博士論文

A Study on Drivers' Mental Condition

〜 Estimating Driver Fatigue Using Sensor Network 〜

運転者の心理状態に関する研究

〜センサーネットワークを用いた運転者の疲労度推定〜

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内容梗概

高齢化に伴い、高齢の運転手による交通事故が増加している。また、道路上での急加速、あおり運転、突然のブレーキングなどの危険な運転行動のニュースもよく見聞きする。交通事故の原因の大きな要素が運転者の心理状態である。このため、自動車のシステムが危険を察知し、アナウンスなどで介入して運転者を健康な心理状態へ導くことで、運転の安全性を高めることが望まれる。将来的には自動運転車の普及が見込まれているものの、現在はそれに先立つ移行期間であり、このようなシステムが特に重要である。しかし、現存する多くの研究は、運転前のリラクゼーション技術や危険な状態への警告に重点を置いており、運転手の心理状態の評価の重要性が見過ごされている。この心理状態評価に関する視点の欠如は、運転安全を確保する際の大きなギャップとなっている。

運転に悪影響を及ぼす心理状態のうち、“疲れ”（疲労）は交通事故の主な要因の一つであり、認知能力と知覚能力が低下する。この低下は不十分な休息、長時間の労働、概日リズムの乱れなどに起因し、注意力、反応時間、意思決定能力などの安全運転に必要な能力を著しく損なう。しかし、既存の研究は運転者の疲労やその他の精神状態を推定するために単一の方法論に頼ることが多く、測定と検証のための包括的かつ体系的な方法論が不足している。

本研究は、自動車の運転者から生体信号データを収集するための包括的なセンサーネットワークを構築し、各種センサーから得られた情報をもとに運転者の疲労度を推定することで、より安全な自動車社会の推進に貢献することを目指す。特に本論文では、高忠実度の運転シミュレータ（DS）と、加速度計、心拍数モニター、EEG センサー、ビデオカメラ、アイトラッカーなどの多様なバイオシグナルセンサーを統合し、運転者の疲労度を推定する新しいアプローチを提案する。実験では、シミュレータ内の運転条件を各種変更し、DS から運転操作データと、センサーから運転者の生理学的データを体系的に収集し、脳波活動、心拍数、顔の表情、身体の動き、眼の動き、運転中の操作データなどを詳細に記

録し、分析することが可能となる。本研究の主たる目的は、運転手の精神状態を正確に特定するための分散型、体系的なフレームワークの開発と検証であり、特に疲労の兆候の特定に焦点を当てる。

本研究では、さまざまなデータタイプ間の相関や関係を詳細に分析し、運転手の心理状態を評価した。生体信号からの心理状態の推定精度を高めるために、自己報告式心理測定ツールを統合したことで、生体信号データの解釈を強化し、運転手の心理状態の包括的な評価を可能にした。分析段階では、高度な顔認識技術の開発を含む洗練された統計的方法を採用した。本手法では、表情の詳細な分析のために顔のランドマークを利用し、さまざまな心理状態の正確な分類を実現した。また、眼球運動の画像化で得られた眼球運動のパターンを分析し、運転者の疲労を評価した。疲労度評価の精度は、補足的なデータセットとの相互参照により確認した。

実験により、センサーネットワークを使用した運転者の心理状態の評価は有用であることが示された。結果の要点は次の 3 点に集約できる。(1)運転者の生体信号、操作データと心理状態の間には相関関係があり、運転者の心理状態評価には、これらを組み合わせることが有用である。(2)アンケートと気分評定尺度は主観的評価ツールとして信頼性がある。(3)顔の表情分析と眼の動きにより、疲労の直接的かつ正確な検出が可能である。これらの結果は、運転者の疲労度推定における本ネットワークの高いポテンシャルを示唆している。

ただし、実験環境において EEG センサーの性能が最適ではなかったこと、アンケート実施に関する制約、運転者と同乗者の画像使用に関するプライバシーの懸念など、いくつかの課題が存在した。今後の研究では、運転者の感情評価のために、コントローラーエリアネットワーク(CAN)データの統合や、ユーザーフレンドリーなウェアラブルセンサーの活用を検討する予定である。この目的は、本研究で得た知見を、より広範で信頼性の高い方法で得られた結果と対比させることである。この研究から得られる洞察と手法は、自動車分野の安全性の向上に寄与することが期待される。

Abstract

In the context of an aging demographic, there has been a notable escalation in vehicular accidents attributed to elderly motorists. Concurrently, the prevalence of hazardous driving behaviors — exemplified by abrupt acceleration, aggressive tailgating, and unforeseen braking — has become a recurrent theme in media coverage. The driver's psychological state is a pivotal element contributing to the causation of these traffic incidents. In light of this, it is imperative to augment driving safety by integrating advanced automobile systems capable of detecting potential dangers. Such systems should proactively intervene through auditory alerts or other mechanisms to steer drivers toward psychological well-being conducive to safe driving practices. The advent of autonomous vehicles is anticipated to be a transformative development in road safety. However, implementing systems addressing driver psychology is paramount in the current transitional phase that precedes the widespread adoption of these autonomous technologies. Despite this, a significant proportion of extant research has predominantly focused on relaxation techniques before driving and alerts for hazardous states, neglecting the criticality of evaluating the driver's psychological condition. This oversight in assessing the psychological states of drivers constitutes a substantial hiatus in the overarching efforts to ensure vehicular safety.

Driver fatigue, a critical factor in traffic accidents, reflected a diminished mental state characterized by a decline in cognitive and perceptual abilities. This deterioration, often attributed to inadequate rest, prolonged mental exertion, or disrupted circadian rhythms, severely impairs critical faculties necessary for safe driving, including attention span, reaction time, and decision-making capabilities. However, it was noted that existing research predominantly relied on single-method approaches for estimating driver fatigue or other mental states, needing a holistic and systematic methodology for measurement and verification.

Our study aims to devise and execute a comprehensive sensor network to gather bio-signal data from individuals operating automotive vehicles. A novel approach was proposed, utilizing an integrated sensor network that comprised a high-fidelity driving simulator (DS) and diverse bio-signal sensors, such as an accelerometer, heart-rate monitor, EEG sensor, video camera, and eye tracker. In the experimental setup, driving conditions within the simulator were varied to methodically collect operational metrics from the DS alongside physiological data from the sensors. This network was observed to diligently record and analyze various physiological and behavioral parameters,

including brainwave activity, heart rate, facial expressions, body movements, eye movements, and operational data during driving. The research's primary goal was to develop and validate a decentralized, systematic framework for precisely determining drivers' mental states, focusing on identifying signs of fatigue.

The research involved an in-depth analysis of the correlations and relationships among various data types to assess drivers' mental conditions. A recognized psychometric tool was integrated to augment the bio-signal data to enhance the accuracy of mental condition determination by bio-signals, facilitating a comprehensive assessment of drivers' mental states. In the analytical phase, sophisticated statistical methods were employed, including developing an advanced facial recognition technique with high detection accuracy. This technique utilized facial landmarks to analyze facial expressions, precisely classifying various mental states. Also, driver fatigue was evaluated by analyzing ocular motility patterns captured in eye movement imagery. This assessment was then corroborated through cross-referencing with supplementary datasets to ascertain the precision of the fatigue determinations. Evaluating drivers' mental conditions using our sensor network proved highly effective. The findings emphasized three key points: (1) The identified correlations among bio-signals, operational data, and emotions to evaluate drivers' mental conditions by highlighting the combined utility; (2) The reliability of questionnaires and emotion levels as subjective evaluation tools; (3) The direct and accurate detection of fatigue through facial expression analysis and eye movement. These results indicated the significant potential of the network in estimating driver fatigue.

However, there were challenges, including the suboptimal performance of EEG sensors in the experimental environment, limitations in questionnaire administration, and privacy concerns regarding the use of driver and passenger images. In response to these challenges, future research endeavors are anticipated to explore the integration of Controller Area Network (CAN) data and more user-friendly wearable sensors for assessing driver fatigue. The objective is to juxtapose these results with those obtained from broader, more reliable methods. The insights and methodologies derived from this study are expected to contribute substantially to advancing safety in the automotive domain.

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Chapter 1

Introduction

Road traffic accidents, a significant global public health concern, are primarily attributable to human errors. These errors, identified in various studies, include speeding, impaired driving due to alcohol consumption, distractions, non-compliance with traffic signals, and neglect of safety equipment [1-1]. A thorough investigation into critical driving scenarios, incorporating essential environmental factors and characteristics of driver behavior during collisions, as shown in Figure 1-1, has uncovered that an overwhelming 82% of vehicle-to-vehicle accidents are caused by human factors [1-2]. This finding underscores the paramount importance of mental states in driving safety.

The study of human factors in driving examines a comprehensive array of elements contributing to driver behavior. The driver's behavior includes, but is not limited to, dynamics such as braking, acceleration, navigation, compliance with traffic regulations, and the extent of human participation in the driving task [1-3]. These elements are crucial to understanding and predicting driver behavior. Central to these factors is the role of inherent human mental traits, with the mental state being of paramount importance. It significantly influences an individual's driving performance, which in turn has direct implications for road safety. This multifaceted approach acknowledges the complexity of human factors in driving and underscores the need for a thorough understanding of how mental traits impact driving behaviors and overall road safety.

The study of mental states, encompassing a range of internal experiences such as perceptions, sensations of pain or pleasure, beliefs, desires, intentions, emotions, and memories, plays a crucial role in the context of driving behavior.

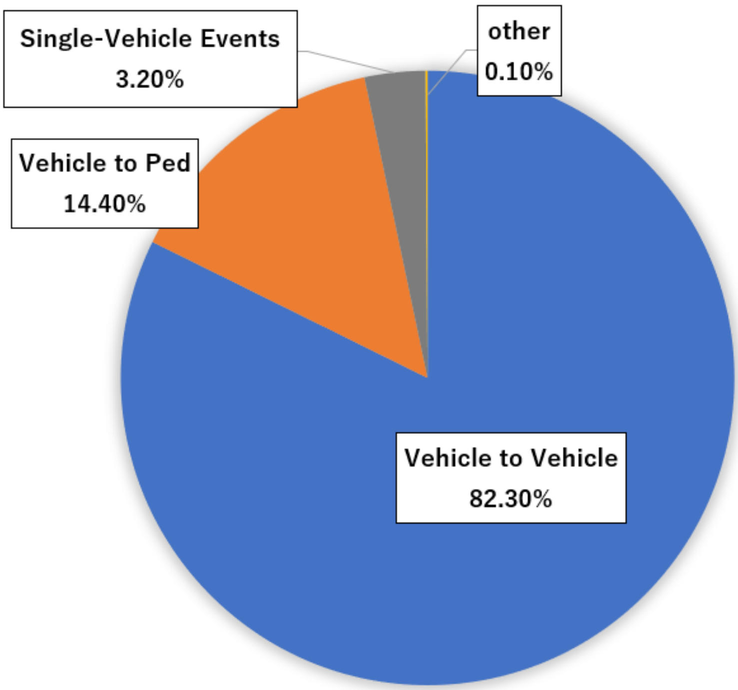


Figure 1-1. Near-Miss incident categories of Japan

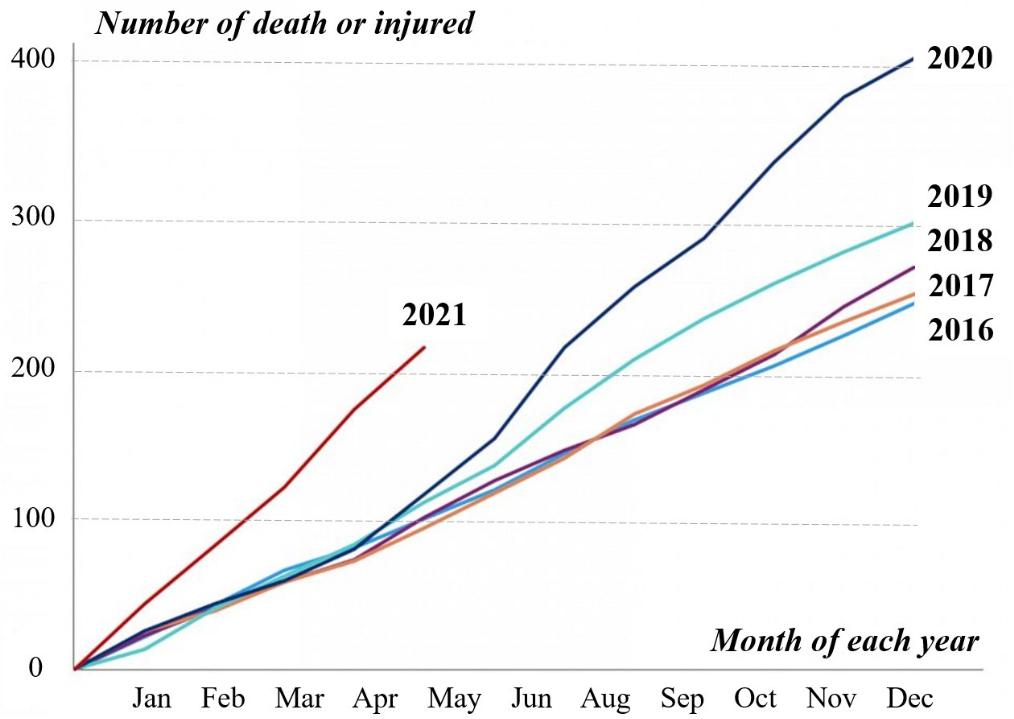


Figure 1-2. Number of people injured or killed in Road Rage shootings [1-8]

These states are inherently subjective, with each individual having exclusive access to their mental experiences, while others can only infer these states from observable behaviors [1-4]. Emotions, a significant component of mental states, profoundly impact driving behavior. Intense emotions can lead to 'rage driving,' characterized by a loss of self-control and aggressive driving behaviors [1-5] [1-6]. Research has shown that drivers under the influence of emotions such as anger or happiness exhibit altered driving patterns, including decreased time-to-collision and extended braking times, compared to those in a neutral emotional state [1-7]. This research indicates that drivers in heightened emotional states pose a greater risk on the road.

To illustrate the severe impact of driver emotions on road safety, two incidents in 2017 and 2019 serve as poignant examples. The first incident involved a rear-end collision caused by a driver experiencing road rage, resulting in fatalities and leading to vehicular homicide charges [1-8]. The second incident occurred when a driver, emotionally agitated and speeding, lost control of his vehicle, leading to a collision with multiple casualties and injuries [1-9]. These cases underscore the need for emotional regulation in driving and highlight the significant legal and societal consequences of emotionally driven road incidents [1-10]. Driver fatigue, encompassing mental and emotional exhaustion, is another critical factor adversely affecting road safety [1-11]. Fatigue results in slower reaction times, diminished attention, reduced situational awareness, and impaired vehicle control. An increase in fatigue-related crashes is evident, especially after prolonged driving periods (Figure 1-3). Internationally, fatigue is recognized as a significant contributor to road accidents [1-13] [1-14], though its full impact is likely underreported.

While well-documented, the link between driver fatigue and increased accident risk remains a subject of ongoing research debate. This debate is partly due to variations in research methodologies and findings [1-15]. While many crashes are attributed to driver fatigue, this does not conclusively establish that fatigue enhances accident risk. Fatigued drivers, who often travel longer distances, may balance the risk per kilometer traveled.

Research also suggests heightened risks among specific groups, such as young or professional drivers, indicating a complex interplay of factors.

