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Safety-First Autonomous Vehicle Technology: Empirical Assessment of Sensor Performance in Diverse Environmental Conditions

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ABSTRACT

Many companies and institutions focus on autonomous vehicles. Accordingly, the commercialization of fully autonomous vehicles is expected to proceed rapidly. Autonomous vehicle companies are already demonstrating or commercializing vehicles on real roads. However, autonomous vehicle data is not disclosed to the public, and related academic research is very rare. In this study, changes in the functional levels of autonomous driving sensors in various environments were analyzed using actual collected autonomous driving data. A hypothesis was established by reviewing previous studies related to the functional levels of sensors, and the hypothesis was verified by comparing actual autonomous driving data using two different statistical analysis methods. The hypothesis was tested using the 2-sample K-S test and the DTW algorithm, with different sensor elements used in each verification stage. As a result of the analysis, we found that sensor performance changed on rainy and cloudy days compared to sunny days. This study confirms that the functional levels of autonomous vehicle sensors change depending on the environment. The results of this study are expected to serve as foundational data for establishing standards and criteria for safety evaluations of autonomous vehicles in the future.

1. Introduction

The SAE standard specifies that level 4 is the point at which driver intervention is not required when operating an autonomous vehicle. Beyond that, the autonomous driving system takes control of all driving functions (SAE, 2021). This means that as the level of autonomous driving technology increases, the role and responsibility of the driver diminish, while the importance of the autonomous driving system and the performance of autonomous vehicles become more significant. The necessity of enhancing the performance of autonomous vehicles for the era of autonomous driving is consistently highlighted, with particular emphasis on the importance of sensing equipment used to perceive and analyzed the surrounding traffic environment (Duan et al., 2021).

Previous studies have examined the functional levels of sensors in autonomous vehicles and analyzed the devices' performance limits and vulnerabilities (Ort et al., 2020; Zhao et al., 2020). This has shown that the performance levels of sensors in autonomous vehicles can vary based on environmental factors such as light levels and weather, as well as road traffic factors such as road markings, congestion, and moving objects (Müller, 2017; Schrepfer et al., 2018; Ponn et al., 2019). However, most previous studies have been limited to predefined experimental environments due to issues with technology security and data acquisition. Additionally, while they have identified the factors that influence sensor performance, they have provided insufficient analysis on the extent of these impacts.

To address the shortcomings of previous studies and present new insights, this study introduced the following distinctions. Firstly, it utilized data collected from actual road environments rather than data collected in controlled experimental settings. Additionally, it aimed to prioritize the factors influencing sensor performance by comparing their relative impacts, thus deriving the order of importance of these influencing factors. This study investigates the factors influencing the performance of autonomous vehicle sensors and examines the extent of performance variation

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depending on these influencing factors.

2. Literature Review

2.1 The Impact of Weather on Autonomous Vehicle Sensors

Zhang et al. (2023) investigates the impact of adverse weather conditions on five major Automated Driving Systems sensors. It enumerates sensor fusion solutions, with perception enhancement through machine learning and image processing methods, such as de-noising, being the core solution. Future Automated Driving Systems sensor candidates and the challenges posed by insufficient relevant datasets were also examined. The study concludes that V2X and IoT have promising potential for future weather research. Emphasis was placed on the need for robust sensor fusion and advancements in sensing under extreme weather conditions.

Sezgin et al. (2023) evaluates the performance of radar, lidar, and camera sensors for autonomous driving under adverse weather conditions such as rain and fog. The research highlights the impact of these conditions on sensor reliability and presents a fuzzy logic and genetic algorithm-based monitoring system to assess and maintain sensor performance. The proposed system demonstrates potential in ensuring safe autonomous driving by continuously evaluating sensor data quality and identifying areas affected by weather.

Yoneda et al. (2019) reviews recognition technologies for automated driving under adverse weather conditions, highlighting the necessity for robust sensor fusion and infrastructure-based solutions. Key challenges include ensuring sensor reliability and designing cost-effective systems. The authors suggest that defining operational domains and application ranges can facilitate the realistic integration of these systems into society.

Steinbaek et al. (2017) conducted a study that aimed to investigate the advantages and disadvantages of the main sensors used in autonomous driving systems, namely Radar, LIDAR, and Vision sensors. Through the study, the authors noted that no single sensor could operate effectively in all environments, which highlights the need for sensor fusion in autonomous driving systems. The authors classified the functional level of sensors into five grades based on different criteria, including range, angular velocity, and weather conditions. This classification allowed for a detailed analysis of the sensors' performance in different environments (Table 1).

Table 1. Comparison of Environment Perception Sensor Capabilities

Items	Radar	LiDAR	Vision
Range	++	+	++
Range resolution	++	++	0
Angular resolution	0	++	+
Works in bad weather	++	0	-
Works in dark	++	++	--
Works in bright	++	+	+
Color / contrast	--	--	++
Radial velocity	++	0	-

Note. Adapted from Next Generation Radar Sensors in Automotive Sensor Fusion Systems, by Steinbaeck et al., 2017, IEEE

In the realm of autonomous driving system development, pivotal components include sensors like Radar, Li-DAR, Camera, and GNSS. De Ponte Müller (2017) underscored the significance of cooperative functioning among these sensors through V2V communication, recognizing their inherent functional limitations in diverse environments. Similarly, Ponn et al. (2019) emphasized the critical role of environmental awareness for ensuring safety, presenting a novel methodology based on sensor range analysis to derive test scenarios. While both studies proposed alterations in sensor functional levels based on the surrounding environment, they were primarily theoretical values derived from sensor specifications.

