of the vehicle (Latitude, Longitude) in degrees
Speed	Speed of the vehicle in km/h
Northing	Northing angle of the vehicle in degrees

Thus, it is necessary to implement a safety application on an external platform. This external platform is connected to the module in order to obtain the information from the vehicular network for the identification of the surrounding vehicles, which in the current application is the motorcycle. Different displaying platforms were evaluated for the Human Machine Interface. Finally, the smartphone was selected due to the high availability and the connecting capabilities included (e.g. Wi-Fi and bluetooth). Modern smartphones are processing systems with far more capacities than most of the embedded systems in current vehicles, representing a cheap and widely available processing unit. In addition, it is easy to download and install an application on the smartphone, implementing the collision warning system. The application, called MotoWarn, has been developed for Android platforms.

MotoWarn is designed to be used in all kind of vehicles, especially those with blind spots where a motorcycle can be unnoticed.

MotoWarn is connected to the DSRC ITS-INSIA module via Wi-Fi. A client-server consultation obtains data from vehicles connected to the network, which are stored in the modules database. Therefore, the DSRC ITS-INSIA module provides the smartphone application with a variety of information about each vehicle, as well as information from the module itself. The information available in the module is displayed in Table 2.

The application can determine using the available data which vehicles are located in the surroundings, providing information about their direction (i.e. approaching or moving away). Besides, information regarding to the type of vehicle is provided, i.e., identifying the motorcycles in the surroundings. All this information is stored in an internal database in order to process it and warn the driver if necessary.

3.2.1. *Graphical interface*

Different interfaces have been tested in order to determine the most effective way to warn the driver, avoiding stress and non-relevant information. The final interface uses both sound and visual stimuli, according to the following assumptions:

- The exclusive use of text was discarded because it causes distraction to the driver.
- The use of sound is reduced to cases of imminent danger to avoid stress to the driver.
- Pop-ups have been used only when launching the application as they are a source of unnecessary distraction.

The system implemented was designed to use images almost exclusively. The visual interface was developed based on squares such as Sivaraman and Trivedi (2014) and Diewald, Möller, Roalter, and Kranz (2012), where the screen is divided into 5×5 squares (Fig. 6), and the vehicle (a car in this case) is placed in the central cell (cell 3.3); the space in front of the vehicle is represented by rows 1 and 2, and the rear positions are represented by rows 4 and 5. These cells have different dimensions depending on the position relative to the car. They also have different behavior depending on whether the motorcycle approaches the car from the front or rear, as the interest in these areas varies.

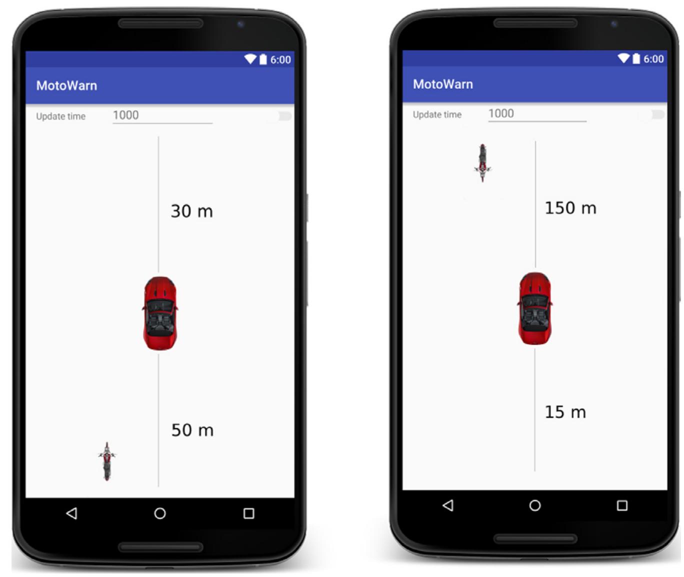

Fig. 6. Diagram of the Motowarn system display.

When both the car and the motorcycle are moving along the same direction, the area of interest is at the rear of the car, acting as blind spot detection system. In this case, the application can reduce the risk of accident due to lateral collision between car and motorbike when performing an overtaking or lane change maneuver. In the event of motorbike approaching in frontal direction, the area of interest is located ahead of the vehicle for frontal collision danger warning.

