Results of a Precrash Application based on Laserscanner and Short Range Radars

Sylvia Pietzsch, Olivier Aycard, Julien Burlet, Trung Dung Vu, Thomas Hackbarth, Nils Appenrodt, Juergen Dickmann and Bernd Radig

Abstract—**In this paper, we present a vehicle safety application based on data gathered by a Laserscanner and 2 short range Radars that recognizes unavoidable collisions with stationary objects before they take place in order to trigger restraint systems. Two different software modules are compared that perform the processing of raw data and deliver a description of the vehicle's environment. A comprehensive experimental evaluation based on relevant crash and non-crash scenarios is presented.**

I. Introduction

In recent years, a lot of research has been done to develop safety applications which help to prevent accidents or mitigate their consequences. The automatic recognition of imminent collisions plays an important role in making traffic more safe. The earlier a potential collision is detected, the more possibilities are available to protect car passengers and other road users. In this document, we describe a system to detect frontal collisions. In case a crash is predicted to happen within the next 200 milliseconds, the system triggers reversible belt pretensioners which bring the passenger into an upright position that is more safe during the crash and removes the belt slack in advance.

The perception of the environment in front of the vehicle is based on data from a Laserscanner and two short range Radars. The advantage of the Laserscanner lies in its large field of view and its high angular and range resolution and accuracy. Radar sensors are in common use for driver assistant systems in cars and complements the system due to immediate velocity measurements and the use of an additional emission type.

An experimental vehicle was equipped with sensors and processing hardware to demonstrate the operational capability of the safety function in real time. It is described in more detail in Section II.

The project comprises two different software modules for sensor data processing that were developed independently by the Daimler AG (module 1) and INRIA (module 2). Module 1 uses grid-based segmentation of the Laserscanner data and Kalman filter techniques for the tracking of objects. Module 2 is based on simultaneous localization and mapping techniques (SLAM) together with the detection and tracking of moving objects. The environment is modeled using an Occupancy Grid. Detected moving objects are tracked by a Multiple Hypothesis Tracker (MHT) coupled with an adaptive Interacting Multiple Models filter (IMM). Our evaluation compares the performance of both modules on the basis of the output of a common Precrash decision module by means of missed and false alarm rates in complex crash and non-crash maneuvers with stationary objects, respectively.

The remainder of this document is organized as follows: In Section II the experimental vehicle together with the used sensors are described. Section III deals with the technical and scientific background of sensor data processing. It gives an overview over the methods that are used within the modules for environmental perception. The results from testing the system in various driving scenarios are presented in Section IV. Finally, Section V summarizes the presented content and gives suggestions for further work.

II. Experimental vehicle and used sensors

The experimental vehicle, a Mercedes-Benz E-Class, is equipped with an Ibeo "ALASCA" Laserscanner mounted below the number plate and two M/A-COM "SRS100" 24 GHz short range Radar prototypes mounted in the front bumper besides the number plate. The Laserscanner is hermetically covered by a box having a black plastic faceplate which is transparent for the emission wavelength while the Radars are mounted behind the serial plastic

Manuscript received January 10, 2008. This work was supported in part by the Information Society of the European Union under the Contract No. 507075 in the framework of the integrated Project PReVENT.

S. Pietzsch is with the Technische Universitaet Muenchen, Chair for Image Understanding and Knowledge-based Systems and works currently for the Daimler AG, 89081 Ulm, Germany (phone: +49 731 505 2236; fax: +49 731 505 4105; e-mail: uni-muenchen.pietzsch@daimler.com)

O. Aycard, J. Burlet and T.D. Vu are with the Laboratoire d'Informatique de Grenoble, Grenoble, France (e-mail: olivier.aycard@inrialpes.fr, jburlet@inrialpes.fr, tdvu@inrialpes.fr)

T. Hackbarth, N. Appenrodt and Dr. J. Dickmann are with the Department for Environment Perception, Research Centre of the Daimler AG, 89081 Ulm, Germany (e-mail: thomas.hackbarth@daimler.com, nils.appenrodt@daimler.com, juergen.dickmann@daimler.com)

B. Radig is with the Technische Universitaet Muenchen, Chair for Image Understanding and Knowledge-based Systems, Garching, Germany (e-mail: radig@cs.tum.edu)

bumper. The technical specifications of the sensors are listed in Table I.

