Fault Prediction and Estimation of Automotive LiDAR Signals Using Transfer Learning-Based Domain Generalization

Sanghoon Lee[1], Jaewook Lee[2] and Jongsoo Lee[*]

[1]*Reliability and Certification Research Laboratory, Korea Automotive Technology Institute, Chungnam, 31214, Korea*
shlee2@katech.re.kr

[1,2,*]*School of Mechanical Engineering, Yonsei University, Seodaemun-gu, Seoul, 03722, Korea*
shlee2@katech.re.kr
lee1jw@yonsei.ac.kr
jleej@yonsei.ac.kr

ABSTRACT

Autonomous vehicles (AVs) are undergoing level 4 technology development and should have a system that can be operated without driver's intervention, so that it must be possible to diagnose failures and predict life cycle themselves. In this study, we propose a technology to estimate signal changes and sensor faults through transfer learning-based domain generalization (TLDG) using limited actual vehicle test information from LiDAR for autonomous vehicles. Because autonomous vehicles operate in various climate/weather conditions over the world, their mechanical, electrical and electronic components must also have stable performance in all environmental conditions. However, an electronic device, especially laser diode (LD), which is one of core components of LiDAR, shows various degradation aspects depending on environmental conditions. We acquired multivariate LiDAR performance data under various environmental conditions through an actual vehicle test driving of about 2,000 km in summer and winter, and based on this, we create the LiDAR fault diagnosis and performance prediction model generalized to the domain under various environmental conditions. Fault prediction and estimation model created through summer and winter data in the environment domain will also adapt to other environmental conditions such as spring and fall. To develop highly accurate performance estimation models under various environmental conditions based on limited data, it is very important to extract correlations and characteristics between data, including environmental conditions. We employ the data augmentation techniques to solve the problem of lack of training data and apply bi-directional Bayesian transfer learning to generalize data and models under uncertainty. To prove the effectiveness of the present study, the data from actual vehicle tests conducted at different temperatures will be divided into train data and test data, and the validity of the generalized degradation performance estimation model will be statistically validated. The proposed domain generalization method, i.e., TLDG can be utilized to estimate signal changes and sensor faults in LiDAR under unexperienced environmental conditions such as weather changes, and even freezing and hot regions.

1. INTRODUCTION

With the advancement of automobile technology, such as autonomous driving, the need for technology to diagnose and predict automobile failures is emerging. For example, there are AI-based vehicle big data analysis, pre-failure diagnosis and remaining life prediction of parts and systems, and predictive maintenance technology, and these technologies ultimately aim to improve vehicle safety and availability. In level 4 autonomous driving, there is no driver intervention, so the system must independently diagnose and predict failures to ensure safety. Real-time fault diagnosis of autonomous systems is being studied in a variety of ways using data-driven approaches.

AV sensors are composed of composite materials and various electronic elements. As a result, the performance of the sensor may vary depending on the weather environment, and abnormal operation of the sensor may occur under severe conditions (Zhao et al., 2023). Abnormality diagnosis is possible by detecting and scoring abnormal information from changes in sensor performance. Real-time fault diagnosis of autonomous driving systems is being studied in a variety of ways, mainly using edge artificial intelligence (edge AI) and data-based approaches (Gültekin et al., 2022). Research on anomaly detection based on statistical and classification techniques has been active (Ahmed et al., 2016), and recently, research on AI technique-based methods such as adversarial learned denoising shrinkage autoencoder (ALDSAE) has also been actively conducted in the field of autonomous vehicles (Fang et al., 2023).

Failure prediction and evaluation using transfer learning-based domain generalization presents an innovative approach to solving key problems in the automotive industry and robotics fields (Xu et al., 2019). Domain generalization techniques frequently provide solutions to rotating machinery fault diagnosis problems. The initial approach developed and verified the model under conditions where both training and test data were available. Recently, a method has been proposed to generalize learned knowledge to a new target domain without assuming the availability of test data (Li et al., 2020). Additionally, a new approach called cross-domain augmentation diagnosis, which enables robust defect detection even when the target domain is unknown, is also being studied (Li et al, 2023). However, previous research addresses domain generalization and domain expansion techniques for signals with repetitive operating patterns, such as rotating devices. This is difficult to apply in problems considering multiple stresses because only limited parameters are covered when performing domain generalization. Because automobiles are used all over the world, all systems must operate in a variety of temperature environments. Therefore, when developing safety improvement technologies such as failure prediction, they must be trained or verified considering the distribution of various climate environments. However, due to the considerable time and financial investments required for collecting data through sensor performance measurements across various temperature environments, there are inevitable limitations to the available training and test datasets. Moreover, since sensor components comprise various electronic elements and composite materials, they demonstrate different operating characteristics upon temperature fluctuations. Consequently, there is the potential for poor performance when diagnosing faults based only on limited training data. This problem can be solved through transfer learning-based domain generalization technology, and in this study, we aim to solve the fault detection problem of LiDAR sensors by applying this technology.