Furthermore, in these two cases the grids sizes varies depending on the direction of the motorcycle and the vehicle. This way, the application adapts the size of the grids to the direction of the car, allowing the increase of the size, focusing in the region of the map where the motorcycle is located:

- Both vehicles in the same direction: the rear grids (rows 4 and 5) cover up to 50 m, and the front grids (rows 1 and 2) covers only 30 m (Fig. 6a).
- Vehicles moving in opposite directions: in this case the focus is located in the frontal grids (rows 1 and 2), which span 150 m, while the rear grids (rows 4 and 5) have virtually no interest and they have a residual assigned value of 15 m (Fig. 6b).

All the aforementioned was designed in order to reduce the attention required from the driver, so that he is not required to stare at the screen to determine its meaning; an arrow has been inserted so it can be clearly distinguished at a glance.

The relative position of the motorcycle with respect to the car is represented in the grid. In order to calculate this position, the distance is computed using the Haversine Distance Eqs. (6)–(10) and the relative angle of the motorcycle with respect to the direction of the vehicle (11–13). To do so, the calculation of the distance involves the earth curvature, following Haverside Distance

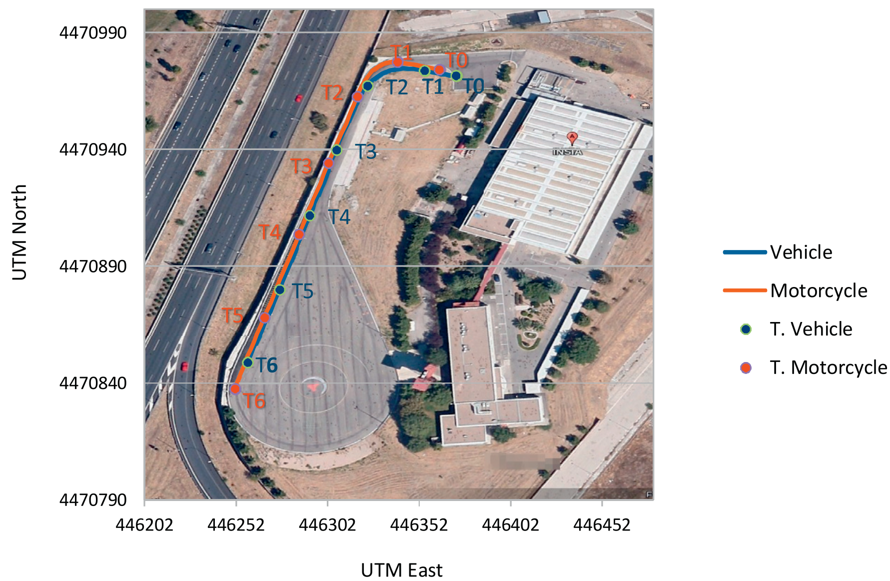

Fig. 7. Experiment 1 trajectories, including the time stamp indicating where the vehicles are located in the specific moment.

calculation.

$$Distance_{Haversine} = R \cdot c \tag{6}$$

where R is the earth radius and c is calculated according to Eqs. 7-13.

$$c = 2 \cdot atan2\left(\sqrt{a}, \sqrt{1-a}\right), \tag{7}$$

where

$$a = sin^2(\Delta lat/2) + cos(lat_{motorcycle}) \cdot cos(lat_{vehicle}) \cdot sin^2(\Delta long/2) \tag{8}$$

$$\Delta long = long_{vehicle} - long_{motorcycle} \tag{9}$$

$$\Delta lat = lat_{vehicle} - lat_{motorcycle} \tag{10}$$

$$Ang_{rel} = Azimut - Ang_{vehicle} \tag{11}$$

$$Azimut = atang\left(\frac{\Delta p}{lat_{motorcycle} - Lat_{vehicle}}\right) \tag{12}$$

$$\Delta p = \left(long_{motorcycle} - long_{vehicle}\right) \cdot \left| \cos\left(lat_{vehicle} + lat_{motorcycle}\right) \right| \tag{13}$$

The last point to calculate is the heading of the motorcycle, i.e. if the motorcycle is approaching or moving away. This factor is calculated according to Eq. (14)

$$\begin{array}{c} if Ang_{Bike} = [Ang_{Car} - 90, Ang_{Car} + 90] : \\ approaching \\ else : \\ moveaway \end{array} \tag{14}$$

Eqs. (15) and (16) determine the square in which the motorcycle will be drawn, depending on whether the motorcycle is moving towards or moving away from the car.

$$Vertical = Distance \cdot \cos(Ang_{rel}) \tag{15}$$

$$Horizon = Distance \cdot \sin(Ang_{rel}) \tag{16}$$

The selection of the distances depends on the vehicle characteristics, the road type and the notice required to ensure that the system works properly.

