A noise analysis of 4D RADAR: robust sensing for automotive?

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Abstract

The sensor suite for assisted and automated driving functions vehicle is critical to the function of a vehicle, but also the first and most important limitation to the level of automation that the system can achieve. The advancement of 4D RADARs, providing better resolution in both azimuth and elevation compared to traditional RADAR, can assist to achieve more robust situational awareness, whilst also providing more data for perception algorithms and sensor fusion. However, like all perception sensors, 4D RADAR is also affected by numerous noise factors. To explore the sources of noise, this work identifies, classifies, and analyses automotive 4D RADAR noise factors. Overall, 22 noise factors have been considered, in combination with their effect on six 4D RADAR outputs. Finally, this work also presents and applies, for the first time, a dissimilarity metric to collected 4D RADAR data in the presence of rain with different intensities. The proposed metric is used to assess the effect of noise on the variability of the measured data, in addition it can be used to compare any 4D RADAR data. The metric, combined with other pointcloud evaluations, shows that as rainrate intensifies, the size of the pointcloud decreases, but also the variation in the measurements increases. This work presents the importance of evaluating, companding, and quantifying noise for 4D RADAR, and can pave the way for more in depth analysis of its modelling and testing of 4D RADAR for assisted and automated driving functions.
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Abstract—The sensor suite for assisted and automated driving functions vehicle is critical to the function of a vehicle, but also the first and most important limitation to the level of automation that the system can achieve. The advancement of 4D RADARs, providing better resolution in both azimuth and elevation compared to traditional RADAR, can assist to achieve more robust situational awareness, whilst also providing more data for perception algorithms and sensor fusion. However, like all perception sensors, 4D RADAR is also affected by numerous noise factors. To explore the sources of noise, this work identifies, classifies, and analyses automotive 4D RADAR noise factors. Overall, 22 noise factors have been considered, in combination with their effect on six 4D RADAR outputs. Finally, this work also presents and applies, for the first time, a dissimilarity metric to collected 4D RADAR data in the presence of rain with different intensities. The proposed metric is used to assess the effect of noise on the variability of the measured data, in addition it can be used to compare any 4D RADAR data. The metric, combined with other pointcloud evaluations, shows that as rain rate intensifies, the size of the pointcloud decreases, but also the variation in the measurements increases. This work presents the important of evaluating, companding, and quantifying noise for 4D RADAR, and can pave the way for more in depth analysis of its modelling and testing of 4D RADAR for assisted and automated driving functions.

Index Terms—Assisted and automated driving, RADAR, Noise Factor, Pointcloud evaluation.

I. INTRODUCTION

Perception sensors are key to enable the autonomy of vehicle driving tasks (e.g. longitudinal and lateral control of the vehicle). In addition, the demand for safe deployment of assisted and automated driving (AAD) functions on road vehicles is continuously increasing, both in government legislation and testing standards such as the new car assessment program (NCAP) [1], [2]. To meet legislation requirements and score high in safety testing, it is expected that more perception sensors will be integrated into road vehicles, allowing safe automated control during a variety of situations. In this context, vehicle manufacturers are striving for higher levels of driving automation, to relive the drivers from tedious driving tasks, improving safety and productivity. In fact, the Society of Automotive Engineers (SAE) has defined 6 levels of driving automation, from level 0 which provides only warnings to the driver, to level 5 where the automated system has full control on the vehicle without need of human intervention [3]. For example, to enable a Level 4 equipped vehicle, it has been evaluated that the estimated number of perception sensors is in excess of 30 units, to provide enough coverage and redundancy [4].

The perception sensors deployed in an automotive sensor suite for assisted and automated driving functions generally comprise of a combination of RADARs, cameras, ultrasonics, and recently some automotive manufacturers have been adopting LiDARs as well, e.g. Volvo, Xpeng, etc. [5], [6]. A suitable selection of sensor technologies is required to ensure that the overall perception of the environment is correct, no matter the situation. The automotive environment on the roads is unpredictable, containing high variability, from natural events, such as rain or smog, to human created events, such as minor alteration of speed signs with stickers [7]. This variability can be linked to an increased number of noise factors, that can affect sensor outputs and uncertainty on the sensor measurements, and it can affect each sensor differently due to different operating principles [8]. RADAR has been considered one of the most robust sensor technologies in automotive, due to the fact that conditions like fog, rain, luminosity, etc. have a lower impact on RADAR data with respect to other technologies [8]. However, traditional RADAR has inadequate resolution, and it is not very suitable to detect small objects or vulnerable road users, VRUs, so traditionally it has been used mainly for the detection of big moving objects, e.g. detecting vehicles in the front of the ego vehicle for Adaptive Cruise Control [9].

