Cognitive Aspect of Emotion Estimation of a Driver

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***Abstract*—Despite rapid advancements in the automotive industry, traffic safety risks persist. Addressing this challenge requires innovative driver assistance technologies. Common accidents result from driver inattention, fatigue, and stress, leading to issues like falling asleep at the wheel and improper acceleration and braking. Our study aims to contribute to advanced driver assistance systems that adapt to drivers' emotional needs, ultimately enhancing road safety. In this paper, we mention the result of our research to estimate drivers' emotions using sensors. For that purpose, we developed a sensor network containing sensors such as EEG, eye tracker, and driving simulator. We explored the relationship. As a result, we confirmed the relation between the driver's emotions, especially sleep conditions, driving speed, duration, and brain wave behavior.**

***Index Terms*—driving support system, emotion estimation, EEG, eye tracking, sensor network, persistent homology**

I. Introduction

Amidst the rapid devolution of the automotive industry, the persistence of traffic safety risks remains a critical concern. Consequently, the development of intelligent and innovative driver assistance technologies becomes imperative. Among the factors contributing to traffic accidents, the most prevalent include falling asleep at the wheel, improper acceleration, and braking errors. These mishaps stem from driver inattention, fatigue, drowsiness, and stress, all significantly contributing to road accidents. In particular, the cumulative effects of fatigue resulting from extended periods of driving can substantially impair a driver's cognitive function and judgment, ultimately leading to drowsiness. Hence, it becomes essential to promptly detect driver fatigue and drowsiness during driving and institute appropriate measures. To address this challenge, there is a pressing need to develop support systems that encourage drivers to take breaks and enhance the in-vehicle environment to optimize comfort.

Given this backdrop, our research endeavors to objectively assess driver fatigue by gathering an extensive array of data, encompassing ElectroEncephaloGraphy (EEG), heart rate, eye movements, and driving activities, all obtained through driving simulators. We aim to scrutinize this data meticulously, with the expectation of delivering valuable insights that can enhance driver safety and mitigate the risk of traffic accidents.

It is worth noting, however, that while EEG holds promise as an excellent indicator of emotional states, practical limitations arise when attempting to employ EEG sensors during driving. Additionally, EEG sensors may provide limited accuracy in measuring neural activity related to emotions occurring beyond the upper layers of the brain. [1].

The remaining part of this paper is structured as follows. Section 2 introduces a variety of related research. We explain the research goal, problems, and objectives in Section 3. The sensors and network we used in the research are explained in Section 4. Section 5 explains the detailed experiment result, and discuss and analyze the result in Section 6. Finally, we present our conclusions in Section 7.

II. Positioning and the Related Works of the Paper

Numerous studies have been undertaken to predict driver fatigue by examining the correlation between drivers' biological signals and their eye movements.

A. Relationship between this study and Cognitive Infocommunications

This paper proposes and uses a sensor system to estimate a driver's mind state and subsequently explore the relationship between emotional states and driving behavior. This study combines artificial and natural cognitive capabilities. The whole system's new hybrid cognitive capabilities fall into the concept of Cognitive Infocommunications [2,3].

One of the branches of Cognitive Infocommunications focuses on Cognitive Mobility, which investigates the entangled combination of research areas such as mobility, transportation, vehicle engineering, social sciences, artificial intelligence, and Cognitive Infocommunications [4,5].

Thus the overall new capability of the combination of the censoring system and the driver leads to a new capability of the whole system that is to improve the driving effectiveness to avoid accidents and further car design outcomes.

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B. Studies Using Heart Rate and Electrocardiogram [6]

This study reported that during the transition from mental fatigue to drowsiness, the number of blinks increased and, conversely, the heart rate decreased.

C. Studies utilizing gaze angle and eye rotation angle [7]

This study used image sensors to generate computational models from gaze and eye rotation angles. As a result, it was reported that the accuracy of measuring mental workload from driving was improved from eye movements.