The Radar sensors and the Laserscanner controller are connected to a controller unit in the trunk by private CAN and Ethernet, respectively. This real time unit hosts a 366 MHz Motorola Power-PC-processor which runs the software for sensor data processing, segmentation, object generation, tracking, sensor data fusion and activation decision.

TABLE I
TECHNICAL DATA OF THE SENSORS

Property	Laserscanner	Short range Radar
Angle	160°	80°
Angle accuracy	+/- 0.5°	+/- 5...10°
Range	0.3 - 80 m	0.2 - 30 m
Range accuracy	+/- 5 cm	+/- 7.5 cm
Scan frequency	25 Hz	25 Hz

In case of unavoidable collisions the reversible seatbelt pretensioners of the front seats are deployed via a private CAN. An additional PC in the trunk acts as a display server connected to a monitor in front of the co-drivers seat to visualize the environment perception and the activation decision. The architecture of the vehicle is shown in Figure 1.

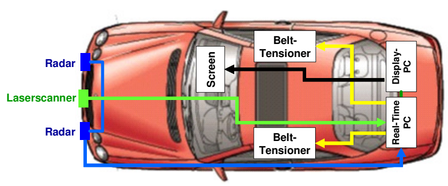

Fig. 1. Hardware architecture of the experimental vehicle showing sensors, actuators, computers and interconnects.

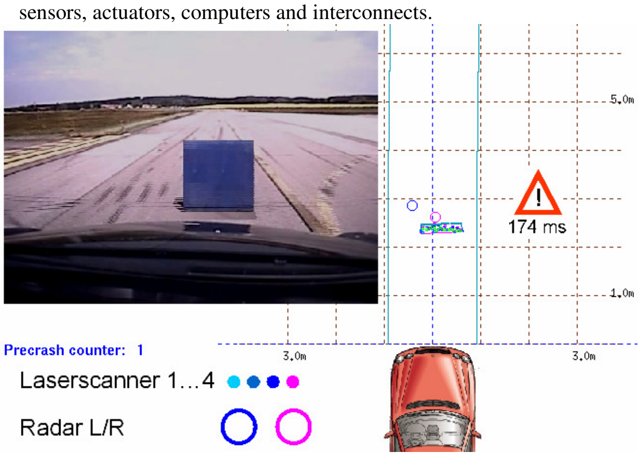

Fig. 2. Visualization of the environment perception on the in-vehicle screen. The Inset shows the scene recorded by the camera behind the windshield.

Figure 2 shows a cutout of the screen exactly at the moment of deployment when the car approaches a foam cube with a constant speed of 50 km/h.

On the screen, the targets seen by the Laserscanner and the Radars are shown as small dots and circles, respectively. The colors symbolize the mounting side of the Radars and accordingly the 4 vertical beam layers of the Laserscanner. The object segments, generated from the scanner targets, are depicted as rectangles. The actual *TTC* (time to crash) of 174 ms corresponds to a distance of 2.4 m. The inset of the figure shows the appropriate picture of the in-vehicle camera which is used for documentation purposes only.

III. Perception Modules

Within the framework of the EU-funded subprojects APALACI und PROFUSION2 of the Integrated Project PReVENT, different modules were developed which perform the signal processing of the single sensors and their fusion. The result is a description of the vehicle's surrounding environment with static and moving objects contained in it. Based on the state vector (position, velocity, orientation angle) that the module estimated for each object relative to the ego-vehicle, the application decides afterwards, whether an inevitable collision will take place within the next 200ms. Furthermore, the Precrash application is i. e. dealing with the suppression of ghost targets and the plausibility check to ensure a robust system behaviour. In the following, we will describe the mode of operation of each perception module.