A. 4D RADAR vs standard RADAR in automotive

Despite the progress in the RADAR technology, with the advent and progressive cost decrease of its antagonist, i.e. the LiDAR (Light Detection And Ranging), several stakeholders have started to question the utility of RADAR, given that its resolution and accuracy cannot fully compete with its infra-red waves based adversary [8]. However, another leap forward by sensing technology has been achieved by the development and production of automotive Imaging RADAR or 4D RADAR (e.g. such as the Continental ARS 548 RDI, Arbe Phoenix Perception Radar [10], [11]), Table I. This type of RADARs produces a LiDAR-like point cloud, giving 3D points of targets/objects.
in the environment, Fig. 1. Moreover, for each detected point, the 4D RADAR provides other measurements (as for conventional RADAR), such as RADAR cross section (RCS) value, relative velocity (between target and ego vehicle), and detected power. One main advantage of the 4D RADAR is that it provides enhanced (smaller) angular and vertical resolution with respect to traditional RADAR. A comparison of the specifications between a traditional automotive RADAR (i.e. the Continental ARS-408) and a 4D RADAR from the same supplier (i.e. the Continental ARS-548) is provided in Table I. This enhanced spatial resolution of 4D RADAR is critical to allow the distinction of small objects close to each other (e.g. VRU) or small objects close to bigger ones (e.g. trucks), or to enable the separation of multiple objects in the far range. Automotive 4D RADAR can give an understanding of the vehicle surroundings (even if resolution and number of points in the point cloud are still inferior with respect to LiDAR), with additional information with respect to LiDAR and with improved weather/environmental robustness [12].

4D RADAR technology is still not widespread in automotive, however, some recent freely available automotive datasets have been created and curated including also the data collected by 4D RADARs, e.g. [13], [14]. In Table II, there is a comparison of recent datasets containing 4D RADAR data for automated functions. Overall, all the datasets contain at least the 3D spatial location of detected points and the speed (or relative speed) of the detected ‘objects’. Some of them also have more variability in terms of including different weather conditions, which is very useful when data degradation needs to be investigated.

B. Noise Factors and automotive perception sensors

Given the importance of the quality of the data provided by the sensor suite, the number of recent works around perception sensors and the effect of weather conditions has increased dramatically [16]–[26]. Moreover, some novel works have proposed to explore and analyse in a holistic way the noise factors which camera and LiDAR are exposed to in the automotive environment, studying the effect of single and compound noise factors [27]–[29]. This paper expand the previous work to consider also 4D RADAR, which is the future of RADAR sensing in AAD [30]. There are a vast array of internal and external noise factors which will affect the data produced by each perception sensor, and this degradation can have implication on perception algorithms and on the overall automated system. Some of these noise factors can be common between the sensors, such as weather, whilst others can be more specific to each sensor, such as lens effects for camera or radome effects for RADAR [31], [32].

C. Contributions

In order to ensure safe assisted and automated driving functions, the understanding of sensor data degradation is key. This work aims to analyse a sensor technology which could shape the way of future autonomy, namely 4D RADAR. Building on previous works on noise factor analysis in automotive, the contribution of this paper are listed below [27], [28].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>ARS-408 (Far Range)</th>
<th>ARS-548 RDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>76-77 GHz</td>
<td>76-77 GHz</td>
</tr>
<tr>
<td>Max Range</td>
<td>250 m</td>
<td>301 m</td>
</tr>
<tr>
<td>Range Resolution</td>
<td>1.79 m</td>
<td>0.22 m</td>
</tr>
<tr>
<td>Azimuth Beam Width</td>
<td>2.2°</td>
<td>1.2°</td>
</tr>
<tr>
<td>Elevation Beam Width</td>
<td>N/a</td>
<td>2.3°</td>
</tr>
<tr>
<td>Antenna Channels</td>
<td>2 Tx/6 Rx</td>
<td>12 Tx/16 Rx</td>
</tr>
<tr>
<td>Virtual Channels</td>
<td>12</td>
<td>192</td>
</tr>
<tr>
<td>Peak Power</td>
<td>12 W</td>
<td>23 W</td>
</tr>
</tbody>
</table>
TABLE II
A COMPARISON OF DATASETS CONTAINING DATA COLLECTED WITH 4D RADAR. IN THE TABLE, THE OUTPUT ‘LOCATION’ CAN BE IN THE FORM OF A POINTCLOUD, THREE DIMENSIONAL CARTESIAN CO-ORDINATES, OR POLAR CO-ORDINATES