In this study, we review the failure modes of LiDAR sensors and select target parameters necessary for failure diagnosis and prediction. The main contributions of the study are as follows:

- Through FMEA analysis of LiDAR defects, we investigate the causal relationship of LiDAR failures that may occur in the vehicle environment, and this allows us to present a practical and versatile model as it deals with hardware level defects by selecting key parameters.
- To solve the problem of accuracy degradation due to outliers encountered in domain generalization problems, we propose an Archimedes spiral-based preprocessing method based on the relationship between input and output data.
- The proposed method provides considerable diversity and flexibility by allowing sensor faults to be predicted with minimal information under diversifying environmental conditions, and the same method can be easily applied for other failure modes.

The rest of the paper is organized as follows. Section 2 gives a failure mode analysis to select key parameters for this study. Section 3 presents preprocessing techniques for outlier data, and Section 4 describes the domain generalization method. The experimentally study is shown in Chapter 5 and finally we conclude in Chapter 6.

2. Failure Mode Analysis

LiDAR uses a laser light source to measure distance and recognize the surrounding environment and obstacles. It consists of various components such as laser diodes, thermoelectric elements, signal processing modules, optical lenses, and galvano scanners. In the driving environment, stresses such as heat, vibration, and electrical noise continuously occur, which can causes breakdowns of LiDAR sensors (Chang et al, 2023). The potential failure modes of frequency modulated continuous wave (FMCW) LiDAR are shown in Table 1. Thermal management of FMCW lidar sensors is directly related to sensor performance. When

Table 1. Failure mode analysis of AV LiDAR sensor

Components	Potential failure mode	Potential effects of failure	Potential factors of failure
Laser device	Decrease light intensity	Loss of distance information	High temp/humid., Thermal fatigue
	Fail to detect a returned signal	Increase in false detection	High humid, Vibration
	Fail to keep managed temp.	Non-operation of the sensor	High/Low temperature
Control board	Open circuit	Non-operation of the sensor	Thermal fatigue, Vibration
	Short circuit	Unintended operation	Ingress of dust and moisture
Lens	Fail to focal length	Increase in missed/ false detection	Thermal fatigue, Vibration
	Surface contamination	Increase in missed/false detection	Ingress of dust and moisture
Galvano-meter	Poor responsiveness of actuator	Decrease in sampling rate of scanning	Low temperature, Vibration
	Optical axis misalignment	Increase in missed/false detection	Thermal fatigue, Vibration

analyzing design vulnerabilities through accelerated stress testing, a failure mode in which the laser output of the LiDAR sensor was suddenly cut off under high temperature conditions was identified. This failure mode occurs when the ambient temperature of the laser diode module rises above approximately 75°C. Considering the climate environment of hot weather regions and the sensor self-heating, it can be classified as a failure mode that requires management because it is a condition that can be sufficiently exposed. The laser diode module uses a Peltier-based thermoelectric cooler (TEC) and controls voltage and current to enable the laser diode to maintain a constant temperature. However, when the ambient temperature exceeds a certain range, TEC control ability is lost, and thermal runaway of the laser diode module occurs.

3. Outlier Detection

In this paper, a study is conducted using the data of the multivariate database acquired through actual vehicle driving test. In the case of actual vehicle driving test data, outliers occur due to uncertainty factors such as road environmental conditions, equipment defects, and frequency errors. To create a robust model, these outliers must be selected and processed in advance and used for training.

As a study on outlier detection, a study has been conducted to propose a fast diagnostic method for internal short circuit (ISC) through local-gravitation outlier detection (Yuan et al, 2023). There is also research on the performance improvement of mechanical failure diagnosis based on audio signal analysis (MFDA) based on outlier detection (Tang et al, 2022).