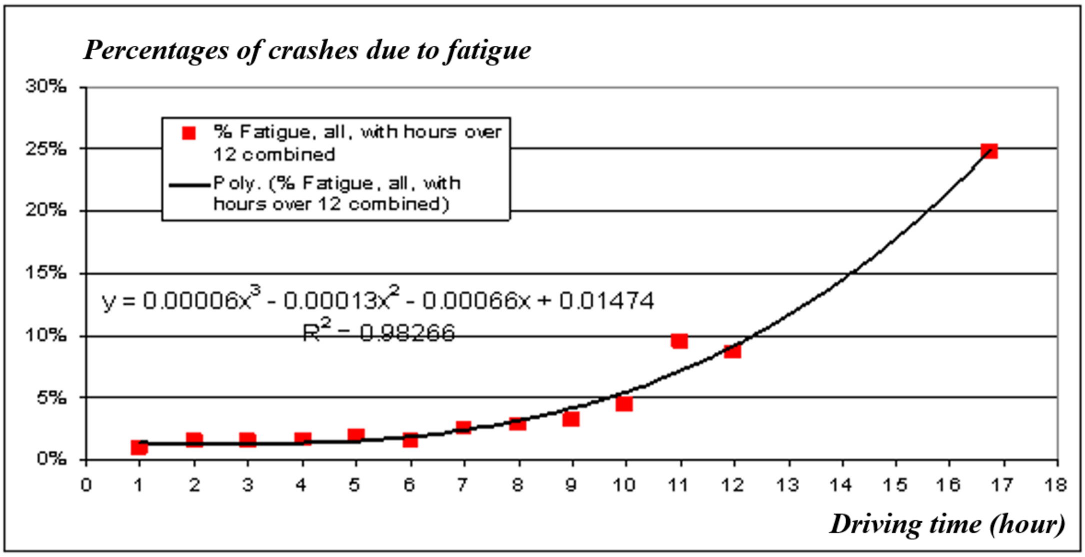


Figure 1-3. Crash risk function of driving time [1-12]

The strategic management of driver mental states, especially recognizing and mitigating emotional conditions that impair judgment, is essential for enhancing road safety. This aspect becomes even more significant in semi-autonomous and autonomous vehicles. In these systems, estimating a driver's emotional state is crucial for modifying vehicle settings in response to the driver's mood, thus facilitating smooth transitions between manual and automated driving modes. Such systems enhance safety by identifying and responding to emotions like stress and fatigue, which are known to lead to hazardous driving behaviors. Furthermore, this approach contributes to the overall well-being of drivers by reducing stress and fatigue, thereby averting long-term health issues. In advanced vehicular technology, the comprehension and management of a driver's mental state enrich the driving experience through personalized settings and play a pivotal role in human-machine interaction. This function includes adapting the level of the vehicle's autonomy to the driver's current state, thereby ensuring a safer and more efficient driving experience.

The automotive industry's growing emphasis on driver assistance technologies to bolster road safety [1-16] underlines the necessity of addressing mental influences, particularly fatigue, in drivers. Accurately estimating mental states during driving is imperative to prevent dangerous behaviors and enhance road safety.

For estimating mental states, our study proposed a comprehensive approach involving a sensor network to collect a wide range of bio-signal data from individuals operating automotive vehicles. We introduced an innovative method employing an integrated sensor network comprising a high-fidelity driving simulator (DS) and various bio-signal sensors. These sensors include accelerometers, heart-rate monitors, EEG, video, and eye trackers. In our experimental setup, driving conditions within the simulator were systematically varied to collect operational metrics from the DS and physiological data from the sensors. This network adeptly recorded and analyzed various physiological and behavioral parameters, such as brainwave activity, heart rate, facial expressions, body movements, eye movements, and operational data during driving sessions. Our research aims to develop and validate a decentralized, systematic framework for accurately determining drivers' mental states, with a particular emphasis on identifying indicators of fatigue. This framework is expected to contribute significantly to the field of road safety by enabling more nuanced and effective management of driver mental states.

Chapter 1 delineates the research's objectives and scope, establishing the foundation for the subsequent investigation. Chapter 2 provides a comprehensive literature review on measuring mental conditions, particularly in the context of automotive safety. This review synthesizes existing research, identifying gaps and setting the stage for the study's unique contributions.

Chapter 3 introduces an innovative methodology for estimating a driver's mental state, employing a sophisticated sensor network. This network primarily comprises a driving simulator (DS) and an array of bio-signal sensors, including accelerometers, heart-rate monitors, electroencephalogram (EEG) sensors, video cameras, and eye trackers. The experimental setup involves varying driving conditions to collect a rich dataset encompassing operational parameters from the DS (such as accelerator pedal position, brake pressure, vehicle speed, and acceleration) and bio-signal data (surrounding brainwave activity, heart rate, facial expressions, and eye movement). Recognizing the complexities inherent in accurately assessing mental states through biosignals alone, we integrate the Positive and Negative Affect Schedule (PANAS) [1-17], a validated self-report tool, to complement the biosignal data and provide a more holistic understanding of driver mental states.

Chapter 4 presents the statistical techniques for analyzing operational and bio-signal data. These include advanced methods like fast Fourier transformation (FFT) [1-18] and K-means clustering [1-19]. A noteworthy aspect of this chapter is introducing a novel facial recognition technique tailored for enhanced accuracy and efficiency in analyzing facial expressions. This method utilizes a sophisticated 42-dimensional feature vector to capture essential facial characteristics and employs a clustering algorithm to effectively categorize mental states, significantly refining the accuracy of emotional assessments.

Chapter 5 elaborates on the experimental framework and analytical methodologies employed to infer drivers' mental states. This section begins with a comprehensive description of the systematic integration of diverse sensor technologies to facilitate a holistic assessment through the augmented juxtaposition of various data sets. The primary goal is to increase the precision and reliability of mental state estimations by harnessing multifaceted data sources. This chapter also provides an overview of the preliminary study conducted before Fiscal Year 2022.

Subsequently, the chapter delineates three distinct research initiatives undertaken since Fiscal Year 2022. The first initiative evaluates driver mentality by correlating driving performance data with responses from the Positive and Negative Affect Schedule (PANAS) questionnaire. The scope of this investigation has expanded to include a thorough analysis of these aspects, emphasizing validating the results derived from sensor data. This expanded scope incorporates a detailed examination of the interplay between various driving behaviors—such as steering patterns, braking consistency, and speed variability—and self-reported emotional states, as per the PANAS questionnaire. This approach facilitates a deeper understanding of the nexus between subjective emotional experiences and objective driving behaviors.

The second project investigates the application of video cameras to estimate driver fatigue, addressing the inherent limitations and unreliability of EEG and ECG sensors. This section progresses beyond the rudimentary use of video imagery for fatigue assessment by integrating facial recognition and body movement analysis. When analyzed collectively, this holistic approach examines how variations in facial expressions and eye movements provide a comprehensive insight into the driver's emotional and mental state. Such a multimodal methodology enhances the precision and depth of fatigue-level evaluations.

The third initiative refocuses on analyzing eye movement as a pivotal metric in evaluating driver fatigue, particularly in employing video cameras within automotive vehicles. This section extensively explores how eye movement patterns are reliable indicators of mental states, predominantly fatigue, during driving. It delves into the intricate correlation between eye movement characteristics and the driver's level of alertness, thereby contributing to a more sophisticated and accurate assessment of driver fatigue. This assessment is further enhanced by introducing topological data analysis in the study of EEG data, aiming to unravel the complex relationship between brainwave patterns and driver fatigue.

In Chapter 6, the research culminates in synthesizing the principal findings and their implications for estimating driver mental states, including reflections on integrating diverse sensor technologies and analytical methods. The chapter acknowledges both the successes and limitations of the study and proposes future research trajectories, focusing on refining methodologies and broadening the spectrum of emotional states examined.

The empirical analysis conducted in this study demonstrates the efficacy of a multifaceted data collection approach in assessing drivers' mental states, particularly underscoring the potential of an integrated sensor network in accurately estimating driver mental states, with an emphasis on fatigue. The key findings of this investigation include: (1) A notable correlation was established between bio-signals, operational data, and driver emotions, emphasizing the collective value of these variables in the evaluation of driver mental states. (2) The study validated the effectiveness of questionnaires and subjective emotional assessments, confirming their utility in understanding drivers' mental conditions. (3) The research successfully estimated driver fatigue by analyzing facial expressions and eye movements. Additionally, it precisely detected specific mental states, such as happiness and anxiety, further demonstrating the potential of this approach in mental state assessment. These findings underscore the significant prospects of employing a comprehensive sensor network for the nuanced and accurate estimation of driver mental states, contributing valuable insights to the field of automotive safety.

However, the study also encountered several challenges. These included the suboptimal performance of EEG and ECG sensors in the experimental context, limitations associated with the administration of questionnaires, and privacy concerns related to the recording of images of drivers and passengers. In light of these challenges, future research is directed toward incorporating Controller Area Network (CAN) [1-20] data and utilizing more user-friendly wearable sensors, such as smartwatches, for a more nuanced assessment of driver emotions. This approach intends to reconcile these findings with those derived from more robust and reliable methods. The insights and methodologies developed through this research are anticipated to enhance safety measures within the automotive industry significantly.

Chapter 2

Research Background

2.1. Mental Condition

Mental condition, alternatively referred to as mental state, demonstrates significant diversity and complexity. Mental condition encompasses a range of phenomena, including perception, belief, desire, intention, emotion, and memory, often displaying considerable overlaps across these categories. Mental states can be dichotomized into sensory states, characterized by sense impressions, and non-sensory states. Further, they are classified as propositional or non-propositional, containing distinct propositional content. A critical distinction exists between intentional states, directed towards specific objects or states of affairs, and non-intentional states, which lack this relational characteristic. In terms of consciousness, mental states may be conscious, encompassing an experiential aspect, or unconscious, devoid of such phenomenality. Additionally, mental states are categorized as occurrent, actively engaging in cognitive processes, or non-occurrent, existing in a latent state without immediate mental influence. Within the realm of rationality, they are evaluated as rational and irrational, contingent upon their alignment with established rationality norms [2-1] [2-2].

2.2. Emotional State

Emotions, a specialized subset of mental states, are characterized by distinct subjective experiences, physiological responses, and behavioral tendencies [2-3]. They significantly influence and are influenced by other mental states, such as beliefs and perceptions. The interplay between emotions and other mental states occurs both consciously and unconsciously. Emotions exhibit notable physiological correlates, aligning with broader physical manifestations of various mental states. Cognitive appraisal theories emphasize cognitive perceptions and interpretations in eliciting emotional responses, highlighting the cognitive-emotional nexus. In clinical psychology, the intricate interaction between diverse mental states and emotions is pivotal for understanding and addressing psychological disorders, as exemplified by the correlation between persistent negative thought patterns and emotional states such as sadness in depression [2-4]. The concept of emotional state often paralleled with mental state, is intrinsically linked to neurophysiological changes, leading to a spectrum of cognitive and affective responses, behaviors, and experiences [2-5]. From a physiological perspective, emotions are experiences closely associated with distinct patterns of physiological activity [2-6]. Recognizing conscious emotional states as integral to human understanding is widely acknowledged, while attributing similar states to non-human entities remains debated in scientific discourse [2-7].

2.2.1. Emotion Classification

The study of emotion classification is a critical aspect of affective science, encompassing ongoing debates and diverse approaches. Researchers approach this complex field from two primary perspectives, leading to distinct types of emotion. Paul Ekman and colleagues advocate for a theoretical framework of emotions as different categories, suggesting universally recognizable fundamental emotions inherent to all humans [2-8]. These foundational emotions—anger, disgust, fear, happiness, sadness, and surprise—are deemed discrete due to their unique identification via consistent facial expressions and specific biological mechanisms [2-9]. Fundamental Emotion Theories propose that emotions like anger or sadness are activated by brain evaluations of stimuli, influenced by an individual's goals or survival instincts, and have distinct functions, expressions, and meanings [2-10]. In contrast, Constructionist Theories in emotion research suggest that emotions are constructed from fundamental biological and psychological elements, such as "core affect" and "conceptual knowledge," rather than being inherently fixed [2-11].

2.2.2. Generation and Expression of Emotion

Emotional responses, prompted by significant internal or external events, are often initiated through specific situational encounters [2-12]. Emotions represent intricate psychological and physiological responses to diverse stimuli and can be precipitated by many factors. They encompass complex constructs that include subjective experiences, cognitive evaluations, expressive behaviors, psychophysiological modifications, and intentional actions. Additionally, emotions frequently intersect with psychological constructs such as mood, temperament, personality, disposition, and creativity. While traditional perspectives often delineate cognitive processes like reasoning and decision-making as separate from emotional cycles, this distinction is only sometimes upheld across some theoretical frameworks.

Contemporary research in fields like clinical psychology and well-being studies is increasingly focused on the dynamic nature of emotions in everyday life. This research explores various facets of emotional states, including their intensity, spectrum, stability, persistence, clarity, and tendency to fluctuate over time. This exploration examines how these emotional dynamics differ among individuals and across various human life stages [2-13].

(1) Emotion generation

The generation of emotions is a multifaceted process encompassing physiological, cognitive, and environmental elements. It begins with detecting an external or internal stimulus, followed by a cognitive appraisal, where the brain assesses its significance. This appraisal, in tandem with physiological responses orchestrated by the autonomic nervous system, culminates in the subjective experience of an emotion.

The Affective Events Theory (AET) is a psychological framework that examines the impact of workplace events on employees' emotions, attitudes, and behaviors within their job context [2-14]. Central concepts of AET include affective events, emotion generation, emotion-driven outcomes, moderating factors, feedback loop, and time lag. As illustrated in Figure 2-1, the theory posits that emotion generation in the workplace starts with an individual's encounter with an event. This encounter is shaped by the individual's mental and emotional states and physical condition, leading to a perception influenced by personal goals and beliefs. This interaction gives rise to a new emotional state, manifesting as specific action tendencies, and simultaneously updates the individual's mental and physical conditions. This process creates a continuous feedback loop, resulting in a cycle of evolving emotional responses that affect workplace behavior and outcomes.

(2) Emotion expression

Concurrently, emotions manifest through expressions and action tendencies, such as

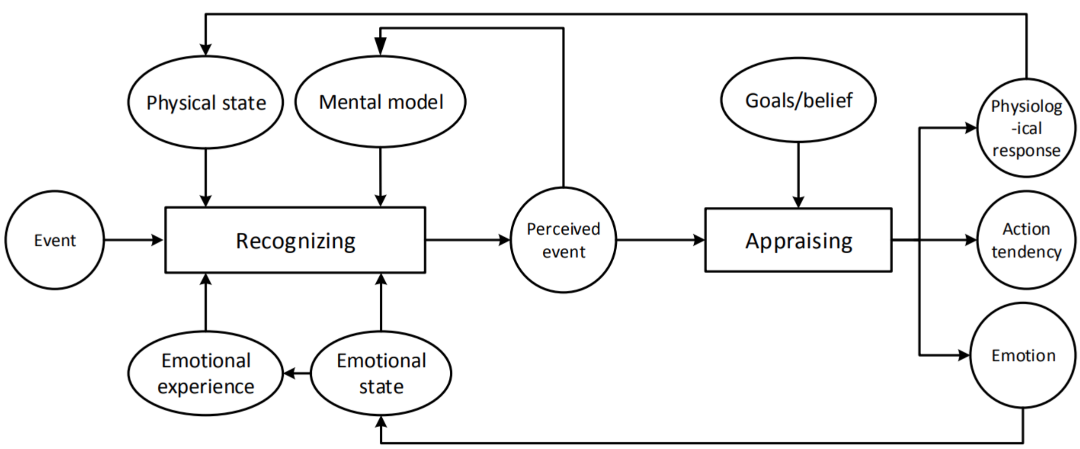


Figure 2-1. Cognitive model of emotion generation process [2-15]

facial expressions and behavioral impulses. The process concludes with emotional regulation and reflection, which are essential for well-being and social functioning. Emotional expression is a multifaceted phenomenon that conveys an individual's emotional state or attitude, manifesting through verbal and nonverbal behaviors [2-16]. This form of expression encompasses various activities ranging from facial movements, such as smiling or scowling, to multiple behaviors. Additionally, emotional expressions can be more complex, involving actions such as writing a letter or presenting a gift. Table 2-1 shows some of Darwin's descriptions of expressive behaviors [2-17].

Table 2-1. Darwin’s descriptions of expressive behaviors

Astonishment	eyes open, mouth open, eyebrows raised, hands placed over mouth
Contemplation	frown, wrinkle skin under lower eyelids, eyes divergent, head droops, hands to forehead, mouth, or chin, thumb/index finger to lip
Determination	firmly closed mouth, arms folded across breast, shoulders raised
Devotion (reverence)	face upwards, eyelids upturned, fainting, pupils upwards and inwards, humbling kneeling posture, hands upturned
Happiness	eyes sparkle, skin under eyes wrinkled, mouth drawn back at corners
Surprise	eyebrows raised, mouth open, eyes open, lips protruded, open hands high above head

The study of emotions in psychology and neuroscience is characterized by diverse theories that differ primarily in their views on emotional expression. Some theories, known as the "basic emotion" perspectives, argue that emotions are biologically innate and consistent across cultures, with specific facial expressions directly indicating emotional states [2-18] [2-19]. Other approaches suggest a more flexible, cognitive-based understanding of emotions, where individual and cultural differences influence emotional responses shaped by personal appraisals of situations [2-20].