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Automotive Use</th>
<th>RADAR Model</th>
<th>Number of Frames</th>
<th>Frame Rate</th>
<th>Data Format</th>
<th>Weather</th>
</tr>
</thead>
<tbody>
<tr>
<td>Astyx (2019) [33]</td>
<td>✓</td>
<td>Astyx 6455 HiRes</td>
<td>~8600</td>
<td>13 Hz</td>
<td>Location, Doppler, Intensity</td>
<td>Day</td>
</tr>
<tr>
<td>RADIal (2022) [34]</td>
<td>✓</td>
<td>Valeo DDM</td>
<td>~25k</td>
<td>5 Hz</td>
<td>Location, Doppler</td>
<td>Day</td>
</tr>
<tr>
<td>View-of-Delft (2022) [13]</td>
<td>✓</td>
<td>ZF FRGen21 3+1D radar</td>
<td>~8693</td>
<td>13 Hz</td>
<td>Location, Radial velocity, Compensated radial velocity, RCS, Time</td>
<td>Day</td>
</tr>
<tr>
<td>K-Radar (2023) [14]</td>
<td>✓</td>
<td>Retina 4ST</td>
<td>~35k</td>
<td>10 Hz</td>
<td>Location, Doppler</td>
<td>Day, Night, Overcast, Fog, Rain, Sleet, Snow</td>
</tr>
<tr>
<td>WaterScenes (2023) [36]</td>
<td>X</td>
<td>Oculii Eagle 4D Radar</td>
<td>~54k</td>
<td>15 Hz</td>
<td>Location, Power, Doppler</td>
<td>Day, Night, Adverse weather</td>
</tr>
<tr>
<td>MSC-RAD4R (2023) [37]</td>
<td>✓</td>
<td>Oculii Eagle 4D Radar</td>
<td>~91k</td>
<td>15 Hz</td>
<td>Location, Power, Doppler</td>
<td>Day, Night, Snow, Artificial fog</td>
</tr>
<tr>
<td>4D Radar Dataset - Autonomous Robot Lab (SJTU) (2022) [38]</td>
<td>✓</td>
<td>ZF FRGen21 3+1D radar</td>
<td>~40k</td>
<td>16 Hz</td>
<td>Location, RCS, Power, Velocity, SNR</td>
<td>Not Specified</td>
</tr>
</tbody>
</table>

1) It presents the state of the art of the use of 4D RADAR in automotive;
2) It considers the specific noise factors that would affect its outputs. This analysis is pivotal for any future design of automated functions based on 4D RADAR.
3) It offers a thorough analysis of which outputs of a 4D RADAR sensors would be affected by the different noise types. Future works will be using this analysis to build adequate noise models for RADAR.
4) It proposes a novel dissimilarity metric to evaluate the degradation of 4D RADAR data.
5) It shows how the novel proposed metric can be applied to real world noisy data, and how data degradation correlates with increased adverse weather.

On the contrary of most of recent works, focused on analysing the effect of a single noise factor on the sensor output, this work highlights the importance of considering multiple noise factors acting simultaneously. This step is the first and most important to build models to compound noise factors and to validate them using the proposed metrics. This paper can strongly contribute to any perception or fusion research which will be based on novel 4D automotive RADAR, and the proposed metric is applicable to validate sensor noise models and to evaluate the quality of produced data.

II. BACKGROUND

This section starts with a short review of the use of RADAR for automotive, and then presents specifically the use of 4D RADAR for AAD functions, looking also into works focusing on noise factors.

A. Use of RADAR in automotive

When the first safety features were introduced onto commercial vehicles (such as automatic emergency breaking, adaptive cruise control, blind spot monitoring, etc.) RADARs started to be considered as a viable sensing solution, as they could provide the possibility to detect targets in the sensor Field of View (FoV), and also they could measure the distance (and the relative speed) of these targets. Moreover, RADAR offered some clear benefits with respect to cameras, e.g. increased robustness to adverse weather, but they were bulkier and more expensive. Particularly the cost of devices in the 77 GHz bandwidth was prohibitive. It is reported that the first 77 GHz automotive RADAR for passenger cars was deployed in 1998 by Mercedez Benz [39]. Through the years, with the introduction of SiGe detectors, and antenna real and virtual
beamforming, both the cost and the size of these devices have been made compatible with automotive requirements. Several commercial vehicles have RADARs seamlessly embedded behind front bumpers or in other suitable positions. This evolution has been promoted by the use of assisted and automated driving functions in more and more vehicles, and by the requirements related to active safety dictated by programs such as NCAP. In the meantime, the antenna technology and algorithms have carried on with their progress, and RADARs have achieved improved angular and velocity resolution, see Table I. This progress is demonstrated also by the recent advent of 4D RADAR, which is a strong competitor of LiDAR, given that LiDAR is still more susceptible to environmental conditions [40].