D. Studies Using Gaze Angle and Eye Rotation Angle [8].

This study has shown that blinking decreased with task load during driving. However, another paper [9] has found the opposite result, that blinking increases with increasing task load, and there still needs to be a clear answer regarding how it can be used.

Furthermore, numerous studies have explored the monitoring of driver emotions using sensors as a means to prevent risk-taking behavior. These investigations involved using multiple driving simulators to simulate realistic driver interactions and estimated driver emotions based on driving performance data. However, these studies did not directly detect emotional data to validate the accuracy of their measurements [10]. In [11], researchers developed a sensor network to establish a mapping relationship among various sensor data to monitor driver emotions. This approach incorporated metrics such as heart rate, skin conductance, skin temperature, and facial expressions. Nevertheless, the research did not address driving performance data closely tied to driving behavior. [12] introduced a non-intrusive emotion recognition system designed for car drivers, employing a thermal camera to enhance Advanced Driver Assistance Systems (ADAS). However, it's important to note that this system has yet to be tested in actual driving conditions, which leaves room for further exploration and validation.

Prior research efforts have explored various avenues in the realm of emotion recognition for drivers. For instance, in [13], an approach centered around facial expressions was introduced. This approach leveraged a comprehensive on-road driver facial expression dataset, encompassing diverse road scenarios and corresponding driver facial expressions during driving. Meanwhile, [14] devised a methodology that combines Local Binary Pattern (LBP) features with facial landmark features to detect driver emotions. This method further employed a supervised machine learning algorithm, specifically a support vector machine, to classify different emotions effectively.

Additionally, [15] put forward an innovative approach, introducing a custom-created Convolutional Neural Network (CNN) feature learning block to enhance the performance of an existing 11-layer CNN model. This augmentation resulted in an improved and faster R-CNN face detector capable of accurately identifying the driver's face. However, it's essential to note that these studies primarily focused on processing facial image data for driver emotion recognition. They did not delve into aspects such as body motion or explore the intricate relationship between driver emotion and driving performance data.

III. Outline of this study

A. Research Goal

This research aims to estimate drivers' emotions during driving to prevent car accidents.

B. Problems and Objectives of the research

While several studies have explored the estimation of driver emotions through means such as brain waves and other bio-signals, there are two notable challenges to consider. Firstly, relying solely on EEG may be problematic due to potential variations caused by the experimental environment, introducing an element of risk. Secondly, the practicality of measuring EEG by having drivers wear sensors while driving is a concern.

To address these issues, we aim to identify alternative sensors that are easy to use, robust, and cost-effective. We will compare these potential sensors with popular vital sensors commonly employed for health monitoring, as well as sensors integrated into vehicles but not worn by individuals. By examining these options, we can explore the feasibility of replacing EEG with more practical sensor solutions for emotion detection in a driving context.

IV. Sensors

We implemented a sensor network for driver emotion monitoring around a driving simulator. In this section, we would like to explain each sensor and outline the network.

A. Driving simulator

To achieve the goal of estimating the driver's emotions by using a drive recorder and analyzing the relation between driver emotions and behavior during driving, we collect driving performance data from the driving simulator such as speed, accelerator pedal degree, brake pedal pressure, steering angle, and distance from the start.

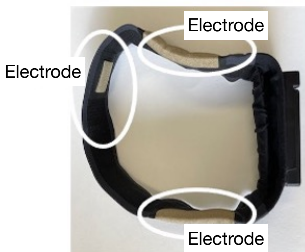

Fig. 1. EEG sensor (headband) [13]

Fig. 2 Eye tracking device [16]

B. EEG sensor

We used an EEG sensor to estimate the mind state of a driver. Typically, EEG sensors are large devices with many electrodes used in hospitals, but using such devices in a car or a driving simulator is not easy [16]. So, we have developed a wearable EEG sensor that can acquire data for several hours without stress, as shown in Figure 1. This EEG sensor has BLE and sends data in real time. The sampling rate is 512 Hz. In this experiment, we used M5Stack Core2 [18] as a receiver of the EEG signal, and the data is written on an SD card in the receiver device. The EEG sensor can output the information listed in Table 1. In addition, our sensor can output two additional information: Attention (concentration, similar to Beta wave) and Mediation (relaxing, similar to Alpha wave) [19].