Dreissig et al. (2023) analyses various approaches to LiDAR perception under adverse weather conditions, focusing on the availability of data, point cloud processing, and robust perception algorithms. It identifies significant gaps in current research and highlights promising directions for future work, emphasizing the need for comprehensive real-world datasets and advanced sensor fusion techniques to mitigate weather-induced performance degradation

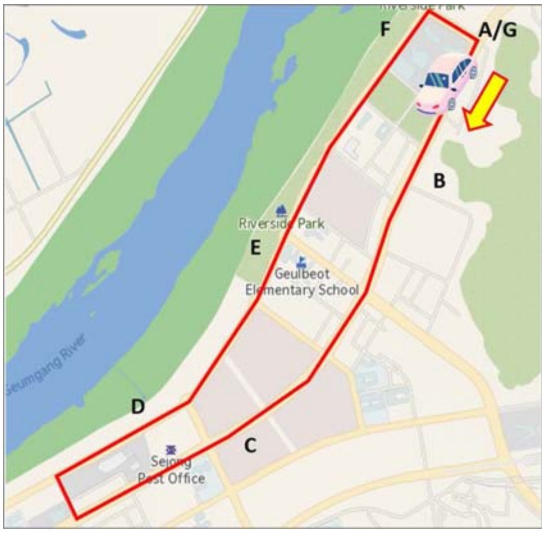
Previous studies suggest that the performance of autonomous vehicle sensors can vary with the weather. It is particularly important to pay attention to the changes in performance not only of image-based camera sensors but also of electronic sensors such as radar and LiDAR. These studies measuring sensor performance were conducted in controlled experimental environments. However, it should be considered that these experimental environments differ from real-world traffic conditions. To obtain more meaningful research results, it is deemed necessary to utilize data collected from actual road environments.

2.2 Methods for Comparing Big Data Samples

Many studies have been conducted, such as analyzing based on the referred test to test big data and using it to improve the sensor function (Lall, 2015; Luo et al., 2015). Big data can be analyzed by examining the distribution of data sets. This method can be extended to identity verification by checking the distribution for two samples.

There are many research methodologies for testing two or more samples. Kim and Lee (2017) compared many distribution-independent tests used to verify the equality of two-sample distributions. They conducted simulations to evaluate the power of each test and confirmed the superiority of the Kolmogorov-Smirnov test. This test has a characteristic that is sensitive to the shape of the distribution (Darling, 1957). In addition, the test was judged to have the best power when test of homogeneity between groups with different sample size

The verification of the equivalence of two samples composed of big data can be performed using statistical methods, as well as algorithm-based pattern matching techniques. A representative methodology is Dynamic Time Warping (DTW), which performs



※ 1 Vehicle drive on the same route on different dates

A. Departure (Start logging)

B. Normal driving at 50km/h

C. School Zone Near Boram Elementary School

D. Driving at 40km/h in the Roundabout

E. The school zone in front of Glebot Elementary School

F. Normal driving at 50km/h

G. Arrival (Stop logging)

Fig. 1. Actual Road Data Acquisition Path

non-linear warping along the time axis of time-series data (Cho and Lee, 2008). The DTW algorithm was first introduced by R. Bellman and R. Kalaba in the 1960s and was first used in speech recognition research in the 1970s. The superiority of this algorithm has been proven, and it continues to be utilized in various fields up to the present (Senin, 2008). In the field of transportation, Taylor et al. (2015) analyzed the diversity of drivers' car-following behavior and situation-dependent behavior based on driver trajectory data using the DTW algorithm.

Two methodologies that enable the verification of the equivalence of samples composed of big data are introduced. The Kolmogorov-Smirnov test allows for statistical verification. The DTW (Dynamic Time Warping) algorithm can measure the similarity of waveforms, making it applicable to non-linear data and time-series classification. A common feature of these methodologies is that they can verify the equivalence of samples even if the sample sizes are not the same. This provides significant advantages when analyzing big data, where it is often difficult to match the number of data points between samples.

3. Data

In this study, driving data collected directly by autonomous vehicles are used. The raw data collected at the time were redefined into a usable form through parsing. This raw data encompasses compressed front camera (1EA) data and compressed corner camera (4EA) data, further categorized into sensor perception data, vehicle data, and autonomous driving controller data. Sensor perception data includes lane and object recognition data obtained from cameras and radar, while vehicle data encompasses information related to speed, acceleration, gear, turn signals, and more. Autonomous driving controller data comprises details such as driving mode, self-driving trajectory, the presence of leading vehicles, stop flag indications, and longitudinal and lateral control command values.

The data were collected between June and September 2021 in Sejong City, South Korea. The same autonomous vehicle collected data over several days from a 6.4 km section of road. The route where the data for this study was collected is illustrated on the map in (Fig. 1). The survey section encompasses various operating environments, detailed in (Table 2) below. Throughout the mentioned period, the data were tested approximately 20 times under varying weather conditions, categorized into sunny, rainy, and cloudy environments. The data storage method involves organizing information into one directory based on the acquisition time. Within this directory, a JSON file is created, containing information on sensor recognition data, vehicle data, and autonomous driving control system data. Additionally, for each frame, image data and LiDAR point cloud data sources are generated.

Table 2. Autonomous Vehicle Data Collection Pathways and Details

Section	Detailed environments for each section
A	Start (Start Record)
B	Autonomous Vehicle drives at 50 kph
C	Takeover, a school zone near Boram Elementary School.
D	Autonomous Vehicle drives at 40 kph in the section with roundabout
E	Takeover, a school zone near Geulbeot Elementary School.
F	Autonomous Vehicle drives at 50 kph
G	Arrive (End of Record)

In the predefined route, transportation facilities such as school zones and roundabouts exist, and the control right is switched twice. Through this scenario, driving in a more complex environment was carried out. The following (Table 3) shows the information of the vehicle used for autonomous driving. The autonomous vehicle used for driving is a Hyundai Sonata, equipped with 4 LiDAR sensors, 5 camera sensors, and 1 Radar sensor. The autonomous driving data collected using this vehicle consists of autonomous driving sensor source data, sensor recognition data, vehicle data, and autonomous driving control system data. Table 4

Table 3. The Characteristics of Autonomous Vehicle

Category	Information
Vehicle	SONATA DN8 (Hyundai)
Number of LiDAR	4
Number of Camera	5
Number of Radar	1

Table 4. Autonomous Vehicle Sensor Function Specification

Item		Specification
Model		FHD390C-USB(D)
Camera	Operating Temperature	-40(Celsius) - +85(Celsius)
	Model	FHD 1080p, 30 fps
	Effective pixels	1/2.7”, 1920 × 1080
	Dynamic Range	120 dB
	Image Signal Processing	AE/AWB, HDR, LFM
	Serializer	V-by-One@HS
	FOV	H60 Degree / H110 Degree
	WaterProof	IP67

represents the specifications of autonomous vehicle sensor functions. Table 5 describes the components of data collected from sensors.

