# „Automotive Radar the Key Technology For Autonomous Driving: From Detection and Ranging to Environmental Understanding“

Juergen Dickmann, Jens Klappstein, Markus Hahn, Nils Appenrodt, Hans-Ludwig Bloecher, Klaudius Werber, Alfons Sailer
Daimler AG, Vehicle Automation and Chassis Systems, Ulm, Germany
E-Mail: juergen.dickmann@daimler.com

***Abstract*— An overview on state of the art automotive radar usage is presented and the changing requirements from detection and ranging towards radar based environmental understanding for highly automated and autonomous driving deduced. The traditional segmentation in driving, manoeuvering and parking tasks vanishes at the driver less stage. Situation assessment and trajectory/manoeuver planning need to operate in a more thorough way. Hence, fast situational up-date, motion prediction of all kind of dynamic objects, object dimension, ego-motion estimation, (self)-localisation and more semantic/classification information, which allows to put static and dynamic world into correlation/context with each other is mandatory. All these are new areas for radar signal processing and needs revolutionary new solutions. The article outlines the benefits that make radar essential for autonomous driving and presents recent approaches in radar based environmental perception.**

***Keywords—Radar, Environmental Perception, Landmark, SLAM, Driver assistance, Active safety, Highly automated Driving, Driverless driving***

## I. I. INTRODUCTION

Automotive Radar has already reached a market penetration that leads to several tens of million units used. It has already grown up to a status were it has found its way into nearly all car manufacturers portfolio in the world. They are used in all platforms from passenger cars via van to heavy trucks and travel busses down to even smallest sedan car platforms. With the introduction of the collision prevention assist®, Radar sensors have become even standard equipment in passenger cars [1]. The major reason for the success story of automotive radar is its physical principle that offers unique performance features at reasonable costs. Among others there are independence from environmental conditions (light, weather), directly measured parameters in space and Doppler velocity, multiple field of view capability and design compatible vehicle integration. Radar performs under conditions, where other sensor types fail and it is capable to virtually look through vehicles (transvision effect) by exploiting reflections between the road surface and vehicle floor and hence makes the invisible visible. Over the decades, the performance requirements increased steadily from simple detector and ranging tasks in blind spot monitoring or cruise control systems up to smart environment perception tasks for present day semi-autonomous evasion and braking functions [2]. However, the utmost push in performance requirement is initiated with the trend towards highly automated driving and down the road, driver less driving. Future automotive radar systems have to provide imaging like capabilities and have to interact in radar networks, which allow for 360° highly comprehensive perception tasks. In former days, single sensor concepts were used, while multi sensor networks composed of four or more short-,mid-, and far range radars are being applied, nowadays [3, 4]. In 2013, the first stride ahead towards higher automation has been made with the fully autonomous Bertha drive of a Mercedes-Benz research sedan [3, 4]. One design rule was that the vehicle had to appear as a serial vehicle, which naturally brought radar into the game. The technical lesson learned was, that higher degree in automation, where the driver is going to be exculpated increasingly from the pure driving task, imposes much higher performance to the environmental perception task radar has to deliver. One important consequence is that radar signal processing has to be extended to machine learning, image understanding and patter recognition concepts to keep radar in the leading edge of remote sensing. The paper will provide an overview on state of the art automotive radar usage deduces future requirements for highly automated driving and will present recent advances in radar based environmental perception.

