An occupancy grid based architecture for ADAS

Olivier Aycard, Trung Dung Vu & Qadeer Baig

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Abstract

Perceiving or understanding the environment surrounding a vehicle is a very important step in advanced driving assistance systems (ADAS). The task involves both Simultaneous Localization And Mapping (SLAM) and Detection And Tracking of Moving Objects (DATMO). In this context, we have developed a generic architecture based on occupancy grid to solve SLAM and DATMO in dynamic outdoor environments. In this paper, we give an overview of this architecture and results obtained in different european projects: PReVENT-ProFusion2, INTERSAFE2 & Interactive.

1 Introduction

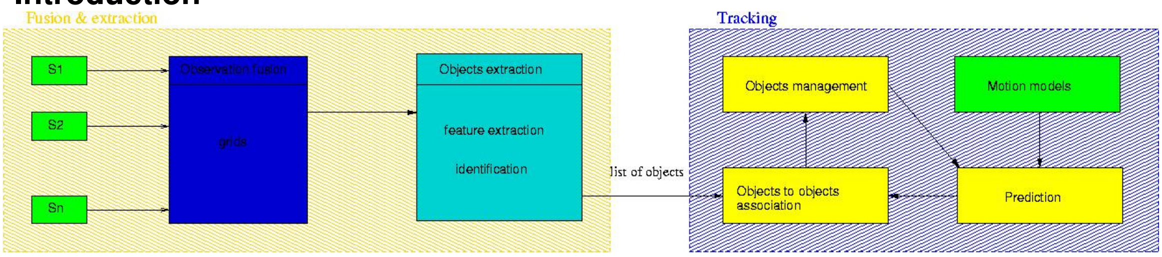


Figure 1 : general architecture of our perception system

Perceiving or understanding the environment surrounding a vehicle is a very important step in advanced driving assistance systems (ADAS) or autonomous vehicles. The task involves both Simultaneous Localization And Mapping (SLAM) and Detection And Tracking of Moving Objects (DATMO). In this context, we have designed and developed a generic architecture based on occupancy grid to solve SLAM and DATMO in dynamic outdoor environments (Figure 1). In this paper, we give an overview of this architecture and results obtained in different projects: PReVENT-ProFusion2 with Daimler[1], CMU public datasets[2] and also preliminary results in INTERSAFE2[3].

2 Daimler demonstrator: PReVENT-ProFusion2 project[1]

2.1 Daimler Demonstrator

The DaimlerChrysler demonstrator car is equipped with a camera, two short range radar sensors and a laser scanner (Figure 2). The radar sensor is with a maximum range of 30m and a field of view of 80°. The data of radar are processed and it delivers a list of moving objects. The maximum range of laser sensor is 80m with a field of view of 160° and a horizontal resolution of 1°. The laser data are not processed. In addition, vehicle odometry information such as velocity and yaw rate are provided by the vehicle sensors. Images from camera are for visualization purpose.

Figure 2 : Daimler demonstrator

Figure 3 : CMU demonstrator

2.2 First level of architecture

In this section, we first summarized the description of the first level of our architecture: Environment Mapping & Localization, Moving Objects Detection. In the last subsection, we describe the fusion between objects detected by laser and radar data.

2.2.1 Environment Mapping & Localization

To map the environment and localize in the environment, we propose an incremental mapping approach based on a fast laser scan matching algorithm in order to build a consistent local vehicle map. The map is updated incrementally when new data measurements of laser arrive along with good estimates of vehicle locations obtained from the scan matching algorithm. The advantages of our incremental approach are that the computation can be carried out very quickly and the whole process is able to run online.