C. Eye tracker

We utilized an eye tracker, specifically the Pupil Core [20], to monitor eye movements accurately, as illustrated in Figure 2. This device provides us with the precise x and y coordinates of the gaze, enabling us to simultaneously capture video footage of the surrounding scenery and the movement of the eyeball.

D. Network

As shown in Figure 3, we established a sensor network for data collection, with certain components connected via Bluetooth Low Energy (BLE [21]) for real-time data transmission. In contrast, other components, such as sensors connected on Controller Area Network (CAN [22]) in the driving simulator, remained offline for security considerations.

V. Experiment and result analysis

A. Experiment Design

We set two test courses in the driving simulator. One is Tokyo Metropolitan Highway (C1), and another is a road in the center of Paris. The details of the setting are shown in Table 1. In the C1 course, we changed the brightness during driving from daytime to evening. In Paris, we used Simulation of Urban Mobility (SUMO) [23] to provide some interference to drivers, such as traffic and unexpected behavior of pedestrians.

On August 9 and 21, 2023, and November 22, 2023, two students of Chuo University (20 years old, and 2years old, owning a driver's license) drove C1 and Paris. The duration of each driving test was 45 minutes. As per our experiences, after 30 minutes, a driver starts to feel fatigued, so we set 45 minutes. In this paper, we label each trial as 20230809-C1-1, C1-2, Paris-1, Paris-2, 20230821-C1-1, C1-2, Paris-1, Paris-2, and 20231122-Paris-5.

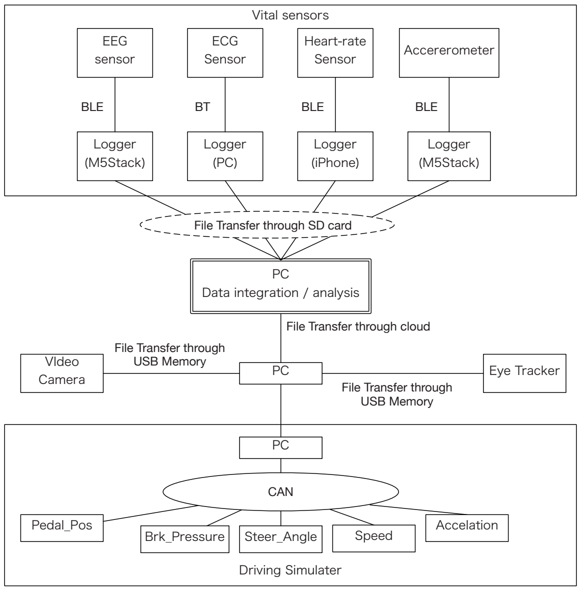

Fig. 3. The system diagram

TABLE II
Brain waves [19].

Frequency band name	Frequency	Brain states
Delta	0.5–4 Hz	Sleep
Theta	4–8 Hz	Deeply relaxed, inward focused
Alpha	8–12 Hz	Very relaxed, passive attention
Beta	12–35 Hz	Anxiety dominant, active, external attention, relaxed
Gamma	Over35 Hz	Concentration

Before and after driving, the test driver answered PANAS (The Positive and Negative Affect Schedule [24]) with 10 Positive and 10 Negative questions to record the mental state. As shown in Figure 4, the score of negative questions increased in all cases, indicating that the test driver consistently reported feeling fatigued after 45 minutes of driving.

B. Fatigue from distance and time

Figure 5 presents the relationship between the number of rounds and the duration of a single round of driving. Notably, it becomes evident that, after several rounds, the lap time increased by approximately 20%. This observation suggests

TABLE I
Test course in the driving simulator.