A. *Module 1: Grid-based Segmentation, Mid-level Fusion and Tracking using Kalman Filter*

Grid-based methods have proven to be efficient to process raw data provided by a Laserscanner. In this module, developed at the Daimler AG, a grid approach is used for segmentation of the laser scan points. The segmentation grid is designed according to the scanner's measuring method. Scan points are processed in polar coordinates. Therefore, the dimensions of the grid denote angle and distance. The cell size increases with the distance to the scanner and the absolute value of the angle, thus enabling a good segmentation even in cases when some target points are lost near the border of the field of view due to low reflected intensity. All scan points of all four vertical layers of the Laserscanner are projected onto the grid. If the number of measurements within a grid cell exceeds a given threshold the cell is marked as occupied. With this threshold the grid works as a filter for outliers. Neighbouring occupied cells are connected to form one segment, afterwards. The procedure is illustrated in Figure 3.

This method allows for fast processing of the laser scans. The grid design influences the segmentation quality. Ideally, a segment should not contain more than one real object and an object should not split up into several segments. Therefore, the dimensions of the grid cells have to be chosen carefully. If the grid cells are too large, neighbouring objects tend to be merged to one segment. Otherwise, if the grid cells are too small, a compact object splits into many small segments. Knowledge on the properties of expected participants in traffic scenes helps to find a suitable grid design.

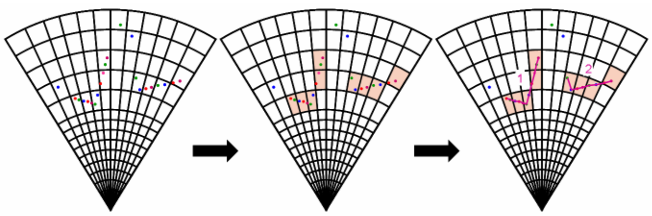

Fig. 3. Segmentation of laser scan points using a grid. Left: Projection of all scan points onto the grid. Middle: Marking of grid cells with more points than a threshold. Right: Connecting of neighbouring marked grid cells and labelling.

From the obtained segments, features that describe the properties of an object like dimension or orientation angle can be extracted. For feature extraction, the minimum angle point, the point with the shortest distance to the scanner and the maximum angle point are used to define a rectangular segment.

The measurements of the Laserscanner and the short range Radars are combined using a midlevel fusion approach which is illustrated in the structure within the large frame in Figure 4. Laserscanner data is processed in the way described above. The Radar sensors deliver filtered and pretracked targets. Both, the Radar targets and the scanner targets which correspond to the segments derived in the preprocessing step are fused within the tracking step.

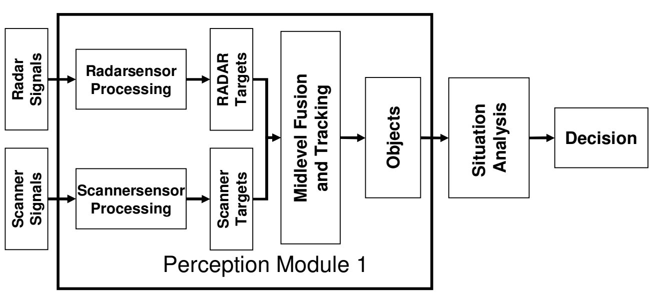

Fig. 4. System architecture. Sensor processing, fusion and tracking are realized by each module independently. The structure inside the large frame depicts the perception module 1. Situation analysis and the decision step are the same for both perception modules.

For object tracking, standard Kalman filter technique is used. The state vector of an object consists of the *x*- and *y*-position, the *x*- and *y*-component of the velocity and the orientation angle. Of course, the orientation angle can only be updated by laser measurements as the Radar sensors deliver point targets only. Conflicts in associating new measurements to existing objects are resolved using the Global Nearest Neighbourhood (GNN) method. Already tracked objects, that are not found again in the actual time cycle are kept and will only be deleted if no corresponding object can be assigned during some cycles in succession. If on the other hand an object can not be associated to any existing track, a new one is created.

The Situation Analysis and Decision Modules right from the large frame in Figure 4 are common for the use of either perception module. Subsequent steps calculate for all objects in the environment in front of the vehicle, whether they potentially hit the sensor vehicle according to the prediction of their movement, and the time to collision (*TTC*), if applicable. The decision for or against an imminent collision is supported by considering statistical data of the object (variance of the velocity in *x* direction, lifetime and number of tracks).