Using occupancy grid representation, the vehicle environment is divided into a two-dimensional lattice M of rectangular cells and each cell is associated with a measure taking a real value in [0,1] indicating the probability that the cell is occupied by an obstacle. A high value of occupancy grid indicates the cell is occupied and a low value means the cell is free. Suppose that occupancy states of individual grid cells are independent, the objective of a mapping algorithm is to estimate the posterior probability of occupancy $P(m| x_{1:t}, z_{1:t})$ for each cell of grid m, given observations $z_{1:t} = (z_1, ..., z_t)$ from time 1 to time t at corresponding known poses $x_{1:t} = (x_1, ..., x_t)$ from time 1 to t.

In order to build a consistent map of the environment, a good vehicle localization is required. Because of the inherent error, using only odometry often results in an unsatisfying map. To solve this problem, we used a particle filter. We predict different possible positions of the vehicle (ie, one position of the vehicle corresponds to one particle) using the motion model and compute the probability of each position (ie, the probability of each particle) using the laser data and a sensor model.

2.2.2 Moving Objects Detection

After a consistent local grid map of the vehicle is constructed, moving objects can be detected when new laser measurements arrive by comparing with the previously constructed grid map. The principal idea is based on the inconsistencies between observed free space and occupied space in the local map.

- If an object is detected on a location previously seen as free space, then it is a moving object.
- If an object is observed on a location previously occupied then it probably is static.
- If an object appears in a previously not observed location, then it can be static or dynamic and we set the unknown status for the object in this case.

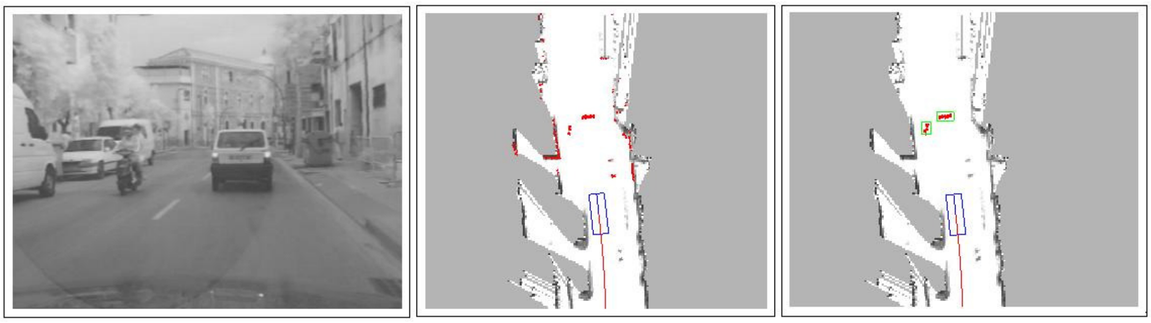


Figure 4: Moving object detection example. See text for more details.

Figure 4 illustrates the described steps in detecting 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. The middle image shows the local static map and the vehicle location with the current laser scan drawn in red. Measurements which fall into 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) and correctly corresponds to the car and the motorbike.

2.2.3 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.

2.3 Second level of architecture

In this section, we briefly summarize the four different parts of the second level of our architecture (Figure 1) to solve the different parts of multi-objects tracking:

- The first one is the gating. In this part, taking as input predictions from previous computed objects, we compute the set of new detected observations which can be associated to each object.
- In a second part, using the result of the gating, we perform observations to objects association and generate association hypothesis. Output is composed of the computed set of association hypothesis. To solve this problem, we use the MHT algorithm]
- In the third part called objects management, objects are confirmed, deleted or created according to the association results and a pruned set of association hypothesis is output.
- In the last part corresponding to the filtering step, estimates are computed for 'surviving' objects and predictions are performed to be used the next step of the algorithm. In this part, we use an adaptive method based on Interacting Multiple Models (IMM).

