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ENHANCED OBJECT DETECTION AND CLASSIFICATION FOR IMPROVED ADVANCED DRIVER ASSISTANCE SYSTEMS (ADAS)

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Abstract. *As the complexity of Advanced Driver Assistance Systems (ADAS) is evolving, data from increasing numbers of experimental sensor technologies is becoming available to support automated risk assessment, action planning and decision making. An integral part of such systems is the ability to extract features from the signals of each sensor technology in order to support the proper classification of the objects detected. In this paper, candidate methods for enhanced object detection are presented and discussed based on previous practical experience from industrial applications. The enhanced object detection will be applied to the signals of a harmonic radar prototype sensor with passive and active tags. This sensor technology is part of an ADAS currently under development. The candidate techniques presented and discussed are: Fast Fourier Transform, Power Spectral Density and Target Model Identification and Parameter Estimation.*

1 INTRODUCTION

Statistics in the E.U. show that accidents resulting in fatalities or serious injuries are mainly caused by collisions of cars with Vulnerable Road Users (VRUs). In an effort to reduce these numbers, Advanced Driver Assistance Systems are being developed to integrate traffic safety applications that exist or are currently under development.

As technologies supporting detection of crashes as they occur and reactions to them have matured, focus has been shifting towards technologies that will enable the detection and identification of potentially hazardous situations before crashes occur. Future applications are expected to become more safety critical and to influence the vehicle's trajectory actively with increased "intelligence". The most promising techniques combine road user data, collected from different sensors and fused at the various processing levels of an ADAS system. One of the new techniques towards early-warning systems is the Harmonic Radar with Tags, which aims to complement conventional radars by revealing undetected vulnerable and other road users using wearable tags.

Such a technique involving the combination of conventional and harmonic radars, in parallel with several other sensor technologies, is the subject of the EC co-funded R&D project of the Framework Programme 7 "Reliable Application Specific Detection of Road Users with Vehicle On-Board Sensors" (ADOSE). Other technologies evaluated in ADOSE include Far InfraRed sensors, CMOS vision sensors, 3D range cameras and Silicon Retina Stereo sensors. ADOSE is part of an extensive effort towards the development of Advanced Driver Assistance Systems (ADAS). It deals mainly with the low-level of a typical ADAS, as shown in Figure 1 below. Specifically, the sensor device technologies and hardware, their refinement (including temporal and spatial common references) and feature extraction [1].

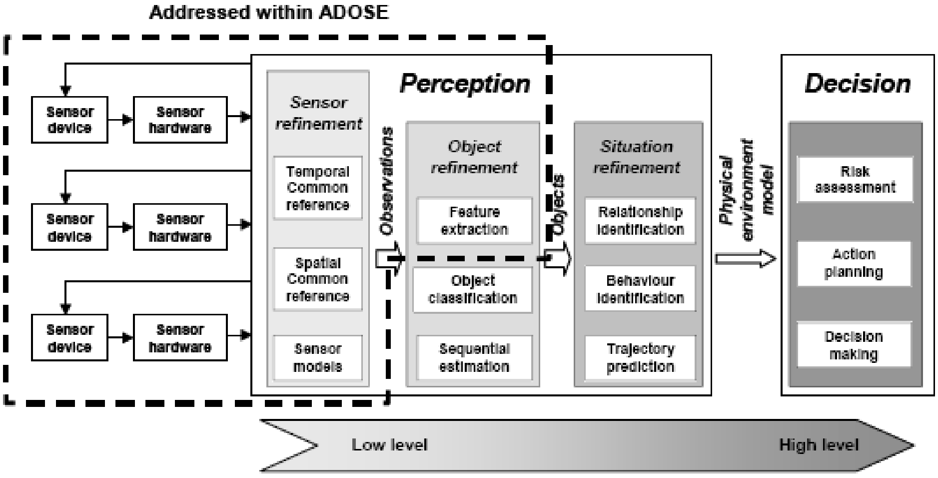

Figure 1. Data processing tasks of a typical driver assistance system and ADOSE objectives

The final area of interest within the ADOSE project is *feature extraction.* In this paper, several candidate methodologies for feature extraction are presented such as Fast Fourier Transform (FFT), Power Spectral Density (PSD) and Target Model Identification and Parameter Estimation (TMIPE). These methodologies are presented and discussed through industrial application examples. The discussions are based upon their suitability to be applied to data from the prototype harmonic radar with passive and active tags.