## II. FUNCTIONAL MILESTONES TO DRIVER LESS DRIVING

A comprehensive overview of the evolution of driver assistance and active safety systems is given in [5]. Over the last decade, DAIMLER, and other car manufacturers all over the world have introduced a large variety of active safety and driver assistance functions [1, 2, 3]. In general, those systems have been developed to operate on highways and to some extend on rural roads. The functional portfolio of those systems covers mainly the following key features, Blind spot detection, Cruise control with Stop and go, Emergency Braking, 360°-Pre-crash sensing and pre-triggering for/of airbags. The introduction of semi - autonomous emergency braking and pre-crash systems was only possible by a dramatic improvement in radar technology and radar network architecture. The key improvements are the introduction of multimodality covering long (250m) and short range distances (0.5-80m) and azimuth angles from ±10° to ± 70° in one sensor-package. First steps towards imaging like capability have been introduced with digital beam forming allowing for SAR concepts combined with high resolution algorithm techniques like linear – or autoregressive progression (APR) and MUSIC as well as architectural changes to achieve improved Doppler resolution [4-6]. Also important are a high angular accuracy, a very fast up-date rate of few 10´s of milliseconds (ms) and small latency of view ms [7, 13]. The evolution of driver assistance or active safety functions towards higher degree of automation can be revealed by considering the evolution of emergency braking systems. For example the Mercedes-Benz PRE-SAFE® Brake improved from a simple braking force enhancement in 2006 to a system that intervenes by braking the car automatically and activates the maximum braking power around 600ms seconds before the unavoidable collision in 2013 [2]. In 2015 an extension to urban areas with pedestrian classification was added [2]. A similar evolution takes place in the parking and maneuvering area. Active parking assists of the former days, enabled the vehicle to search for a suitable parking space, and to park automatically at the press of a button, with the driver retaining control of the accelerator and brake at all times. The present evolution state is the advancement to parking pilot, where the driver can remote controlled park his car via a smart phone app from outside of the vehicle [8]. Even in those state of the art functions radar mainly performs according to its traditional role, detection and ranging of dynamic objects, based on a point representation. One first example how pattern recognition and image understanding concepts enable new safety functions is driving lane prediction. Exploiting the reflections from guard rails, gravel and lawn, this information enables emergency braking in curves and in snow conditions where optical lane information is missing [9, 10, 11]. Some basic pedestrian classification for NCAP and braking functions is the first step of radar contributing semantic information for a system reaction.

It is quite obvious that the trend in higher automation level will continue up to autonomous driving on highways as well as in urban areas. At this utmost stage, there will be no driver in the loop. As a consequence, the autonomous car driving performance will be depending on the degree of completeness of the essential environmental information the sensor-set up is going to provide. Comparable to the human being that utilizes many different sensors (ears, eyes etc.) highly automated vehicles will use many different sensor types. The difference to present fusion concepts like “region of interest” is that all sensors will have to provide similar information in order to achieve the required robustness via a fusion concept like “n sensors out of m sensors see the same”, [29]. As a consequence, the standard performance portfolio of radar has to be dramatically enhanced. The following chapter will deduce the challenges for future automotive radar.

## III. RADAR REQUIREMENTS

As shown with the Bertha Drive it could be shown, that autonomous driving on both interurban and inner city routes is feasible even with a vehicle and sensor-set-up that is not dramatically different to a standard serial vehicle. The goal of this experiment was to show that autonomous driving is not limited on highways and similar structured environment [3, 4, 12, 13]. On its way, the self-driving S-Class had to deal autonomously with a number of highly complex urban situations, which were either enabled or aided by radar.

In addition to far range operation in driving direction for highway and rural road operation, in urban scenarios 360° near- and mid-range distance of the vehicles environment will become also important. This along with a wider azimuthal observation horizon in order to cover e.g. crossing scenarios, roundabouts or pre-crash situations in driving direction as well as side- and rear-crash situations. Dramatically shrinking time scales in terms of observation- and time to react horizons as well as a huge larger number of static and dynamic object- and motion types compared to classical ACC and collision mitigation functions have to be coped with [14]. On top of that, urban areas provide manifold occasions for false detections, mirror targets and clutter. This all together imposes dramatic challenges to the radar signal processing engineer.

The traditional segmentation in driving, manoeuvring and parking tasks vanishes at the driver less stage. Situation assessment and trajectory/manoeuver planning need to operate in a more thorough way. Hence, fast situational up-date, motion prediction of all kind of dynamic objects, object dimension, ego-motion estimation, (self)-localisation and more semantic/classification information, which allows to put static and dynamic world into correlation/context with each other is mandatory. All these are new areas for radar signal processing and needs revolutionary new solutions. In addition to that interoperability-interference avoidance/mitigation- of all radars per vehicle and with those already in other vehicles has to be guaranteed at the same time. This becomes more relevant with further increased market penetration and numbers of radars per vehicle [15]. The specific challenges on radar, deduced from the special traffic situations learned during the Bertha drives are described in detail in [13, 14]. A brief summary is roundabouts, crossings of all kinds, lane-change, over-/underride areas, different objects with various motion models like cyclists, pedestrians, sedan, truck buss etc., pre-crash situations from all directions, cut-in situations in merged lanes, navigation and localisation in large areas, (self-) localisation in small parking areas, parking lot identification.

