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A Framework to Analyze Noise Factors of Automotive Perception Sensors

Pak Hung Chan (陳柏鴻)[1], Gunwant Dhadyalla[1], and Valentina Donzella[1]

[1] WMG, The University of Warwick, Coventry, CV4 7AL, United Kingdom

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Abstract— Automated vehicles (AVs) are one of the breakthroughs of this century. The main argument to support their development is increased safety and reduction of human and economic losses; however, to demonstrate that AVs are safer than human drivers billions of miles of testing are required. Thus, realistic simulation and virtual testing of AV systems and sensors are crucial to accelerate the technological readiness. In particular, perception sensor measurements are affected by uncertainties due to noise factors; these uncertainties need to be included in simulations. This work presents a framework to exhaustively analyze and simulate the effect of the combination of noise factors on sensor data. We applied the framework to analyze one sensor, the LiDAR (Light Detection and Ranging), but it can be easily adapted to study other sensors. Results demonstrate that single noise factor analysis gives an incomplete knowledge of measurement degradation and perception is dramatically hindered when more noises are combined. The proposed framework is a powerful tool to predict the degradation of AV sensor performance.

Index Terms— LiDAR, perception sensor, noise, simulation, rain, occlusion, intelligent vehicles, autonomous and automated vehicles.

I. INTRODUCTION

The current role and use of vehicles is expected to dramatically change in the next decade due to the introduction of conditional and full automation [1]. In fact, the Society of Automotive Engineers (SAE) has defined 6 levels of vehicle automation (L0-L5) in their standard [2]. To achieve higher levels of automation (L3-L5, [2]), automotive systems will need to be fault tolerant or fault operational, therefore increased robustness to noise factors will be required by the electronics systems and the sensors.

In order to navigate the complex road environment, vehicles will need to be able to create their own world model, and this model will rely on the information gathered by a plethora of sensors, above all the environmental perception sensors (ultrasonic, vision, RADAR and LiDAR) [3-4]. Currently, no one of the mentioned sensors is able to give reliable and robust detection independently under all environmental and road conditions, consequently a combination of different sensor technologies will be required for L3-L5.

RAND Corporation calculated that roughly 5 billion miles are required to be driven by a fleet of automated vehicles (AVs) to demonstrate a 20% lower fatality rate than the human driver with 95% confidence [5]. Therefore, it is key to use simulations to accelerate AV development. There are different approaches to test AVs, and several research groups, automotive suppliers and manufacturers believe that the generation of simulation scenarios can uncover some of the system and sensor failure modes and can support the safety analysis [6-7]. In AVs, sensors will provide the link between the real world and the autonomous control systems (ACSs). Sensor information quality is fundamental to support the ACS to evaluate the scene and swiftly plan the next action. However, the continuous presence of different noise factors causes fluctuations in the sensor data quality. Furthermore, different sensor technologies are affected by the noise factors in different ways and with outcomes that will depend on the specific technology, e.g., low light condition can hinder obstacle detection using vision sensors.

From a simulation perspective, undertaking the same driving scenario with different environmental conditions can provide critical information on how different noise factors would affect the perception sensors and as a consequence the ACS decision. Many commercial simulation suites for automated vehicles currently only provide a partial means to implement effects of noise sources on the sensor output. This study presents a framework to identify the noise factors affecting a sensor technology. This information can then be used to analyze the identified noise factors, and to model the effect of single or multiple noises on sensor response. Here, the proposed framework is used for the first time to model the effect of multiple noise factors on automotive LiDAR response, building on the single noise model proposed in Goodin et al. [8]. Our approach can be applied to other perception sensors with few *ad hoc* modifications.