2 THE AUTOMOTIVE RADAR DATA

The most important properties of radar sensors are, the capability to measure with accuracy the distance & the relative velocity of the tracked target, the high weather robustness, and, the possibility for multi-target detection depending on its resolution. In addition to these typical radar measurements, it is of great interest to develop radar data processing techniques that will extract additional features of a tracked object such as *shape, orientation, profile signature, size, maneuver intention*, etc.

Conventional and Harmonic radars may work together (Figure 2) as complementary sensors (by complementing their Field of View), competitive sensors (for improved reliability and accuracy) or collaborative sensors (to derive new combined features). By combining conventional and tag returns, it is possible to detect more targets especially the smaller and vulnerable ones. Larger road users, clutter & noise often hide the smaller and Vulnerable Road Users (VRUs) from conventional radar. By attaching the harmonic tag, the road user becomes visible for the harmonic radar, which ignores anything not wearing a tag, and is easily tracked by the accompanying Radar Electronic Control Unit (ECU) software.

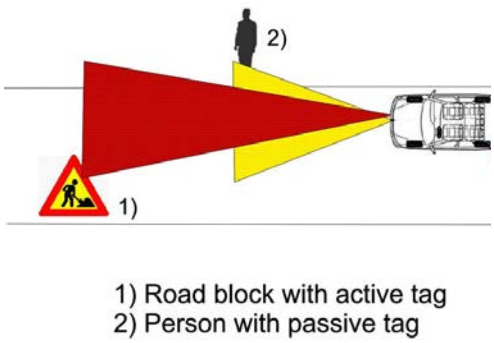

Figure 2. Combined use of passive and active tag with an harmonic radar

Once the standard processing and combination of all radar data is completed, an accurate estimate of the target’s dynamic properties becomes available and ready to be forwarded to other levels of processing or fusion technique. The raw radar data from the sensor itself, i.e. the complex waveforms as shown in Figure 3, still contain valuable information that remains to be extracted.

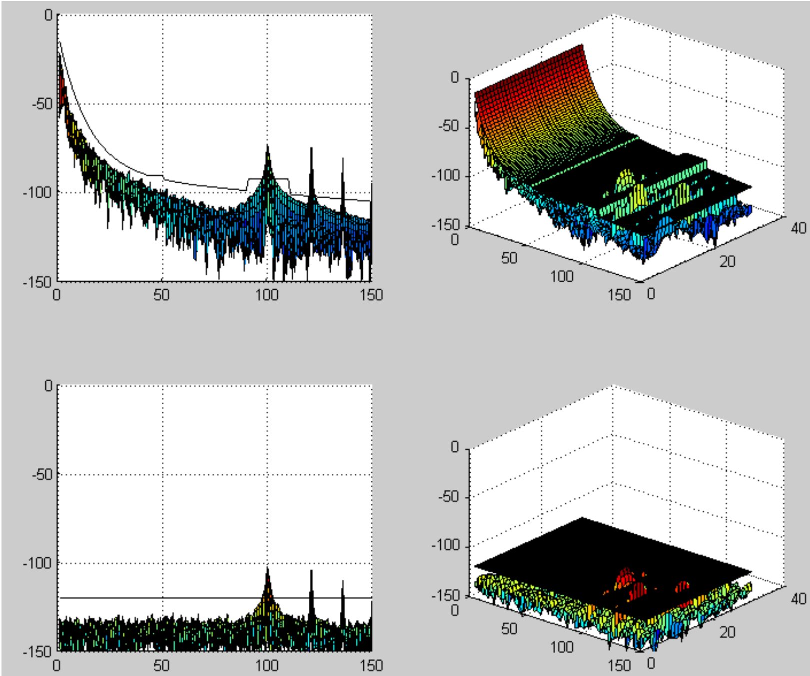

Figure 3. Simulated return signals from conventional (upper) & harmonic (lower) sensors

3 ROLE OF THE ENHANCED FEATURE EXTRACTION MODULE

The architecture of the radar Electronic Control Unit (ECU) with the processing algorithms is modular and consists of several modules and sub-modules (Figure 4). The major modules include those for: the I/O, the measurement data pre-processing & detection for each radar sensor, the car sensors, the track maintenance, filtering, track prediction, and the enhanced features extraction. The *enhanced feature extraction* module aims to identify the additional defining characteristics besides *position*, *velocity* and *acceleration* that will enhance our perception of the tracked object. These characteristics can be signal properties or behavior patterns such as: *shape*, *orientation*, *profile signature*, *size*, *maneuver intention*, etc.