Three types of sensors were attached to the autonomous vehicle used in the experiment. Unfortunately, not all types of sensing data could be identified, so we utilized data from the Radar and Camera sensors. The elements composing the Radar sensor recognition data are as follows (Table 6). The elements composing the Camera sensor recognition data are as follows (Table 7).

Table 6. Radar Sensor Recognition Data Element

Classification	Explain	Unit
ObjNo	Object Number	-
ID	Object ID	-
Status	Status	-
LiteralRate	Lateral speed	m/s
Angle	Angle	deg
Range	Distance	m
Speed	Relative Speed	m/s
PosX	Relative distance X	m
PosY	Relative distance Y	m

4. Methodology

4.1 Two-Sample Kolmogorov-Smirnov Test

The two-sample Kolmogorov-Smirnov test is an identity test proposed by Smirnoff (1939) and is a representative non-parametric test. To understand the distribution according to various environments, the K-S test, which can test the identity of two groups, was argued to be the most ideal statistical methodology for analyzing the data, and the study was conducted. Also, the reason for choosing the test method is that it has the best power in the fit test between groups with different sample sizes. Data acquired from actual driving of autonomous vehicles are non-continuous values and are suitable for non-parametric tests.

The empirical cumulative distribution function of the two-sample Kolmogorov-Smirnov test is as follows Eq. (1) (Basic assumptions are independent)

Table 5. Components by Actual Autonomous Vehicle Data

Data	Detail
Source data of AV’s Sensor	Front and corner camera image data, LiDAR point cloud data
Sensor recognition data	camera recognition result (lane, object), Front Radar object recognition result.
Vehicle data	vehicle speed, acceleration, steering angle, gear, turn signal, GPS location, etc.
Autonomous driving control system data	Autonomous driving mode (Auto/Manual), driving trajectory of vehicle etc.

Table 7. Camera Recognition Data Element

Classification	Explain	Data	Unit
Type	Left lane type	0-dashed 1-solid 2-undecided 3-road edge 4-double lane mark 5-Botts’dots 6-invalid	-
Quality	Recognition Quality	0,1-Low Quality 2,3-high Quality	
View Range	Physical view range of lane mark	Range: 0 ~ 127.996	m
ParC0	Lane Position Parameter	Range: -127 ~ 128	m
ParC1	Heading Angle Parameter	Range: -0.357 ~ 0.357	rad
ParC2	Lane Curvature Parameter	Range: -0.02 ~ 0.02	n/a
ParC3	Lane Curvature Derivative Parameter	Range: -0.00012 ~ 0.00012	n/a

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[-\infty,x]}(X_i) \tag{1}$$

$F_n(x)$: Cumulative probability function of the observed sample

The statistics of the K-S test are as follows Eq. (2).

$$D = sup_x|F_m(x) - G_n(x)| \tag{2}$$

In the above, $F_m(x)$ and $G_n(x)$ are the empirical cumulative distribution function of x and y. Also, the D is the test statistic, which is the maximum value of the difference between two cumulative distribution functions.

Similarity, The Kolmogorov-Smirnov Goodness-of-Fit Test is a concept proposed by Massey Jr (1951) to test the fit between two groups based on the largest difference between the empirical cumulative distribution function and the hypothetical cumulative distribution function. The purpose of the test is to test whether one sample group has the same distribution as the hypothetical probability distribution such as normal distribution (Priest, 1983). Therefore, it was deduced that it was not a methodology suitable for this study, which had to derive whether the two sample groups had the same distribution. Accordingly, a two-sample Kolmogorov-Smirnov test was adopted as one of the methodologies for analyzing the data set of this study.

4.2 Dynamic Time Warping

The DTW algorithm searches for the alignment with the least cumulative cost, which is referred to as the warp path. According to Keogh and Pazzani (2001), the approach using DTW can also be applied to identify the optimal alignment between two time-dependent data series. The DTW algorithm is also suitable method for processing large vehicle tracking datasets. The formula and visualization for the DTW algorithm are as follows Eqs. (3) – (6); (Table 8).

Table 8. Table for DTW to Measure Similarity between Time Series Data

Y / X	1	2	3	⋯	n-1	n
1	D(1, 1)	D(1, 2)	D(1, 3)	⋯	D(1, n-1)	D(1, n)
2	D(2, 1)	D(2, 2)	D(2, 3)	⋯	D(2, n-1)	D(2, n)
3	D(3, 1)	D(3, 2)	D(3, 3)	⋯	D(3, n-1)	D(3, n)
…	…	…	…	…	…	…
m-1	D(m-1, 1)	D(m-1, 2)	D(m-1, 3)	⋯	D(m-1, n-1)	D(i-1, n)
m	D(m, 1)	D(m, 2)	D(m, 3)	⋯	D(m, n-1)	D(m, n)

$$DTW(X, Y) = c_p(X, Y) = min\{c_p(X, Y), p \in P^{L \times K}\} \tag{3}$$

$$D(1, n) = \sum_{k=1}^{n} c(x_1, y_k), n \in [1, K] \tag{4}$$

$$D(m, 1) = \sum_{k=1}^{m} c(x_k, y_1), n \in [1, L] \tag{5}$$

$$\begin{aligned} D(1, n) = \min\{D(m-1, n-1), D(n-1, m), D(n, m-1)\} \\ +(x_n, m), n \in [1, L], j \in [1, K] \end{aligned} \tag{6}$$

Using Eqs. (4) and (5), we calculate the elements of the rows and columns of the DTW table, and use Eq. (6) to calculate the remaining elements. Finally, we use Eq. (3) to calculate the dynamic similarity between the two data sets, which is DTW; the more similar the two data sets, the closer the value will be to 0 (Im and Kim, 2020). The DTW algorithm is a technique that allows for the analysis of two independent time series data by adjusting the time points. Based on these characteristics, we adopted a time series test based on the DTW algorithm as a second methodology for analyzing the data set of this study.