B. 4D RADAR for assisted and automated driving

Related to safety standards and evaluation, frameworks like Euro NCAP have proposed and developed a set of tests to assess the safety of specific functions on road vehicles. Currently, there are 5 assessment categories: general, adult occupant protection, child occupant protection, VRU protection, and safety assist. In the safety assist collision avoidance testing criteria, there are clear benefits to be able to detect the speed of a target vehicle in front. Out of the perception sensors, RADAR would provide target velocity, and it is relatively more robust under different weather and lightning conditions. In addition to that, 4D RADAR provides enough resolution to be able to detect VRU, and the algorithms related to 4D RADAR detection, and VRU in particular, are evolving rapidly [41], [42], as further discussed in the next paragraph. Tables I-II provide a good summary of the specifications of a commercial 4D RADAR and also of what type of 4D RADAR data can be found in recent freely available automotive datasets.

There are several works using the above mentioned datasets and 4D RADAR data to implement improved perception; some papers are based on re-using previously proposed deep neural networks (DNNs) for LiDAR pointclouds [13], others propose ad hoc solutions, particularly addressing the issue related to the sparsity of the data [42]–[45]. Palffy et al. proposed for the first time to apply a LiDAR PointPillars architecture to 4D RADAR data to implement 3D object detection on the VoD dataset. In an ablation study, they demonstrate the positive effects of having elevation and speed in the 4D RADAR data, and they show improved performance with respect to other techniques (PointPillars is used as baseline) [43]. Cheng et al. developed a UNet based architecture which detects targets and learns their distribution in more complicated scenes. RPDNet outperforms traditional techniques to identify points belonging to objects, while removing noise and clutter. The Authors used a self collected dataset, exploiting LiDAR to automatically generate labels for the dataset [44].

Moreover, there is a significant number of works proposing to integrate sensor fusion using 4D RADAR data to improve the overall perception performance [36], or to use camera-4D RADAR or LiDAR-4D RADAR fusion to improve the 3D object detection capability using only data generated by a sensor type [41], [46]. For camera-4D RADAR fusion, the addition of camera data significantly improves the perception performance, particularly related to VRU and to far static vehicles. Also the combination LiDAR-4D RADAR shows improved performance with respect to state of the detection using only LiDAR.

C. Works on automotive RADAR noise

RADARs are used in a wide variety of fields, from terrestrial surveys to medical and physiological sensing, each being affected by a different set of noise factors. Doerry has provided an overview of underlying principles of noise related to the RADAR hardware and basic principles, and a method to measure and quantify this type of noise, generally arising from background electromagnetic noise, temperature, current stability or signal processing [47].

There are numerous works investigating noise factors which have a significant effect on automotive RADAR, ranging from vehicle bumpers and paint, to weather effects [25], [48]. RADARs are generally placed at the front of the vehicle, allowing for unrestricted view of the area in front of the ego vehicle. Often, they are placed behind the front bumper or locations such as behind the manufacturer’s badge. Dash et al. investigated the effect of a vehicle bumper on a MIMO RADAR [48]. Vehicle bumpers can cause a reduction in transmitted power, and may also alter the radiation profile and affect the ambiguity in estimating the direction of return. The Authors simulated the MIMO RADAR with a curved bumper model of different relative permittivity. The results show that the bumper creates a bi-directional loss, but the loss does not increase as the relative permittivity increases [48]. Vehicles can also come in a variety of colours, Winter et al. presented a work on the permittivity of the coating layer of a vehicle bumper [49]. Each layer of the bumper (substrate, basecoat and clearcoat) has an associated loss which can be calculated theoretically and compared with real measurements. Interestingly, two different colours of paint were used and measured (green and silver) and there is a 0.2 dB difference in their transmission [49]. Some manufactures are also integrating RADAR into the vehicle’s front grill to avoid the losses associated with passing through the bumper. However, this placement exposes the RADAR to the external vehicle environment. Norouzian et al. presented signal reduction measurements of a radome being contaminated with various materials which vehicle could encounter, such as water film, sand, ice, fuel and leaf. At 77GHz, water films and fresh leaves creates the highest signal reduction [26]. Additionally, Norouzian also performed attenuation measurements during different snow events with different snowfall intensities (with wet and dry snow fall). In both scenarios, there is a increase in attenuation as the snowfall rate increases [26]. Gourva et al. used an indoor weather simulation facility for fog and rain to measure the
influence on RADAR detection. Different automotive targets, such as a car and traffic signs are placed in the field of view of the radar, within the weather generated. The Authors stated that fog generated did not impact the radar measurements. However, the generated rain caused increased variations in the detected point locations, velocity and RCS [25].