Course	Time/round	SUMO	Brightness change (in 45 min)
Tokyo Metropolitan Highway C1	About 10 min	No	0-10 min 4:00 PM, 10-20 min 6:00 PM 20-30 min 7:00 PM, 30-40 min 7:30 PM 40-45 min 8:00 PM (with road lighting)
Paris City Area Course	About 6 min	Traffic and Pedestrian crossing road	No

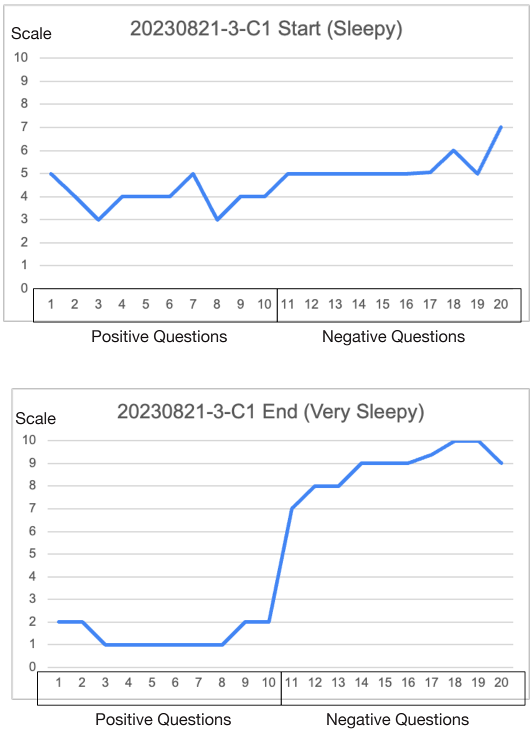

Fig. 4. Example of the result of PANAS

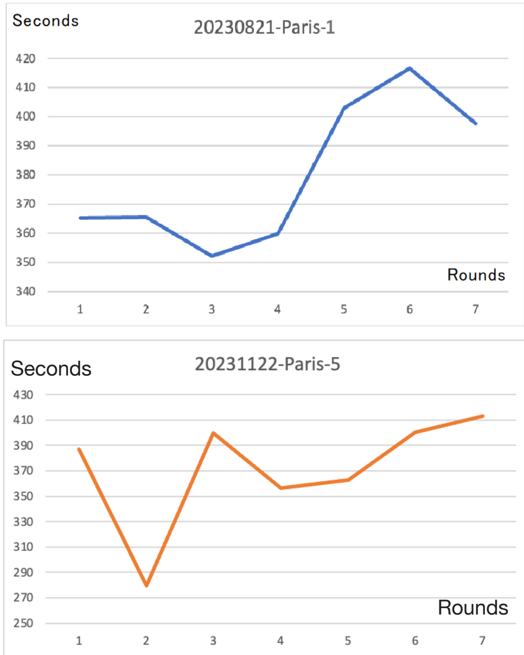

Fig. 5. Example of rap time of each round

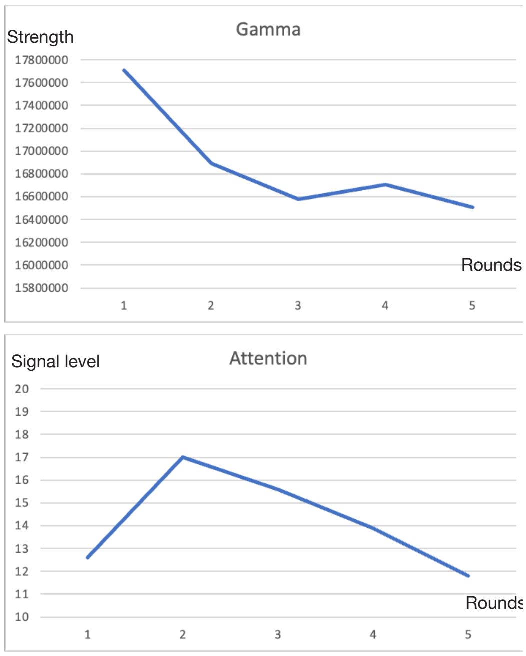

Fig.6. Trend of Gamma and Attention of 20230821-C1-1 (going down along the timeline)

that a driver's concentration tends to decline after experiencing fatigue, resulting in a slowdown in driving speed.