4. Tests

The performed tests involved specific challenging situations where the two technologies compared had to face specific difficulties and they had to prove their usefulness in real road situations. These tests included low visibility corners and crosses, and overtaking maneuvers, as well as normal approaching and following maneuvers. Each specific situation represented a challenge to each of the systems, proving their advantages and disadvantages. Figs. 7–16 show the tests.

Time has been divided into several instants T0, T1... in order to identify relevant moments of the experiment. Both vehicles, motorcycle and car, travelled at a constant speed between 30 km/h and 50 km/h. This speed range was selected according to the average speed in cities and close corners, the two simulated situations. The DSRC ITS-INSIA transmitted their information with a frequency of 2 Hz.

4.1. Experiment 1: pursuit

This experiment represents the real world traffic situation when a car is moving following a motorcycle. Fig. 7 shows both car and motorcycle trajectories with several instants T0...T6 labeled, including car and motorcycle positions. These labels allow to understand the evolution of the trajectory along time and to compare the location of both vehicles at a given time.

The evolution of the distance between car and motorcycle can be seen in Fig. 8, where the distances between vehicles computed by both systems are provided, as well as the discrepancy among them; this last information is provided in absolute values. Discontinuities in detections are due to misdetections in the computer vision based approach. The results show distances between 6 and 20 m and the evolution of the discrepancy between both systems. The system combining Laser scanner and camera offers more accurate measurements thanks to the use laser scanner for obstacle detection, but needs direct vision of the motorcycle with both laser and camera.

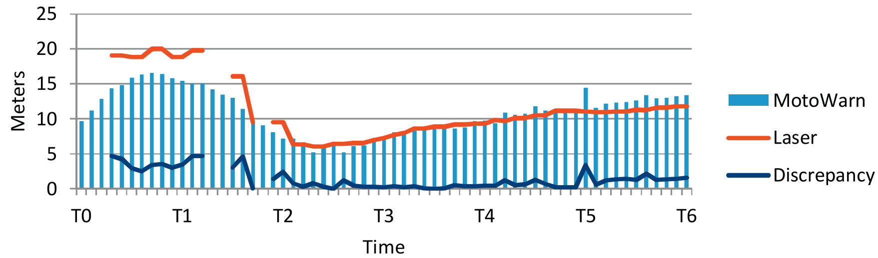

Fig. 8. Experiment 1. Distances measured by both systems and discrepancy between them in absolute values.

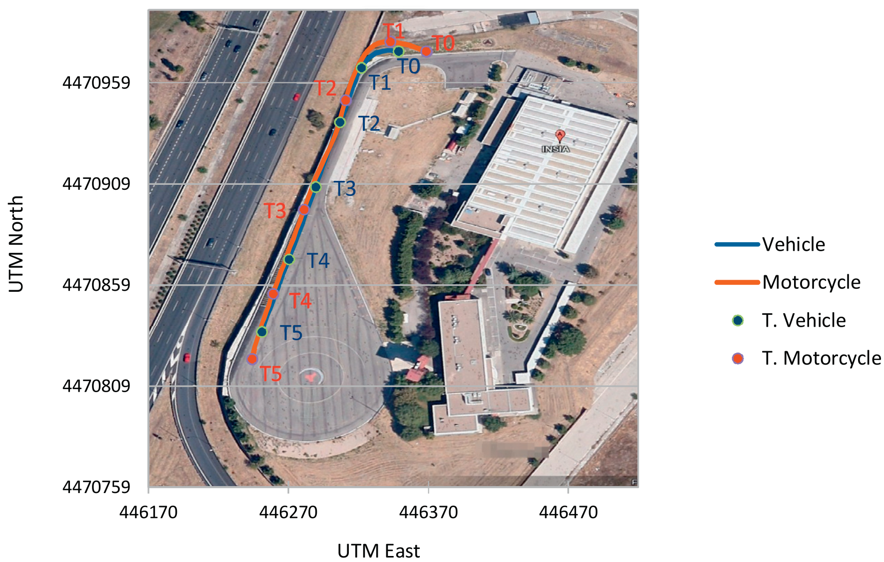

Fig. 9. Experiment 2 trajectories. Time stamp T0…T5 indicates where the vehicles are located at the specific moment.