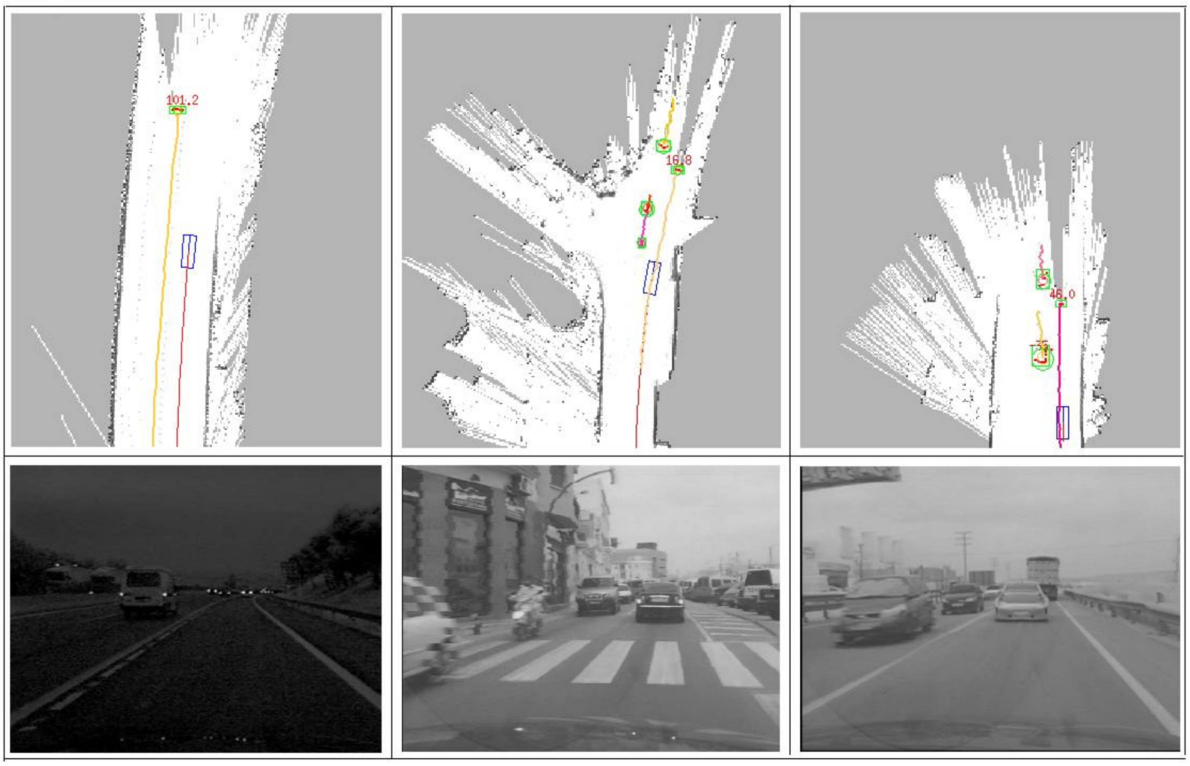


Figure 5: Experimental results for different environments

2.4 Experimental Results

The detection and tracking results are shown in Figure 5. 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 blue box along with its trajectories after correction 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.

Our architecture has been validated in complex crash and non-crash scenarios and compared with Daimler architecture[4]. To conduct the experiments, we built up a comprehensive database that consists of short sequences of measurements recorded during predefined driving maneuvers. 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. As a general result it can be stated that a reliable collision detection is achieved with both perception modules. Whereas Module of Daimler enables a lower false alarm rate, the crash detection rate of our module is very high (98.1%). in urban areas.

3 CMU demonstrator: Navlab dataset[2]

3.1 CMU demonstrator

In this part, we detail the public dataset obtained on the CMU demonstrator (Figure 2) . This dataset was collected using a SICK laser scanner mounted on a moving vehicle (Figure 2). The vehicle was driven in real-life traffics. The maximum laser range of the scanner is 80m with the horizontal resolution of 0,5°. We only use laser data and odometry vehicle motion information such as translational and rotational velocity (speed and yaw rate) are computed and provided by internal sensors. Images from camera are only for visualization purpose.