From each radar category a different set of information, regarding the Road User, will be extracted. The conventional radar returns depend on the size, orientation and reflectivity of the object, as well as, on its shape and its Radar Cross-Section (RCS). On the other hand, the harmonic radar returns depend on the reflecting tag, its size and orientation, and its technology (passive or active) or returned information. The estimated dynamics may also provide more information such as road user orientation, user dynamic model, user mobility status, etc., that can be extracted with the proper estimation & identification algorithms. Groups of identical reflections might also be determined, e.g. road barriers or intersections, even groups of pedestrians and their location with respect to road limits.

In summary, this module will attempt to extract enhanced features of three main types:

1. Object Appearance Features
   - Pattern analysis of the road user size/shape from conventional data (signatures).
   - Road user RCS analysis and comparison to a signature database
   - Road user RCS changes in relation to its trajectory direction
   - Harmonic return analysis in relation to the tag technology & return signal
   - Harmonic return analysis in relation to the size of the tag
   - Harmonic return analysis in relation to tag orientation and the line-of-sight
2. Object Dynamic Features
   - Dynamic parameter estimation of the road user
   - Dynamic model identification of the user behavior and maneuver detection
   - Radar Car related dynamics of the road user (static/moving/collision/etc.)
3. Combined Features
   - Single or group of users
   - Environment features
   - Maneuver intention

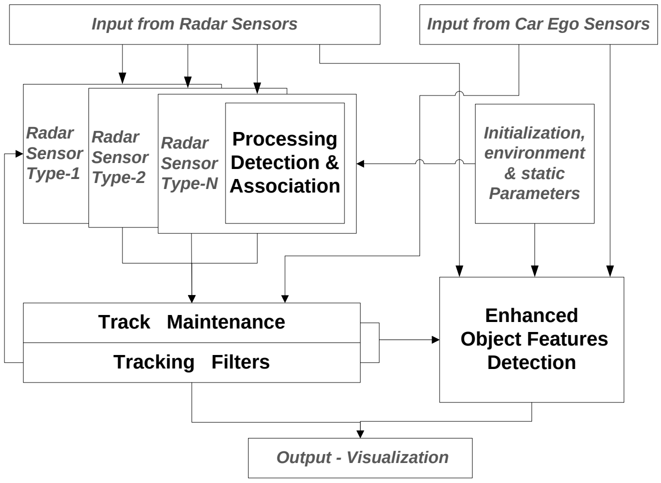

Figure 4. The Intelligent System for Enhanced Features Detection in the overall Radar ECU architecture.

4 CANDIDATE FEATURE EXTRACTION METHODOLOGIES

4.1 Fast Fourier Transform

A major challenge in the aeronautics industry is the reduction of emitted pollutants, which translates to the reduction of fuel consumption. One of the possible solutions for achieving this goal is the reduction of aerodynamic drag caused by the turbulent flow. Such reduction can be achieved by delaying the transition from laminar to turbulent flow resulting in reduction of the drag. When the flow in the front part of the wing is laminar, the dominant cause of transition from laminar to turbulent flow are the Tollmien–Schlichting (TS) instabilities.

The TS instabilities are generated by external disturbances which propagate downstream. These instabilities were first predicted by Tollmien in 1929, their growth rate was calculated a few years later (1933) by Schlichting and the first experiments which proven their existence were conducted by Schubauer and Skramstad in 1948.

There are in general two possible approaches for reducing the TS instabilities: passive, which involves utilizing the properties of materials and geometric shapes on the wing surface to interfere with the generation of the instabilities, and the active approach, which involves the use of sensors along the flow to detect the instabilities as they are generated and actuators to react to the instabilities and dampen them.

In figure 5 an example of TS instabilities is shown, where one can observe the erratic nature of the signal[2]. The active approach for reduction involves determining the signal in question in order to calculate and reproduce it with a difference of 180^{o} degrees in phase in order to cancel each other out. In this case, this approach would be extremely intensive computationally and there is also the factor of time to consider. The flow is travelling at high speeds and the active system used must be able to measure the signal and create the counter-signal fast enough to generate it at the actuator location before the flow has passed it by.