Paek et al., the creators of the K-Radar dataset, have also presented the results generated by a perception algorithm in different weather conditions to compare 4D RADAR to LiDAR [14]. The authors used Radar Tensor Network with Height (RTNH) with the captured 4D Radar Tensor data to create 3D bounding boxes for detected objects. These results were compared against detection performance using a neural network with 2D-DCB backbone (RTN). The results show that the inclusion of height information is beneficial and increases the accuracy of the detection, showing the importance of the increase elevation resolution of 4D RADAR. Compared to LiDAR PointPillars performance in detection, the RTNH results using the 4D RADAR measurements provided better performance across the different weather conditions, especially during the fog and snow events [14].

In the work by Lutz et al., the Authors identified that clustering algorithms of 4D RADAR data can be heavily influenced in case of extremely noisy data and might incorrectly identify points [50]. As a consequence, the Authors employed different trained classification algorithm to identify noisy RADAR points, and used them with DBSCAN algorithms. The results showed that noise removal in the Astyx HiRes 2019 dataset can improve the clustering V-Measure performance [50]. However, there hasn’t been works providing an overview of noise factors affecting automotive radar sensor in general, and even more on 4D RADAR.

As previously mentioned, and as demonstrated by most of the works discussed in Sections I-II, automotive perception sensors are exposed to numerous noise factors which affect the quality of the output sensor data, however most of the works are focusing on analysing the noise factors one by one in isolation. Some commonly investigated noise factors are weather (such as rain, snow and fog) and water films on sensor [25], [26]. However, recent works have started to propose a more holistic approach to noise factor analysis, and in fact Chan et al. and Li et al. have developed a framework to break down the noise factors on LiDAR and camera, identifying 16 and 30 factors respectively [27], [28]. In this noise framework, the five types of noise specified in the p-diagram are carefully considered to determine a list of sensor specific noise factors, and for each noise factor, its effect on specific sensors outputs is discussed. This paper leverages this previous work and applies it for the first time to 4D RADAR, moreover discussing how 4D RADAR data can be mutually compared (point cloud to point cloud comparison).

III. ANALYSIS OF 4D RADAR NOISE FACTORS AND DATA DEGRADATION METRICS

This section presents a breakdown of the noise factors affecting 4D RADAR, some criteria when selecting the noise factors and the main 4D RADAR outputs data that will be affected. Finally, the section shows how the noise in 4D RADAR pointclouds can be quantified, by applying the metrics proposed in the previous section to 4D RADAR data collected in a weather facility.

A. Criteria for the analysis

A general block diagram of an automotive RADAR is shown in Fig. 2, as mentioned before the working principle is similar to traditional RADAR. Noise can be introduced at each of these steps, but this paper focuses on the effect of these internal noise factors and of external ones on the outputs of the RADAR, i.e. the “Point Cloud Detections” block in Fig. 2.

This work presents a breakdown of associated noise factors for automotive 4D RADAR in Table III. This table was composed using the framework first presented by Chan et al. [27]. To better define the noise factors described in the table, some criteria were established to analyse RADAR.

1) Noise factors are grouped into categories, when possible, e.g. ‘weather’ noise encompasses rain, snow, fog, etc.
2) Noise factors are considered as causing variations of the sensor output data that would increase uncertainty of the measurement above the nominal value.
3) Any factors which may affect the processing outside of the sensor, e.g. misalignment in sensor suite positions affecting sensor fusion, are not considered.
4) Noise factors which are mitigated by processing such as calibration as still included since the sensor data is still affected (and calibration might change over time).
5) ‘Corner cases’ are not included in the list of noise factors, this is clarified in Sec IV-A.

B. Affected outputs of the sensor

For each one of the noise factors identified in Table III, it is considered if they will affect the following 4D RADAR outputs:

1) location - the detected point location in Cartesian or polar co-ordinates relative to the RADAR’s co-ordinate system;
2) max range - the maximum range at which a target can be detected;
3) RCS - the Radar Cross Section is an estimation of how reflective is the target for the specific RADAR frequency...
(it is based on the size, material properties, angle of incidence on the target, etc.);
4) velocity - the differential radial velocity of the detected point can be calculated using Doppler effect;
5) target Power - it is the power reflected back to the RADAR receiver for each detected point (it depends on emitted power, RCS, other propagation and noise losses, etc.);
6) Signal to Noise Ratio (SNR) - it is value estimated by the RADAR based on target power and an evaluation of the noise floor.