4.3 Hypotheses and Research Procedures

Based on the reviewed self-driving literature sensors, the mentioned

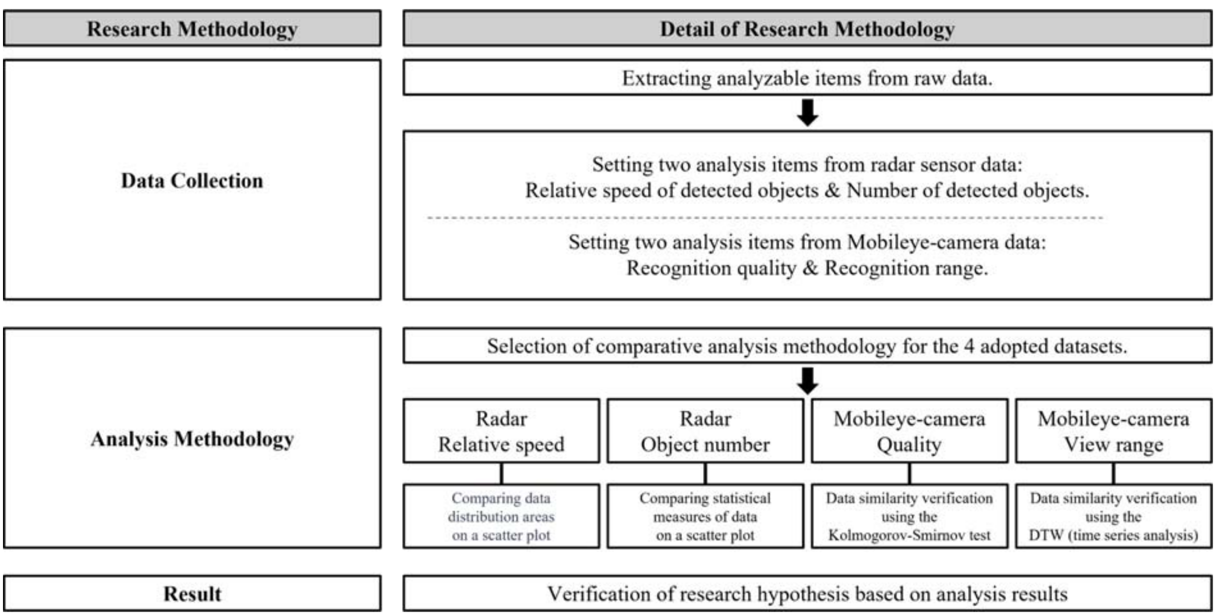


Fig. 2. Visualization of the Research Process and Detailed Contents

methodology was applied to establish a theoretical hypothesis that can be compared with actual self-driving data. Among self-driving data, the sensors that can be analyzed in sensor recognition data are cameras and radar sensors. As a result, a hypothesis was established that there would be a change in the functional level of the sensor depending on the weather environment, and this was verified through subsequent research.

In this study, the analysis method can be divided into three stages: data collection, data analysis, and conclusion. During the data collection stage, the task involves selecting suitable data for analysis from the raw data collected by autonomous vehicles. In the data analysis stage, the collected data is analyzed using the most appropriate methods for each dataset and conducting homogeneity test. In the conclusion stage, the analysis results are compiled to validate the research hypotheses. The chart of research process can be confirmed in the following (Fig. 2).

5. Analysis

5.1 Radar Sensor Datasets Analysis

As there was a slight difference in the start and end points depending on the investigation period and environment, the start and end points were matched for each frame and the analysis conducted.

The analysis of radar sensor datasets focused on “Relative Speed” and “Object Number”. To gain a comprehensive understanding of the collected Relative Speed and Object Number data, a scatter plot was generated. In order to mitigate the influence of outliers stemming from intermittent sensor errors or external environmental factors, only the data within the 30th to 70th percentiles of the scatter plot were considered, defining this range as the normal data range.

The normal range of the scatter plot, represented by Relative Speed data, was determined to be approximately -70 kph to 140 kph