In general, laser measurements are able to describe the position and shape of real existing objects very accurately. Radar sensors help to suppress ghost targets or targets based on objects that are irrelevant for Precrash applications like plants or steam coming out of street drains. All in all, the presented Precrash system based on a Laserscanner fused with short range Radars reliably detects different kinds of collisions with stationary objects in front of the car, as our evaluation in Section IV will show.

B. Module 2: Grid Based Fusion with Moving Object Detection and Tracking

The perception module developed by the e-Motion group (http://emotion.inrialpes.fr) of LIG Laboratory and INRIA Rhône Alpes is based on the approach called *grid based fusion* [1]. The idea of this approach is to develop a new framework to multi-sensor fusion called occupancy grids (OGs) [2]. An OG is a stochastic tessellated representation of spatial information that maintains probabilistic estimates of the occupancy state of each cell in a lattice. In this framework, each cell is considered separately for each sensor measurement, and the only difference between cells is the position in the grid. The main advantage of this approach is the ability to integrate several sensors in the same framework, taking the inherent uncertainty of each sensor reading into account, contrary to the geometric paradigm. The major drawback of the geometric approach is the number of different data structures for each geometric primitive that the mapping system must handle: segments, polygons, ellipses, etc.

Taking into account the uncertainty of the sensor measurements for each sequence of different primitives is very complex, whereas the cell-based framework is generic and therefore can fit every kind of shape and be used to interpret any kind and any number of sensors. For sensor data integration, OGs only require a sensor model which is the description of the probabilistic relation that links a sensor measurement to a cell state, occupied or empty.

As our objective is to have a robust perception using multi-sensor approaches to track the different objects surrounding a car, the grid based fusion approach is combined with multi-objects tracking techniques.

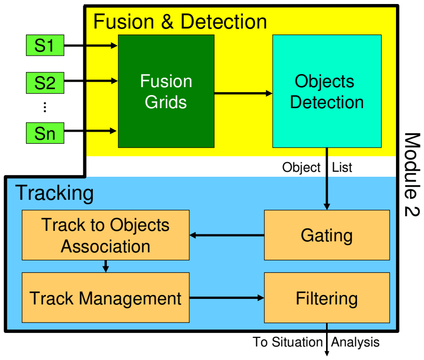

Fig. 5. The fusion grid based architecture (module 2). This Module replaces the large frame in Fig. 4 when running the second application variant.

The whole architecture is depicted in Figure 5 [1] and is composed of two levels :

1) The fusion and extraction level where the environment is mapped and sensor data fusion is performed using occupancy grids and finally the moving objects are extracted from the grid [3].
2) The tracking level where the objects present in the environment are tracked using the Multiple Hypothesis Tracking (MHT) method [4].

In the next part, we describe in detail both levels of our architecture.

1) Fusion and Detection level

a) Mapping the environment using occupancy grids

The vehicle environment is divided into a two-dimensional lattice of rectangular cells and each cell is associated with a measure taking a real value in between 0 and 1, indicating the probability that the cell is occupied by an obstacle. A high value of an occupancy grid indicates the cell is occupied and a low value means the cell is free. Assuming that occupancy states of individual grid cells are independent, the objective of a mapping algorithm is to estimate the posterior probability of occupancy for each cell of the grid. The lattice of cells is a type of Markov field and many assumptions can be made about the dependencies between cells and especially adjacent cells in the lattice. In the used approach, independent sensor models are used for each cell, which is a strong hypothesis but very efficient in practice since all calculus could be made for each cell separately. It leads to an expression of a joint distribution for each cell permitting to update the probability of occupancy. Details of the simultaneous localization and mapping (SLAM) technique can be found in [1, 3], the used sensor models refer to [5, 6].

b) Extraction of moving objects

Figure 6 illustrates the detecting of moving objects. The leftmost image depicts the situation where the vehicle is moving along a street seeing a car moving ahead and a motorbike moving in the opposite direction.