Emotions are expressed through various channels, offering unique insights into our feelings. Facial expressions are immediate and potent, with specific looks for different emotions: Vocal cues like tone, pitch, and speed add depth to emotional expression; Body language, encompassing posture, and gestures, communicates emotions ranging from comfort to defensiveness; Physical reactions, such as movement and posture provide involuntary cues and convey emotions. Touch is a tactile form of emotional expression, with its nature and context significantly affecting its interpretation.

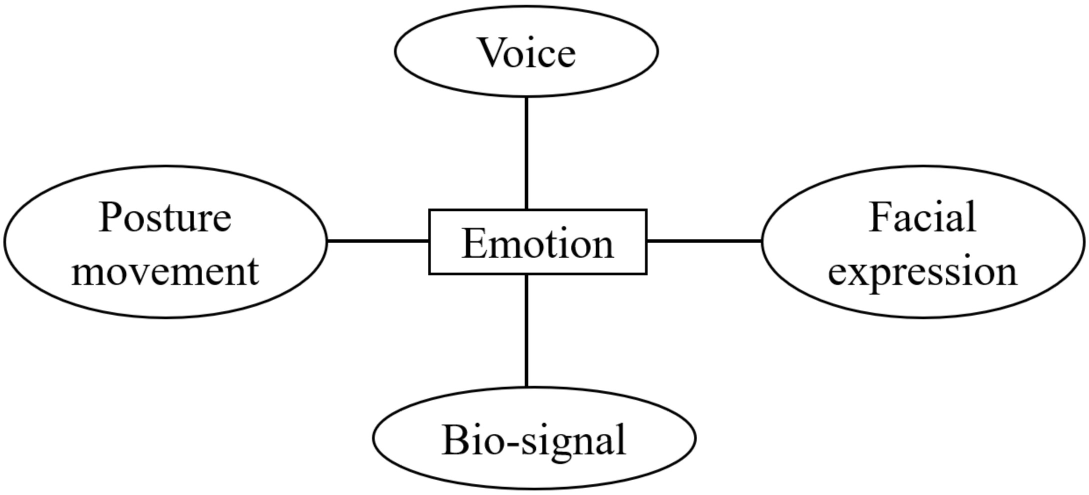


Figure 2-2. Universal expressions of emotion

2.2.3 Driver Emotion

The emotional state of a driver, henceforth denoted as "driver emotion dynamics," encapsulates a spectrum of affective experiences encountered during the operation of a vehicle. These emotional nuances are not merely peripheral but pivotal, as they substantially influence the control of the car, the decision-making process, and, by extension, traffic safety. Given their pronounced and tangible impact on driving behaviors and consequent outcomes, an in-depth exploration and comprehension of these affective dynamics are imperative. The most prevalent driver emotions influencing driving operations can be categorized into six archetypes.

(1) Stress/Anxiety

Stress can emanate from the pressures of time constraints, such as urgency stemming from delay or persistent life stressors linked to occupational or domestic duties. Anxiety may be tied to specific driving contexts, prior negative experiences on the road, or a broader spectrum of anxiety disorders. Stress can induce rushed and aggressive driving behaviors, while anxiety often leads to indecision and overcaution. Both states can impair concentration, increasing the probability of driving mishaps and collisions.

(2) Anger

Anger in drivers can be triggered by traffic congestion, perceived discourteous actions from other motorists, or personal emotional turmoil brought into the vehicle. Additionally, anger may accumulate over a journey due to minor irritations. This emotion is often expressed through aggressive driving behaviors synonymous with road rage, including tailgating, incessant honking, hostile gesturing, and verbal confrontations. Such behaviors can precipitate dangerous driving actions and increase the risk of conflicts or accidents.

(3) Fear

Fear in drivers can stem from previous traumatic vehicular incidents, challenging driving conditions like inclement weather, or apprehension linked to specific driving scenarios. Fear can cause a driver to hesitate, excessively slow down, or apply brakes unpredictably. It may also lead to avoidance strategies, with drivers opting for longer or less familiar routes to circumvent their fear's focal point.

(4) Happiness/Contentment

Personal achievements, enjoyable life events, pleasant companionship within the vehicle, or a general sense of well-being on a particular day may influence this positive emotional state. While happiness typically results in a relaxed driving approach, it can sometimes lead to distractions, as drivers might become preoccupied with thoughts or activities that are sources of their contentment.

(5) Surprise/Shock

Often triggered by unexpected events, such as narrowly averted accidents, wildlife entering the roadway, or unpredictable actions from other road users, the emotion of surprise or shock can elicit sudden and potentially hazardous driving responses, including abrupt braking or swerving. While these reflexive actions may be necessary for mysterious purposes, they can also result in disproportionate responses that introduce new risks, especially if they lead to a loss of vehicular control.

Recognizing and understanding these emotional states and their precursors enables drivers to anticipate better and mitigate their impacts. Strategies for managing these emotions include instituting regular rest breaks, practicing relaxation techniques, or seeking professional intervention for more profound emotional disturbances, which can significantly enhance road safety and drivers' overall well-being.

2.3. Fatigue State

Fatigue represents a multifaceted mental and emotional state characterized by diminished energy, vigilance, and attention, distinct from normal tiredness resulting from daily activities. Its complexity and varied presentations pose substantial challenges in identifying its origins, particularly in diseases with diverse pathologies, such as autoimmune disorders [2-21]. In medical and psychological research, the concept of fatigue encompasses a multifaceted and often complex state of exhaustion or tiredness, distinct from mere sleepiness. This portion of the doctoral paper delves into the nuanced definition, classification, and measurement of fatigue, providing a thorough overview of this critical subject.

2.3.1. Definition of Fatigue

Fatigue, in its academic definition, is a multidimensional construct characterized by a profound sense of exhaustion or weariness, distinct from normal sleepiness. It commonly follows extensive physical or mental activities, yet it can also present independently of such exertions. This condition, characterized by its persistence even after rest or sleep, suggests possible underlying medical causes. In medical discourse, fatigue is acknowledged as a complex and multifaceted phenomenon, often with an indeterminate etiology. It is associated with a variety of medical conditions, including autoimmune diseases, organ failure, chronic pain syndromes, mood disorders, infectious diseases, and post-infectious states. In healthcare, the term 'fatigue' extends beyond the ordinary energy depletion attributable to daily activities and necessitates more precise and nuanced terminology to encapsulate its diverse manifestations.

2.3.2. Classification of Fatigue

Fatigue can be categorized into two principal types: mental and physical fatigue.

Mental fatigue is a transient decline in cognitive function, typically during prolonged cognitive tasks. Influenced by individual cognitive capacity, sleep quality, and overall health, it is empirically associated with reduced physical performance and presents symptoms like drowsiness, lethargy, and impaired attention [2-22]. The spectrum of fatigue encompasses a range of symptoms that include both physical and psychological elements, such as frequent yawning, drooping eyelids, a noticeable decrease in movement and speech speed, diminished concentration and cognitive focus, heightened irritability, mood instability, visual disturbances (e.g., blurred vision), physical discomforts (e.g., headaches, dizziness), muscle weakness, cognitive impairments, changes in motivation, and appetite variations. These symptoms are influenced by factors such as sleep deprivation, physical overexertion, psychological stress, and underlying health conditions. The chronic nature of fatigue has profound implications on an individual’s functional capacity and quality of life, highlighting the necessity for effective management strategies. Mental fatigue significantly contributes to motor vehicle accidents, often resulting from extended driving, insufficient rest, or prolonged exertion [2-23]. Its exacerbation during typical rest periods is evidenced by reduced reaction times, decreased alertness, impaired judgment, and an increased risk of microsleeps, adversely impacting driving performance.

Physical fatigue results from muscle activity, while mental fatigue arises from prolonged cognitive activities. The classification also includes central nervous system fatigue and muscle fatigue, with ongoing scholarly debate regarding their distinction or integration within a unified fatigue framework affecting various life aspects.

2.4. Mental State Measurement Method

Expressions of emotion constitute the external manifestations of internal affective states, which can be observed and quantitatively analyzed through several methods.

(1) Facial expression analysis

Facial recognition technologies using dashboard-mounted cameras analyze facial expressions to infer emotional states. This interdisciplinary approach integrates psychophysiology, cognitive science, artificial intelligence, and automotive engineering to improve driver welfare and traffic safety. Privacy and ethical considerations are paramount in this approach, necessitating informed consent, secure data management, and discreet monitoring systems. Paul Ekman's research demonstrated the cross-cultural recognition of facial expressions, contributing significantly to this field.

(2) Vocal expression analysis

Vocal affect is a primary conduit for emotional expression throughout human development and adult life, especially in modern contexts where telephonic communication is prevalent [2-24]. Hughlings Jackson's observations of patients with linguistic impairments due to left hemisphere brain damage revealed their capability to convey emotions vocally. This observation suggests a potential role of the right hemisphere in mediating vocal emotional expressions [2-25].

(3) Physiological monitoring

Emotional states can be inferred from physiological signals, including heart rate, skin conductance, electromyography, respiratory rate, pupillometry, and thermal imaging. These methods, crucial for comprehensive emotion research, are complemented by EEG-based brainwave pattern analysis, which offers insights into the cerebral basis of emotions. Additionally, photoplethysmography (PPG) and electrocardiography (ECG) are employed for pulse signal analysis, reflecting emotional state changes [2-26] [2-27].

(4) Behavioral observation

From an evolutionary perspective, body movements and postures indicate emotional states and intensities. They serve adaptive functions in response to events affecting an organism's well-being. Inertial Measurement Units (IMUs) and Vehicle Telemetry, measuring specific forces and vehicle handling, further contribute to this analysis [2-28].

(5) Self-report survey

Self-report measures and questionnaires are pivotal in psychological research for assessing emotions, attitudes, and behaviors. These tools encompass various formats, such as Likert scale questionnaires, Visual Analog Scales, and frequency or intensity scales. Famous examples include the Positive and Negative Affect Schedule (PANAS), the Beck Depression Inventory (BDI) [2-29], and the State-Trait Anxiety Inventory (STAI) [2-30]. While these methods provide subjective insights and are straightforward to administer, they are prone to biases like social desirability and interpretational variability. Their effectiveness is maximized with other observational or physiological measures for a holistic understanding of emotional and behavioral patterns.

2.5. Related Research

In driver mental condition research, several methodologies have been employed to analyze data collected during or after driving, primarily encompassing three types of research. This section will concisely overview these methods and highlight their respective limitations.

2.5.1. Investigations Utilizing Self-Report Questionnaire

Study [2-31] comprehensively analyzed the factor structure of self-report instruments designed to assess drivers' behaviors and emotions in young adults. This analysis identified four primary factors: reckless driving behaviors, negative emotions related to driving, aggressive driving in response to other drivers' actions, and perceived aggression from other drivers. This investigation underscored the substantial overlap in these self-reported measures and suggested the necessity of further research in underexplored domains such as perceived aggression. Subsequently, study [2-32] undertook a systematic literature review comparing self-report methodologies to objective measures in driving behavior analysis. This review revealed that certain driving behaviors, notably those experienced in high-stress scenarios, exhibit congruence between self-reported and accurate assessments. In contrast, significant divergences were observed in others, such as states of sleepiness and vigilance.

Notably, the use of self-report questionnaires in assessing drivers' mental state is relatively limited. PANAS, the reliable and valid instrument for evaluating effect, has seen sparse application in the context of mental state measurement.

2.5.2. Studies Using Single Sensor

Research [2-33] introduced an innovative vehicular safety system harnessing EEG technology for the analysis and modulation of drivers' mental states, applying valence-arousal models for emotion classification and integrating music therapy to influence these mental states, thereby aiming to reduce accident risks associated with emotional disturbances. Study [2-34] employed ECG technology for monitoring and stabilizing driver emotion, offering functionalities including physiological data display, data recording, signal processing, and analysis. Furthermore, research [2-35] proposed an approach focusing on facial expressions using data from a drive recorder. This approach utilized a comprehensive dataset of driver facial expressions corresponding to various road situations captured during driving.

However, analyzing a driver's mental state remains complex and challenging, and reliance solely on single sensor data can be inadequate and inaccurate for practical estimation. Additionally, extracting meaningful insights from ECG or EEG data is fraught with challenges, including the need to discern representations invariant to inter- and intra-subject variations and dealing with the intrinsic noise inherent in ECG data recordings. Furthermore, facial expression recognition studies, particularly those employing Convolutional Neural Networks (CNN) [2-36], often face significant hardware demands for large-scale data analysis.

2.5.3. Studies Implementing Decentralized System

Article [2-37] discussed a novel strategy for creating a driver monitoring system by tracking eyelid and eyebrow movements as indicators of fatigue. It proposed a unique approach using a reverse Plutchik's paraboloid of emotions model for emotion recognition through facial expression analysis via video cameras and external algorithms. Study [2-38] introduced a body sensor network that utilizes real-time EEG and other sensors to detect human emotions, mainly focusing on tiredness and stress, which are pertinent to traffic accidents. The findings suggest the feasibility of quantifying drivers' emotions and the role of such architectures in accident prevention by continuously monitoring driver emotions. Non-Invasive Monitoring Methods: Research [2-39] presented a non-intrusive and non-distracting technique for monitoring driver emotions and fatigue, employing ECG, GPS, and other data collected from wearable sensor systems.

These sensor networks primarily focus on expressing emotions through biometric signals using two or three types of sensors, emphasizing fatigue or stress measurement.

2.6. Conclusion

Assessing a driver's mental state is an intricate and multifaceted task, demanding diverse methodologies. Current research presents various approaches, each offering distinct advantages and inherent limitations. Though providing valuable insights, self-reporting questionnaires often uncover needs to be more consistent when juxtaposed with objective metrics, particularly in high-pressure scenarios. Investigations employing single-sensor modalities like EEG or ECG demonstrate potential for real-time emotion monitoring. Yet, they grapple with challenges about data variability and the necessity for sophisticated analytical tools. Conversely, decentralized networks utilizing multiple sensors are proficient in detecting a broad spectrum of emotional states, with a notable emphasis on identifying fatigue and stress, pivotal factors in driving safety. Consequently, an all-encompassing approach to analyzing drivers' mental conditions should incorporate diverse data sources, including physiological signals, facial expressions, and subjective self-reports.

Recognizing these insights, adopting a multifaceted strategy becomes essential for effectively analyzing drivers' mental conditions. This approach should encompass various sensors and data sources, including physiological signals, facial expressions, and self-reports. It requires an integrated analytical approach that effectively merges qualitative insights derived from self-reports with the quantitative accuracy of sensor data.

Chapter 3 will explore the development of an advanced sensor network specifically designed for driving contexts. This network will integrate the strengths of various methodologies, focusing on detecting a wide array of emotional states and the precise assessment of critical conditions such as driver fatigue. This integrated system aims to augment our comprehension of drivers' mental conditions by bridging the divide between different research methodologies, thereby creating safer and more responsive driving environments.

Chapter 3

Driver Mental State Estimation System

3.1. Objective of the System

As mentioned in Chapter 2, this research is dedicated to formulating an integrated methodology for assessing a driver's mental state, focusing on quantifying driver fatigue. The cornerstone of this approach is a sophisticated sensor network meticulously engineered to collect and integrate a wide array of biosignal data. This network encompasses a variety of parameters, including body movements, electrocardiogram (ECG), electroencephalogram (EEG), heart rate, facial expressions, and critical indicators of driving performance such as steering behavior, braking actions, and accelerator usage. Figure 3-1 illustrates the primary data types monitored during driving scenarios.