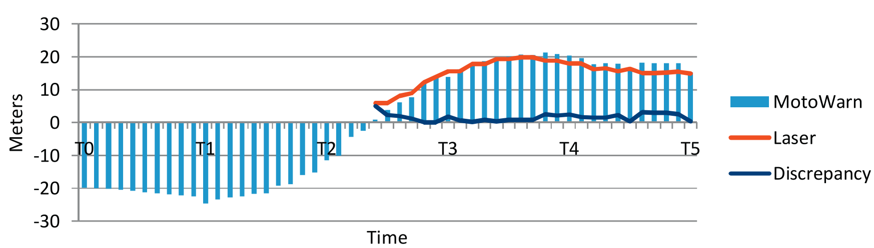

Fig. 10. Experiment 2. Distances measured by both systems and discrepancy between them in absolute values.

The accuracy of the laser scanner for obstacle detection provides a trustable ground truth information for accuracy measurement in the V2V based detection system.

4.2. Experiment 2: overtaking

This experiment represents the situation of a motorcycle overtaking a vehicle. Fig. 9 shows the trajectories and positions of car and motorcycle.

Fig. 10 shows the evolution of the detections from both systems. As it is shown, Motowarn shows the distance between the vehicles before and after the overtaking manouver, while Laser and camera system detects the motorcycle after the overtaking manouvre, when it enters the field of vision of both camera and laser.

4.3. Experiment 3: straight cross

The traffic situation with a cross in a straight segment of the road is represented in Fig. 11. The motorcycle and the vehicle are driving in a two-way road in opposite directions, and trajectories and positions of both automobiles are included. As Fig. 10 shows, both vehicles cross in the instant T3, in a straight road segment.

As Fig. 12 shows, Motowarn continuously tracks vehicles' positions, disregarding the distance. Laser and camera system detects and identifies the motorcycle only while it is in front of the vehicle and up to the distance appropriate for laser detection and camera classification. On the other hand, laser measurements are more accurate when available.

4.4. Experiment 4: low visibility curve cross to the right

This situation is depicted in Fig. 13, and represents the situation of a cross in a low visibility curve, when the vehicle equipped with the laser and camera system approaches the turn to the right. It is important to note that this circumstance allows the vision system for a longer view of the road, because during the turn to the right, the road is still ahead of the vehicle.

As Fig. 14 shows, the motorcycle is detected by the laser and camera system accurately while in front of the vehicle, if no obstacle occludes it. The Motowarn system tracks continuously both

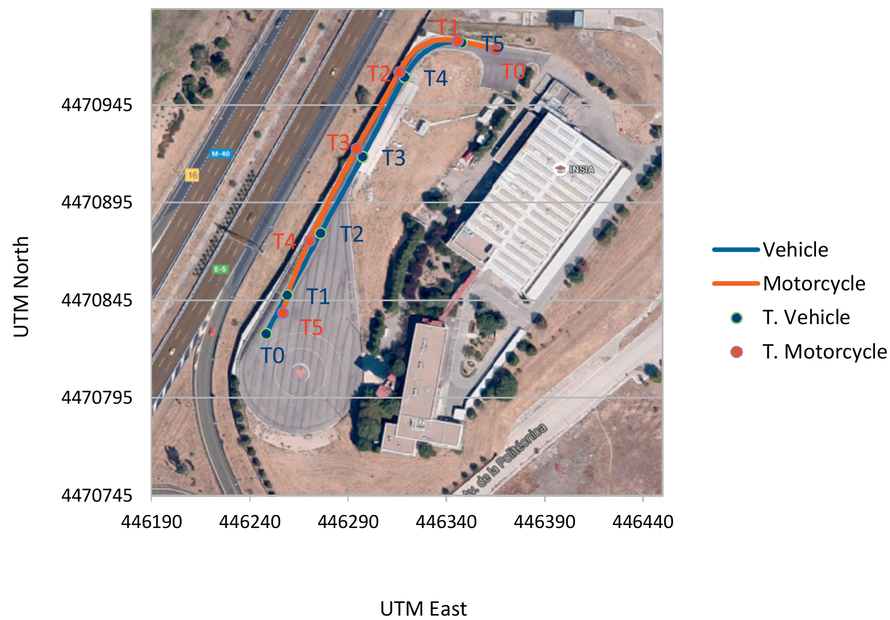

Fig. 11. Experiment 3 trajectories, with the time stamp indicating where the vehicles were located at the specific moment.