C. Fatigue from changing brightness

Figure 6 illustrates the connection between brightness levels and changes in emotion detected through EEG. As the driving rounds progress, the road becomes darker, and a corresponding decrease in driver concentration is evident. This pattern is consistent with the trends observed in C1 driving data. Conversely, during driving experiences in Paris, there was no significant decline in attention levels. Hence, we can infer that darkness has a detrimental impact on a driver's attentiveness, potentially contributing to increased fatigue and decreased concentration during nighttime driving scenarios.

D. Relation between EEG and eye tracking

Figure 7 illustrates the link between Gamma brainwaves and eye blinks. Our analysis of Paris data revealed a consistent pattern: when Gamma fell below 1.0E7, indicating reduced brainwave activity, the driver often lost concentration, leading to eye blinks or closures (below the red line in Figure 7). This suggests Gamma changes are a valuable indicator of tiredness, especially sleepiness, aligning with the driver's drowsiness in the latter part of the round. Additionally, this finding underscores the significance of eye tracking as a reliable method for monitoring the driver's movements and quantifying their level of fatigue while actively engaged in driving.

E. Relation between facial recognition and eye tracking

Facial expressions directly reflect emotions, and body motion strongly associates with emotions [25]. To estimate a driver's stress and fatigue, we harnessed the effectiveness of a widely used drive recorder, capable of capturing facial expressions and body movements. Consequently, in this study, we amalgamated driving performance data from a driving simulator with facial expression and body motion data obtained from a drive recorder for a comprehensive correlation analysis.

For facial expression recognition and head motion measurements, we utilized MediaPipe Face Mesh [26], with

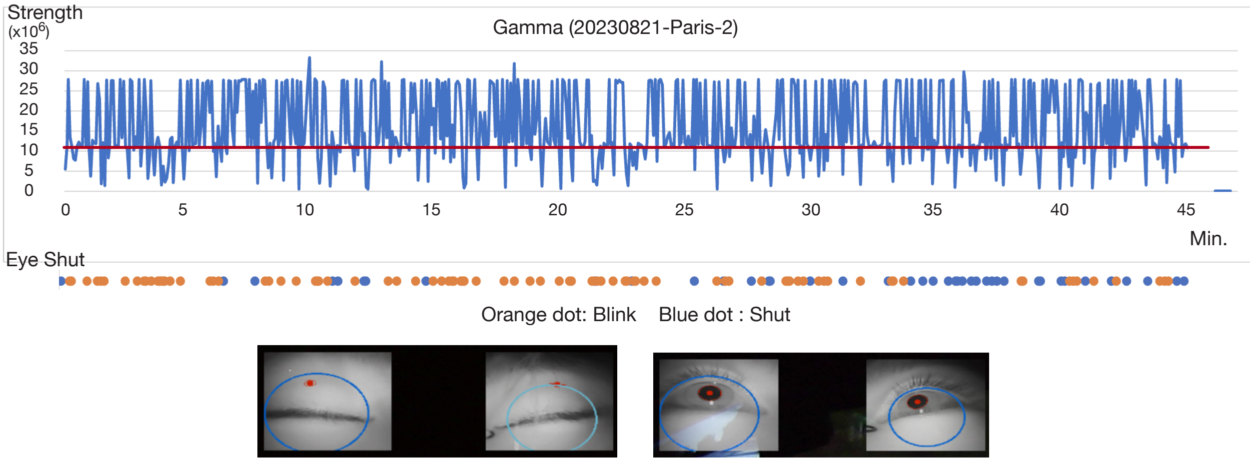

Fig. 7 Relation between Gamma wave and eye blink

prior video image preprocessing carried out using OpenCV [27]. This allowed us to visualize driving performance data concerning the accelerator pedal, brake, and steering, shedding light on their relationship with concurrent facial expressions and body motions. To assess the drive recorder's performance, we conducted a comparative analysis of emotion measurement results obtained through the drive recorder and those from an EEG sensor as our previous study [28]. This approach facilitates an evaluation of the drive recorder's effectiveness in gauging driver emotions and provides a low-cost and easily implementable method for collecting data on drivers' facial expressions through video footage was proposed.