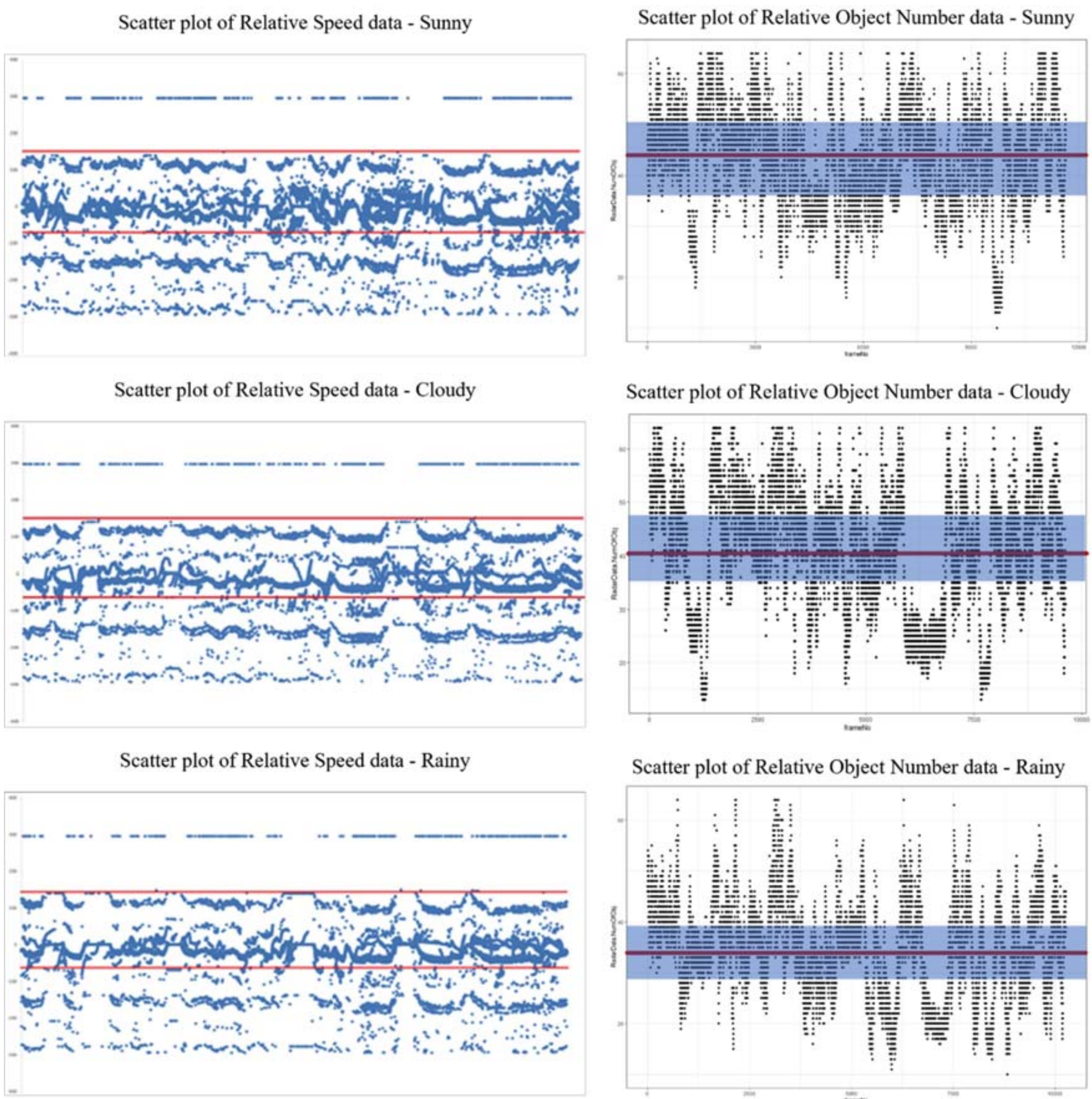


Fig. 3. Scatter Plot of Radar Sensor Data: (a) Relative Speed, (b) Object Number-Right

on a clear day. Extending this speed range to the scatter plot of cloudy and rainy days allowed for a visual comparison of the Radar's ability to recognize Relative Speed under varying weather conditions. The overall data pattern was explored through scatter plots, amalgamating a substantial number of Frame datasets to generate graphs depicted as areas. The critical focus was on observing the density of data marked in blue within the normal range specified by the red line, as illustrated in (Fig. 3(a)). It is evident that the area occupied by the blue color in the graph on clear days is broader than on other weather conditions. Additionally, subtle differences were noticeable when comparing rainy and cloudy days. These findings suggest a discernible impact of weather conditions on the performance of autonomous vehicle sensors.

Table 9 displays the results for the number of objects collected by the radar in autonomous vehicles per frame, categorized by weather conditions. The objective is to measure the performance variation of the radar sensor based on different weather conditions, utilizing the number of detected objects as the performance metric. For an unbiased comparison, we observed the average value and the range between the 30th and 70th percentiles, followed by a general interpretation of the analysis results. The highest number of detected objects occurred on clear days (42.8), while the lowest was observed on rainy days (34.3). The number of detected objects on cloudy days fell between the values for clear and rainy days (40.7). Similar patterns were observed in the range between the 30th and 70th percentiles, suggesting a degradation in sensor performance due to varying weather conditions. The scatter plot and data distribution trend can be observed in the following (Fig. 3(b)).

5.2 Camera Sensor Datasets Analysis

As the data is divided into left and right lanes, data sets surveyed in sunny, rainy, and cloudy weather environments were constructed respectively. The acronyms of the configured datasets are (Table 10) and the acronyms are used in the analysis subsequent. The dataset consists of data observed in three types of weather environments, and analysis was performed on sunny-rain and sunny-cloudy data based on the data surveyed on a sunny day. For the analysis method, test of homogeneity between the two data sets was performed using the two-sample Kolmogorov-Smirnov test and Time series clustering based on DTW algorithm.

Preferentially we performed a homogeneity verification on the dataset consisting of the recognition Quality items from the Camera recognition data. We adopted the two-sample Kolmogorov-Smirnov test as the verification technique. Tables 11 to 13 provide basic statistics on the lane recognition quality levels of the camera sensor based on different weather conditions. The quality levels are categorized from 0 to 3, where 0 and 1 represent Low Quality, and 2 and 3 represent High Quality.

Specifically, Table 11 presents basic statistics for the recognition quality level values of the left lane. Table 12 provides basic statistics for the recognition quality level values of the right lane, and Table 13 represents the Kolmogorov-Smirnov test values conducted based on the values of both lanes.

Through the analysis, it was determined that the calculated p-value in all tests was less than 0.05, leading to the rejection of the null hypothesis that the distributions of the two groups are the

Table 9. Descriptive Statistics of Detected Objects Number (Radar data)

Classification (Number of objects detected)	Sunny	Rainy	Cloudy
Average	42.8	34.3	40.7
70 Percentile	48	39	48
50 Percentile	43	35	42
30 Percentile	37	30	35

Table 11. Descriptive Statistics on the Left Lane Area (Camera data)

Lane Quality	Sunny_left	Rainy_left	Cloudy_left
Min.	0.000	0.000	0.000
Q1	1.000	0.000	1.000
Median	2.000	2.000	2.000
Mean	1.937	1.679	1.957
Q3	3.000	3.000	3.000
Max.	3.000	3.000	3.000

Table 12. Descriptive Statistics on the Right Lane Area (Camera data)

Lane Quality	Sunny_right	Rainy_right	Cloudy_right
Min.	0.000	0.000	0.000
Q1.	0.000	0.000	0.000
Median	2.000	2.000	2.000
Mean	1.897	1.573	1.811
Q3	3.000	3.000	3.000
Max.	3.000	3.000	3.000

Table 10. Camera Lane Recognition Data Elements and Descriptions

Lane	Data	Description
Left Lane	Sunny_left (SL)	Data collected from the left side of the vehicle on a clear day
	Rainy_left (RL)	Data collected from the left side of the vehicle on a rainy day
	Cloudy_left (CL)	Data collected from the left side of the vehicle on a cloudy day
Right Lane	Sunny_right (SR)	Data collected from the right side of the vehicle on a clear day
	Rainy_ right (RR)	Data collected from the right side of the vehicle on a rainy day
	Cloudy_ right (CR)	Data collected from the right side of the vehicle on a cloudy day

Table 13. The Result of Two-sample Kolmogorov-Smirnov Test

Lane	Data	D	p-value
Left Lane	Sunny_left & Rainy_left	0.082977	2.2e-16
	Sunny_left & Cloudy_left	0.18848	2.2e-16
Right Lane	Sunny_right & Rainy_right	0.074743	2.2e-16
	Sunny_right & Cloudy_right	0.15384	2.2e-16

same. This affirmation confirms that the functional level of sensors undergoes changes in adverse weather conditions compared to the theoretically constructed sunny days. Illustrated in (Fig. 4), the empirical cumulative distribution functions for the comparison group are presented based on weather and lane conditions.