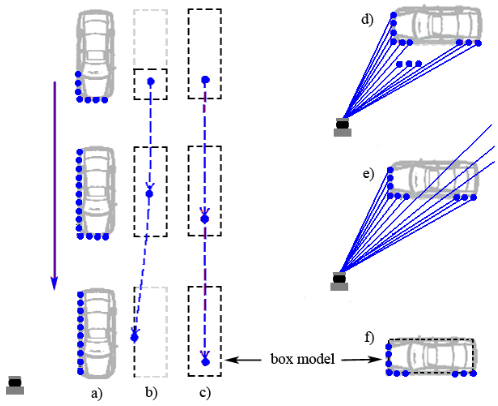


Figure 6 : Known problems with laser-based detection and tracking. (a) an example of a car approaching the laser scanner; (b) car tracking using centers of laser impact bounding-boxes leads to incorrect result; (c) correct tracking using car model; (d)(e) objects can be divided into several segments making tracking harder that requires object merging, track grouping; (f) using car model can overcome these problems.

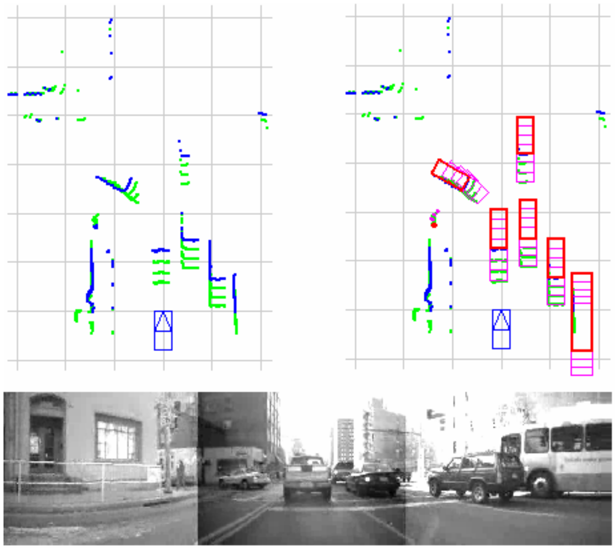


Figure 7 : Example of an interpretation of moving objects from laser data. (a) four scans consecutive: in blue is current scan and in green are scans in the past; (b) one possible solution including seven tracks of four cars and one bus represented by red boxes and one pedestrian represented by red dots which are imposed on the range data; (c) situation reference

3.2 Improvements of the architecture

Conventionally, as introduced in [1], we separate detection and tracking as two independent procedures: the detector and the tracker. At each time step, the tracker takes a list of observations about moving objects returned by the detector together with observations in the past to solve the data association over the observation space to find correct object trajectories (or tracks) then apply filtering techniques to estimate dynamic states of moving objects. In this conventional approach, since moving object detection at one time instant usually results in ambiguities that makes the data association become more difficult with missing detections or false alarms. Here we introduce another approach which combines detection and tracking together. We present a probabilistic method for simultaneous detection and tracking of moving objects taking history of measurements that allows the object detection process to make use of temporal information and facilitates a robust tracking of the moving objects. Moreover, noting that moving objects are detected as free-form in the detection process presented previously. An advantage of this method is that it can be used to detect any kind of objects without knowing a prior knowledge about that objects. However, this suffers from well-known problems with laser-based tracking as explained in figure 6. Here we take a model-based approach and introduce predefined models to represent typical moving object classes. We distinguish four classes of moving objects: bus, car, bike, pedestrian (motorcycles and bicycles belong to the bike class). We use a box model of fixed size to represent bus, car, bike and a point model to represent pedestrian.

Our algorithm to solve DATMO is summarized as follows. We formulate the detection and tracking problem as finding the most likely trajectories of moving objects given data measurements over a sliding window of time (Figure 7). A trajectory (track) is regarded as a sequence of object shapes (models) produced over time by an object which must be satisfied the constraint of both an underlying object motion and the consistency with measurements observed from frame to frame. In this way, our approach can be seen as a batch method searching for the global optimum solution in the spatio-temporal space. Due to the high computational complexity of such a scheme, we employ a Markov chain Monte Carlo (MCMC) technique that enables traversing efficiently in the solution space.