We would like to propose a signal processing method through Archimedes spiral as a new outlier detection method. Using the following method, Archimedes spiral can be used to create a deep learning model that is generalized to the domain without overfitting. When Archimedes Spiral is expressed using a polar coordinate system, it can be expressed as Equations (1) using the real constant a, b and the angle θ. Changing the parameter b controls the distance between loops. Since we want to check that the output value changes for the input variable, we just need to check how the distance of the spiral changes at a specific angle set as the input variable. Here, when input data is x_{input} and output data is y_{output}, it can be expressed as Equation (2). Next, to solve the problem that is not visually clear by setting the starting point as the origin when drawing the spiral, the data was normalized between 2π and 4π at the start of the second spiral, as shown in Equation (3) and (4). When the data is sorted through this, data including the uncertainty factor appears as an area, and data processing based on the confidence interval is possible according to the data area.

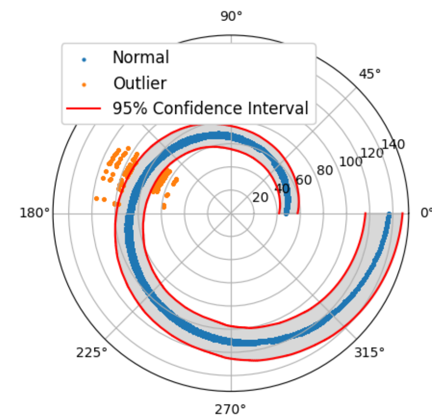
$$r = a + b \cdot \theta \tag{1}$$

$$(r, \theta) = (x_{input} \cdot y_{output}, x_{input}) \tag{2}$$

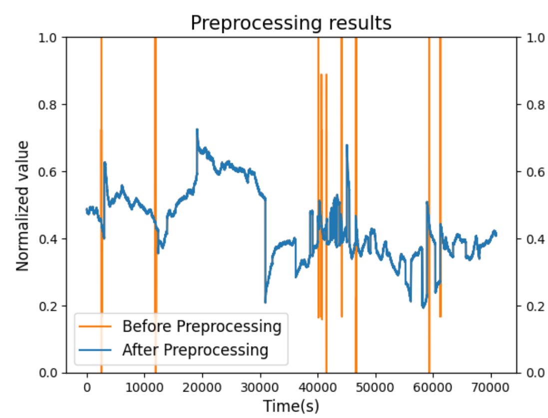
$$x_{normalized} = \frac{x_{raw} - x_{min}}{x_{max} - x_{min}} \tag{3}$$

$$\begin{aligned} x_{input} &= 2\pi \cdot x_{normalized} + 2\pi \\ y_{output} &= 2\pi \cdot y_{normalized} + 2\pi \end{aligned} \tag{4}$$

As illustrated in Figure 1, if you enter the temperature data of LiDAR in x and the current TEC current to be estimated in y, normal data and outlier data are distinguished. In addition, it is possible to statistically process the outlier of the data through the confidence interval. Ultimately, we want to create a regression deep learning model through the data classified as normal and generalize it to the domain.



(a)



(b)

Figure 1. Archimedes spiral of LiDAR temperature to TEC current of laser diode, (a) Archimedes spiral, (b) Comparison of preprocessing results

4. Transfer Learning-Based Domain Generalization

In this paper, we propose a transfer learning-based domain generalization method to overcome the limitations of data acquisition under various environmental conditions, including extreme conditions. It is known that transfer learning can improve predictive performance in terms of interpolation or extrapolation of the model by utilizing only a small amount of data from the target domain based on the model generated using the source domain (Weiss et al, 2016). However, domain generalization differs in predicting physical phenomena in the unseen domain region using improved models. We intend to gradually transfer a small amount of data to the target domain, use it to predict data in the new unseen area, and use it again as target data for transfer learning to generalize the domain. As illustrated in Figure 2, First, we created a regression model based on deep natural network (DNN) that predicts TEC current using temperature, humidity, current, and voltage data for the underlying source domain. Next, after importing the feature extraction area of the underlying source domain model to be untrainable, transfer learning was performed by adding new layers for transfer learning.