The x-axis delineates the lane quality levels, while the y-axis represents the cumulative distribution values. In each graph title, values corresponding to the control group are depicted in red before the title, and values corresponding to the comparison group are represented in blue after the title. This visual representation further emphasizes the observed distinctions in sensor performance based on weather and lane conditions.

Next, we performed homogeneity verification on a dataset consisting of View Range items from Camera recognition data. We adopted Time Series Cluster Analysis using the DTW algorithm as the verification technique The time series data consists of a total of six types by combining View Range data by weather and dividing it for the left and right sides of the autonomous vehicle. Naming of time series data follows the definition in (Table 10). (Fig. 5) illustrates the processed time-series data of the camera sensor recognition of the autonomous vehicle collected frame by frame.

The X-axis of the graph represents the elapsed time of data collection (Frame Progression). The Y-axis represents the view range of the camera sensor. The color of each time-series graph is differentiated based on the weather conditions. In this figure, it can be observed that graphs of different colors do not overlap or exhibit similar patterns. This indicates variations in sensor functionality depending on the weather, suggesting the need to examine the extent of differences that occur.

We conducted time series clustering analysis using the DTW algorithm for the generated six datasets. The analysis aimed to verify the performance difference of sensors according to weather conditions. If the similarity between time series is high, there is no performance difference in sensors according to weather conditions. Conversely, if the similarity between time series is low, it can be concluded that there is a performance difference in sensors according to weather conditions. The verification of time series similarity based on the DTW algorithm can be confirmed by analyzing the distance (warping path) between time series matrix elements. During the analysis process, we search for the path with the smallest sum of Warping Path, and the total sum of the path becomes the DTW distance. The DTW distance represents

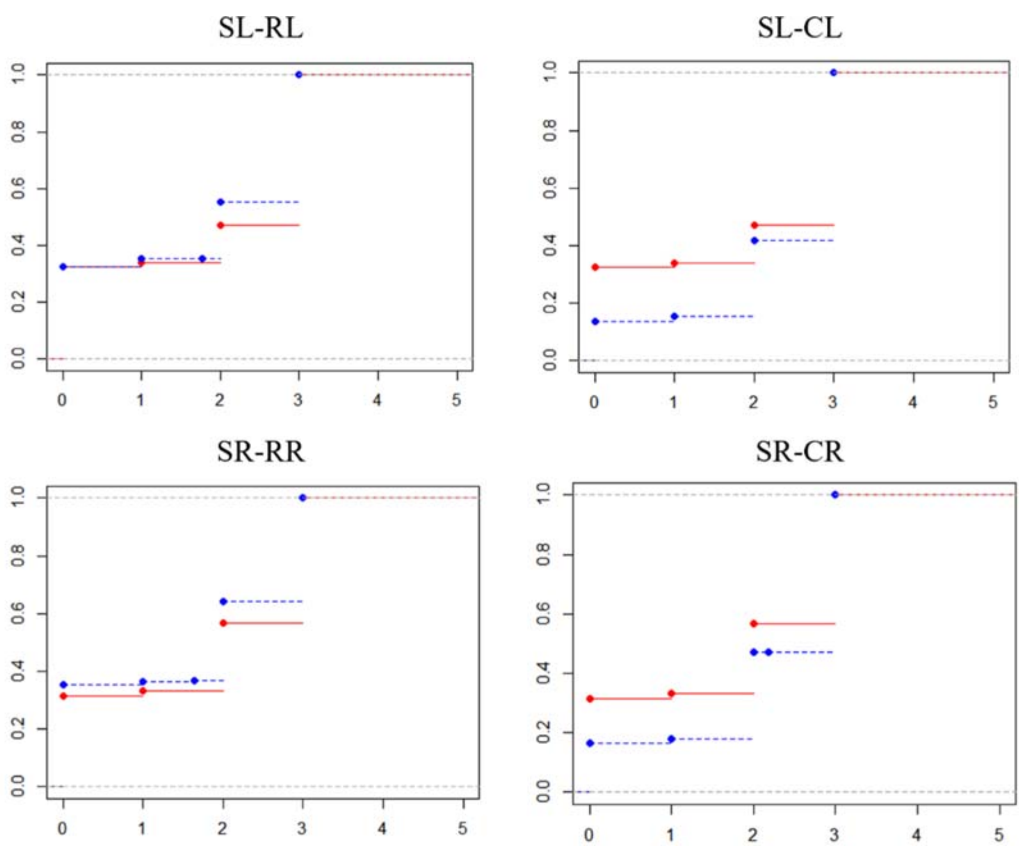


Fig. 4. The Empirical Cumulative Distribution Functions of Camera Sensor Recognition Data (Recognition Quality data)