This approach can be simplified if certain characteristic features can be extracted from the signal. In this case, FFT was applied to analyse the frequency content and amplitude of the signal (Figure 6). From resulting FFT plot one can determine the few major contributing frequency components that characterise the TS instabilities for the given experimental setup and flow velocity. Thus, the active flow control approach can be focused on the specific frequencies in order to tackle the major part of the phenomenon while requiring considerably less computational power and time to calculate the proper attenuation signal.

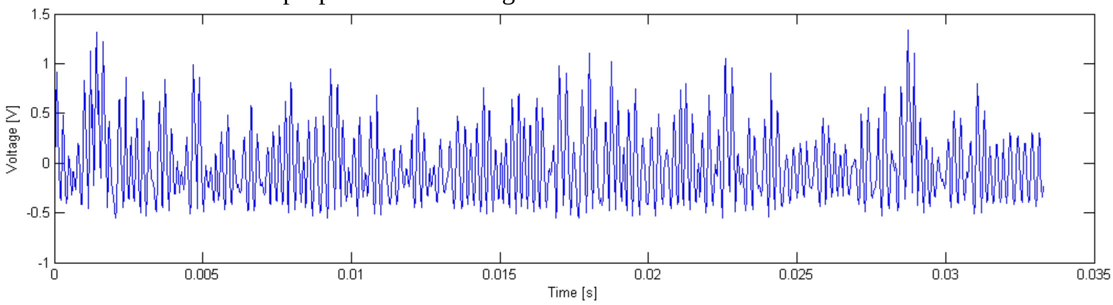

Figure 5: Signals from sensors acquired without operating the control

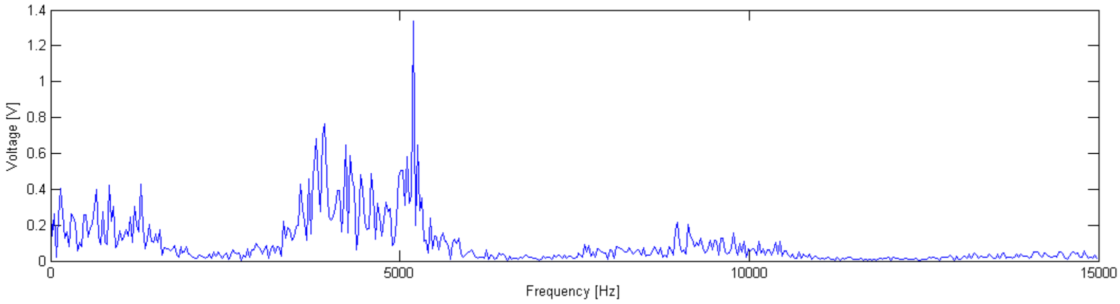

Figure 6: Spectra of the signals acquired from sensors without operating the control

4.2 Power Spectral Density

An important issue in aircraft maintenance is the proper detection of faults that occur in the aircraft's engine. In such an application, the authors developed an Artificial Neural Network for fault detection on a radial compressor[3]. The goal was to be able to determine faults with the least possible amount of measurement data. In such industrial applications, the time and cost involved in performing tests and measurements is critical. The approach followed for this application involved the use of components which corresponded to the Blade Pass Frequency, the first harmonics and the sub-harmonics of the vibration spectrum of the engine's radial compressor (one of the engine's main components). Measurements were made for vibration, pressure and sound at multiple operating points for normal and fault operation conditions.

For each set of acquired data the Power Spectral Density (PSD) was calculated. The PSD is defined as the Fourier Transform of the autocorrelation sequence of the time series. An equivalent definition of PSD is the squared modulus of the Fourier transform of the time series, scaled by a proper constant term. The PSD describes how the power (or variance) of a time series is distributed with frequency.

Then the difference in the PSD data between the healthy and faulty condition was calculated. From the resulting PSD the "fault signature" was obtained by extracting only the data corresponding to the rotor orders which to multiples of the rotational speed. Thus the data resulting from this procedure constitute of a vector of values and each value is the PSD difference value for the corresponding rotor order. This procedure is depicted in figure 7.