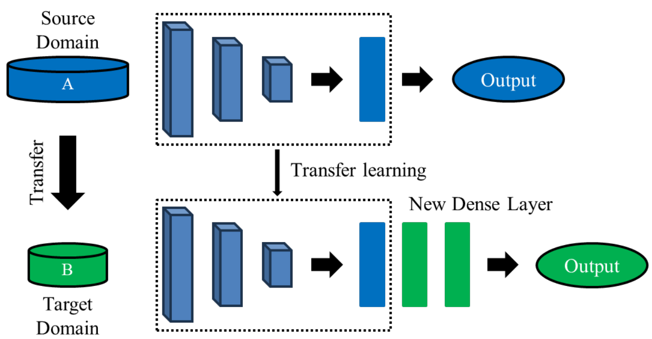


Figure 2. Architecture of transfer learning

5. Experimental Study

5.1. Datasets

In this paper, LiDAR data acquired through actual vehicle driving data in summer were used. Temperature, humidity, current, and voltage data were measured including TEC current of the Laser diode, and actual vehicle driving test data of more than 1000 km including city, country, and highway were acquired. The sensor used was the FMCW 4D LiDAR G-Series from Infoworks, and the internal and external temperatures of the sensor were measured using the SHT45-AD1B temperature sensor from Sensirion. Actual vehicle test data was obtained by installing the LiDAR on a Hyundai Azera and collecting TEC current and temperature data under actual driving conditions. Through this, 283,706 data points were acquired every 0.25 seconds. As illustrated in Figure 3, The left axis represents temperature, and the right axis represents TEC current. The environmental temperature is 28.96°C to 45.65°C, and in the case of TEC current, it may be confirmed that outlier exists. Among them, 268,402 data in which outliers were removed were selected through outlier detection based on Archimedes spiral. In addition, the ratio of training, validation, and test data was divided into 0.6, 0.2 and 0.2, and normalization was performed and used for training and model evaluation. For training, the temperature range of the training data and the temperature range of the test data were set by setting the scenarios of interpolation and extrapolation, respectively. And for transfer learning, 0.5% of the test data was arbitrarily extracted and set as data from the target domain.

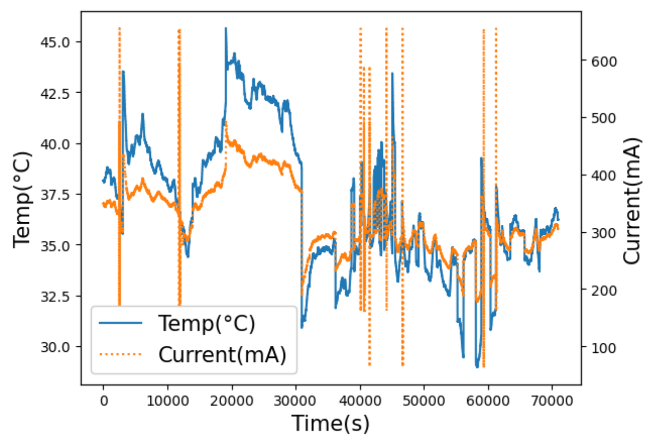


Figure 3. Actual driving test data for temperature (°C) and TEC current (mA)

5.2. Results

This paper proposes a method for predicting data based on outlier detection and transfer learning using actual driving data. All data were utilized in a state where outlier detection was conducted by Archimedes spiral. This method shows superior performance compared to other preprocessing techniques. Specifically, when comparing accuracy using methods interquartile range (IQR) and Hampel filter, the outlier detection performance was 3.23% for method IQR and 83.26% for method Hampel filter, while our proposed method demonstrated a performance of 100%. Before represents the result before performing transfer learning, and after represents the performance after transfer learning. First, looking at interpolation case 1, data from 35°C to 40°C were used as test data, and other data were used as training data. Although the error improved from 0.01 to 0.0009 based on mean absolute error (MAE), the r-squared of the DNN model was so good that the interpolation problem did not require transfer learning. This was also shown in the case of interpolation case 2. However, in the case of extrapolation, the performance error of the model before transfer learning is relatively large. However, if improvement is made through transfer learning, in case 3, it improved from 0.81 to 0.96 based on r-squared, and MAE also improved from 0.027 to

Table 2. Comparison table of transfer learning results

Scenarios	Case	Train data (°C)	Test data (°C)		R-squared	MAE
Interpolation	Case 1	28.96 ~ 35.00, 40.00 ~ 45.65	35.00 ~ 40.00	Before	0.98	0.010
				After	0.98	0.009
	Case 2	28.96 ~ 33.00, 43.00 ~ 45.65	33.00 ~ 43.00	Before	0.97	0.021
				After	0.99	0.011
Extrapolation	Case 3	28.96 ~ 40.00	40.00 ~ 45.65	Before	0.81	0.027
				After	0.96	0.010
	Case 4	28.96 ~ 35.00	35.00 ~ 45.65	Before	0.77	0.066
				After	0.99	0.014

0.010. Finally, in the case of case 4, which used only data up to 35°C as training data, it improved from 0.77 to 0.99 based on r-squared, and MAE also improved from 0.066 to 0.014. The results of case 4 are expressed visually through Figure 4. The prediction accuracy gradually decreases in the case of test data far from the area of the train data. However, after transfer learning, prediction accuracy has improved even in areas away from training data.