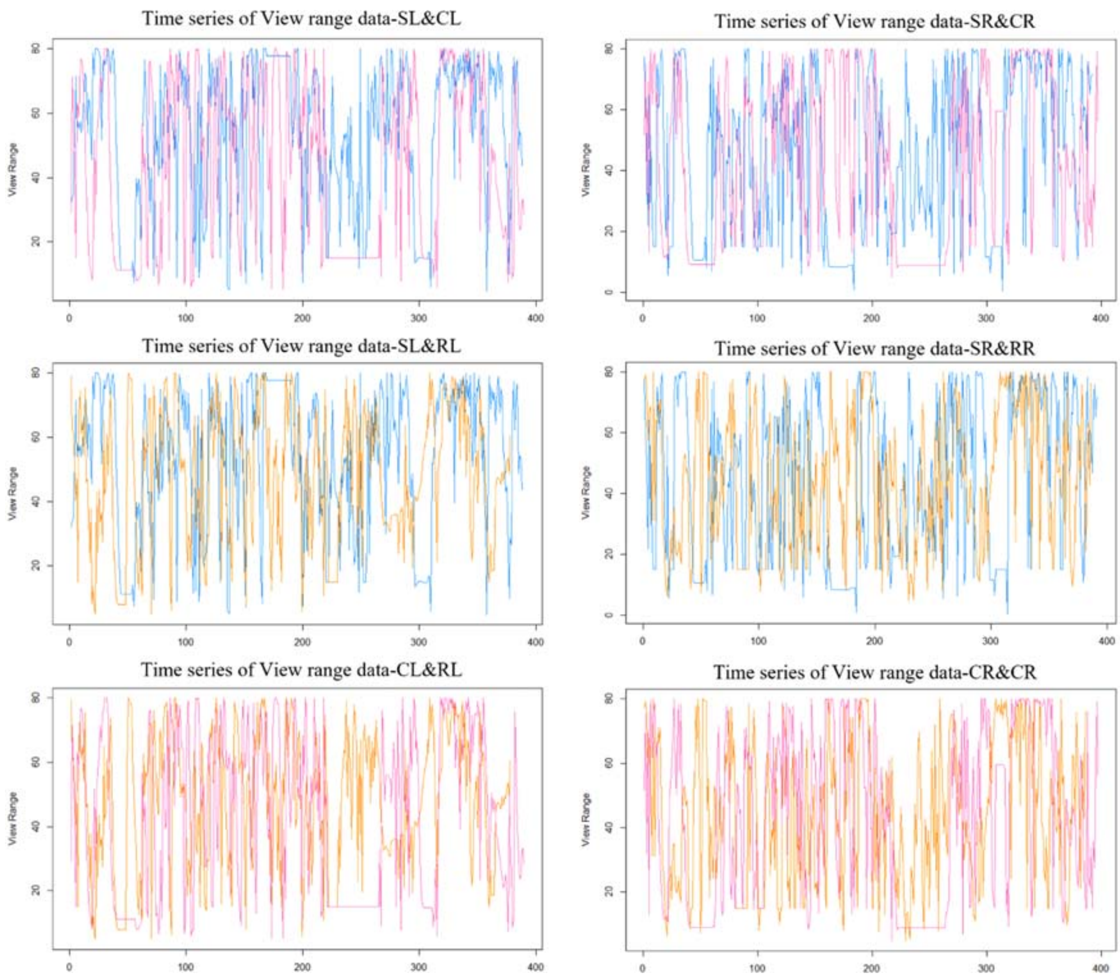


Fig. 5. Time Series of Camera Sensor Recognition Data (View range data)

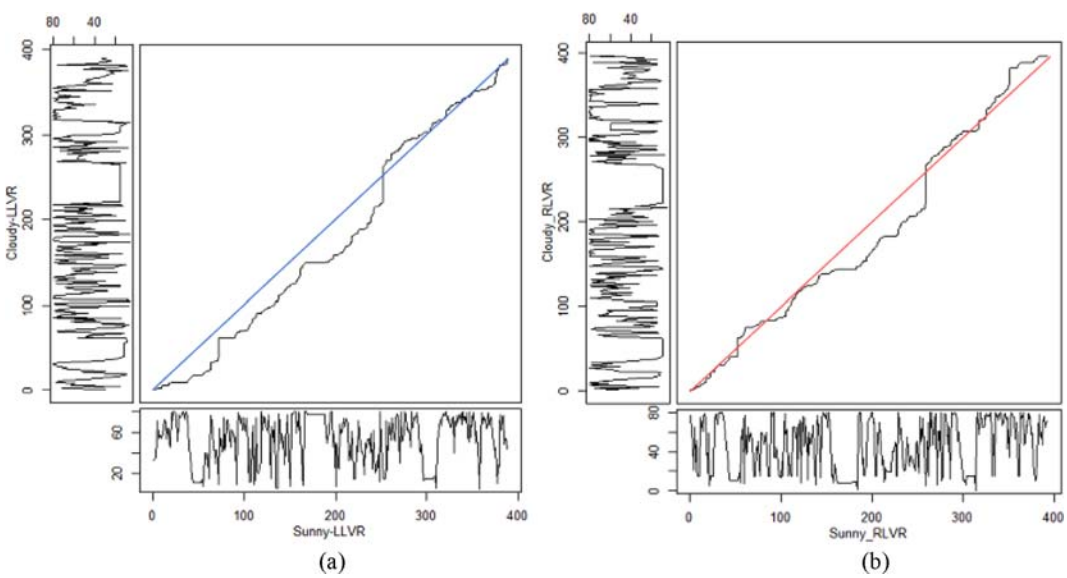


Fig. 6. DTW Results: (a) Sunny_left & Cloudy_left, (b) Sunny_right & Cloudy_right

the final similarity value, and the results of the similarity analysis between each time series cluster are shown in Figs. 6 to 8 and Table 14.

Based on the DTW algorithm, the results of the time series similarity analysis showed that the DTW distance between sunny-cloudy days was the smallest, while the DTW distance between