As described e.g. in [4, 13, 14, 16, 17, 18], the HW-architectural solution can be achieved for example over a two-step strategy. First, enhance the imaging performance of each radar sensor. In detail, provide higher spatial (range and angle) and Doppler resolution. Endow multi Field of View (range and azimuth angle) mode capability per sensor. Employ appropriate interference counter measures and avoid the mixture of CW like (PN-code/CDMA) with FMCW based modulation schemes [15, 19, 20]. Second, equip the car with multiple radar sensors and enable them to operate as a common network- quasi as one radar organism. Adjust the radars in that way, that the dark areas vanish and the FoV´s overlap most to provide redundancy. The output of this radar-radar fusion can be considered in the subsequent fusion step as provided from a common electronic radar-skin.

The fusion of radar sensors with different cycle times can be solved e.g. with out of sequence tracking/fusion techniques as described in [7]. The Bertha configuration is shown in figure 1. The third step is purely based on signal processing. Adopt machine learning, pattern recognition and mobile robot algorithm concepts to radar data. With reference to e.g. laser scanner or vision based data, radar provides measured data in all dimensions accompanied with the Doppler velocity. Resolution and accuracy of the data are quasi constant over the entire field of view.

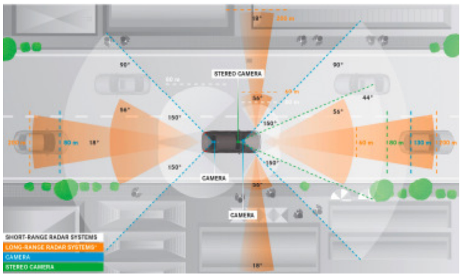

Fig. 1. Example of a radar-configuration for driver less driving, [3, 4]

This is a huge advantage of radar technology. Although radar data will never get a comparable data density like those optical sensors (at automotive costs and vehicle integration conditions), but settling time of filters, convergence of filters and dynamic parameters like relative speed will be faster, more mature and robust. System availability enhanced.

## IV. RADAR PERCEPTION APPROACHES

For some of the challenges listed above approaches to solve them are described below.

*Dense Point Cloud Generation:* This is the most important development target. With increased number of detections per target (see III), the more likely is a successful application of machine learning and pattern recognition concepts. Since each detection comes along with a Doppler value, smart representation techniques can be applied [16, 21-24, 38, 39]. One example is shown in Fig. 2. Future object representation has to provide much more enhanced information. These are object dimension, object orientation, motion-prediction and classification information. Moreover, distributed targets tend to split into many objects, which cause problems in an unambiguous representation and tracking. In order to meet automotive cost targets, a compromise between HW enabled resolution and the use of high resolution algorithms has to be found.

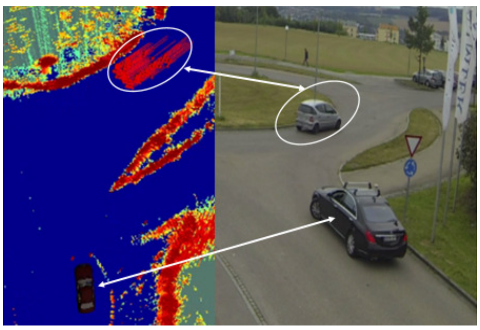

Fig. 2. Example of dense point cloud representation of dynamic objects [23].

*Radar-Grids*: Representation of the static environment is a relatively new area of radar signal processing. A method originally developed for in-door mobile robot trajectory planning are occupancy grids. The method was developed to provide a detailed 3D representation by using low resolution ultrasonic sensors [25]. Manifold modifications have been used to serve as problem solver for many different tasks during the Bertha-drive and subsequent product developments and called radar-grids. Among others they can be used for driving lane prediction, free path description, parking lot detection, SLAM for parking, landmark extraction, sensor-fusion and many more, [9-11, 26-31, 39, 46]. Figure 3 shows one example of driving lane prediction under snow conditions.

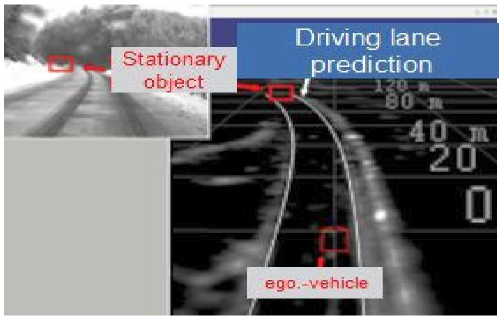


Fig. 3. Radar-Grid map as basis for driving lane prediction [9-11]

*Co-representation of static and dynamic environment:* As mentioned above, to correlate static and dynamic world is mandatory for autonomous driving. From radar-grids a free path can be derived and semantic information extracted. Correlating dynamic objects into a grid based representation allows a better understanding of the actual situation. Tracking by using local radar-grids is another method to correlate dynamic and stationary world. First results of both approaches are shown in Fig.4 and Fig.5 and described in [32-34, 36, 39].