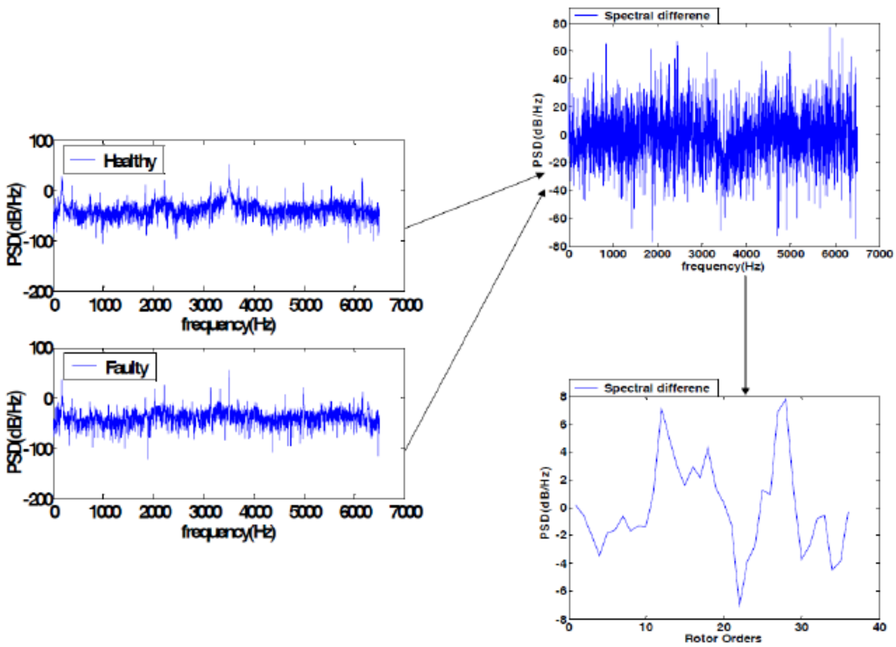

Figure 7. Procedure followed for obtaining the input data used for the fault detection technique

A fault signature vector was calculated for each measurement point for each fault type. In order to have better diagnostic results, good degree of discriminability amongst the signals should be achieved. Furthermore the division of the performance curve into different ranges allows a grouping of the signatures. Thus before using these data for the fault detection technique, a normalization of the data was performed.

In the community involved in vibration analysis of turbo-machines, as well as active noise and vibration control in propeller aircraft, it is a well-known fact that unsteady blade row interactions generate discrete frequency tones at blade pass frequency and its harmonics. The blade pass frequency (or rotational frequency of the blades) is the rate at which the blades pass by a fixed position. The Blade Pass Frequency (BPF) equals to the number of blades times their rotational speed. This behaviour has also been observed, as expected, in the present experiment. The evidence of this behaviour is shown in Figure 8 where the Power Spectral Densities for acceleration and fluid pressure are plotted for both the healthy and the faulty condition.

Thus, based on the specification of the radial compressor, the authors decided that the input of the ANNs will initially consist of the following three data, aiming is utilizing the minimum amount of data necessary:

- the first blade pass frequency
- the second blade pass frequency
- the third blade pass frequency

The resulting ANN successfully identified faults of the radial compressor based on the features extracted from the Power Spectral Densities of the acceleration and fluid pressure.

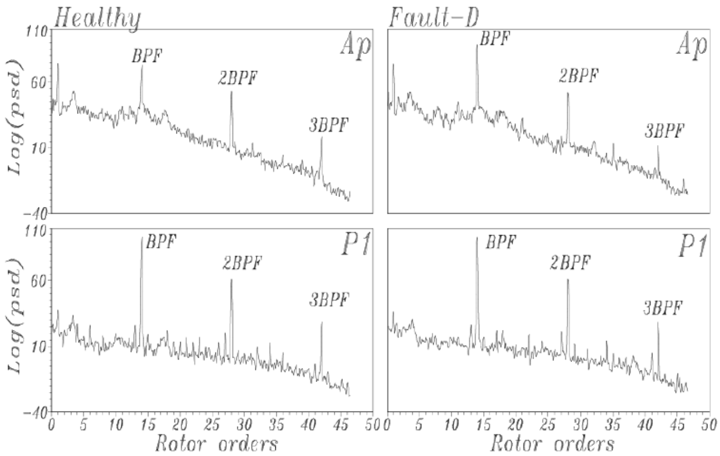

Figure 8. Acceleration (upper plots) and fluid pressure (lower plots) Power Spectral Density plots for healthy and faulty conditions

