A study on self-diagnosis/prediction technology for LIDAR sensor of autonomous vehicles

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ABSTRACT

Along with the development of autonomous driving technology, the need for self-failure diagnosis and Remaining Useful Life (RUL) prediction technology for core parts for autonomous driving is increasing. In particular, the characteristics of the light detection and ranging (LIDAR) sensor exposed to the outside further increase the need to apply fault diagnosis and RUL prediction technology considering various environmental variables. In this study, based on the accelerated degradation test of LIDAR, the failure mode was analyzed. Through this, LIDAR failure due to thermal runaway, which is the first failure type in high temperature conditions, was identified, and whether there were major environmental data that could identify thermal runaway was identified. In the case of LIDAR's thermal runaway phenomenon, a study on an algorithm to identify the precursor symptoms of failure in an accidental failure situation is conducted. Afterwards, through the actual vehicle test process, various environmental variable information is analyzed for correlation with LIDAR internal sensor data, and the abnormal data for the temperature of the internal parts of the LIDAR is predicted through the external environmental sensor.

1. INTRODUCTION

Along with the development of autonomous driving technology, the need for self-failure diagnosis and Remaining Useful Life (RUL) prediction technology for core parts for autonomous driving is increasing. In particular, the characteristics of the LIDAR sensor exposed to the outside further increase the need to apply fault diagnosis and RUL prediction technology considering various environmental variables.

In this study, first, an accelerated degradation test was conducted to analyze the failure mode of LIDAR. For the test, a situation in which the temperature of the chamber was gradually raised was assumed. The state of the LIDAR was also checked by additionally installing various sensors in the internal structure of the LIDAR. Through this test, it was found that the thermal runaway phenomenon occurred first in the laser diode part of the LIDAR, and when the threshold point was crossed, the thermal runaway phenomenon was rapidly accelerated. Next, the sensor data to determine the failure was analyzed, and through this, the failure of the laser diode inside the LIDAR was examined. Afterwards, data with high internal failure correlation and correlation analysis were conducted through sensors that collect environmental data attached to the outside of LIDAR to create a deep learning model that estimates internal data in actual driving situations for the external environment. Finally, it predicts the abnormal data of LIDAR that can be predicted under continuous driving conditions.

2. ACCELERATED DEGRADATION TEST

2.1. Experimental Conditions

The accelerated degradation test device used in this study consists of a chamber for experimentation, a device for monitoring sensor data, and a datalogger for reading environmental data, as shown in Figure 1. For the accelerated degradation test for temperature, the temperature of the chamber was set at 80 degrees Celsius, and the Thermal Electric Cooler (TEC) temperature was changed to 16 degrees Celsius, 25 degrees Celsius, and 35 degrees Celsius.

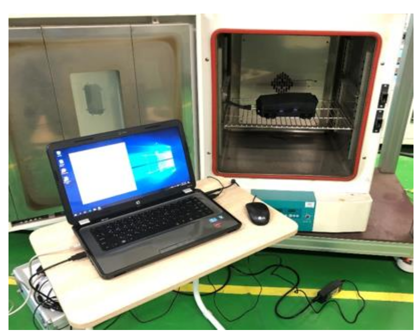

Figure 1. Configuration of experimental setup.

2.2. Experimental Results

As shown in Figure 2, the results of the accelerated degradation test for temperature showed that thermal runaway phenomenon occurred from around 2.5 voltage based on the TEC voltage. Therefore, the sensor data value at 2.5 voltage was used as the point of threshold, and this point was used as the critical point.

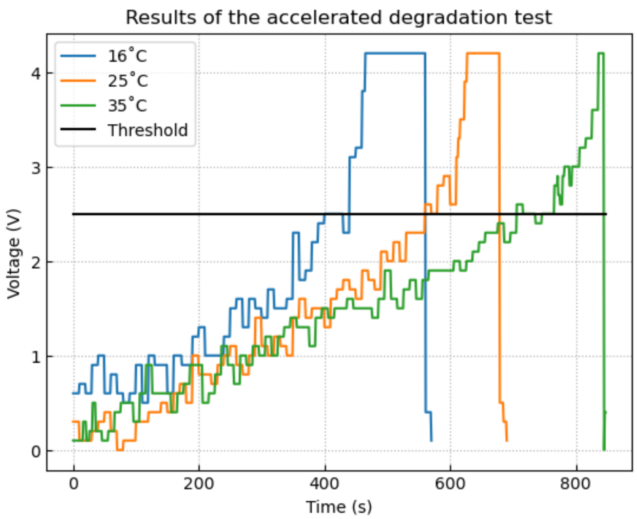

Figure 2. Results of the accelerated degradation test.