One effect arising from some noise factors, but not a output parameter which is specified in the following section, is the variation in emitted frequency. This can arise from component noise in the oscillator, or movement of the radar due to causes such as vibrations and vehicle speed. Often, these variations can be balanced by feedback and does not affect the final output. If not accounted for, emitted frequency variations can affect all of the outputs listed above.

C. Evaluation of Noise effect on 4D RADAR data

The work in automotive to establish the quality of perception sensors’ data is scarce and sparse. For camera, some of the work on image quality can be reused and there is the IEEE P2020 committee working to propose a common way to assess image quality for automotive, to date LiDAR and RADAR data are assessed in different and inadequate ways. To the best of the Authors’ knowledge no works have proposed metrics to quantitatively establish the degradation of 4D RADAR data.

This paper proposes for the first time to use a distance-based probability distribution function (PDF) to have an estimation of the difference between pointclouds collected by 4D RADAR, similar to what has been done in LiDAR pointclouds [65].

1) Distance-based PDF: To compute the spatial dissimilarity between a pair of point clouds, one PDF that captures the spatial distribution of the pointcloud is created for each pointcloud that needs to be compared. Each PDF contains the pairwise distances between points in one single point cloud as a function of distance.

2) PDF Comparison Method: After forming the PDFs for each pointcloud, we ensure that they have the same number of bins to enable a fair comparison. Various geometrical distances exist to compare two vectors. In this work, the widely adopted Manhattan distance is chosen, as it provides a measure of dissimilarity between the two PDFs, with larger values indicating greater dissimilarity. Let $P_A$ and $P_B$ denote the bin values in the $n$-discrete PDF representation of the point clouds $A$ and $B$, respectively. The Manhattan distance distance is defined as Eq. (1).

$$d_M = \sum_{i=1}^{n} |P_{A_i} - P_{B_i}|$$  \tag{1}

The proposed metric is generated to be bounded between 0 and 1, the higher the value the more dissimilar are the pointclouds. A value of 0 indicates two identical pointclouds.

3) Other metrics: It has been observed that, in the presence of noise, the number of points in a pointcloud might vary and e.g. decrease due to absorption, reduction of ‘nominal’ maximum range, etc. [66]. Therefore, to understand the effect of noise, it might be useful to combine the above proposed dissimilarity index with an evaluation of returned points, points with speed, points in a region of interest, etc. An example of the type of information that can be gathered by such measures and the proposed metrics is shown in Sec. IV-D.

IV. RESULTS AND DISCUSSION

The results presented in Table III capture the causes that can generate erroneous/degraded data as output of the RADAR, however this section further discusses some controversial cases (e.g. corner cases and malicious attacks, see Sec. IV-A and Sec. IV-C), and some RADAR specific issues, see Sec. IV-B. Moreover, across all the noise factors, some of them can temporarily be calibrated for or mitigated via software and hardware countermeasures (e.g. ageing), whereas weather effects are the most highly variable and unpredictable. It is therefore demonstrated how to apply the proposed dissimilarity metric to evaluate the difference between 4D RADAR pointclouds due to rain precipitation, Sec. IV-D.

A. Intended/corner case

There are situations during the capture of the data which may be seen as a noise factor, but they are inherently due to the technology and the specific, ‘uncommon’ situation/scenario. For example, depending on the shape, reflectivity and orientation of a target, the power reflected back to the receiver can change drastically. There are cases where object shapes have been designed to minimise reflections (i.e. limiting perpendicular surfaces, using ‘ad hoc’ materials, etc.), and hence reduce distance in which it can be detected, as well as the perceived RCS of the object. These types of design are critical e.g. in military applications [67]. Additionally, coatings can be designed and applied to absorb radio waves and ‘hide’ objects from the RADAR. Liubetski et al. has created a sample coating which can absorb over 90% of electromagnetic energy of a RADAR [68]. The above mentioned are ‘special’ cases by design, but also the shape of the road, road infrastructure, clutter, side lobes of emitted waves can cause situations in which targets in the ‘detectable’ range are not detected, these cases are usually unpredictable (and difficult to reproduce when designing test cases) and are considered ‘corner cases’, and they are not specifically covered in this noise factor analysis.