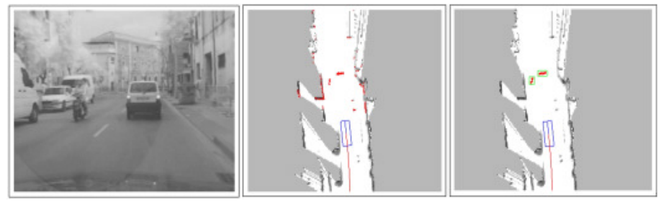

Fig. 6. Example for moving object detection. The blue rectangle represents the ego-vehicle.

The middle image shows the local static map and the vehicle location with the current laser scan drawn in red. Measurements which fall into a free region in the static map are detected as dynamic and are displayed in the rightmost image. After the clustering step, two moving objects are identified (in green boxes) which correctly correspond to the car and the motorbike.

c) Fusion with radars

After moving objects are identified from laser data, we confirm the object detection results by fusing with radar data and provide the detected objects with their velocities. For each moving object detected from laser data as described in the previous section, a rectangular bounding box is calculated and the radar measurements which lie within the box region are then assigned to corresponding object. The velocity of the detected moving object is estimated as the average of these corresponding radar measurements.

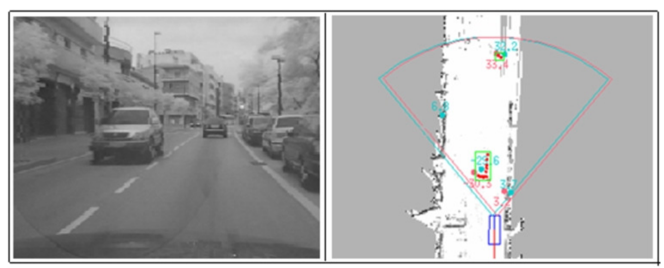

Fig. 7. A moving object detected from laser data is confirmed by radar data.

Figure 7 shows an example of how the fusion process takes place. Moving objects detected by the Laserscanner are displayed in red with green bounding boxes. The targets detected by two radar sensors are represented as small circles in different colors along with corresponding velocities. We can see in the radar field of view, that two objects detected by the Laserscanner are also seen by two radars so that they are confirmed and their velocities are estimated. Radar measurements that do not correspond to any dynamic object or fall into another region of the grid are not considered.

2) Tracking level

In this part of our architecture, a Multiple Hypothesis Tracker (MHT) is used to solve the association problem of new extracted objects with tracks, each track corresponding to a previously known moving object. It also permits to detect and reject spurious extracted objects (generated by sensors' noise) and to identify new moving objects incoming in the sensors' range.

The basic principle of MHT is to generate and update a set of association hypotheses during process. An hypothesis corresponds to a specific probable assignment of observations with tracks. By maintaining and updating several hypotheses, none irreversible association decisions are made and ambiguous cases are solved in further steps.

As shown in Figure 5, our multi-object tracking method is composed of four different parts:

• The first one is the gating. In this part, taking as input predictions from previous computed tracks, we compute the set of new detected objects which can be associated to each track.

• In a second part, using the result of the gating, we perform object to tracks association and generate association hypotheses, each track corresponding to a previously known moving object. The output is composed of the computed set of association hypotheses.

• In the third part, called track management, tracks are confirmed, deleted or created according to the association results which yield final track trees as output.

• In the last part corresponding to the filtering step, estimates are computed for 'surviving' tracks and predictions are performed to be used in the next step of the algorithm. In this part we use an adaptive method based on Interacting Multiple Models (IMM) permitting to deal with motion uncertainties. More details about this efficient method are given in [7][8].

Illustrating the perception module results in three different types of scenarios which are shown in Figure 8. The images in the first row represent online maps, and objects moving in the vicinity of the vehicle are detected and tracked. The current vehicle location is represented by a blue box along with its trajectories after being corrected from the odometry. The red points are current laser measurements that are identified as belonging to dynamic objects. Green boxes indicate detected and tracked moving objects with corresponding tracks displayed in different colors. Information on velocities is displayed next to detected objects if available. The second row are images for visual references to corresponding situations.