4.3 Target Model Identification & Parameter Estimation

While the methodologies discussed above mainly apply to the raw radar signals of each return, object features can also be extracted by tracking an object's acceleration and direction criteria over time. Typical object tracking uses linear techniques such as *linear Kalman filters* that are adequate for simple tracking schemes [4,5]. Kalman filter tracking uses a linear dynamic model of the target or road user that handles its position, velocity and acceleration (state vector *x*). In order to detect and extract more properties of a tracked object, behavioral categories or *user models* can be defined which incorporate specific parameters and relationships observed and defined from the target returns over time. The resulting user models are in general nonlinear and/or with structural uncertainties. The enhanced user models require more elaborated techniques for state & parameter estimation.

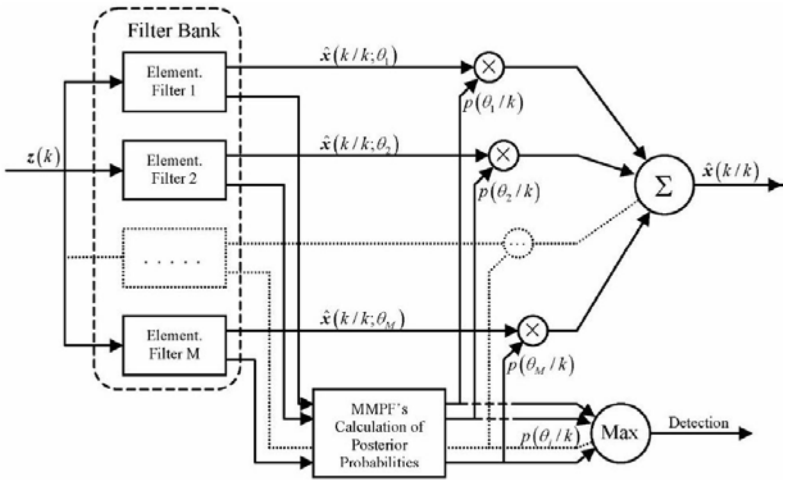

Figure 9. The general structure of the Multi-Model Partitioning Algorithm.

Depending on the parametric or structural uncertainty, several techniques may be applied for estimation and identification of the unknown road user features. Nonlinear filters such as the Extended Kalman Filter (EKF) are adequate for some cases, while the more general adaptive or multi-model partitioning algorithms (MMPA) may handle almost any user model uncertainty case. The MMPA use a parallel bank of Kalman or EKF, which operate concurrently on the same radar measurements (Figure 9). Each filter is based on a different dynamic road user model.

Based on its weighting factors p the MMPA algorithm adaptively selects for each road user a model that corresponds to the maximum a posteriori probability. If the road user behavior, i.e. the model parameters θ, change the algorithm senses the variation and adjusts the corresponding a posteriori probabilities. The multi-model partitioning algorithm is adaptive in the sense of being able to track model changes in real time.

5 NEXT STEPS

The radar ECU software developed for the harmonic radar prototype has been tested using simulated radar data and scenarios of variable complexity. Special tools have been applied or are being developed to support the testing procedure. The methodology for enhanced feature extraction module remains to be finalized and developed, upon the production and analysis of the first experimental data sets from the harmonic radar prototype, still under development at the time of publication. When finalized, the radar and its ECU will be installed on an experimental vehicle of the ADOSE project, for Demonstration of operation in real-life scenarios.

6 CONCLUSIONS

Systems such as ADAS, which incorporate different sensor technologies, require methodologies to determine and extract features from the signals of each sensor that will aid in the classification of objects identified in order to support automated risk assessment, action planning and decision making. The introduction of new sensors, such as the Harmonic Radar, in an ADAS system requires complex processing software architecture. The radar ECU, in addition to the classic detection and tracking tasks, must perform an early fusion of the complementary radar data to reveal undetected road users.

Candidate methodologies for enhanced feature extraction were presented and discussed through industrial application examples. As soon as the first experimental data sets become available from the harmonic radar prototype currently under development, these methodologies will be applied and tested in practice in order to formulate the finalized enhanced object detection module of the harmonic radar ECU.

7 ACKNOWLEDGMENTS

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