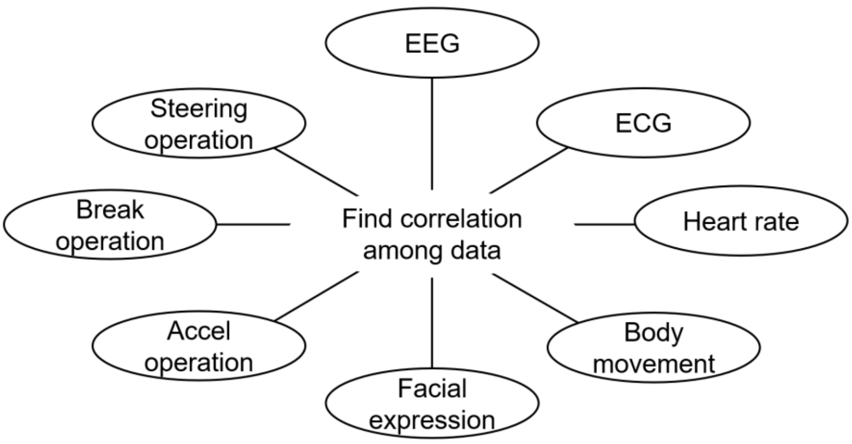


Figure 3-1. Fundamental data collected during this research

Additionally, this system captures comprehensive data related to driving operations, encompassing metrics such as accelerator pedal positioning, brake pressure, vehicle velocity, and acceleration. These objective data sources are further complemented by subjective data acquired through meticulously structured questionnaire surveys. The overarching objective of this system is to achieve a nuanced and precise quantification of driver fatigue by analyzing this complex tapestry of multi-modal data. Integrating these diverse data streams is anticipated to yield a robust and reliable framework for assessing driver mental state, ultimately enhancing driving safety and performance.

3.2. Sensor Network

The selection of specific sensors, as outlined in Table 3-1, was made to fulfill the objectives set forth in the experimental design.

Table 3-1. Vital sensors and data

Vital sensors	***Sensor data***
Driving simulator	Speed, Acceleration, Brake pedal pressure, Steering angle, Distance
Accelerometer	Body movement
ECG	Heart signal
EEG	Brainwave
Heart rate monitor	Heartbeat pulse
Drive recorder	Facial expression, Body movement, Posture
Eye tracker	Eye movement

3.2.1. Outline of the Sensor Network

The architectural framework of the system employed in this study is elucidated in Figures 3 and 2. This diagrammatic representation delineates the dual sectors of the sensor network: the upper sector focuses on sensors near the human subject. In contrast, the lower sector is devoted to data acquisition from the driving simulator. Additionally, Figure 3-3 presents a graphical depiction of the placement of wearable sensors on the body.

Data transmission from these sensors is facilitated through Bluetooth Low Energy and standard Bluetooth protocols, directing the data flow to recording devices such as M5Stack units and personal computers (PCs). Subsequently, this data is stored on Secure Digital (SD) cards, enabling offline integration and subsequent analysis on a PC, which are measures taken primarily for security considerations. The system incorporates a video camera and an eye tracker to complement this setup and monitor the subject's alertness and eye movement patterns. Simultaneously, the driving simulator is equipped to record crucial driving performance metrics, including pedal positioning, brake pressure, steering angle, vehicle speed, and acceleration. These parameters are captured via a Controller Area Network (CAN) as referenced in [3-1]. The collected data from these varied sources are then methodically compiled and analyzed to identify and understand the interrelations among these diverse datasets. This intricate setup captures a comprehensive data set to detect fatigue-induced changes in a driver's behavior and physiological state.

3.2.2. Specification of Vital Sensors

(1) Driving Simulator

Advanced driving simulation systems facilitate a realistic emulation of driver interactions within simulated scenarios, serving as entertainment platforms and as integral tools in driver education programs within academic and private sectors [3-2]. Beyond their educational utility, these systems are instrumental in diverse research domains, including human factors and medical studies, where they analyze driver behavior, performance, and attention. In the automotive industry, Driver safety systems are pivotal for developing and assessing new vehicle designs and the evolution of Advanced Driver Assistance Systems (ADAS). These systems offer controlled, replicable laboratory settings essential for testing and validating the increasing multitude of user interfaces and ADAS technologies.

Figures 3-4 depict a representative model of a DS. In our study, the DS was in a dedicated experimental chamber equipped with a 180-degree panoramic projection screen capable of dynamically adjusting lighting conditions to simulate various driving environments. Automotive data metrics such as vehicle speed, steering angle, brake pressure, and accelerator pedal position were captured at 50 samples per second through a CAN designed for seamless inter-device communication.

(2) Accelerometer

Participant body movement was quantified using multiple accelerometers, specifically the WT901BLECL model [3-4], as illustrated in Figure 3-5. This accelerometer is proficient in measuring parameters like acceleration, angular velocity, angle, and orientation. It incorporates a Bluetooth Low Energy (BLE) 5.0 communication module [3-5], notable for its reduced power consumption, thus extending operational time to over 10 hours. Data captured by this accelerometer is relayed to an M5 Stack [3-6], a compact processing unit compatible with mobile battery operation.

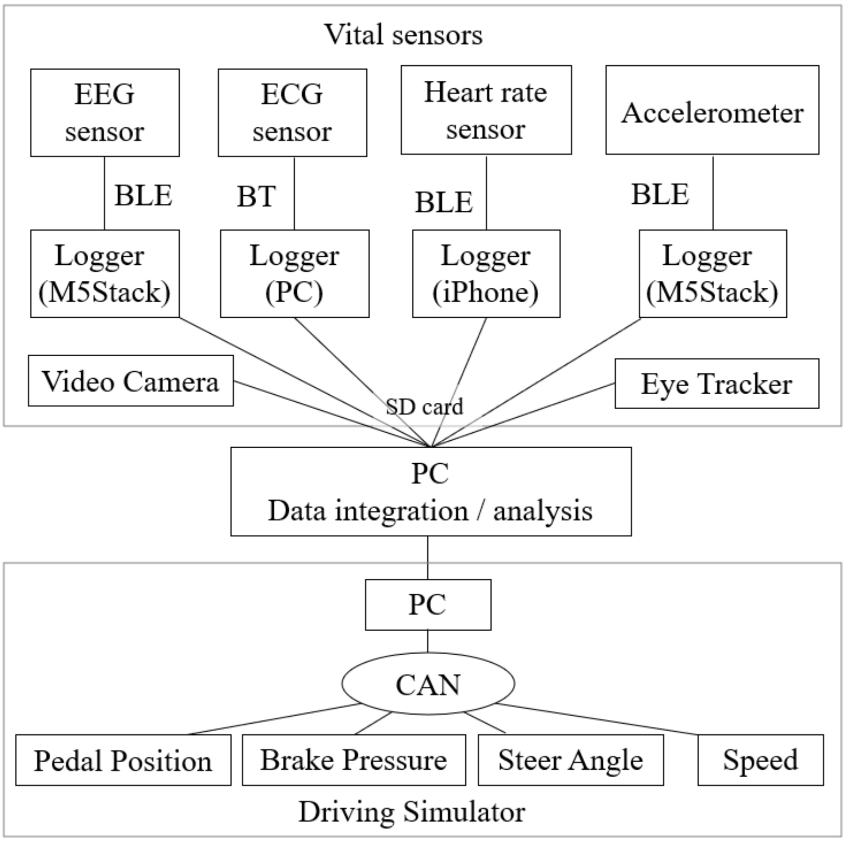


Figure 3-2. System diagram for experiments

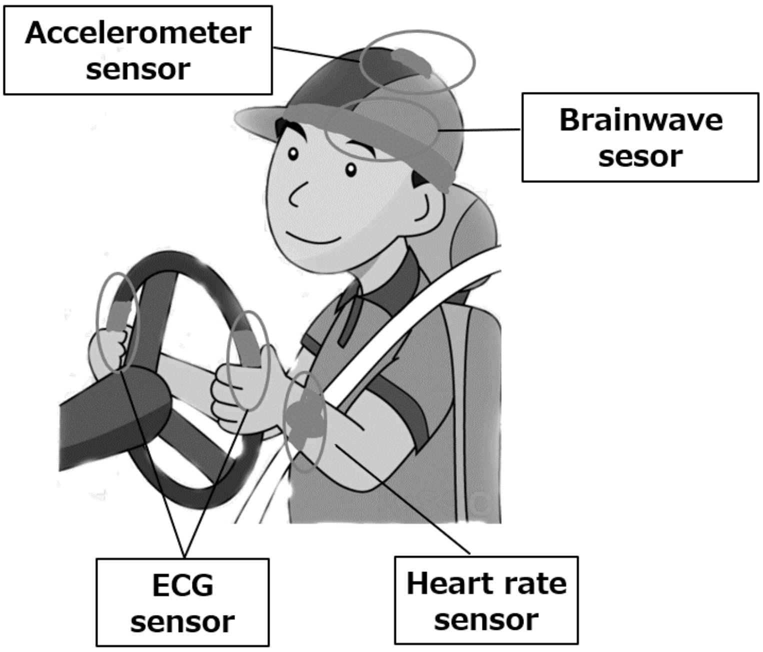


Figure 3-3. Diagram of wearable sensors

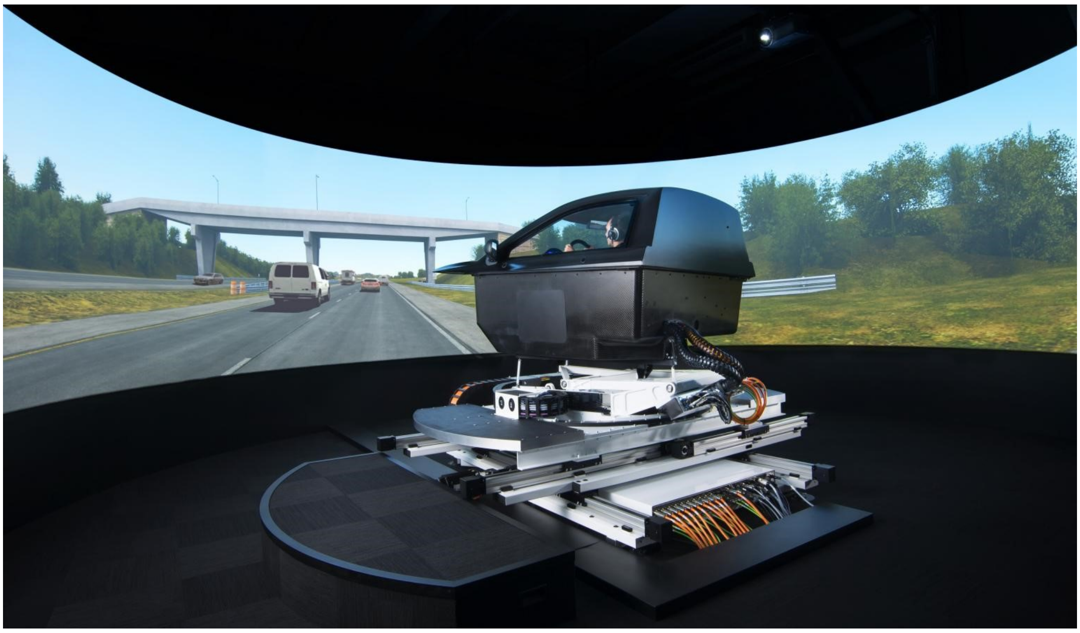


Figure 3-4. Example of driving simulator [3-3]

Figure 3-5. Accelerometer for body movement detection

(3) EEG

Brainwave activity was monitored using a non-invasive EEG sensor by Mindsall Inc [3-7]. This sensor, as depicted in Figure 3-6, captures EEG data 10 times per second from the frontal lobe through contact points at the forehead and ears, with the transmitted data being collected in an M5Stack.

(4) ECG

An ECG sensor, also developed by Mindsall Inc., was employed for detailed cardiac signal acquisition. Data from this sensor were likewise transmitted to an M5 Stack. The ECG sensor was strategically integrated into the vehicle's steering mechanism, ensuring continual contact with the driver's fingers.

(5) Heart Rate Sensor

Heart rate measurements during the driving simulations were conducted using an Apple Watch [3-8] (Figure 3-7) positioned on the participant's wrist. This device employs a photoplethysmography sensor for continual heart rate monitoring, with data computations executed by an integrated application at one-minute intervals.

(6) Drive recorder

We incorporated a high-definition drive recorder, with specifications of 1920 × 1080 resolution and a 23-fps frame rate, mounted at the front of the DS. This recorder, positioned approximately 1 meter from the driver at a 30-degree angle relative to the driver's face, efficiently captured facial expressions, body movements, and incident records during the simulation.

(7) Eye tracker

We utilized an eye tracker for precise ocular movement tracking, as shown in Figure 3-8. This device uses the dark pupil technique and a 3D model for accurate monitoring capable of both binocular and monocular modes. It features a 5-point calibration system with multiple methods and compensates for slippage using the 3D model. The device achieves 0.60º accuracy and 0.02º precision and includes two eye cameras and a scene camera with various resolution options (up to 1080p at 30 Hz). It supports 3D and 2D gaze and pupil measurements, requires a USB-C connection, and operates with desktops or laptops running Pupil Core software. Real-time data is managed through Pupil Capture software with interference for gaze data, pupillometry, and videos, while post hoc analysis is conducted via Pupil Player software.

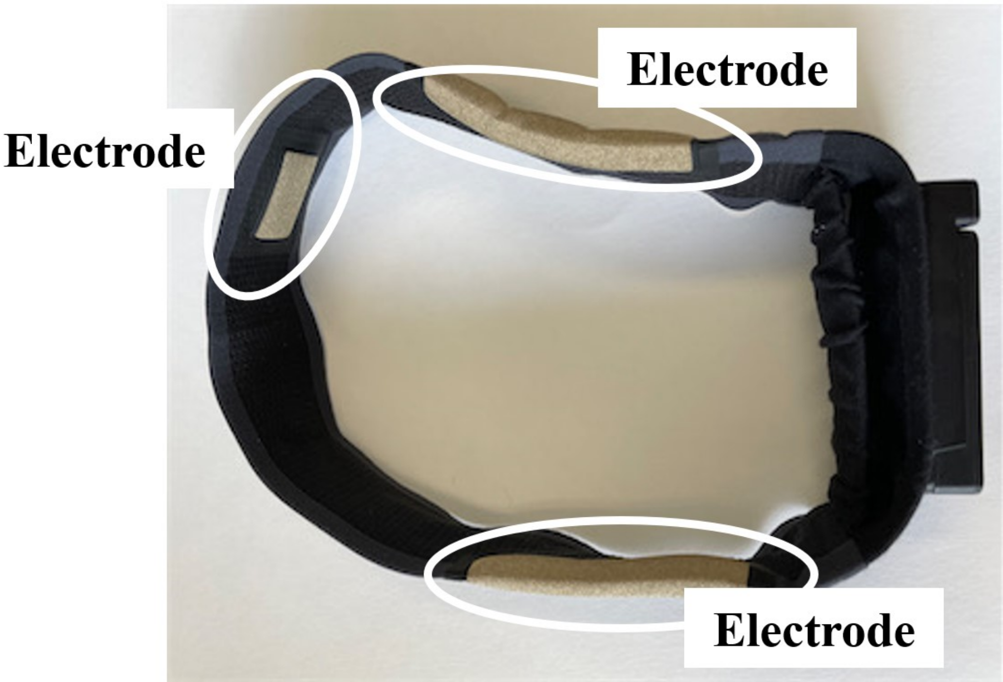


Figure 3-6. Headband-style EEG sensor

Table 3-2. List of brainwave data

Frequency band	***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	Over 35 Hz	Concentration

Figure 3-7. Apple Watch for heart rate detection

3.3. PANAS Questionnaire Survey

The Positive and Negative Affect Schedule (PANAS) represents a psychometrically robust self-report instrument comprising two distinct 10-item scales, each meticulously designed to assess the dichotomous realms of positive and negative affect quantitatively. Renowned for its reliability and validity, PANAS is an indispensable tool in empirically evaluating affective states, effectively gauging the spectrum of mental experiences.

In our experimental framework, it was implemented as a pivotal tool for estimating emotional states in both pre-and post-experimental conditions. The PANAS instrument encompasses a carefully curated array of adjectives, each chosen to encapsulate specific emotional states. These descriptors include: 'Strong,' 'Inspired,' 'Active,' 'Enthusiastic,' 'Interested,' 'Excited,' 'Proud,' 'Alert,' 'Determined,' 'Attentive' to delineate positive affect; and 'Afraid,' 'Scared,' 'Upset,' 'Ashamed,' 'Guilty,' 'Nervous,' 'Distressed,' 'Irritable,' 'Jittery,' 'Hostile' to represent negative affect. Participants were required to rate their emotions on a five-point scale, serving as subjective indicators of their affective state (as illustrated in Figure 3-9). This personal emotional data was then meticulously compared against other quantitative datasets, thereby enabling a holistic understanding of the emotional impacts of the experimental conditions.

Figure 3-8. Eye tracking device [3-10]

- Subject No. :
- Date and time:
- Location:
- Check the boxes for your current mood, using the example as a guide.