II. FRAMEWORK FOR NOISE ANALYSIS

There are manifold factors that can affect sensor performance; recent works have focused on the modeling of noise on perception sensors [9-10]. Accurate models of automotive sensors and noise factors are required if simulations are to be used to prove that an ACS is safe in the scenario under test, particularly when environmental conditions are challenging for the sensors (e.g. rain for LiDAR, fog for camera, etc.). As mentioned, the ACS bases its actions on sensor perception. With an inaccurate sensor model, the ACS will have inaccurate data to work with and hence the fidelity and validity of these simulations will be limited.

Here we used a well-established system analysis technique, the parameter diagram, or p-diagram (inset in Fig.1), to identify all of

Corresponding author: Pak Hung Chan (Pak.Chan.1@warwick.ac.uk).

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the possible noise sources that can affect the performance and behavior of a sensor, nominally a LiDAR. P-diagram is used in reliability engineering to analyze a complex system/subsystem, to understand its interactions, and also to separate different noise factors that will deviate the system from its ideal behavior [11]. We hereby propose to use it as a tool to support a thorough analysis of noises and variations that have an impact on automotive sensor performance. The standard five noise factor types of a p-diagram are listed in Table 1, first column. Based on these factor types, we have classified different noise sources (second column in Table 1) and analyzed which sensor output/reading they will affect. Based on this understanding, the noise factors can be modeled, and included in simulation or emulation tools. To the best of our knowledge, we have considered the noise factors that will affect LiDAR response.

In the case of the LiDAR, we have analyzed how noise factors will affect the parameters used to build the pointcloud, a 3D point collection representing the detected environment. There are three main parameters used to generate the pointcloud: intensity, I, time of flight, ToF, and emission angle, Ψ,Θ [12]. Intensity can be used to identify material properties of the target, and to assist in clustering (combined with spatial information). Noise affects the detected intensity, to the point that some points can have intensity below the detection threshold. ToF principle is used to calculate the distance to an object. This value is sensitive to the optical flight path, which changes depending on ambient permeability and permittivity (affected by weather and environmental conditions such as humidity, rain, etc.). The emission angle is the direction the light is emitted at from the sensor light source. If this is different to what the LiDAR is programmed to believe, it will cause an incorrect location of the point. An additional parameter, point coordinates (x, y, z), determines the location in the 3D space where the light have been reflected. Noise on coordinates arises from reflections and refractions that divert the beam away from its original path. The coordinates can be affected also by malicious attacks and interference with other LiDAR units.

For the LiDAR to detect a reflection, the return signal must be above a certain intensity threshold (that will depend on the LiDAR receiver). There is also a minimum detection range, nominally between 0.2 m and 1 m [12-13]. By applying noises to the LiDAR simulation, datapoints can artificially fall outside these limits, but they cannot be physically detected by the sensor and they have to be removed in our model. Fig. 1 shows the suggested process through a flow diagram, modified from Goodin et al.; the cylindrical blocks and blocks with bold font represent our additions [8].

III. LiDAR AND NOISE MODELS

Fig.1 shows the flow to simulate a LiDAR sensor, and to add the noise factors identified via the p-diagram analysis to the simulation. Noise types are identified by numbers corresponding to noise factors, summarized in Table 1. In fact, we propose to extend the model in [8], to take into account several different noise sources and the LiDAR parameters they will affect. Rain is just one of the many noise factors that need to be modeled. Furthermore, we considered that the noise sources will not affect only ToF and intensity, but also the pointcloud point coordinates and angle (dotted box in Fig.1).

Depending on the sensor to be simulated, multiple noise factors may have to be modeled and suitably combined, and this will change based on their independence or dependence.

Table 1. P-diagram noise factors and the LiDAR parameters affected by these factors, namely: Intensity, I, Time of Flight, ToF, emission angle (Ψ,Θ), and point coordinates (x, y, z).