*Ego-motion estimation:* As mentioned above, the estimation of the precise ego-vehicle's motion is a key capability for the localization of mobile robots (hence highly automated vehicles) to integrate new measurements into the radar-grid-map and tracking filter where the ego-motion has to be compensated to obtain the absolute motion of the tracked object. For radar-grids it is of similar importance. In [16, 35-38] algorithm concepts have been proposed, that allow to determine in a single shot the complete 2D motion state of the ego vehicle (longitudinal, lateral velocity and yaw rate). The key is a joint spatial- and Doppler-based Ego-Motion Estimation. It evaluates the relative motion between radar sensors with excellent Doppler resolution and their received stationary reflections (targets). Due to the Doppler information the method is very robust against disturbances by moving objects and clutter. The motion estimation is also free of bias and drift. It provides excellent results for highly nonlinear movements. The advantage compared to standard vehicle odometry sensors is that especially in slippery terrain or during high-dynamic maneuver wheel speed sensors contain nonsystematic errors due to wheel slip and slide can be compensated. They have systematic errors caused by kinematic imperfections, unequal wheel diameters or uncertainties about the exact wheelbase. The Doppler approach is insensitive to the interaction of the vehicle to the ground.

*Radar-based localization:* Radar-Grid-Loc, Reliable-Radar-Objects-Map, Semantic-Radar-Grid-Map, Radar-Landmarks are algorithm concepts used for localization and parking tasks, [39-47]. The parking manoeuver can be structured in the sub-tasks, self-localisation and mapping (SLAM), free driving path extraction, collision prevention, parking lot identification and finally parking itself into the parking lot. Localisation and mapping in urban environment faces natural long-term variation of the surroundings, for example parked cars leave its place and dustbins are transitional appearances. Robustness is achieved from multiple observation of the same location at different times as these may provide important information on static and mobile objects. For efficient mapping, the environment should be explored in parallel. The approach operates through a stochastic analysis of previous observations of the area of interest. The model uses a grid-based Markov chain to instantly model changes. An extension of this model by a Levy process allows statements about reliability and prediction for each cell of the grid [40]. The approach also provides a solution on how multiple observations represented by grid maps have to be aligned into one mutual frame. The solution is using an image processing approach of group-wise grid map registration. For registration, a rotational-invariant descriptor is proposed in order to provide the correspondences of points of interest in radar- based occupancy grid maps. As pairwise registration of multiple grid maps suffers from bias, a graph-based approach for robust registration of multiple grid maps is use. This will facilitate highly accurate range sensor maps, [40-42]. Classification using neural network or deep learning techniques allow the generation of semantic-radar-grids. This eases situation analysis and parking lot identification, [43, 44]. In [31, 46, 47] a novel Rough Cough based approach is pursued to extract landmarks using amplitude-based radar-grids for localisation in normal driving mode, where standard radar-grid map based SLAM approaches suffer from required HW resources. The Rough Cough algorithm approach enables online image recognition and registration. It is applicable to input images that can be aligned by an Euclidean transformation. Based on an extension of the Hough transform it is well-suited for massive parallel processing. Thus, the extraction of features for landmarks/features can be based on point like features as well as distributed areas the radar can detect. Radar landmarks are insensitive to different environmental changes (dark vs. bright or winter vs. summer appearance), which provide robustness and quality of service of the system.

*Motion-Prediction:* Gaining milliseconds reaction time and reducing the number of hypotheses is a key issue in situation analysis and trajectory planning. If any sensor could provide fast information about changes in the motion state of dynamic objects in the cars vicinity would make trajectory planning much easier and robust. With the exploitation of the azimuthal Doppler profile as described in [16, 24, 38] even within a single shot motion prediction of vehicles is possible by adopting the dense point cloud approach using either single radars or stereo-radar configuration,. This is illustrated in Fig.7. The figure shows the identification of a change in the yaw-rate much earlier as present day serial tracking filter can do. Hence, radar can detect yaw-rate changes earlier as a human eye can recognize any vehicle rotation. The Doppler distribution can be used as input state in tracking filters. The benefit is manifold. Transition time of the filter is drastically reduced, non – linear motion can be easily tracked and massive object information up to classification can be deduced. For example, the fact that the wheels' velocity differ from the vehicle's chassis velocity can be exploited.