Ex)	Happy	______________________	Sad
	Relief	______________________	Anxiety
	Awake	______________________	Sleep
	Tired	______________________	Fine
	Fun	______________________	Bored
	Comfortable	______________________	Uncomfortable

- Heart rate:
- Please describe any other feelings you may have.

Figure 3-9. Example of PANAS questionnaire

Chapter 4

Methodological Approach for Data Processing

This section explains the detailed methods implemented to process the main data collected from the driver emotion monitoring system for mental state estimation.

4.1. FFT Algorithm for Brainwave

The Fast Fourier Transform (FFT) is indispensable in brainwave data analysis due to its efficiency in transforming time-domain signals into the frequency domain, enabling precise characterization of brainwaves. Its computational expediency is crucial for managing large datasets, a common challenge in neuroscientific research. FFT's role in signal processing extends to noise reduction and artifact filtering, enhancing data quality. Additionally, its ability to maintain temporal resolution allows for examining dynamic brain activities. The application of FFT facilitates spectral analysis, which is crucial for assessing power distribution across different frequency bands, and its standardization aids in comparative studies. This multifaceted utility underscores FFT's vital role in advancing the understanding of brain function and clinical diagnostics within neuroscience.

In the EEG sensor, a brainwave sensor was used, whose chip detects brainwave data and mainly calculates β wave (attention, 8–14 Hz), α wave (mediation, 14–30 Hz), and γ wave (excitement, above 30 Hz) values. We used the FFT algorithm to calculate the three kinds of values every second as a temporal sequence to estimate the change of emotion state more easily.

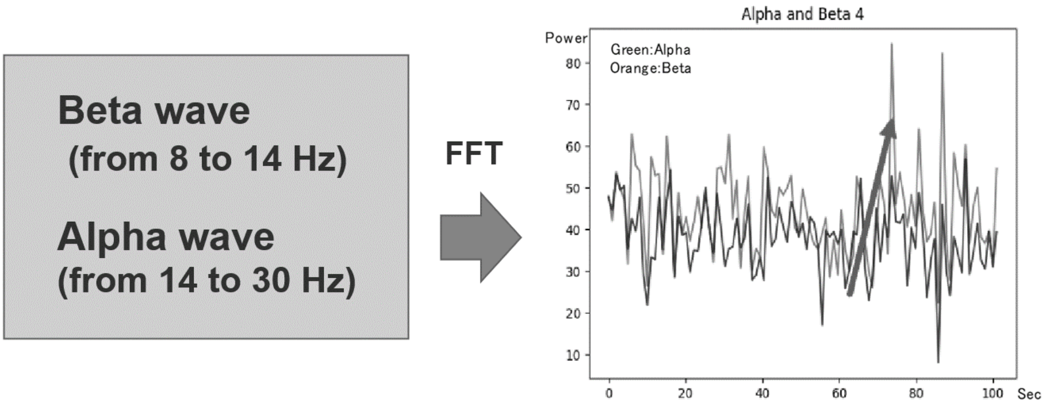


Figure 4-1. Transformation of brainwave by FFT

4.2. Persistent Homology for Brainwave

Persistent homology constitutes an analytical approach in computational topology aimed at identifying and quantifying topological characteristics of space across varying spatial resolutions [4-1]. This method operates under the premise that topological features that exhibit persistence over an extensive range of spatial scales are more indicative of the intrinsic properties of the underlying space. Such features are considered less likely to result from sampling errors, noise, or biases introduced by the selection of specific parameters. This approach distinguishes meaningful topological information and artifacts from the aforementioned external factors.

To provide some intuition for the persistent homology, let us consider a typical way of constructing persistent homology from data points in an Euclidean space, assuming that the data lie on a sub-manifold. The aim is to infer the underlying manifold's topology from finite data. We consider the *r*-balls (balls with radius *r*) to recover the manifold's topology, 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 of the disjoint r-balls. On the other hand, if *r* is too large, the union becomes a contractible space.

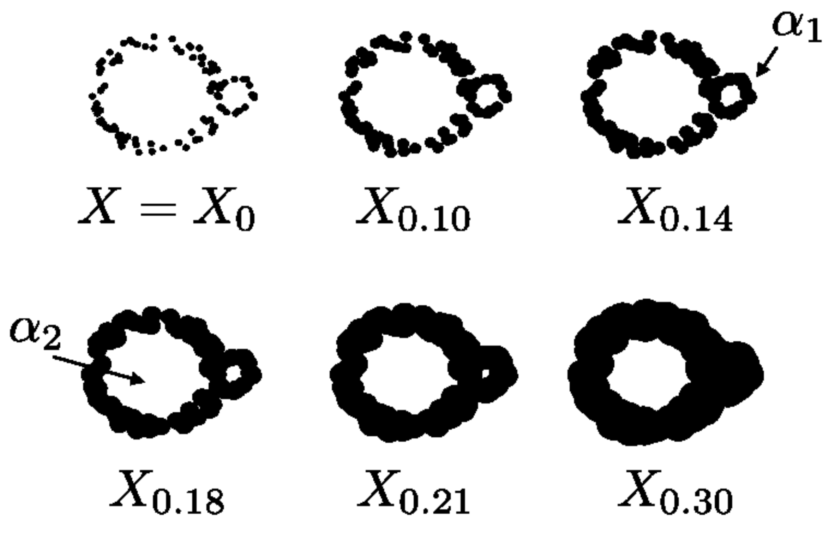


Figure 4-2. The union X_r of *r*-balls at points sampled with noise [4-2]

Persistent homology can consider all r simultaneously and provides an algebraic expression of topological properties and 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 $(bi, di) \in D$, called a generator of the persistent homology, represents a topological property (e.g., connected components, rings, and cavities), which appears at X_{bi} and disappears at X_{di} in the r-ball model. Then, the persistence $di - bi$ of the generator shows the robustness of the topological property under the radius parameter.

Persistent diagram is an analytical tool for visualizing data derived from persistent homology. This diagram is a graphical representation structured with two principal axes, namely 'Birth' and 'Death,' that delineate the emergence and dissolution of topological features within a dataset. As illustrated in Figure 4-3, the 'Birth' axis, positioned horizontally, marks the inception of a topological part, typically a hole, as observed from an initial, localized perspective of the data set. Conversely, the 'Death' axis, oriented vertically, signifies the point at which this topological feature ceases to exist, correlating with a transition from a local to a more comprehensive, global view of the data. The discrete points plotted on the diagram correspond to these topological features, with their spatial relationship to the 'Birth' and 'Death' axes indicating the respective moments of their appearance and disappearance. Critically, components of substantial significance are denoted by points that lie considerably distant from the diagonal line where 'Birth' equals 'Death.' Such features, persisting over a broad spectrum of scales, are less likely to be

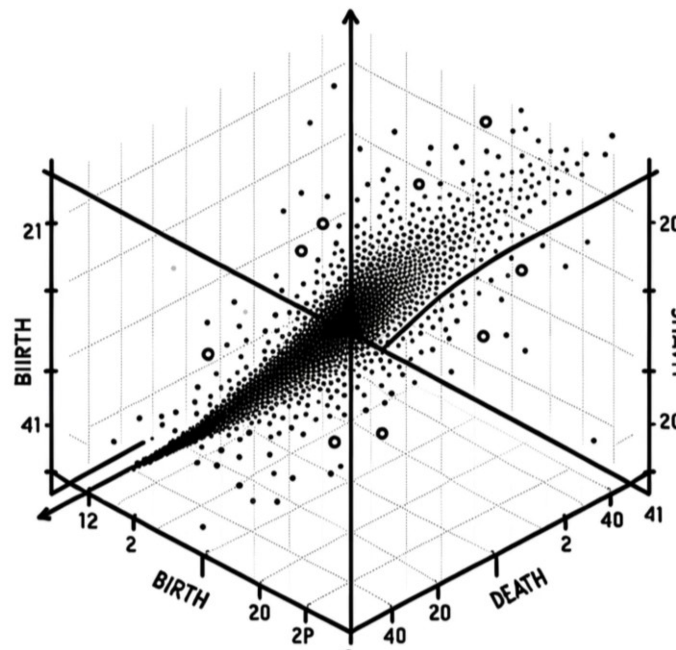


Figure 4-3. Sample of Persistent Diagram

attributable to noise, thus highlighting their potential importance in the underlying data.

We use HomCloud [4-3], a tool for visualizing persistence, to create a 3D graph of Alpha, Beta, and Gamma waves for relation analysis.

4.3. PANAS Item Evaluation

In our methodological examination of the data derived from PANAS, we adopted a comprehensive and systematic approach. The initial phase involved independently scoring the PANAS responses for positive and negative affect domains. This phase was followed by computing descriptive statistics, illuminating overarching trends in affective states. For each item on the PANAS questionnaire, whether indicative of negative or positive affect, a score ranging from 1 to 20 was assigned based on the drivers' markings. We meticulously observed and calculated the average negative and positive effect values. Our study's crucial aspect was comparing these average values and assessing their variation from pre- and post-experiment phases. This comparison offered a nuanced understanding of the changes in affective states, potentially attributable to the experimental conditions or interventions.

To ensure the reliability of these scales, a measure that guarantees the consistency and dependability of the measurement instruments is applied. An essential component of our analysis also included evaluating the distributional properties of the data, a critical step in determining the suitability of various statistical tests for subsequent studies. Our approach further encompassed a correlational detailed survey. This facet of our research aimed to uncover the intricate relationships between affective scores and other pertinent variables. Such an analysis provides a deeper understanding of the underlying psychological dynamics.

4.4. Recognition Method for Facial Expression

Facial expressions are integral to manifesting emotions; body movements often reflect psychological states. Our research focuses on facial expression recognition, utilizing computational techniques to analyze these expressions. Recognizing the resource-intensive nature of large-scale machine learning models, we propose an efficient, cost-effective approach. This approach involves leveraging an open-source facial detection model combined with the K-Means clustering algorithm [4-4]. This preliminary classification of facial expressions integrates data from the DS's operational metrics and visual information from a drive recorder.

4.4.1. Facial Image Pre-processing

We utilize OpenCV [4-5] for video processing and MediaPipe Face Mesh [4-6] for landmark detection in facial expression classification. The pre-processing stage involves identifying facial landmarks - specifically around the eyes, nose, and mouth to facilitate expression recognition [4-7]. Given the transient nature of facial movements, a rapid and precise face detection model is crucial. Our methodology employs the MediaPipe Face Mesh, offering real-time, high-accuracy detection of 468 facial landmarks with minimal input requirements.

We decided to use the MediaPipe Face Mesh solution, which provides a high-accuracy face detector and estimates 468 face landmarks in real-time, requiring only a single camera input to achieve our goal. To evaluate the performance of the MediaPipe face detector, The accuracy of this model is assessed by calculating the Face Detection Rate (FDR) across six video recordings. Let the number of frames of a video be N_i, and the number of frames where the driver's face is detected in the video be N_{di}. We can calculate FDR in the following way.

$$FDR = \frac{\sum N_{di}}{\sum N_i} \tag{1}$$

where $i \in \{1, 2, \dots 6\}$.

The result shows that the driver's face is present in every video frame, and our analysis indicates a meager false detection rate, under 0.1%. Consequently, in our experimental setup, the False Detection Rate (FDR) is approximately equivalent to the Mean Average Precision (mAP) [4-8]. However, challenges arise due to the dim interior lighting within the seat, potentially hampering the effective detection of the driver's facial outline. Analysis of video samples reveals an FDR of 24.90%, indicating that the driver's face was undetected in most instances. To mitigate this issue, we employed OpenCV to modify the contrast and brightness of the facial images, aiming to identify an optimal set of parameters for enhanced face detection. The image processing is defined mathematically: let $f(x, y)$ represent the pixel values of the source image, and let $g(x, y)$ denote the pixel values of the processed output image. The image brightness and contrast adjustment is achieved through the following mathematical expression.

The subdued lighting within the driver's seat presented a significant challenge for facial outline detection. Our results indicate that the False Detection Rate (FDR) for six video samples was 24.90%, signifying that, in most instances, the detector did not accurately detect the driver's face. To address this issue, we used OpenCV to adjust the facial images' contrast and brightness to identify an optimal parameter for improved face detection. The mathematical representation of this image processing is as follows: let $f(x, y)$ denote the pixel values of the original image, and $g(x, y)$ represent the pixel values of the adjusted output image. The subsequent expression governs the modification of image brightness and contrast.

$$g(x,y) = \alpha \cdot f(x,y) + \beta \tag{2}$$

where x and y indicate that the pixel is located in the x-th row and y-th column.

The parameter α, which controls contrast, was varied between 0 and 3, while the parameter β, influencing brightness, ranged from 0 to 100. An exhaustive analysis was conducted for each parameter set, and the FDR was calculated. A subset of these results is presented in Table 1, showcasing the FDR for α values between 1.0 and 2.0 and β values from 0 to 50. The data reveals a peak FDR of 63.75% at α=1.5 and β=35. However, this detection level was deemed insufficient for accurate expression recognition and necessitated further comprehensive analysis. It is hypothesized that the MediaPipe detector's inability to discern the driver's facial outline, exacerbated by extraneous visual noise, contributed to the low FDR. To enhance the FDR, we implemented a method of segmenting images and manually refining the recognition scope. As depicted in Figure 4-2, the recognition area was explicitly confined to around the driving seat, with a resolution of 700 × 700 pixels. This approach yielded a significantly improved FDR of 95.35% at α=1.5 and β=35, a satisfactory level for subsequent analyses.

4.4.2. Expression Classification

The efficacy of facial expression recognition through dividing facial landmarks into distinct regions has been corroborated, displaying notable accuracy as indicated in the literature [4-9] [4-10].

Figure 4-4 illustrates our methodology for extracting 42 specific landmarks, designated as $P_{1,1}, P_{1,2}, \ldots, P_{1,20}$ in the mouth region, $P_{2,1}, P_{2,2}, \ldots, P_{2,11}$ in the left eye region, and $P_{3,1}, P_{3,2}, \ldots, P_{3,11}$ in the right eye region, which serve as fiducial points on the face. To quantify the variation of these landmarks with facial expressions, we established a unique origin point within each region (highlighted as red points in Figure 4-4). The distance D_{ij} between each landmark and its corresponding origin point in a frame where a face is detected is calculated using the following expression:

$$D_{ij} = \left| P_{ij}(x,y) - \frac{1}{N_l} \sum P_{ij}(x,y) \right| \tag{3}$$

where $j \in \{1, 2, \ldots 20\}$ and N_l = 20 when i = 1; $j \in \{1, 2, \ldots 11\}$ and N_l = 11 when i = 2 or 3.

Consequently, we aggregate these distances into a feature vector V for each frame where a face is recognized, enabling the classification of facial expressions based on vector data:

$$\boldsymbol{V}(D_{1,1}, D_{1,2}, \dots, D_{ij}, \dots, D_{3,11}) \tag{4}$$

Given facial expressions' complexity, intensity, and unpredictability, we employed K-Means clustering to analyze the multi-dimensional data pertinent to facial classification.

Figure 4-4. Recognition scope fixed around driving seat

Table 4-1. Parts of FDR with different parameter sets

	0	***5***	***15***	***25***	***30***	***35***	***45***	***50***
1.0	24.90	24.98	26.58	28.51	31.49	30.97	34.91	35.30
1.1	29.02	29.98	31.83	32.80	34.91	35.00	36.99	37.91
1.2	31.74	32.98	34.23	35.29	34.96	36.23	39.86	42.78
1.3	36.03	37.61	40.35	42.64	44.03	43.98	45.25	45.21
1.4	44.64	47.92	52.08	51.94	53.09	53.24	55.02	51.24
1.5	50.95	53.50	55.75	59.01	62.55	63.75	61.55	60.43
1.6	48.02	49.23	53.26	55.93	56.22	57.04	56.24	56.37
1.7	46.63	45.94	49.08	54.66	54.95	56.37	52.08	49.42
1.8	40.82	42.88	47.84	50.38	53.90	53.01	48.08	45.39
1.9	37.03	39.95	46.37	50.08	50.73	48.63	45.15	42.49
2.0	35.23	34.96	43.95	42.91	43.85	41.87	41.73	37.35

Without prior knowledge of the specific facial expressions manifested during driving, we categorized the images into six classes. These classes correspond to the six primary facial expressions delineated in basic emotion theory: happiness, sadness, anger, fear, surprise, and neutral. The image dataset was subsequently partitioned into six clusters. The Scikit-Learn Python library [4-11] was utilized for this data processing.