3. ACTUAL VEHICLE TEST

3.1. Test Conditions

In the case of the actual vehicle test, data were collected in three road environments of City, Country, and Highway, 1000 km each, and 3000 km in total, divided into summer and winter. In the driving situation, additional sensors were attached to the outside of the LIDAR as shown in Figure 3, to obtain information on various environmental variables. Measurements were made with a sampling rate of 5Hz, and the types of data that can be acquired and the acquisition process are shown in Figure 4.

Figure 3. LIDAR with additional sensors.

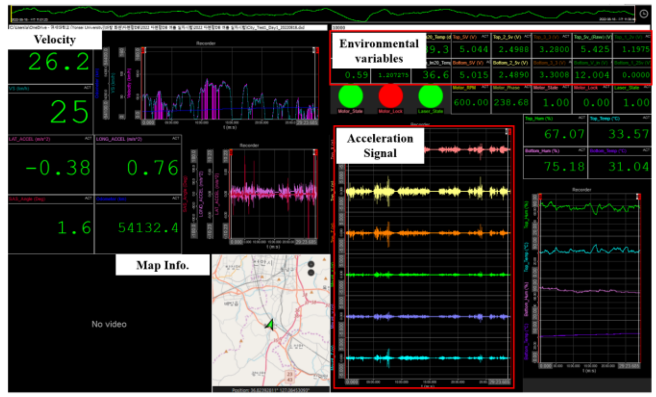

Figure 4. Actual vehicle driving data collection screen.

3.2. Actual Vehicle Test Data

A self-developed user interface was constructed to secure the data of Figure 3. Among the data collected through this, the main environmental data is shown in Figure 4. The data collected at 5Hz was extracted using rms and mean characteristics, and a GUI was additionally developed to classify data according to various conditions occurring in the real vehicle driving environment, so that each data in the desired driving situation could be labeled. Finally, we tried to estimate the board-based top/bottom temperature through temperature and humidity data. Then, by using the estimated top/bottom temperature of the board, it is possible to estimate the temperature of the FPGA, which will be used as major failure determination data. In addition to that, various data in Table1. We will continue to incorporate various models to construct the most accurate regression model.

3.3. Correlation Analysis

A correlation analysis was conducted between the temperature voltage data of the laser diode where the core failure occurs and the environmental variables. As shown in Table 1, it was found that the LIDAR upper and lower temperatures, humidity, and FPGA temperature had a correlation coefficient of more than 0.5 with the temperature of the laser diode. Afterwards, a deep learning model was implemented to predict the temperature of the laser diode.

4. ANOMALY DETECTION

Anomaly detection was performed to identify the characteristics of the failure of the data and to distinguish between normal and abnormal data. First, the data in case of thermal runaway for the voltage set as the threshold was classified through labeling, and the area in which complete failure was identified was identified. In this study, six significantly different physical characteristics were extracted through correlation analysis results and feature extraction, principal components analysis (PCA) was performed using the six extracted characteristics, and Anomaly detection was performed in the reduced dimension. Machine learning classification techniques using k-nearest neighbors (KNN) and deep learning classification techniques using convolutional neural network (CNN) were used as the main algorithms, but we plan to study preprocessing techniques and deep learning algorithms that can further improve performance through future research. As a result, the prediction accuracy so far is 92.3%, so we plan to continue the research while accumulating future data.