*Object classification:* A spin-off of azimuthal Doppler profile analysis is vehicle classification. In [38] a fully automated approach calculates the Normalized Doppler Moment, describing the Doppler signature of each reflection based on the Doppler distributions of wheels. Locations with high values reveal the positions of the wheels. Besides the classification, the vehicle's orientation and therefore the driving direction can be estimated. Furthermore the position of the rear axle is estimated, which is essential for a reliable prediction of rotational movements and yaw rate estimation. Classification as small or large scale vehicle as well as dimension estimation can be deduced, see Fig.8.

*Sensor-fusion* between laser-scanner and radar further improves the semantic information density and dimension estimation of objects. Both sensor types are con-genial. Laser-scanner provide high resolution information about the objects contour, while radar provides Doppler information and a dense point cloud also of the "inner" part of vehicles due to the transvision effect. Thus tracking of extended dynamic objects become more reliable and robust [48-51].

## V. Open Issues

Although great progress has been already made, the following issues remain open and need further engagement and innovative solutions.

- Very-low speed or stand still imaging performance.
- Size reduction while maintaining detection performance in order to close dark areas in the 360° coverage and get sensors easier integrated into the vehicle.
- Ultra- near range detection performance, ideally close to nearly zero cm.
- Higher spatial resolution.
- Cognition/Adaptability.
- Use of the 76-81 GHz band for situation adaptive tailoring of range resolution and range coverage.
- Interoperability.

- Height measurement capability.
- Classification/Semantic capability for a more mature situation understanding.

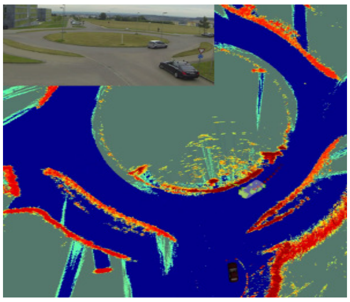

Fig. 4. Co-representation of static and dynamic objects. The dynamic object is represented by a dense point cloud into the static grid map, [23].

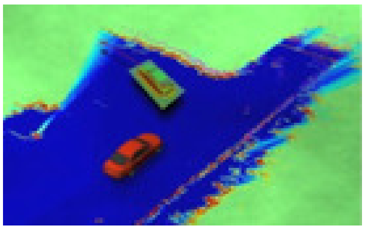

Fig. 5. Using local radar-grids in combination with a radar-grid to combine static and dynamic world in one representation is shown after [32].

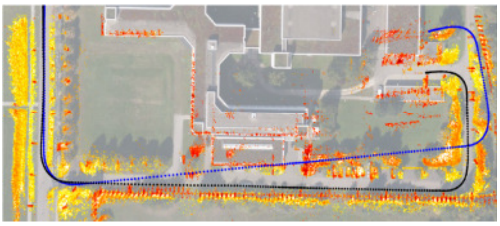

Fig. 6. Integrated ego-motion data of two radar sensors combined (black) and standard vehicle odometry (blue). Targets are mapped using radar-ego-motion and their intensity is represented by the color [yellow to red]. Start point: Top Left. (Aerial photography by GeoBasis-DE/BKG, Google), [35].

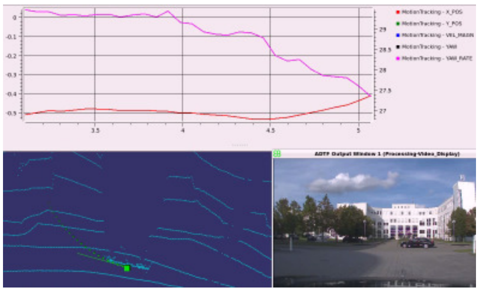

Fig. 7. Upper grahics shows the detection of the change in the yaw-rate with the new motion-prediction appoach. Lower left compares the velocity vector of a serial tracking outcome (cube) with the new approach (dots). Lower right shows the test situation.

## VI. Conclusion

The lesson learned from the Bertha drive experiment is, that present performance of serial automotive radar is not sufficient for driver less driving tasks. Future development of imaging like performance that allows for comprehensive understanding of static as well as dynamic environment including height information is a decisive factor in this concern.

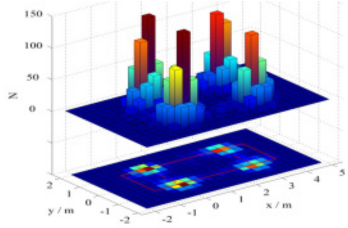

Fig. 8. Accumulated wheel detections over the complete sequence in the targets vehicle's coordinate system (contour - line, axles - dashed line), [38].

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