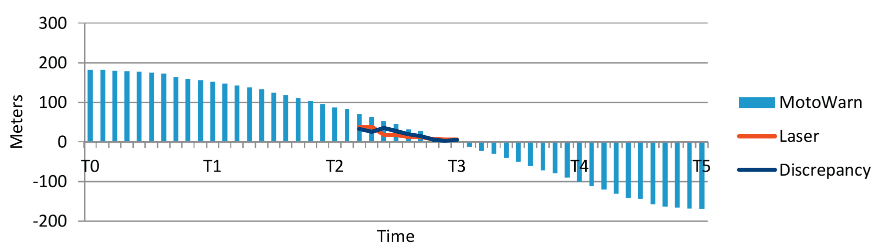

Fig. 12. Experiment 3. Distances measured with both systems and discrepancy between them in absolute values.

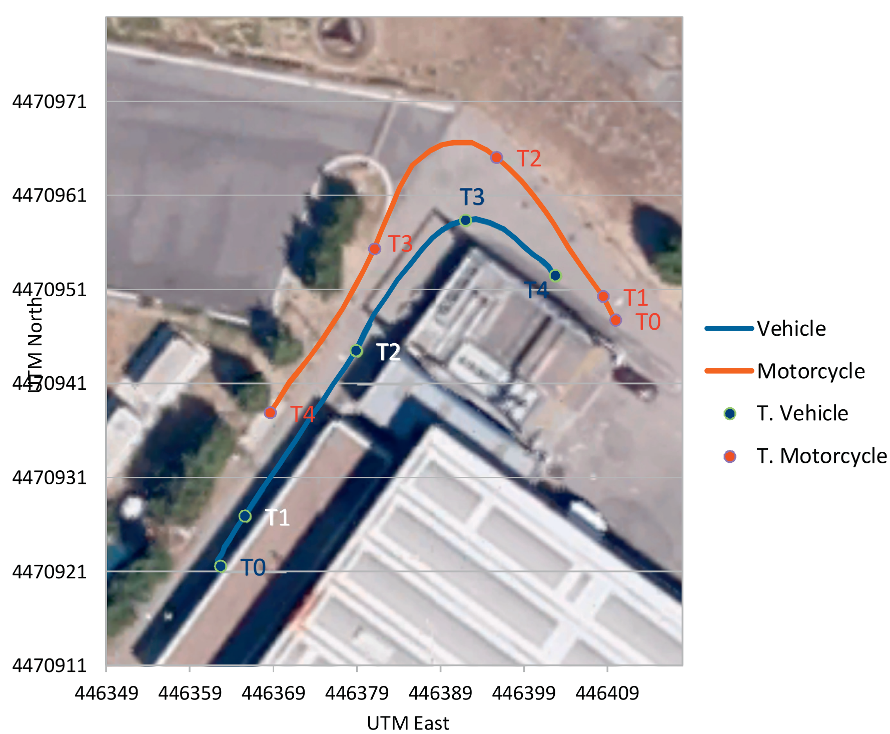

Fig. 13. Experiment 4, trajectories, with time stamp indicating where the vehicles were at the specific moment.

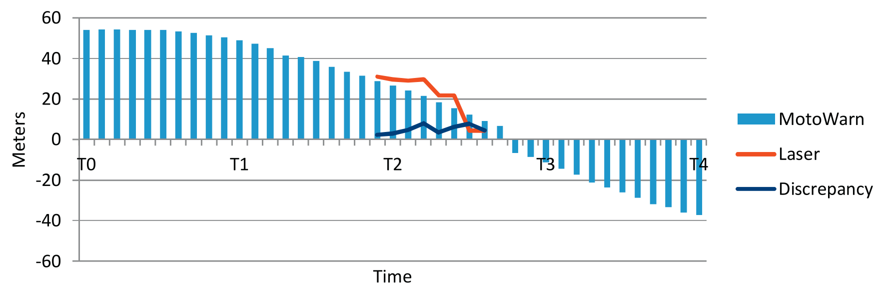

Fig. 14. Experiment 4. Distances measured with both systems and discrepancy between them in absolute values.