Factor Type	ID/ Noise Factor	I	ToF	Ψ,Θ	x, y,z	Description
Piece to Piece	01. Laser Diode	✓	✓			Light emission is affected by the variability of fabrication parameters [14].
	02. Mounting			✓		Can affect the emission direction [12].
Change over Time	03. Emitter	✓	✓			Fluctuation/degradation of emitter power, bias, wavelength shift [15].
	04. Mechanics			✓		Wear in mechanical parts resulting in offsets and misplacement
	05. Receiver	✓	✓			Degradation could result in a responsivity wavelength shift and could result in lower or higher intensity recorded for a specific wavelength
	06. Circuits	✓	✓			Electronic circuit components degradation/aging over time
Usage	07. Multiple Returns	✓			✓	From multiple objects in beam path, ground, beam divergence [12]
	08. Motion			✓		Vehicle vibration, speed, acceleration, ground holes, etc.
	09. Clock Speed		✓			The clock is used as reference for the ToF (instability, errors) [16]
	10. Lens Damage	✓			✓	Dispersion effects reducing intensity and refraction may result in a return from a location that is not expected from the beam path
Envi-ronment	11. Weather	✓	✓			LiDAR is affected by weather conditions, such as rain, snow, fog, etc. [8, 10].
	12. Obstruction	✓			✓	Lens can be obstructed by objects, rain, mud, etc. Water drops can result in lensing effect, reduce intensity, etc. Mud can occlude the laser beam.
	13. Ambient Conditions	✓	✓			These conditions can affect light propagation. Temperature affects optical, electronic, mechanical components. Luminosity affects detector performance.
System Interac-tions	14. Malicious Attacks	✓			✓	External systems can disrupt the emissions and/or reception, e.g. by absorbing and reemitting at altered times or other methods [17].
	15. LiDARs				✓	Other LiDAR units can cause interference, false detection, etc.
	16. EMI	✓	✓		✓	Internal and external electrical components interactions

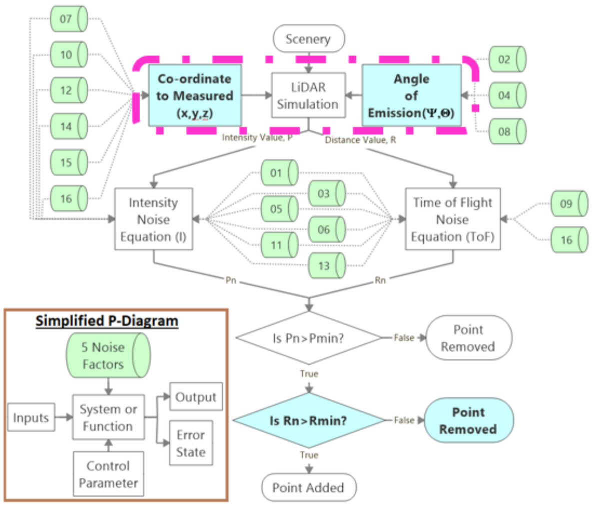

Fig. 1. LiDAR simulation flow with addition of noise factor sources (cylindrical blocks) from p-diagram (inset). The noise numbers in figure correspond to numbers in Table 1.

As the focus of this paper is to demonstrate a process to analyze and combine noise models and their effect on automotive environmental sensors, we have implemented a LiDAR model that includes two noise sources: a rain model, modified from Goodin et al. [8], and partial occlusion of the lens, blocking the emission of some LiDAR laser beams. These two noise factors are independent and can be applied as two separate noise models acting on ideal power and range, P_i and R_i. The proposed model considers first which points are removed due to the occlusion, f_{Occ} (the light beam will not be emitted by the unit) and then adds the rain noise model, f_{Rain}, to the residual points, as shown in the Eqs.1-2. Rain will affect the range and power accordingly to Eqs. 7 and 9 from Goodin et al. [8]. The mentioned model is based on experimental data valid only up to 7 mm/h (heavy rain [18]), therefore we used this value to maximize the effect of rain in our model [19].

$$Pn_i = f_{Rain}\left(f_{Occ}(P_i)\right) \tag{1}$$

$$Rn_n = f_{Rain}\left(f_{Occ}(R_i)\right) \tag{2}$$

The described model can be adapted to work and to combine several noise models, with different levels of fidelity.