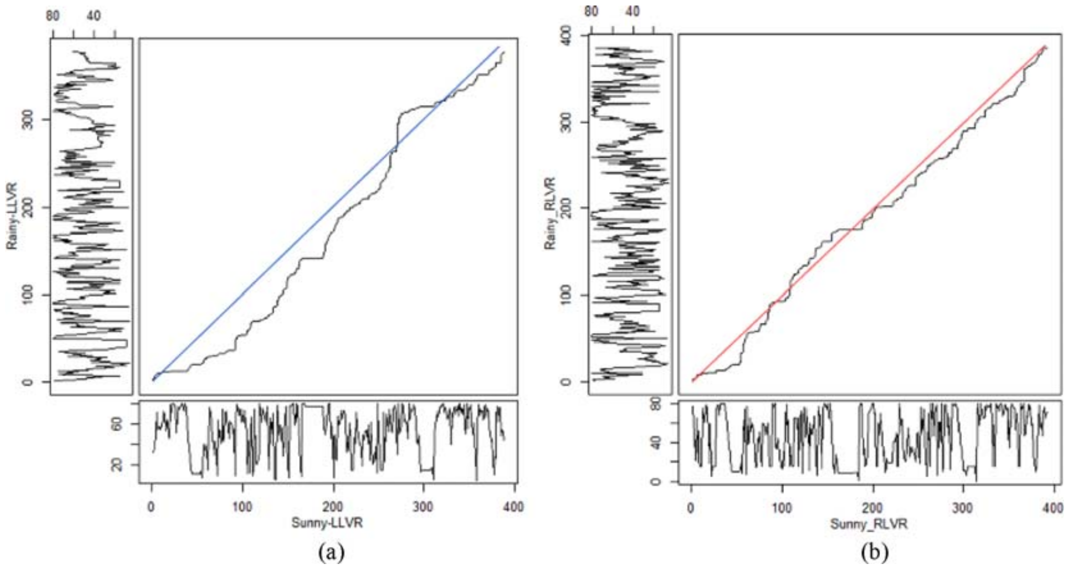


Fig. 7. DTW Results: (a) Sunny_left & Rainy_left, (b) Sunny_right & Rainy_right

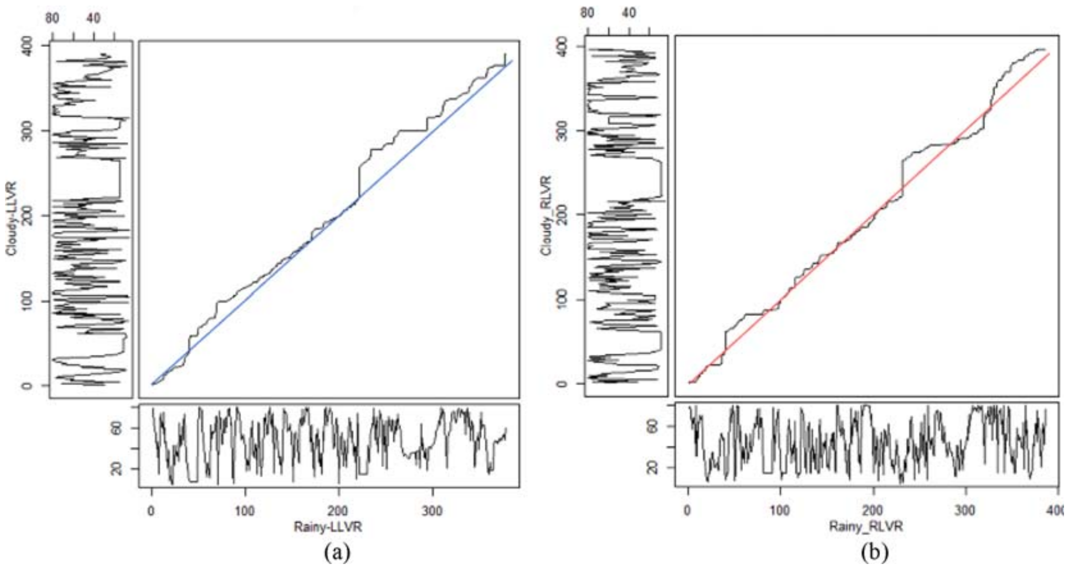


Fig. 8. DTW Results: (a) Cloudy_left & Rainy_left, (b) Cloudy_right & Rainy_right

Table 14. Results of DTW Distance Analysis between Time Series Clusters

Classification	Sunny & Cloudy	Sunny & Rainy	Cloudy & Rainy
Left Lane	3090.32	3537.31	3370.62
Right Lane	3635.84	3884.95	3641.42

sunny-rainy days was the largest. DTW distance on a cloudy-rainy day was analyzed to have a value between the previous two groups. These results reveal that there is a difference in sensor performance depending on the weather environment, especially on rainy days.

5.3 Brief Conclusion

Analyzing changes in sensor functionality concerning environmental factors relied on the examination of sensor recognition data obtained from the actual autonomous driving data collected during the survey phase. The camera and radar sensor recognition data were compiled to form a dataset. The evaluation of sensor performance levels did not focus on specific scenarios or isolated moments but encompassed an overall assessment of data collected throughout the driving process along a predetermined route. While sensor performance degradation might occur on clear days due to specific points or external reflective objects, these instances are deemed negligible when compared to the total driving time. Consequently, we assume that data collected on clear days represents a baseline for normal sensor performance. Building on this assumption, we proceeded to verify differences in sensor performance levels between cloudy and rainy days.

Confirmation of disparities in sensor performance levels based on weather conditions is derived from a reverse inference drawn from the outcomes of similarity testing. The results of similarity testing among weather groups indicated a lack of resemblance between the groups. This substantiates the independence of each weather group, implying differences in sensor performance levels contingent on weather conditions.

6. Conclusions

This study investigates how autonomous driving sensors adapt to different environments using data from autonomous vehicles. We established hypotheses through literature review and analyzed sensor data collected in sunny, rainy, and cloudy weather conditions. Two specific elements per sensor were selected, and datasets were created for analysis. To test the hypothesis, we applied the appropriate analysis methodology to each sensor data. For the Recognition Quality data, we applied the Kolmogorov-Smirnov test to test the homogeneity of the datasets for each weather event. For the View Range data, we applied the DTW algorithm to test the similarity of the time series data for each weather event.

According to our analysis findings, the highest similarity was observed in the data set of sunny and cloudy days, while the lowest similarity was found in the comparison between sunny and rainy days. The similarity between the data set of cloudy and rainy days fell between the values of the previous two results. These out-comes substantiate our research hypothesis that sensor performance varies based on weather conditions. Specifically, the analysis results highlight distinctions in sensor performance related to weather, thereby validating our initial hypothesis.

This study is significant as it examines sensor performance using real driving data from autonomous vehicles, unlike traditional research done in controlled environments. We investigate how weather conditions affect sensor performance, offering important insights. Safety evaluation is crucial for autonomous vehicle commercialization, requiring an index to assess environmental recognition. Implementing algorithms to adjust speed according to environmental conditions is vital for safety. Restricting vehicle speed in severe weather conditions aligns with regulations but may hinder technological advancement.

Through our research, we have identified variations in the functional levels of autonomous driving sensors. We anticipate that expressing these changes within specific ranges or values could serve as criteria or scales for evaluating the safety of autonomous driving. In future research, our objective is to develop quantitative metrics for assessing the functional levels of autonomous vehicle sensors. Additionally, we aim to enhance sensor performance verification by collecting more precise multidimensional data, refining considerations for weather conditions, spatial environments, and traffic scenarios beyond the scope of the data utilized in this study.

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