B. Mirroring and other detrimental effects

Some common and well known issues related to traditional RADAR, but that equally affect 4D RADAR performance are ghost objects, multi-path reflections, interference, and mirroring on objects such as road surface or guardrail. These noise factors are partially captured in Table III, but they require further explanation, given their frequency and also their relationship with specific scenarios (so in some cases they can be
### Table III: Automotive 4D Radar Noise Factors Identified through the Proposed Framework. RF stands for Radio Frequency

<table>
<thead>
<tr>
<th>Factor Type</th>
<th>ID/Noise Factor</th>
<th>Location (Max Range)</th>
<th>RCS</th>
<th>Velocity</th>
<th>Target Power (NF)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piece to Piece</td>
<td>01. Alignment of components</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Misalignments due to assembly and manufacturing tolerances, affecting RF emission [51]</td>
</tr>
<tr>
<td></td>
<td>02. Fabrication Variability</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Silicon and System-on-a-Chip fabrication (containing antenna, modulator, etc.)</td>
</tr>
<tr>
<td></td>
<td>03. Radome</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Alignment/shape of radome affecting emission angle/power [52]</td>
</tr>
<tr>
<td></td>
<td>04. Signal Processing</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Quantisation error, component efficiencies</td>
</tr>
<tr>
<td>Change over Time</td>
<td>05. Ageing of Electronics</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Aging of critical components can reduce effectiveness of the processing/emission/reception [53]</td>
</tr>
<tr>
<td></td>
<td>06. Misalignment with Radome</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Vibrations over time causing internal/external alignment issues [54]</td>
</tr>
<tr>
<td></td>
<td>07. Degradation of Radome</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Contaminants and degradation will affect dielectric properties</td>
</tr>
<tr>
<td>Usage</td>
<td>08. Misplacement of the Sensor</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Sensor located in different location compared to original calibration</td>
</tr>
<tr>
<td></td>
<td>09. Vehicle Impact</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Heavy impact resulting in internal/external alignment issues</td>
</tr>
<tr>
<td></td>
<td>10. Chemicals/Contaminants/Component</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Ingress of humidity/particles affecting attenuation/transmission, chemical reaction/damage to radome</td>
</tr>
<tr>
<td></td>
<td>11. Obstructions</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Material near field, water, leaves, snow, on radome or bodywork [26], [55]</td>
</tr>
<tr>
<td></td>
<td>12. Vehicle Dynamic Settings</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>These settings affect the amount of vibrations and may shift relative position of the radar [20]</td>
</tr>
<tr>
<td></td>
<td>13. Firmware/Memory/Software Corruption</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Corruption can occur in the memory, dynamic or static, which can cause profound effects on the firmware and software, as well as the signal processing</td>
</tr>
<tr>
<td></td>
<td>14. Component noise</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Each component will naturally have variability and with usage there might be unexpected behaviours [56]</td>
</tr>
<tr>
<td>Environment</td>
<td>15. Extreme Temperature</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Electrical/mechanical components extreme variations [57]</td>
</tr>
<tr>
<td></td>
<td>16. Adverse Weather</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Weather particles can cause attenuation, back-scattering, absorption [25], [26]</td>
</tr>
<tr>
<td></td>
<td>17. Object Clutter</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Clutter might create reflections and ghost objects [58], [59]</td>
</tr>
<tr>
<td></td>
<td>18. Multipath Reflection</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Reflection of RF waves due to side lobes, causing increased noise floor and potential for detection of false points [60], [61]</td>
</tr>
<tr>
<td></td>
<td>19. Road surface conditions (e.g. wet surface)</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Road surface can be covered by water, ice, sand etc. which can reflect and attenuate the RF wave</td>
</tr>
<tr>
<td>System Interaction</td>
<td>20. Vehicle Bodywork (Bumper)</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Bodywork might reflect/absorb RF, altering beam profile [48], [49], [62]</td>
</tr>
<tr>
<td></td>
<td>21. Power Supply</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Instability and fluctuations of power supplied</td>
</tr>
<tr>
<td></td>
<td>22. Electromagnetic interference of</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td>Internal EMI, inducing noise into analogue circuit</td>
</tr>
<tr>
<td></td>
<td>electrical and electronic components</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Automotive RADARs operating in the same spectral region [63], [64]</td>
</tr>
<tr>
<td></td>
<td>23. Cross Device Interference</td>
<td>✓✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓✓</td>
<td></td>
</tr>
</tbody>
</table>