IV. SIMULATION OF NOISY LiDAR

The proposed process (p-diagram and simulated noise models) can be applied to any LiDAR pointcloud datasets. Therefore, to demonstrate the deployment of this process, we used an open access MATLAB dataset (lidarData_ConstructionRoad.pcap) [20]. This dataset contains a multitude of LiDAR scans from a vehicle driving along a road; one of the scans (the 100th) is shown in Fig. 2. The used dataset was generated using a HDL-32E Velodyne LiDAR, with 32 vertical channels and a 360° horizontal field of view. In Fig. 2, points corresponding to the ego-vehicle (i.e. the vehicle with the scanning LiDAR) have been removed, and a grey box has been added to represent it. The ego-vehicle has just passed a crossroad; three vehicles are passing on the left and there is one vehicle in the front. To the right, there are three vehicles stationary waiting to cross the junction, and around the ego vehicle, there are some traffic objects (black circles).

Each point in the pointcloud has its spherical coordinates, ToF, emission angle and intensity data. We added to the pointcloud data the modeled noise factors: a rainfall of 7 mm/h, and an occlusion of lasers 13 to 17 in the pointcloud. These parameters were chosen to maximize the effects of each noise factor on the selected LiDAR scan (Fig. 2); however, the effects of the noise factors will vary depending on the considered road scenario. After adding the noise factors, we filtered the points with power too low and with range too short to be detected by the LiDAR (we have used 0.1% of emitted power and 0.9 m respectively, but these values will depend on the used LiDAR); this process is represented by the diamond blocks in Fig.1. In Fig. 2-3 we have removed ground points for visualization using an available Matlab function [20].

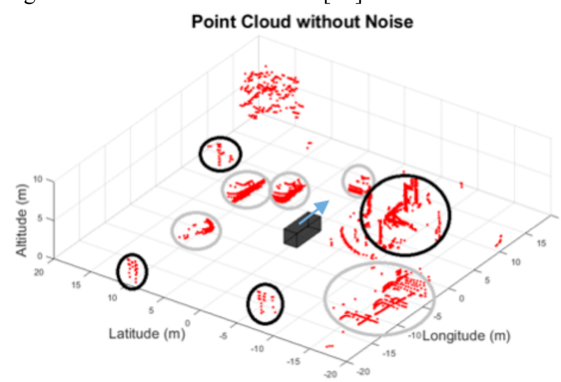

Fig. 2. Visualization of the 100th scan of the LiDAR pointcloud, with vehicles circled in grey and infrastructure objects in black.

V. RESULTS AND DISCUSSION

Clustering is one of the techniques used to gain a better understanding of the key elements in sensor data. We have post-processes our noisy pointcloud data using MATLAB "clusterdata" function to cluster the points belonging to different objects; this function employs a hierarchical clustering algorithm [21]. Fig. 3 shows the clustered noisy data for laser occlusion (a), for the modeled rainfall (b), and for the combined noise factors (c); each cluster is represented by a different color in the figures.

A. Occlusion Noise

In this model, Fig. 3a, the points emitted by occluded lasers were removed. As a consequence, there is a *loss of data*; several points belonging to the vehicle in the front and the three vehicles on the left are not in the pointcloud anymore. There are still some clustered points in the vehicle positions (see ovals), but their classification would be hindered, if not impossible. The occlusion had little effect on other objects, demonstrating that this noise factor impacts only specific areas of the pointcloud, depending on their positions.

B. Rain Noise

This model, Fig. 3b, changes the range and intensity of LiDAR points, causing *distortion of data* and making object identification harder. To the left of the ego vehicle, the three vehicles are more similar to random cluster of points than a smooth surface. To the right of the vehicle, the shift in the detected point locations due to rain noise prohibits the function (from [20]) from identifying some of them as ground points, thus preventing removal. The three vehicles on the right are also clustered together with no resemblance of their original shapes.