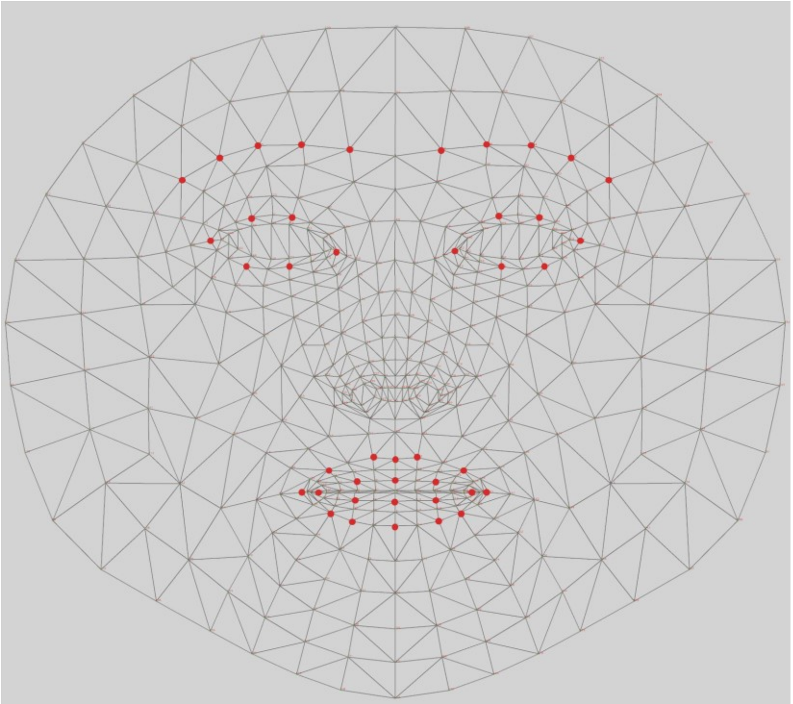


Figure 4-5. Landmarks detected from facial expression [4-7]

Table 4-2. Computational parameters for clustering

Number of clusters	*n_clusters* = 6
Maximum number of iterations	*max_iter* = 300
Number of times of centroid initialization	*n_init* = 10
Allowable error of convergence	*tol* = 0.0001

4.5. Body Movement Measurement

In addition to facial expression analysis, we explored body motion measurement through video imaging, focusing on head and hand movements. Body motion and posture are instrumental in conveying emotional information in daily contexts [4-12]. However, the confined driving posture presents challenges for detecting body motion, as the in-car video recorder cannot capture the entire body, which is crucial for pose landmark detection. As a viable alternative, we computed the coordinates of the head *H* (*x, y*) as a pivotal point for body motion assessment.

$$H(x,y) = \frac{1}{42}\sum P_{ij}(x,y) \tag{5}$$

Thus, we can evaluate the motion intensity of head M_t by calculating the absolute value of the difference between *H* (*x, y*) and its mean value for a frame in time *t*.

$$M_t = \left| H_t(x,y) - \frac{1}{N_f}\sum H_t(x,y) \right| \tag{6}$$

where N_f is the number of frames of a video.

Hand motions are also indicative of mental and emotional states. For instance, drivers often engage in self-touching behaviors, such as touching their face or hair, when experiencing boredom. These motions were identified manually, with the corresponding occurrence times recorded, revealing several instances of such behaviors.

4.6. Eye Movement Measurement

Eye tracking technology represents an advanced integration of optical tracking and computational analytics for eye movement measurement. It utilizes an ocular camera and eye tracking device for real-time capture of eye movements, enhanced by algorithms for dark pupil tracking and 3D visual modeling, ensuring high accuracy. A vital feature of the system is its ability to autonomously detect eyelid dynamics, such as blinks and closures, crucial for assessing fatigue through blink frequency, which correlates with cognitive strain. The blink detection algorithm categorizes blink patterns for immediate and retrospective analysis, offering insights into mental workload and stress levels from blink rate data.

Considering dispersion and duration thresholds, this method provides a comprehensive framework for analyzing visual attention and cognitive processing. Specifically, monitoring driver fatigue focuses on eye closure and blink frequency to assess fatigue levels effectively in real-time operational settings.

Chapter 5

Experimental Design and Data Analysis

5.1. Research Overview

5.1.1. Objectives of the Research

(1) Research goal

The primary goal of this research is to develop and validate a decentralized, systematic framework for accurately determining drivers' mental states, with a particular focus on identifying signs of fatigue. We achieve it by devising and executing a comprehensive sensor network that gathers a wide array of bio-signal data from individuals operating automotive vehicles. The network integrates various technologies, including a high-fidelity driving simulator, accelerometer, heart-rate monitor, EEG sensor, video camera, and eye tracker. The aim is to enhance vehicular safety by providing a more holistic and precise method of assessing drivers' mental conditions, especially during the critical transitional period preceding the widespread adoption of autonomous vehicles.

(2) Sequential research methodology

We have meticulously structured our research methodology into several sequential phases to attain the stated research objectives. This systematic approach is designed to ensure the thoroughness and accuracy of our study, as detailed in the following steps.

- Step 1: Development of an Integrated Sensor Network

The foundational phase entails establishing a sophisticated sensor network. This network integrates a high-fidelity driving simulator and bio-signal sensors, including accelerometers, heart-rate monitors, and EEG sensors. The amalgamation of these varied technologies is vital for capturing a broad spectrum of data, which reflects the driver's physiological and operational states.

- Step 2: Data Collection Under Diverse Conditions

The subsequent phase is the systematic data collection upon the network's establishment. Participants will operate vehicles within the simulator across a variety of driving conditions. This stage is dedicated to methodically compiling operational metrics from the DS alongside physiological data from the sensors, encompassing parameters such as brainwave activity, heart rate, facial expressions, and body movements.

- Step 3: Data Analysis Employing Advanced Methodologies

The amassed data will undergo comprehensive analysis. We propose applying sophisticated statistical methods, as existing techniques may prove insufficient or inappropriate for this research due to their inherent limitations.

- Step 4: Integration of Psychometric Assessment Tools

Given the potential unreliability and insufficiency of solely relying on sensor data for estimating drivers' mental states, the integration of a self-report survey assessing mental states is under consideration. This psychometric tool is anticipated to augment the accuracy of mental condition evaluations derived from bio-signals, thereby offering a more holistic assessment of the driver's psychological state.

- Step 5: Cross-Referencing and Validation of Findings

The results obtained from sensor data and psychometric evaluations will be cross-referenced to validate the accuracy of the mental state estimations. This crucial step aims to verify the precision of fatigue determinations and to authenticate the comprehensive assessments of drivers' mental conditions.

- Step 6: Evaluation and Refinement

The final phase involves appraising the efficacy of the sensor network in discerning driver fatigue and other mental conditions. This stage will also address challenges encountered during the research process, including issues with sensor accuracy or data anomalies. Evaluating the identified correlations among the data and systematically addressing any experimental difficulties is imperative in refining the research methodology.

(3) Experimental design

Our study explicitly selects participants of varying genders and driving experiences to acquire a diverse range of experimental data for comprehensive analysis and comparison. Moreover, to enrich the dimensions of our data, we implement a variety of experimental conditions throughout the research process. This strategic approach is intended to ensure that the collected data comprehensively reflects the responses and behaviors of different demographic groups under various driving environments, thereby enhancing the accuracy and reliability of the research findings.

- Participant Demographic

The experimental cohort comprised male and female students enrolled at Chuo University, predominantly in their twenties. These participants were stratified into two groups based on their familiarity with driving: one group consisted of individuals experienced in driving, while the other included those with minimal or no driving experience. Each group was subjected to a pair of driving simulations under identical vehicular conditions to ensure experimental consistency.

- Experimental Condition

The driving simulations were conducted on two meticulously designed courses: the Tokyo Metropolitan Highway (C1) and a local Paris Road. The specific parameters of these simulations are detailed in Table 3-3. In the C1 scenario, an experimental variable altered ambient brightness levels during the driving simulation. Conversely, the Paris Road simulation utilized the Simulation of Urban Mobility (SUMO) [5-1] platform to introduce dynamic elements such as variable traffic conditions and unpredictable pedestrian behaviors, mimicking real-world driving challenges.

Before and following each simulation, participants complete the PANAS questionnaire, which includes ten items each for assessing positive and negative affective states. The examinee did this survey to ascertain the psychological impact of the driving experience on the participants. As delineated in Figure 4, there was a notable elevation in the scores of the negative affective responses post-simulation, suggesting a consistent trend of increased fatigue or stress following 45 minutes of driving. This outcome underscores the potential psychological impact of prolonged driving under varying environmental conditions and offers valuable insights into driver well-being and safety.

Table 5-1. Detail of test courses in the driving simulator

Course	***Time/round***	***SUMO***	***Brightness change***	
Tokyo Metropolitan Highway C1	10 min	No	0-10 min 10-20 min 20-30 min 30-40 min 40-45min	4 PM 6 PM 7 PM 7:30 PM 8 PM (with illumination)
Paris City Area Course	6 min	Other traffic, Pedestrian crossing road	No	

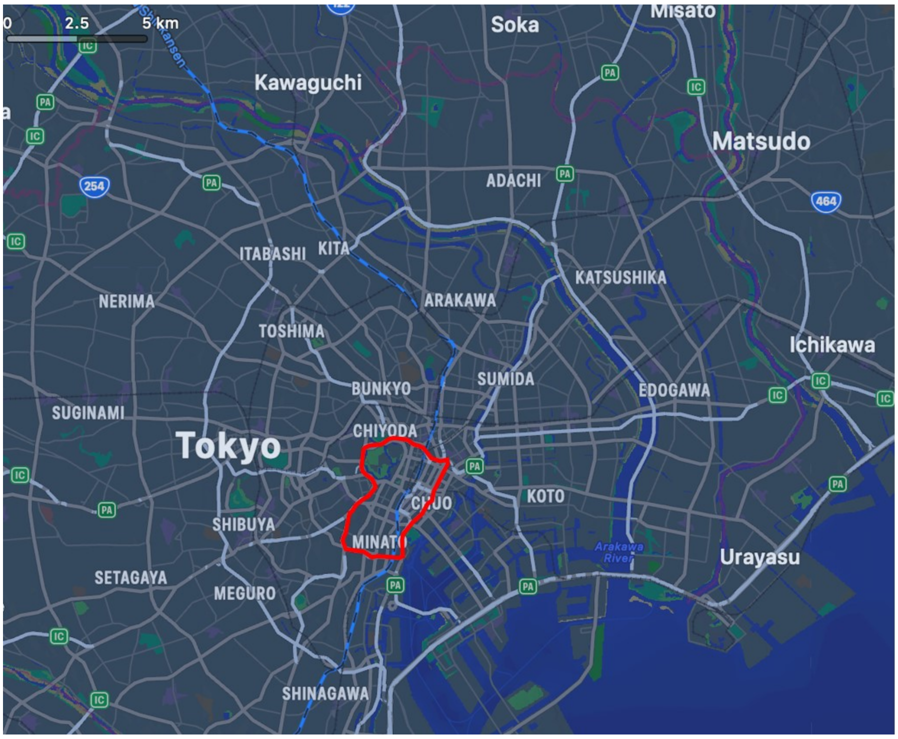


Figure 5-1. Tokyo Metropolitan C1 Expressway (red line)

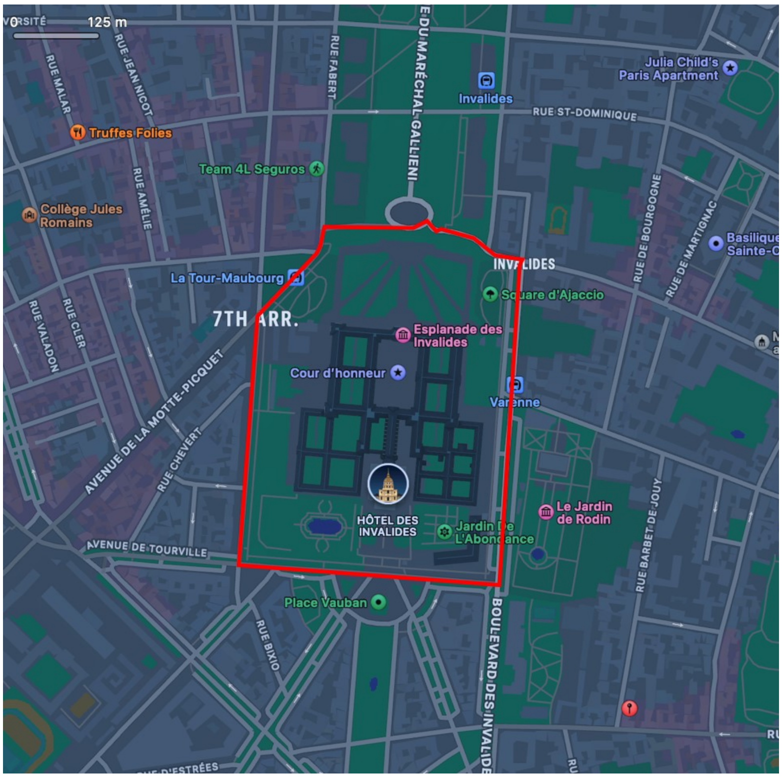


Figure 5-2. Roads in Paris (red line)

5.1.2. Previous Studies

(1) Overview of previous studies

In fiscal year 2019, We developed a sophisticated sensor network to assess drivers' mental states during driving, with the primary objective of enhancing road safety [5-2]. This network comprises a variety of sensors: accelerometers for detecting head motion, electrocardiogram (ECG) sensors, electroencephalogram (EEG) sensors, and heart rate monitors. These are augmented by data from a driving simulator, which captures vital vehicular metrics such as speed, steering wheel angle, brake pressure, and other relevant driving performance indicators. The convergence of these data streams provides a holistic overview of the driver's mental state by integrating biological signals and behavioral patterns.

The previous study explored the interplay between bio-signal and operational driving data, uncovering correlations between biological signals and psychological states. Notably, heart rate and EEG metrics emerged as potential indicators of stress levels in varying driving contexts. The preliminary findings suggest that the sensor network effectively gathers pertinent data, particularly emphasizing the value of ECG and heart rate measurements in deducing emotional states. This study lays the groundwork for future in-depth investigations of driver mental states and the evolution of a more streamlined, practical sensor network for real-world application.

(2) Problems occurred in previous studies

Despite these advancements, the project encountered several practical challenges, especially in implementing EEG and ECG sensors. Multiple factors influence the reliability of EEG data, and the intrusive nature of EEG equipment hinders its integration into standard driving environments. Those problems highlight the necessity for more practical, durable, and cost-efficient sensor alternatives to complement or replace EEG sensors, thereby ensuring the viability of this technology in everyday driving conditions.

5.1.3. Methodological Framework for Upcoming Experiments

Considering the challenges identified in the preceding study, it is imperative to adopt strategies that address these issues to enhance the accuracy and reliability of the data collected from the established sensor network. A primary measure to be considered is incorporating a self-report survey methodology. This approach would involve participants providing subjective feedback on their mental state, serving as a means to validate and cross-reference the physiological data obtained from the sensor network. Such a method can help assess the correlation between the subjective experiences of drivers and the objective data captured by the sensors, thereby increasing the credibility of the findings. Furthermore, integrating additional sensors into the existing network is recommended to improve the precision of assessments regarding drivers' mental states. Introducing new sensors, possibly ones that are less intrusive and more advanced in technology, can provide a more nuanced understanding of the psychological and physiological aspects of driving. This setup could include sensors that monitor eye movement, skin conductivity, or even facial expressions, each potentially serving as a novel indicator of mental states. By broadening the scope of data collection, the study can achieve a more comprehensive and multi-dimensional understanding of drivers' mental conditions, thus paving the way for more accurate and reliable safety measures in the context of vehicular operation.

In this research, we comprehensively evaluate the performance of various sensors within both experimental and practical settings. This evaluation aims to understand these sensors' efficacy and reliability in real-world applications. Furthermore, we engage in a detailed analysis of the biosignals data acquired from these sensors. The primary objective of this analysis is to investigate the correlation between the biosignals and an individual's mental state. Through this investigation, we aim to identify a more feasible and accurate index for assessing mental states. This endeavor is crucial for understanding the interaction between physiological markers and psychological conditions.