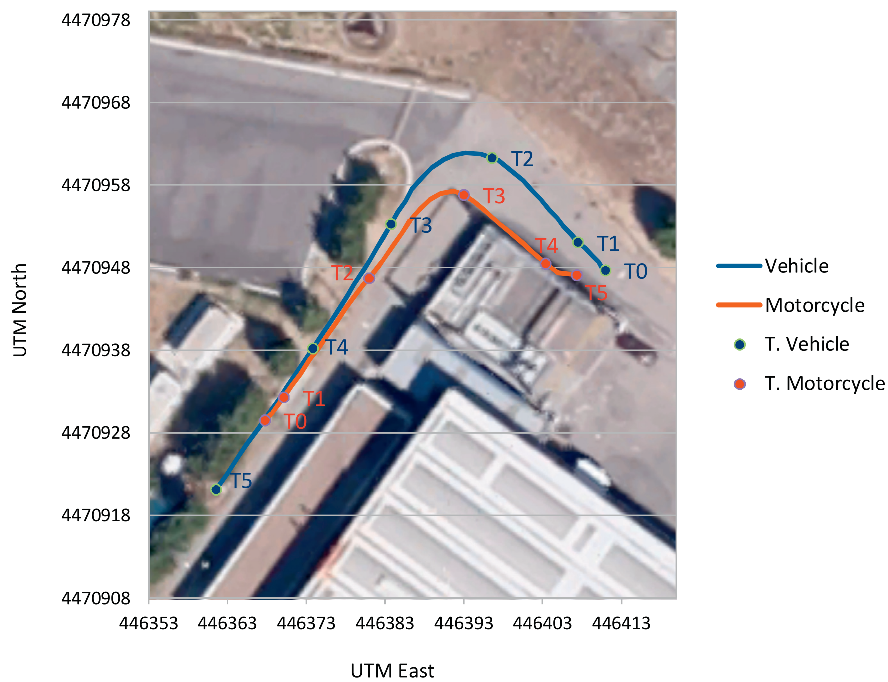

Fig. 15. Experiment 4 trajectories, with the time stamp indicating where the vehicles were located at the specific moment.

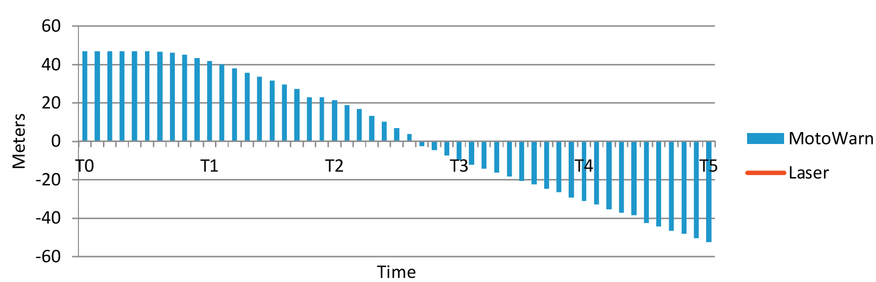

Fig. 16. Experiment 5. Distances measured with both systems and the discrepancy between them in absolute values. No values are provided for laser and discrepancy since there were no detections for laser and vision systems.

positions, in every part of the curve; however, system accuracy is low in short distances.

4.5. Experiment 5: low visibility curve cross to the left

This situation is depicted in Fig. 15, and represents the situation of a cross in a low visibility curve, when the vehicle equipped with the laser and camera system approaches the turn to the left. It is important to note that this circumstance does not allow the vision system to see the road at all times, because during the turn to the left, the road is not in front of the vehicle, thus it is out of the range of both sensors, laser and camera.

Fig. 16 shows the continuous track of both vehicles by Motowarn, while the laser and vision system is occluded by the apex of the curve, and later by the geometry of the curve, placing the motorcycle out of the field of view.

4.6. Mean discrepancy

Finally, Table 3 summarizes the discrepancy for the system by providing the standard deviation and the mean discrepancy for the detections, and all of the detections together in the consolidated column. As it is shown, the discrepancy can be severe in specific situations when distances are high and the laser and vision system is not able to detect the motorcycle.

Table 3
Mean and standard deviation discrepancy per experiment, and aggregated.