We analyzed the connection between facial recognition and eye tracking, with a specific emphasis on the occurrence of eye closures. In Figure 8, we present six distinct patterns of facial classification observed during the experiment, which, in turn, allow us to infer four primary emotions: (1) Neutral, (2) Anxiety, (3) Boredom, and (4) Fatigue. Our primary focus lies on fatigue as it relates to the sensation of tiredness while driving. Table 3 presents the number of reported fatigue feelings and occurrences of eye closures per 5-minute intervals. The low p-value obtained from the T-Test (0.4) further validates the strong relationship between eye movements and facial expressions, supporting our hypothesis that eye tracking effectively correlates with driver emotion, particularly in instances of fatigue.

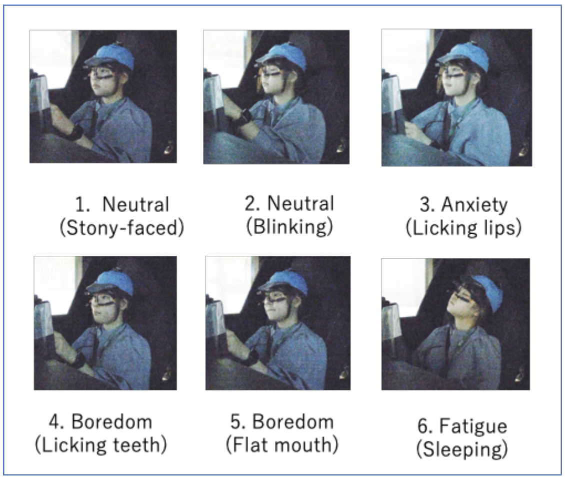

Fig.8 Six patterns from facial recognition

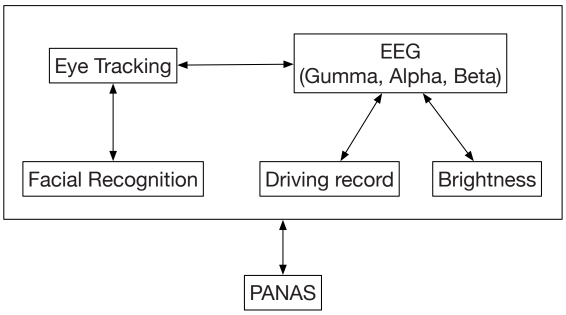

Fig. 9 Relation of information that was found from the experiment

VI. Discussion

This paper aims to estimate a driver's emotion by investigating the relation between EEG, driving record, brightness, eye tracking (eye shut), and facial recognition. At this moment, we found the relation as shown in Figure 9. Unfortunately, we could not collect enough data to analyze the relation between these data and other data such as car operation (pedals, steering), heart rate, and body motion.

Firstly, we compared the facial expression estimation of fatigue by face recognition (Fig. 10) and the number of eyes shut (= sleepiness) by eye tracker (Fig. 11). The number of eye closures tends to increase with each round of testing. The same trend is observed on different experimental days and with different subjects. In contrast, there is a difference in the trend of facial expression estimation of fatigue even when the same

TABLE III
THE NUMBER OF FATIGUE AND EYE SHUT EVERY FIVE MINUTES.

	~05:00	~10:00	~15:00	~20:00	~25:00	~30:00	~35:00	~40:00	~45:00
Fatigue	1	5	1	1	4	5	3	10	9
Eye shut	2	2	4	0	3	5	6	13	0

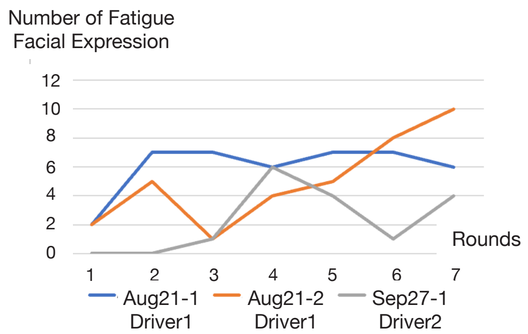

Fig.10 Number of fatigue from facial recognition (Paris, different driver)