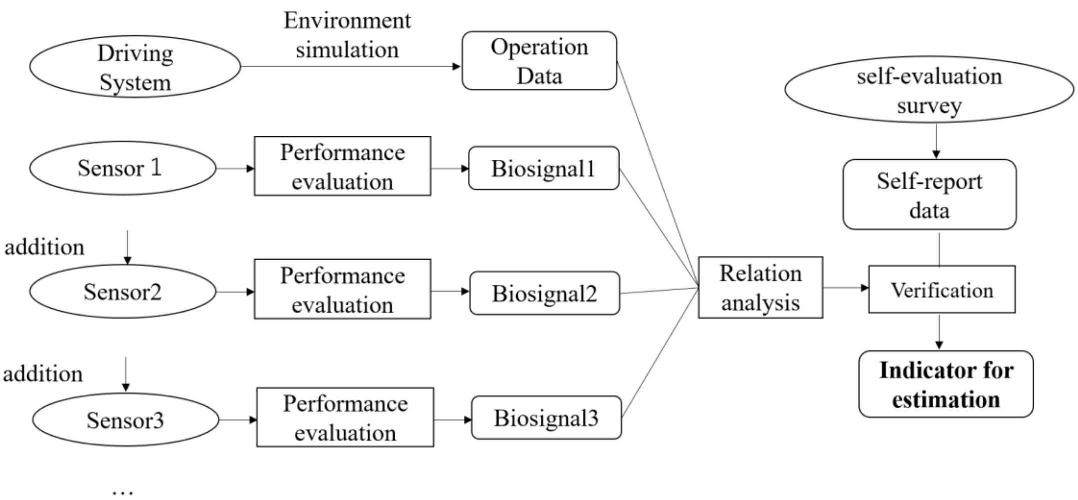


Figure 5-3. Framework of this research

5.2. Assessment of Mental State by Comparative Data Analysis

5.2.1. Research Objective

Expanding upon the insights from Section 5.1, we estimate drivers' mental states using data from the sensor network. The primary objective is to validate the accuracy and reliability of these mental state estimations by incorporating a self-report survey methodology. This validation process entails a comprehensive comparative analysis, juxtaposing driving performance data with self-reported mental states as quantified by PANAS. The goal is to establish a correlation between objective sensor data and subjective self-assessments, reinforcing the sensor network's credibility and effectiveness in evaluating drivers' mental states.

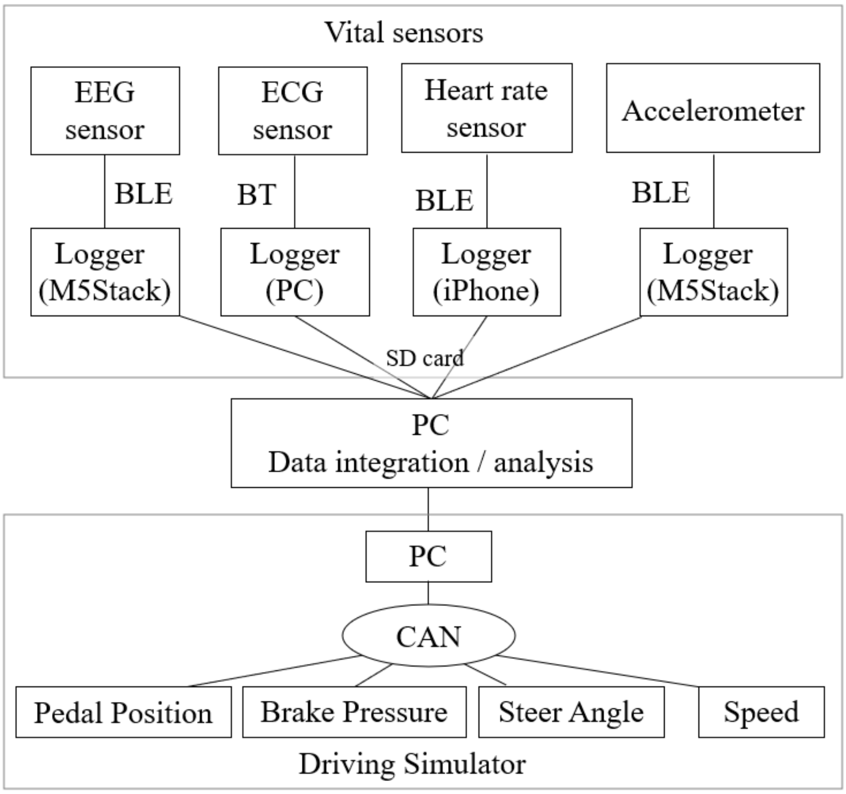


Figure 5-4. Diagram of sensor network implemented in FY2021

5.2.2. Experimental Method

In Fiscal Year 2021, We refined the research methodology to incorporate a dual approach: employing the PANAS-based emotion estimation alongside a five-level emotion rating scale for subjective assessments, as documented in Reference [5-3]. The focal point of the study was to quantify mental states by establishing a correlation between driving performance data and PANAS responses, thereby verifying the accuracy of the sensor network's predictions. A congested traffic course was designed to test participants under stress-inducing scenarios to emulate real-world driving conditions. The experiment featured advanced heart-rate monitors, accelerometers, and brainwave sensors for comprehensive data collection. Figure 5-4 illustrates the schematic layout of our sensor network. The experimental scope was also broadened to include simulated driving situations on the Metropolitan Expressway and in urban settings [5-4], encompassing diverse traffic scenarios such as congestion, traffic light waits, and sudden vehicle maneuvers. A single participant was involved in this phase to assess the effectiveness of data acquisition from the integrated sensor network.

5.2.3. Result Analysis

(1) Mental state measurement from heart rate data

Heart rate data, presented in Figure 5-5, further elucidates the physiological responses across different trials: Trial 1 (11:35~12:20), Trial 2 (13:30~14:15), Trial 3 (15:00~15:45) deviated from this pattern. During this trial, the driver encountered three accidents, leading to notable spikes in heart rate coinciding with each collision event, which suggests a direct impact of stressful events on physiological state during driving.

(2) Mental state measurement from PANAS data

Analysis of emotional responses, as depicted in Figure 5-6, was conducted using questionnaires. The mood indices predominantly declined post-driving during the first and second trials. This trend suggests that the driver experienced significant fatigue after 45 minutes of driving. Conversely, the mood indices did not demonstrate a similar decline in the third trial. This anomaly could be attributed to two factors: the occurrence of multiple accidents during the drive potentially sustained heightened emotional responses, and the anticipation of completing the final trial may have positively influenced mental states.

(3) Mental state measurement from brainwave data

Figure 5-7 presents the correlation between emotional estimations and the PANAS framework. The data revealed an increasing trend in attention ratios from Lap 2 to Lap 4, aligning with the PANAS-derived mood indices' upward trajectory post-driving. This alignment underscores the PANAS framework's effectiveness in evaluating drivers' emotional states.

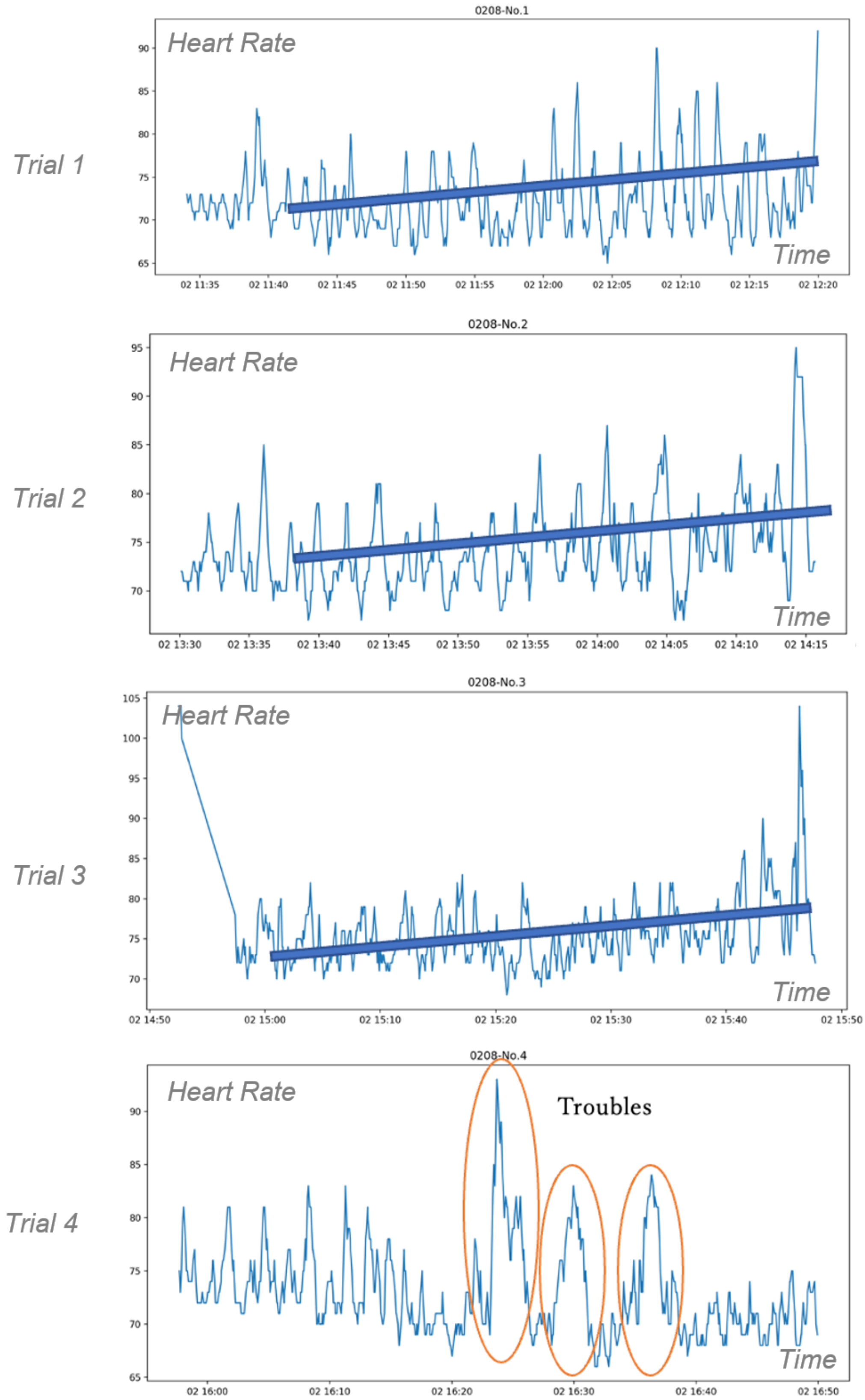


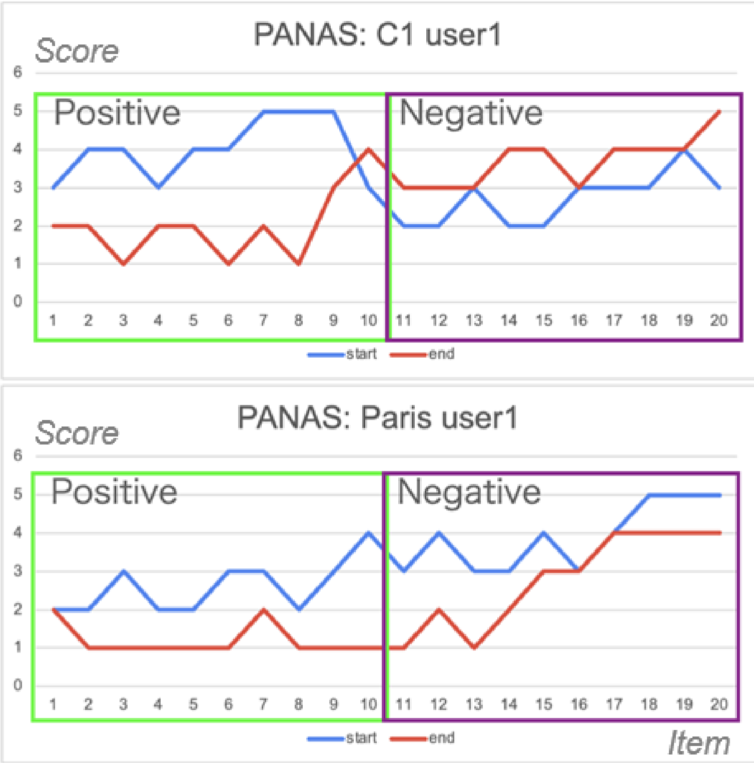
Figure 5-5. Heart rate variation in four trials

5.2.4. Conclusion

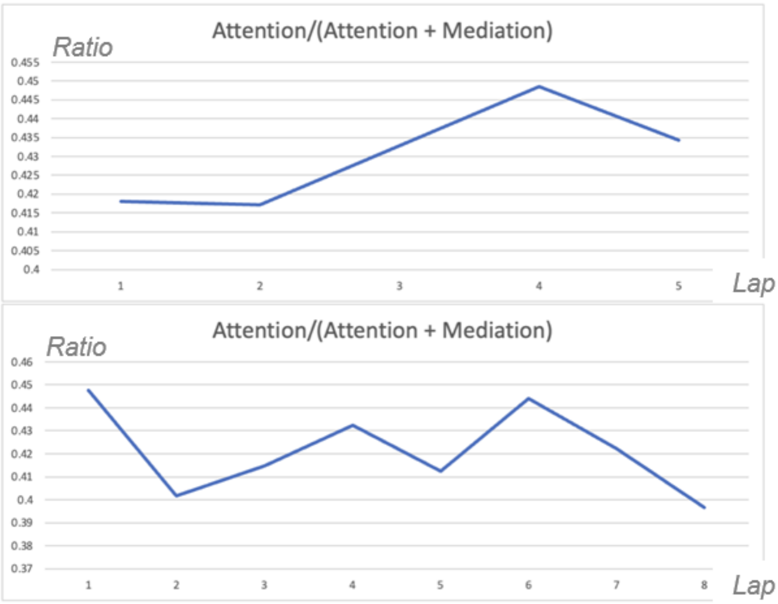
The outcomes of this research demonstrate the effectiveness of PANAS as a robust tool for assessing the mental state of drivers. The comparative analysis, which juxtaposed the data from PANAS with the readings obtained from the sensor network, revealed high coherence between self-reported emotional states and sensor-based estimations. This consistency underscores the reliability of both methodologies in capturing drivers' mental states. Integrating self-reported emotional assessments with objective sensor data has facilitated a more nuanced and in-depth understanding of drivers' mental states across varying conditions. By combining subjective emotional feedback with objective physiological and performance metrics, this comprehensive approach provides a richer context for understanding driver behavior.

This comprehensive analysis considerably deepens our understanding of driver fatigue. The findings from this study are valuable both academically and practically, especially in enhancing road safety and promoting driver well-being. Accurately assessing drivers' mental states is crucial for developing targeted interventions to prevent fatigue-related incidents. This proactive approach is essential for creating safer driving conditions. Importantly, PANAS has emerged as a viable tool for future applications in driver fatigue estimation. Combined with objective sensor data, its effectiveness in capturing subjective emotional states forms a robust foundation for advanced fatigue detection measures. This research marks a pivotal advancement in the field, harnessing the combined strengths of psychological self-assessment tools and state-of-the-art sensor technology to combat driver fatigue.

Figure 5-6. Mental state variation based on PANAS results



(a) Comparison of PANAS scores pre- and post-experiment



(b) Variation of attention ratio in two rounds

Figure 5-7. Comparison between PANAS and attention ration

5.3. Assessment of Fatigue State by Driving Video Analysis

5.3.1. Research Objective

Addressing the limitations noted in Section 5.2, this section focuses on overcoming the challenges related to using ECG and EEG sensors, which are susceptible to environmental noise and disturbances, affecting data accuracy. The goal is to enhance the estimation of driver fatigue by integrating additional sensor modalities that are reliable, cost-effective, and highly efficient. This approach seeks to complement the existing sensor network with video analysis techniques to observe and interpret visual cues, such as facial expressions and body language, for a more robust and precise assessment of driver fatigue.