In Figure 8, the leftmost column depicts a scenario where the ego-vehicle is moving at a very high speed of about 100 km/h while a car moving in the same direction in front of it is detected and tracked. On the rightmost is a situation where the ego-vehicle is moving at 50 km/h on a country road. A car moving ahead and two other cars in the opposite direction are all recognized. Note that the two cars on the left lane are only observed during a very short period of time but both are detected and tracked successfully. In the third situation depicted in the middle, the ego-vehicle is moving quite slowly at about 20 km/h in a crowded city street. More results and videos can be found at http://emotion.inrialpes.fr/~tdvu/videos/.

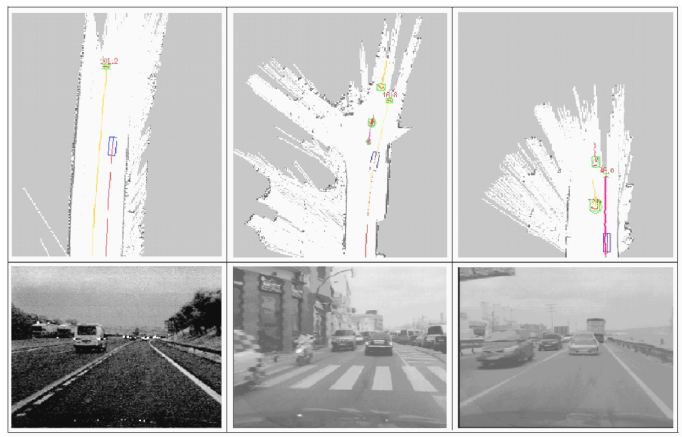

Fig. 8. Results obtained using the perception module for different environments.

IV. EXPERIMENTAL RESULTS

The application has been validated in complex crash and non-crash scenarios. To conduct the experiments, we built up a comprehensive database that consists of short sequences of measurements recorded during predefined driving maneuvers. These maneuvers comprise factual and near missed collisions with stationary objects at different velocities, in curves, with deceleration, sudden lane changes and lane changes of a leading vehicle obstructing the sight to

TABLE II
RESULTS FOR COMPLEX NON-CRASH SCENARIOS

Scenario	Ego velocity [km/h]	Number of tests	False alarms/False alarm rate	
			Module 1	Module 2
Near-missed passing of cylinder	40, 60	9	0 / 0%	0 / 0%
Near-missed passing of cube	40, 60	6	0 / 0%	0 / 0%
Near-missed passing of cylinder after curve (45°)	40, 60	29	0 / 0%	3 / 10.3%
Emergency brake, distance to cylinder after brake not greater than 1.5m	40, 60 (at start)	19	1 / 5.3%	1 / 5.3%
Lane change maneuver to avoid a collision with a cube	30, 40, 50, 60, 70	22	0 / 0%	0 / 0%
Gate passing	30, 50	6	0 / 0%	0 / 0%
Gate passing after curve (45°)	30, 50	4	0 / 0%	0 / 0%
Total		**95**	**1 / 1.1%**	**4 / 4.2%**

the obstacle. In the maneuvers, foam cubes and cylinders served as crash objects. To measure the quality, we counted the false alarms that occurred in non-crash scenarios and the missed alarms in case a collision was not detected by the application. Table II compares the results for the non-crash scenarios for the two different modules and Table III lists the results for the crash scenarios.

TABLE III
RESULTS FOR COMPLEX CRASH SCENARIOS

Scenario	Ego velocity [km/h]	Number of tests	Missed alarms/Missed alarm rate	
			Module 1	Module 2
Collision with cylinder, varying points of impact	20, 40	24	0 / 0%	0 / 0%
Collision with (paper) cylinder at high speed, varying points of impact	60, 120	8	2 / 25.0%	0 / 0%
Collision with cube, point of impact has high offset	40	7	0 / 0.0%	1 / 14.3%
Collision with cylinder after curve (30°, 45°)	30, 40, 60	20	2 / 10.0%	0 / 0%
Collision with cylinder or cube after emergency brake	20, 40 (at crash time)	7	0 / 0%	0 / 0%
Collision with (paper) cylinder after emergency brake at high speed	60, 80 (at crash time)	9	2 / 22.2%	0 / 0%
Collision with cylinder after lane change maneuver	40, 50	23	1 / 4.3%	1 / 4.3%
Collision with cylinder after leading car lane change	40, 50	4	0 / 0%	0 / 0%
Total		**102**	**7 / 6.9%**	**2 / 1.9%**