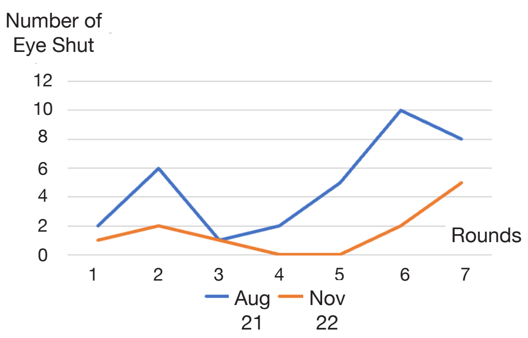

Fig.11 Number of eye shut (Paris, different driver)

subject is tested on the same day (Aug. 21-1 and Aug. 21-2 in Fig. 10). This result suggests that there is a limitation in finding fatigue estimation by face recognition.

For the lap time, as shown in Figure 5, each additional lap is getting longer. This result suggests a similar trend between eye tracking data and the number of laps (= driving time).

Then, we compared the EEG and other data. TGAM outputs raw data at 512 Hz and aggregated values of each brain wave band (Delta, Theta, Alpha, Beta, and Gamma) per second. However, it is difficult to read their interrelationships because EEG changes significantly from one second to the next. Therefore, we applied topological data analysis (TDA) [29] to analyze EEG data (Alpha, Beta, and Gamma). The basic technology of TDA is persistent homology. The following is an overview of persistent homology from [29].

"A key mathematical apparatus in TDA is *persistent homology*, which is an algebraic method for extracting robust topological information from data. To provide some intuition for the persistent homology, let us consider a typical way of constructing persistent homology from data points in a Euclidean space, assuming that the data lie on a sub- manifold. The aim is to make inference on the topology of the underlying manifold from finite data. We consider the r-balls (balls with radius r) to recover the topology of the manifold, as popularly employed in constructing an r-neighbor graph in many manifold learning algorithms. While it is expected that, with an appropriate choice of r, the r-ball model can represent the underlying topological structures of the manifold, it is also known that the result is sensitive to the choice of r. If r is too small, the union of r-balls consists simply of the disjoint r-balls. On the other hand, if r is too large, the union becomes a contractible space. *Persistent homology* [30] can consider *all* r simultaneously, and provides an algebraic ex- pression of topological properties together with their persistence over r. The persistent homology can be visualized in a compact form called a *persistence diagram* $D = \{(b_i, d_i) \in R^2 \mid i \in I, b_i \leq d_i\}$, and this paper focuses on persistence diagrams, since the contributions of this paper can be fully explained in terms of persistence diagrams. Every point $(b_i, d_i) \in D$, called a *generator* of the persistent homology, represents a topological property (e.g., connected components, rings, and cavities) which appears at X_{b_i} and dis- appears at X_{d_i} in the r-ball model. Then, the *persistence* $d_i - b_i$ of the generator shows the robustness of the topo- logical property under the radius parameter. "

We used HomeCloud [31], a tool for visualizing persistence; we created a 3D graph of Alpha, Beta, and Gamma for the Paris orbit on Aug.21, 2023 (2nd trial, by driver1) and the Paris orbit on Nov.22, 2023 (5th trial, by driver2). The graph of persistence generated from the 3D data of Alpha, Beta, and Gamma is shown in Figure 12. Most of the points lie on the X=Y line, but the points away from it represent the features of the data.

In Figure 13, the envelopes are added for the big-picture view of the points. It can be seen that the shape of the envelope for each lap is similar, even though two drivers with different driving skills and different schedules are driving on different dates. This result indicates that some changes may be occurring similarly for each lap. In the future, we plan to analyze the EEG movements related to fatigue by analyzing the EEG in more detail.