3.3 Experimental Results

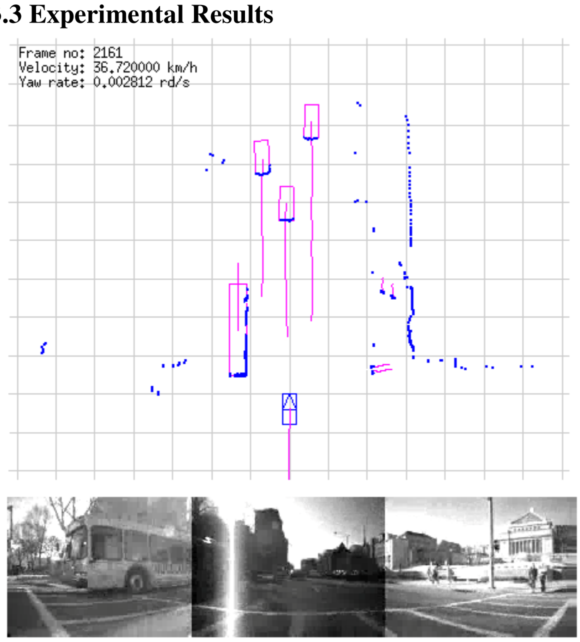
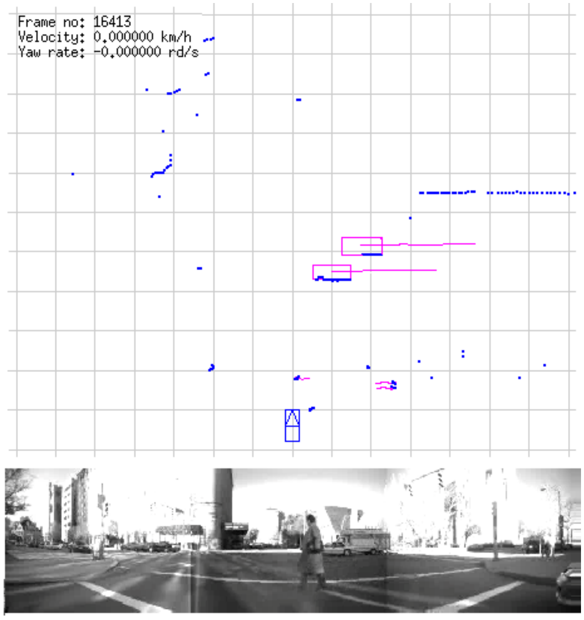


Figure 8 : (a) Different class of objects



(b) occlusion example

Figure 8(a) shows an example of our detection and tracking algorithm in action. In the ego-vehicle's view, the detected moving objects and their trajectories are shown in pink color with current laser scan is in blue color. Moving objects in the situation include a bus moving in the opposite direction on the left, three cars moving ahead, two pedestrians walking on the left pavement and the other two pedestrians passing the intersection. Figure 8(b) shows an example of our detection and tracking algorithm when an occlusion occurs. Even if only a part of the second car is detected by the laser, we are able to track this occluded car.

With initial evaluations, the MCMC detection and tracking outperforms the detection and tracking using MHT in our previous work [1] in terms of a higher detection rate and less false alarms.

4 Intersafe2 demonstrator[3]

4.1 Intersafe2 demonstrator

Figure 9 illustrates the chosen sensor set and coverage area. The sensor set-up includes sensors which are already in serial cars available, namely front ACC radar and rear-looking radar for lane change support. These sensors are accompanied by a stereo camera system to the front with high field of view of about 60°. A scanning laser with a field of view of about 160° and dedicated radar sensors directed to +90° and -90° respectively are foreseen for measuring the objects coming from the side. These sensors are able to measure position, velocity and some geometrical parameters of the relevant objects at intersections.