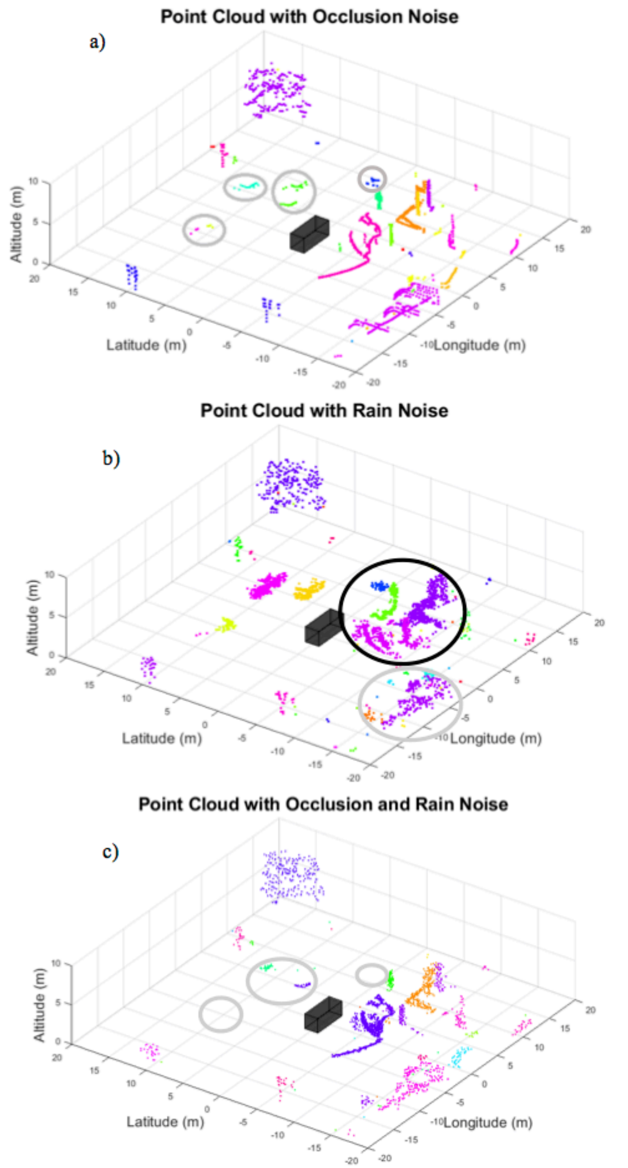

Fig. 3. Visualizations of LiDAR pointcloud 100th scan with noises added to the points: a) LiDAR lasers 13-17 occlusion; b) rainfall of 7 mm/h; c) the combination of the two noises. Vehicles are circled in grey and infrastructure objects in black.

C. Combined Occlusion and Rain Noise

The final step in our process, Fig. 3c, is to apply the two noises simultaneously, as per Eqs. 1-2. With *data loss* (due to occlusion, Fig. 3a) and *distortion* (due to rain, Fig. 3b) acting separately, obstacles are still clustered and detected. However, with the *compound noise* (Fig. 3c) most of the targets, even in close proximity, are missing or not discernable (grey circles). The combination of the noise models further emphasizes data degradation and impaired object detection. Particularly, of the three vehicles on the left side, only two of them are identified as clusters, but do not resemble the profile of a vehicle, the vehicle in the front is also no longer a cluster.

VI. CONCLUSION

We have proposed a flexible framework to analyze automotive environmental perception sensors weaknesses and noises. The process starts with the sensor p-diagram to break down all the possible noise factors, then the outcome is used to understand and model the effects of each noise on sensor data. In this manuscript, we used the process to combine the effects of two independent noise factors on LiDAR data, and demonstrated that their combination completely impairs object detection even in the short range (5-10m). Finally, the proposed process can be easily applied to other perception sensors, e.g. ultrasound, vision, thermal and RADAR.

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