	Experiment #1	Experiment #2	Experiment #3	Experiment #4	Experiment #5	Aggregated
Mean Discrepancy[in meters]	1.44	1.58	18.84	5.03	N/A	3,35
Standard Deviation[in meters]	1.44	1.18	12.64	2.19	N/A	2.45

5. Conclusions

Two motorcycle detection approaches were presented in this paper, based on the recent technologies available for ADAS applications. The first approach, based on laser scanner and computer vision, takes advantage of two technologies already available in modern vehicles. The second technology used is based on the upcoming advance in V2V communication ready to be deployed in next generation vehicles. The two systems represent state of the art technology, with promising results providing a step forward on their respective fields.

The computer vision and laser scanner approach is a widely used configuration. This paper presents an advance and provides motorcycle detection showing interesting results. As it was stated in the test section, the main drawback of this system is the smaller detection range, which can represent a severe drawback in specific scenarios such as the presented in test 5. However, the high accuracy of the laser scanner detection, and the immunity to IT related threads, such as connection losses, signal interferences, etcetera, makes it a very interesting tool, able to detect with high accuracy and performance. In the performed test there were specific situations where the lack of a tracking algorithm led to misdetections. This issue will be solved in further implementations, reducing the misdetection rate. Limitations in the detection range could also be overcome by adding further sensors able to cover a higher range. However, the short detection distance provided by the tests is more difficult to overcome, and it may represent a greater problem when circulating at higher velocities.

The Motowarn system performance provided very promising results. This novel technology is ready to be deployed in the next generation of vehicles, and the presented tests proves the reliability and the high range that it provides. One of the main advantages of this technology is the ability of providing overtaking maneuver and blind spot detection at high distances with a single device. However, the distance measurement accuracy is still an important issue to take into account when providing vehicle warning system. Besides, further testing should be performed in order to measure the vulnerability of the system to other IT technologies risks, such as connections problems, cyber-attacks, or interferences.

Finally, it is important to notice that the vision and laser systems are based on a single vehicle, i.e. no cooperation is necessary form other vehicles in the road, and sensors can be installed in a single vehicle. Motorwarn, on the other hand, requires a specific consensus, which involves two devices communication and reliability from both sides in order to provide trustable detection. This is a well-known problem and several works have already tried to handle these situations.

Based on the aforementioned points, the presented work represents a step forward in the protection of motorcycle drivers in the following fronts: First providing a fusion based motorcycle detection and classification. Second providing V2V communication based system. Finally, the tests performed allowed to provide empirical based information of the advances and disadvantages of each of the two technologies.

First computer vision and laser scanner approach provides state of the art based detection with accurate localization provided by the laser scanner. However, this technology lacks of a lower field of view and it is strongly sensitive to occlusions. The use of the laser scanner, reduces the false positives which may arise due to the use of computer vision approaches, such as the presented in Tai and Song (2010), Chiverton (2012), Hall and Birchfield (2010) and Phatanasrirat and Phiphobmongkol (2009). On the other hand, the addition of computer vision approach, based on HOG features and SVM allows to provide vehicle detection, by means of a powerful vision technique, which proved great performance in previous works, such as García et al. (2014).

On the other hand, the V2V approach provides reliable vehicle detection, based on a two way communication consensus, which offers a higher detection range. The limitation of this technologies are the security inherent to the use of V2V communication and the dependence on a good GPS signal, which may be degraded due to different physical phenomena. On the other hand, the main advantage of this novel system is the absence of visual occlusion, which offer a higher trustability in all possible scenarios. This advantage represents a clear advance in relation to the aforementioned works available in literature.

Each of the presented systems provided advantages and disadvantages, and depending on the situation each of them may represent a good solution. However, the combination of both systems would lead to a safer driving experience with a highly efficient motorcycle detection system, since each of the systems complements the other providing trustable and accurate detection within a high range.

Future works will focus in several lines, the first one is the development of a fully fused algorithm, which will take advantage of the use of both technologies presented in this paper, and the strengths that both of them provide, developing a complete expert system for road safety. Furthermore, an advanced tracking algorithm will be included, such as the one presented in Garcia et al. (2017), that will increase the performance of the overall fused algorithm. The communication system will be included in an complete road safety application, which will allow to provide, not only motorcycle detection, but protection for all vulnerable road users, such as pedestrians, as (Hussein, Garcia, Armingol, & Olaverri-Monreal, 2016). Finally, further works will also focus in the usability of the mobile phone based approach, and the acceptability by smartphone users.

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