Considered more as ‘corner cases’, unpredictable and difficult to replicate. Interference, or ‘mutual-interference’ (device to device) of automotive RADAR has been well analysed in the literature for traditional RADAR - most of the basic principles of interference will be applicable and affect 4D RADAR too, as the modulation type, working principle, and frequency bands and modulation bandwidth used are shared. A good overview of traditional automotive RADAR is presented by Hakobyan and Yang, and they also offer some insights into mitigation of interference [69]. Wang et al. presented a study on probability of interference between RADARs based on their basic working principle and a bidirectional distribution of vehicles in multi-lane scenario. The Authors studied the effects of interference and proposed and compared some mitigation solutions [70]. Torres et al. proposed to use the graph theory to find out the minimum number of orthogonal resources can be supported in a specific scenario - but how this aspect is related to modulation/band allocation in real automotive
RADARs is not discussed [71]. It is possible that mutual interference would be slightly mitigated by the beamforming process in 4D RADAR (and reduced beam divergence), but to the best of the Authors’ knowledge to date there are no specific studies to confirm this hypothesis. Another significant issue with RADAR is multipath reflection and the creation of ghost objects, for example investigated in [16], [21]. Interestingly, a RADAR ghost dataset has been created, but the data are limited to traditional RADAR [16]. Similarly to interference, it is expected that also 4D RADAR will suffer from the appearance of ghost targets, as the working principle is the same.

Some of the effects mentioned in this section can be partially mitigated by the post-processing and filtering, however it is usually not transparent how this processing happens within the RADAR and the data produced can be quite noisy depending on the specific use case/scenario.

C. Malicious attacks

Malicious attacks are a real concern for highly automated systems, especially in automated vehicle due to the damage that can be caused by misleading perception sensor data. There are multiple ways to attack a sensor, but they normally revolve around enforcing or creating a noise which will mask or affect the data captured [72], [73]. Generally, different malicious attacks to active sensors can: saturate the detector, so real objects are not detectable anymore; create spurious and random noisy points, so real detected points are masked; create points for ‘not existing’ objects, etc. Again, Table III is more meant to identify internal or external occurring noise factors, but overall malicious attacks can leverage data degradation to further temper with sensor outputs.

D. 4D RADAR data collection and evaluation

To demonstrate how noise can be evaluated in Automotive 4D RADAR, the metric proposed in Sec. III-C is applied to noisy data collected in controlled environment. The measurement were carried out at the CEREMA facility, which can generate different rainrates in an indoor measurement chamber [74]. A 4D RADAR was used to capture a static scene with a Euro NCAP vehicle target at 15 m distance from the sensor, the target is shown in Fig. 1. A range of rainrates was generated in the facility: 0 mm/h, 17 mm/h, 50 mm/h, 101 mm/h, and 175 mm/h. For each rainrate, multiple pointclouds were collected (and noting was changing in the collection except the rainrate), and they were compared between each other using the dissimilarity index, Sec. III-C. Then the indexes calculated for each rain rate were averaged, generating one mean dissimilarity score per rainrate (including a score for no rain). In this way, each averaged value measures the variability in the pointclouds within the same rainrate, so it is linked to the amount of noise in the specific situation. As previously mentioned, the higher the index, the more the variability between the compared pointclouds. The calculated dissimilarity scores as a function of the rainrate are shown in Fig 3, solid red plot (right axis). Moreover, the Figure shows the variation of number of total points returned by the pointcloud (solid blue plot), and the number of points with measured speed not zero (dashed blue plot). All the measures clearly capture an increase of noise in the pointclouds due to the increasing rainrate: (i) the dissimilarity index has a growing trend, indicating that the higher the rain the more the difference between pointclouds induced by the rain; (ii) the number of returned points decreases with higher rainrates, probably due to increased absorption/reflections by rain droplets; (iii) more points with speed are detected, indicating a significant amount of rain droplets detected by the RADAR. In conclusion, the proposed dissimilarity metric, in combination with other measures, provides a powerful tool to correlate increased amount of noise in the environment with growing variability in the measurements by a 4D RADAR.

V. CONCLUSION

This work builds on the previously proposed noise factor analysis to provide, for the first time, a holistic view of noise factors affecting automotive 4D RADAR data output [27]. It is critical to understand the noise factors presented, classified and analysed in the presented work, and they can be used to evaluate their effect on perception and decision-making processes in the driving functions.

Moreover, noise factors needs to be compared and quantified, and this paper proposes a novel approach, based on a dissimilarity metrics, to evaluate the difference between 4D RADAR pointclouds. The approach was tested using real collected data, and it was observed that under increasing rainrates, the amount of returned points significantly decreases and the pointclouds produced have higher dissimilarity scores, meaning higher variability and more noise. The proposed approach can be used to compare data with different amount of noise, but also to evaluate if sensor noise models are a faithful representation of the real collected data.

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REFERENCES