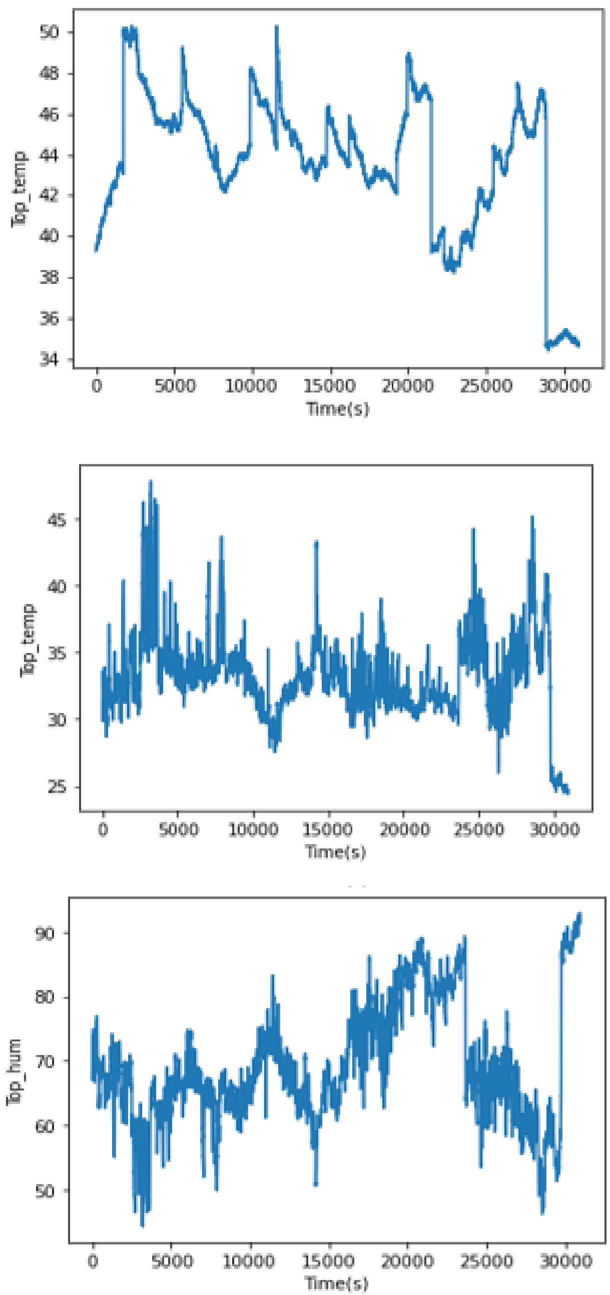

Figure 4. Board Temperature Data and External Sensor Data

Table 1. Correlation analysis of the laser diode temperature with different environment variables.

Environment variables	Pearson coefficient
Voltage	0.25
Current	-0.39
Temperature	-0.57
Humidity	0.43
Temperature-Top	-0.57
Temperature-Bottom	-0.57
Acceleration-x	0.09
Temperature-FPGA	-0.56
Gyroscope-z	0.54
Gyroscope-x	-0.07

5. CONCLUSION

Accelerated degradation test was used to identify the failure type of LIDAR. Through this, it was possible to analyze the thermal runaway phenomenon in detail, and using the actual vehicle test data, a deep learning model for predicting the thermal runaway phenomenon using an external sensor was created. In addition, by conducting an analysis on the dimension that can detect abnormalities, if data is collected in the future, we plan to continuously conduct research on how to systematically manage the data.

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BIOGRAPHIES

Jaewook Lee is an Integrated M.S. and Ph.D. student in Mechanical Engineering at Yonsei University. His research interests are on the field of prognostics and health management (PHM), deep learning-based data augmentation and knowledge transfer learning.

Jongsoo Lee received his B.S. degree in Mechanical Engineering from Yonsei University, Seoul, Korea, in 1988 and M.S. degree in Aerospace Engineering from the University of Minnesota, Minneapolis, MN, in 1992. He received Ph.D. in Mechanical Engineering from Rensselaer Polytechnic Institute, Troy, NY, in 1996. Dr. Lee is a professor at School of Mechanical Engineering, Yonsei University, Seoul, Korea since Fall of 1997. His research areas include multi-physics design optimization (MDO) & prognostics ad health management (PHM) with industrial artificial intelligence of data augmentation and knowledge transfer learning