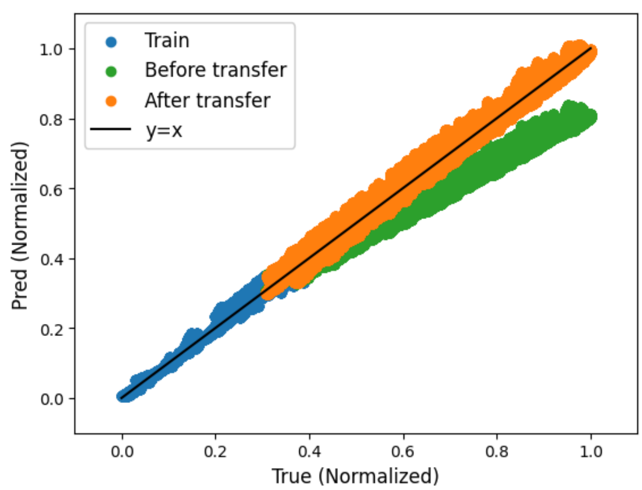


Figure 4. Extrapolation result for Case 4 in Table 2

6. Conclusion

In this paper, we propose a transfer learning-based domain generalization model for FMCW LiDAR signals that change with external temperature changes. This introduces a new approach to predicting LiDAR sensor errors by allowing sensor behavior to be predicted in unseen regions. LiDAR failure mode analysis justifies the selection of TEC current as a predictor and experimentally demonstrates the nature and validity of this signal. Real-world driving data often contains outliers due to various errors, and using Archimedes Spiral-based data preprocessing improves the prediction accuracy of the model. In the generalization task, temperature, humidity, current, and voltage data from the source domain were used, and transfer learning was performed using a DNN-based regression model and a new Dense Layer. The generalized model showed high accuracy and proved to be effective for extrapolation. Extensive training data covering a variety of climate conditions can further improve the accuracy of this model. The existing model was developed using only summer data, but future iterations will incorporate winter data to develop a domain generalized model that takes low-temperature environments into account. Through interpolation methods, it may be possible to predict sensor failure under all climatic conditions in Korea. Our goal is failure prediction under severe weather conditions. This is an extrapolation technique, and we plan to develop a domain-generalized model that can predict failures in hot areas like Phoenix or even in extreme cold areas like Minneapolis. This research could have important implications for diagnosing and predicting electronic component failures at the vehicle level and could be widely applied to other components as well.

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BIOGRAPHIES

Sanghoon Lee received his B.S. and M.S. degrees in Automotive Engineering from Kookmin University, Seoul, South Korea, in 2008 and 2009, respectively. From 2009 to 2011, he worked as a research engineer at the Korea Institute of Science and Technology (KIST), Seoul, South Korea. Since 2011, he has worked at the Reliability and Certification Research Laboratory of the Korea Automotive Technology Institute (KATECH), Cheonan, South Korea, where he is currently a principal researcher. He is currently pursuing a Ph.D. in mechanical engineering from Yonsei University, Seoul, South Korea. His research interests include failure-based lifetime prediction and the health management of automotive systems.

Jaewook Lee received his B.S. degree in Mechanical Engineering from the Yonsei University, Seoul, South Korea in 2021. He is currently pursuing an Integrated M.S. and Ph.D. student in Mechanical Engineering at Yonsei University, Seoul, South Korea. His research interests are on the field of prognostics and health management (PHM), signal processing, deep learning-based data augmentation and knowledge transfer learning.

Jongsoo Lee received B.S. and M.S. in Mechanical Engineering at Yonsei University, Seoul, Korea in 1988 and 1990, respectively and Ph.D. in Mechanical Engineering at Rensselaer Polytechnic Institute, Troy, NY in 1996. After a research associate at Rensselaer Rotorcraft Technology Center, he has been a professor of Mechanical Engineering at Yonsei University since 1997. His research interests include multi-physics design optimization (MDO), reliability-based robust optimization, virtual product design and development, model-based system engineering (MBSE), prognostics and health management (PHM), and industrial artificial intelligence of data augmentation, transfer learning, domain adaptation, domain generalization and domain randomization with applications to structures, fatigue/durability, lifetime prediction, noise and vibration problems.