As a general result it can be stated that a reliable collision detection is achieved with both perception modules. Whereas Module 1 enables a lower false alarm rate, the crash detection rate of Module 2 is very high (98.1%). The three false alarms in the scenario where we pass the cylinder in a curve occurred in cases of getting extremely close to the obstacle. In contrast, no false alarms occurred at all when the vehicle suddenly changes the lane to avoid a collision with an obstacle standing on the road. Emergency brake maneuvers challenge the tracking system because of the divergent motion scheme. In our evaluation, only 1 out of 19 test drives resulted in a false alarm for each module.

In a second experiment we tested the application in normal traffic on highways, rural roads and in urban areas. To achieve representative results we performed the test drives during day time to cover different traffic situations like rush hour, traffic jam and stop-and-go. Furthermore, the test drives were partly conducted under adverse weather conditions like rain, fog, wet roads and traffic spray. All in all, we covered a distance of 1600 km, running the application in real time. There were no wrongly detected collisions in any of these environments.

V. CONCLUSION AND OUTLOOK

In this paper we compared two approaches that perform the data processing and object generation fusing Laserscanner and short range Radar sensors. The obtained description of the vehicle's environment in terms of static and moving objects serves as a basis for safety systems that trigger restraint systems in case an unavoidable collision will take place.

Comprehensive tests show, that a good detection performance for frontal collisions is achieved with both approaches. The application was running stable in a hard real-time environment and has been extensively tested in real traffic scenarios. The function has been demonstrated in a public event during the 2007 PReVENT IP Exhibition in Versailles.

Future works will extend the perception modules in order to improve the detection of collisions with moving objects and with the major goal to shift the activation decision in a time region greater than 200 ms. This includes the refinement of motion models and object models to give a more meaningful representation of detected objects with specific shapes and behavior.

REFERENCES

[1] O. Aycard, A. Spalanzani, J. Burlet, C. Fulgenzi, TD. Vu, D. Raulo and M. Yguel. "Grid based Fusion and Tracking", in *Proc. of the IEEE Intelligent Transports Systems Conference (ITSC'06),* Toronto, 2006, pp. 450-455.

[2] A. Elfes, "Occupancy grids: a probabilistic framework for robot perception and navigation", Ph.D. dissertation, Carnegie Mellon University, 1989.

[3] T. D. Vu, O. Aycard, and N. Appenrodt, "Online localization and mapping with moving object tracking", in *Proceedings IEEE Intelligent Vehicle Symposium,* Istanbul, 2007, pp. 190-195.

[4] S.S. Blackman and R. Popoli, *Design and Analysis of Modern Tracking Systems.* Boston: Artech House, 1999.

[5] M. Yguel, O. Aycard, D. Raulo and C. Laugier, "Grid based fusion of offboard cameras", in *Proc. IEEE International Conference on Intelligent Vehicles,* Tokyo, 2006, pp. 276-281.

[6] M. Yguel, O. Aycard and C. Laugier (2006), "Efficient GPU-based Construction of Occupancy Grids Using several Laser Range-finders", in *Proc. IEEE International Conference on Intelligent Robot and Systems*, Beijing, 2006, pp. 105-110.

[7] J. Burlet, O. Aycard, A. Spalanzani and C. Laugier, "Pedestrian tracking in car parks: an Adaptive Interacting Multiple Model based Filtering Method", in *Proc. IEEE Int. Conf. on Intelligent Transportation Systems,* Toronto, 2006, pp. 462-467.

[8] J. Burlet, O. Aycard, A. Spalanzani and C. Laugier, "Adaptive Interactive Multiple Models applied on pedestrian tracking in car parks" , in *Proc. IEEE Int. Conf. on Intelligent Robots and Systems,* Beijing, 2006, pp. 525-530.