4.2 Current Architecture and future improvements

Our primary goal was to perform laser processing for local SLAM and detection of moving objects. We have applied methods developed in [1]. Ongoing work is about the fusion of data from laser & stereovision. Currently, we are planning fusion at detection level, object segments detected in vision and laser scans will be fused together to get a more consolidated view.

4.3 Preliminary results

In Figure 10, the first column shows a left turn scenario where the demonstrator car is turning left and a cyclist is going to right in front of the vehicle. This cyclist is detected and tracked. In the second column we have a scenario where a moving vehicle is coming from opposite direction and demonstrator is crossing a vehicle on its right. In both of the cases, precise trajectories of the demonstrator are achieved and local maps around the vehicle are constructed consistently.

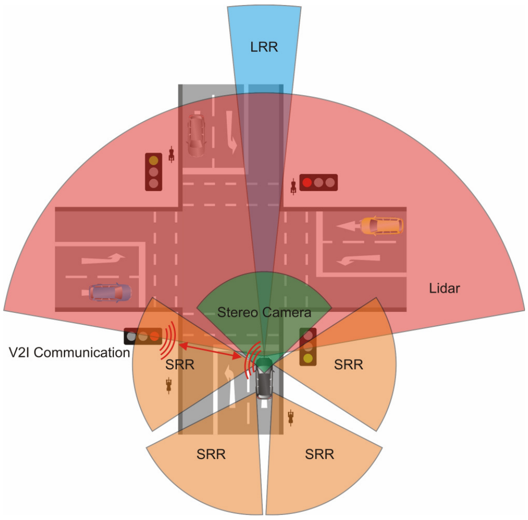


Figure 9 : Intersafe2 demonstrator

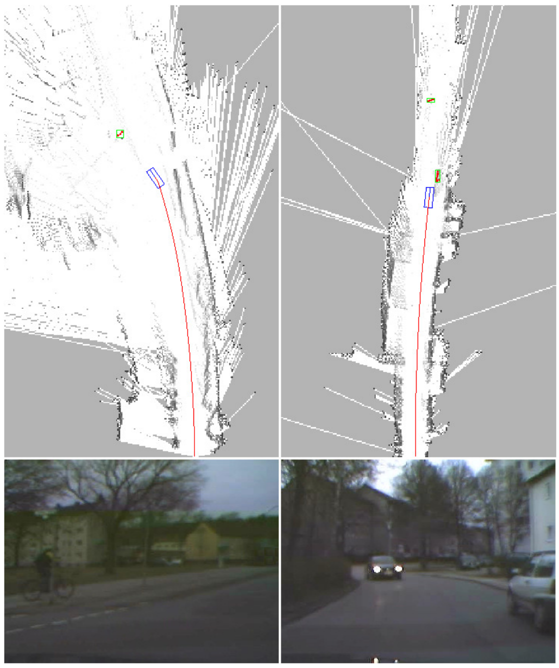


Figure 10 : local SLAM + moving objects detection

5 Conclusion and perspectives

In this paper, we presented the architecture developed in our group for perception systems for ADAS. This architecture has been used in the european project PReVENT-ProFusion2 in cooperation with Daimler [1] and also with Volvo Truck [5] (not presented here). It has been also used with CMU demonstrator[2], and is currently used in the european project intersafe2[3]. More results and videos can be found at http://emotion.inrialpes.fr/~tdvu/videos. We are currently involved in the european project Interactive-Perception. In this project, we will extend our architecture for the Daimler demonstrator, and cooperate with TRW on low level fusion between radar & vision.

6 Acknowledgements

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Contacts: Olivier Aycard, Trung-Dung Vu & Qadeer Baig

University of Grenoble1
Grenoble, FRANCE
E-mail: Olivier.Aycard@imag.fr, Trung-Dung.Vu@imag.fr, Qadeer.Baig@imag.fr