VII. CONCLUSION

This study aims to estimate driver emotion by using several data that we can acquire while driving a car to prevent car accidents. For that purpose, we developed a sensor network around a driving simulator using an EEG sensor, accelerometer, heart rate sensor, and eye tracker.

The paper's novel contribution is that the result displayed a relation between the driver's emotions, especially sleepy

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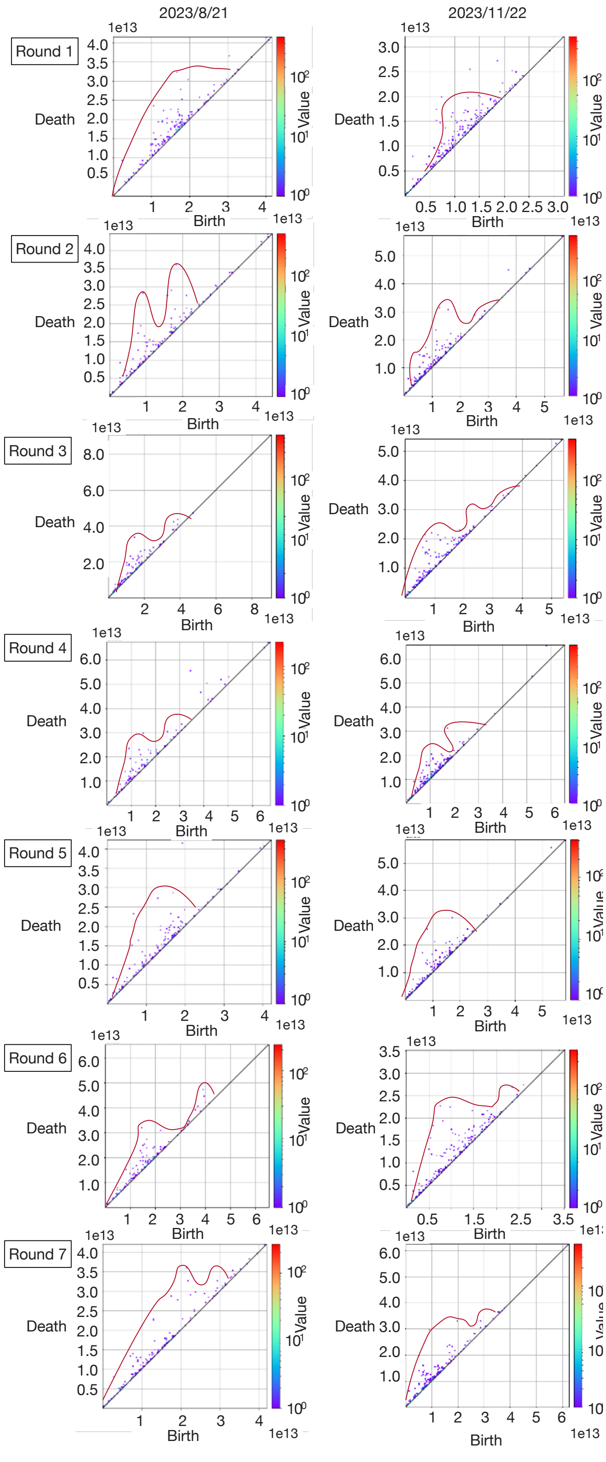

Fig. 12 Persistent homology graph of brain waves (Alpha, Beta, and Gamma)

conditions, driving speed, driving duration (=driving distance), and brain wave behavior. This result will make it possible to realize a safety-driving support technology.

However, at this moment, as motioned in section VI, our analysis was not yet sufficient because of the limited number of data. If we get enough data, we could understand the relation of information around a car to understand the driver's emotions.

However, this study showed the effectiveness of Cognitive Mobility, that is a part of Cognitive Infocommunication science.

As a further study, we need to do two things. The first is to analyze the data and information relation using new techniques such as persistent homology. The second is to acquire the Mental State Index, such as PANAS while trying to explain the mental state in language.

Our final target is to realize a system to detect the dangerous mental state related to car accidents and provide information to change the situation using a simple wearable sensor such as a smartwatch and CAN data.

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