5.3.2. Experimental Method

In Fiscal Year 2022, our study embraced a holistic approach by integrating facial image recognition to analyze mental states, specifically focusing on driver fatigue. This method involved sophisticated video analysis to capture and interpret facial expressions and body language [5-4] [5-5]. The aim was to enhance the precision of driver fatigue evaluations through this multi-modal approach. High-definition video cameras were installed within vehicles to meticulously record drivers' facial expressions, body movements, and any incident occurrences. This visual data was synchronized with automotive metrics, including accelerator pedal position, brake pressure, steering angle, speed, and acceleration. Additionally, the integrated sensor network also captured vital biosignals, such as EEG, ECG, and heart rate. Figure 5-8 illustrates the detailed configuration of this sensor network.

The experimental setup involved two female and one male student from Chuo University, who navigated different routes on the Tokyo Metropolitan Expressway and in Paris. This varied selection of driving environments was intended to elicit a wide range of mental and physiological responses for a comprehensive analysis. The methodological design aimed to validate the effectiveness of this integrated video and sensor-based approach by comparing its outcomes with the established PANAS framework.

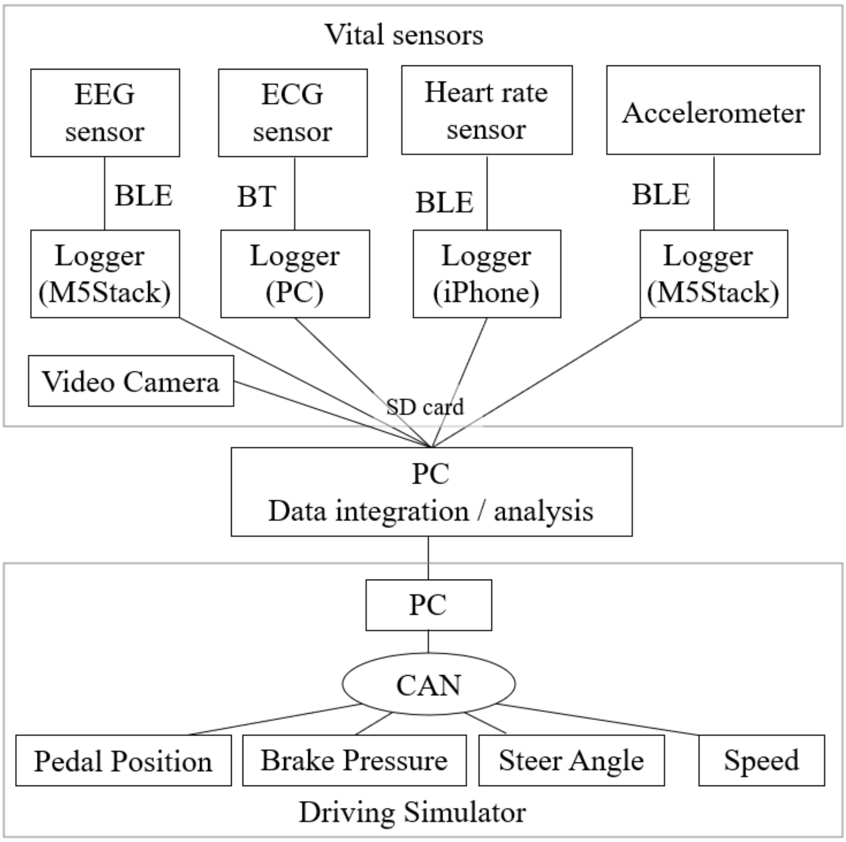


Figure 5-8. Diagram of sensor network implemented in FY2022

5.3.3. Result Analysis

(1) Relation between Facial Expression and Mental State

Figure 5-9 presents an array of images systematically classified into six distinct patterns utilizing the K-Means clustering algorithm. This classification method efficaciously discerned four discrete mental states based on the analysis of facial expressions: Neutral (Figure 5-9(1), 5-9(2), and 5-9(3)), Happiness (Figure 5-9(4)), and Fatigue (Figure 5-9(5)). These categorizations, which are the outcome of detailed facial landmark analysis, demonstrate the remarkable potential of facial imaging technology in accurately identifying and distinguishing specific mental states.

Figure 5-10 depicts the mental spectrum of participant (a) during the Paris driving simulation. This series of images encapsulates a spectrum of emotions, ranging from Neutral (Figure 5-10(1), 5-10(2), and 5-10(3)), to Anxiety (Figure 5-10(4)), Surprise (Figure 5-10(5)), and culminating in Fatigue (Figure 5-10(6)). Notably, this figure illustrates how certain facial expressions, such as lip clipping, are prevalently associated with specific driving scenarios, such as the anticipation and response to traffic signals.

This correlation offers profound insights into the drivers' mental responses and adaptations in varying driving contexts.

A comparative facial expression analysis between participant (b) and participant (a) on the Paris driving course is detailed in Figure 5-11. This juxtaposition underscores the heterogeneity in facial expressions exhibited by different individuals, even when subjected to similar mental stimuli. The images are systematically categorized into three principal mental states: Neutral (Figure 5-11(1) and 5-11(2)), Anxiety (Figure 5-11(3), 5-11(4), and 5-11(5)), and Fatigue (Figure 5-11(6)). This comparison accentuates the individualistic nuances in mental expression and its consequential implications on driving behavior and performance.

(2) Relation between body motion and mental state

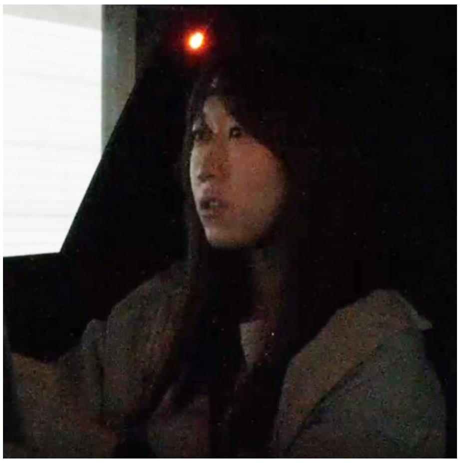
Figure 5-12 showcases an analysis of head motion data gathered from two distinct driving scenarios: one featuring examinee (a) on the Paris course and the other with examinee (b) on the Tokyo Metropolitan Expressway course. The data, normalized to maximum values, illustrate head movement intensity over a 45-minute drive.

On the Paris course, at intervals marked 00:21, 00:31, and 00:39, significant head movements were noted when the driver was at traffic lights, as shown in Figure 5-12(1). This pattern suggests that periods of inactivity (like waiting at traffic lights) could evoke feelings of boredom or anxiety, leading to notable changes in posture and increased head movement, possibly as coping mechanisms for these emotions.

Conversely, the Tokyo Metropolitan Expressway scenario presented more challenging conditions, especially as the environment transitioned from day to night (beginning at 00:29) and during tunnel passage (around 00:40). Figure 5-12(2) indicates a marked rise in head motion intensity with decreasing light, peaking in the tunnel. This result implies increased vigilance and careful driving in low-light conditions, likely due to enhanced visual scanning efforts by drivers.

Additionally, manual video analysis was conducted to monitor hand movements, such as touching the face or hair. As detailed in Figure 5-13, during the Paris course, examinee (a) was observed engaging in face-touching behaviors six times, particularly while stopped at traffic lights between 00:30 and 00:40. These behaviors predominantly occurred during the wait, suggesting that idle periods may trigger boredom, leading drivers to perform self-touching actions as a form of distraction or self-comfort.

(1)



(2)

(3)

(4)

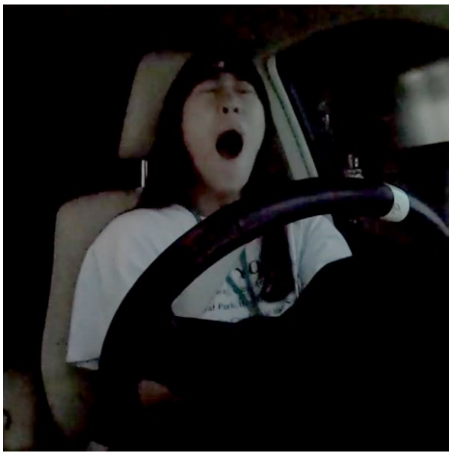
(5)

(6)

Figure 5-9. Classification results of examinee (a) during Tokyo C1 course

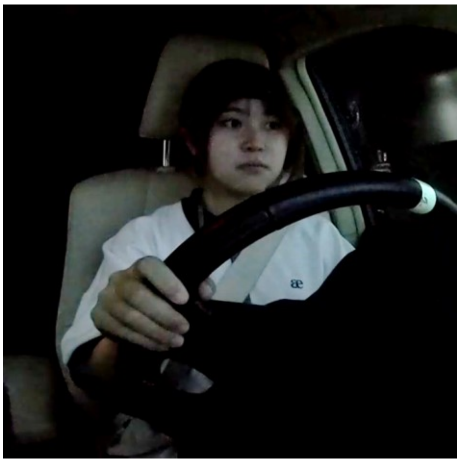

(1) (2)

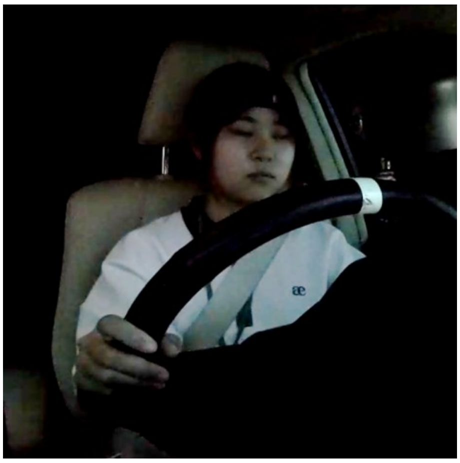

(3) (4)

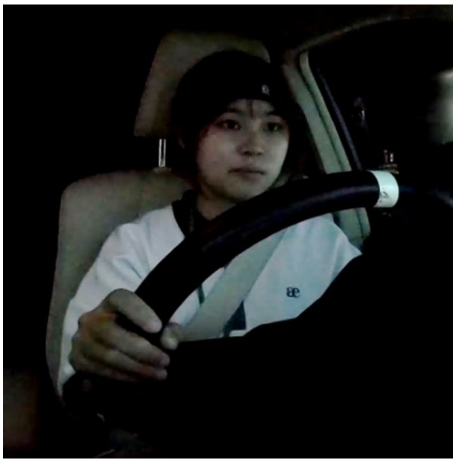
(5) (6)

Figure 5-10. Classification results of examinee (a) during Paris course

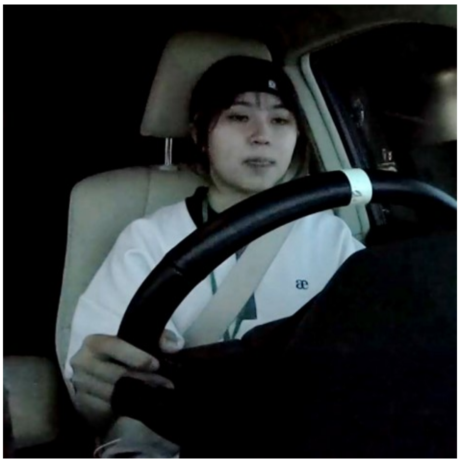




(1) (2)

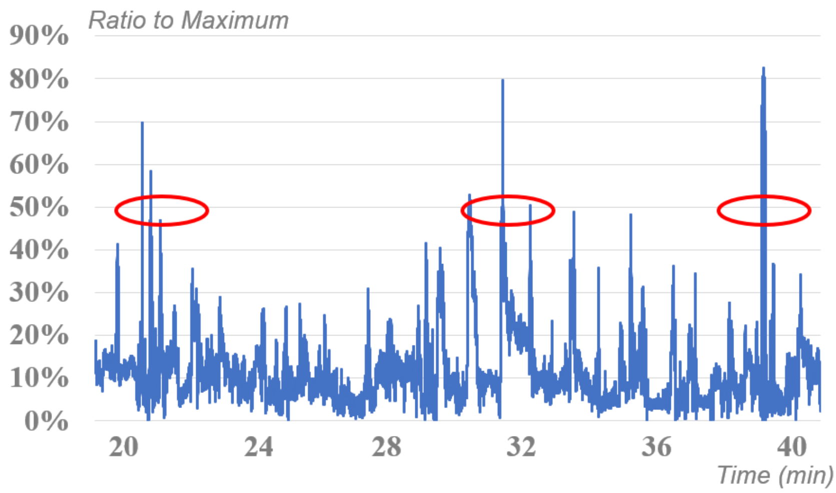


(3) (4)

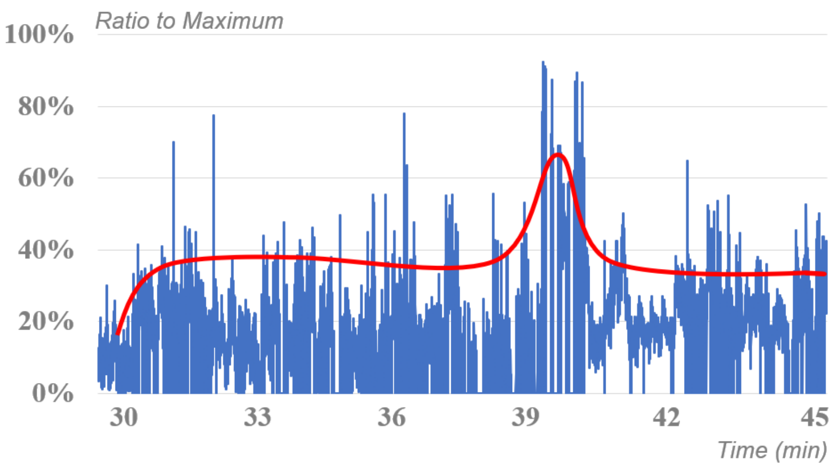


(5) (6)

Figure 5-11. Classification results of examinee (b) during Paris course



(1) Examinee (a) on Paris course



(2) Examinee (b) on Tokyo course

Figure 5-12. Parts of head motion variation during two driving courses

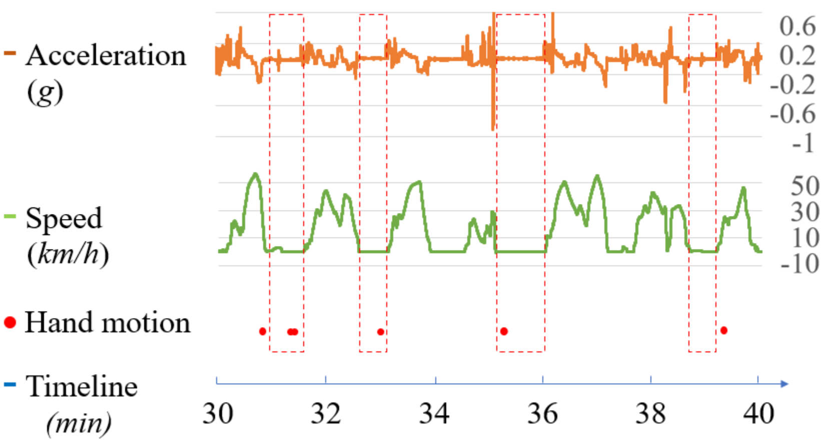


Figure 5-13. Comparison between head motion and driving data

(3) Relation between driving data and mental state

Undertook a comprehensive comparison of facial expressions and body motions with automotive operating data to elucidate the correlations among these variables. Specifically, data from an experiment conducted on the Paris course were analyzed. This analysis revealed five distinct mental states: Neutral, Happiness, Fatigue, Anxiety (identified from facial expressions), and Boredom (inferred from manually recorded hand motions). These mental states were visually represented with colored dots on a timeline in Figure 5-14(a). Concurrently, variations in head motion were plotted in Figure 5-14(b), while automotive operating data, encompassing pedal usage, steering behavior, and brake application, were illustrated in Figures 5-14(c), (d), and (e).

- Body motion as a reflection of mental states

The results indicate that emotions such as boredom and anxiety, particularly during waiting periods, are reflected in specific head and hand motions. Notably, Figure 5-14(b) shows that fatigue levels rise significantly after 20 minutes of driving, corresponding with an increase in head motion intensity from 00:20 onward. However, no significant deviation in head motion was observed in happiness or surprise, suggesting that body motions can partially infer certain mental states.

- Relevance of brake pedal pressure to fatigue

Analysis of Figures 5-14(a) and (b) reveals a stable facial emotion during 00:18 - 00:19 and 00:42 - 00:43, with a gradual decrease in accelerator pedal usage. This pattern suggests a decline in the driver's attention and a slight increase in brake pedal usage post-fatigue onset. Conversely, during periods of frequent mental change (00:24 - 00:26 and

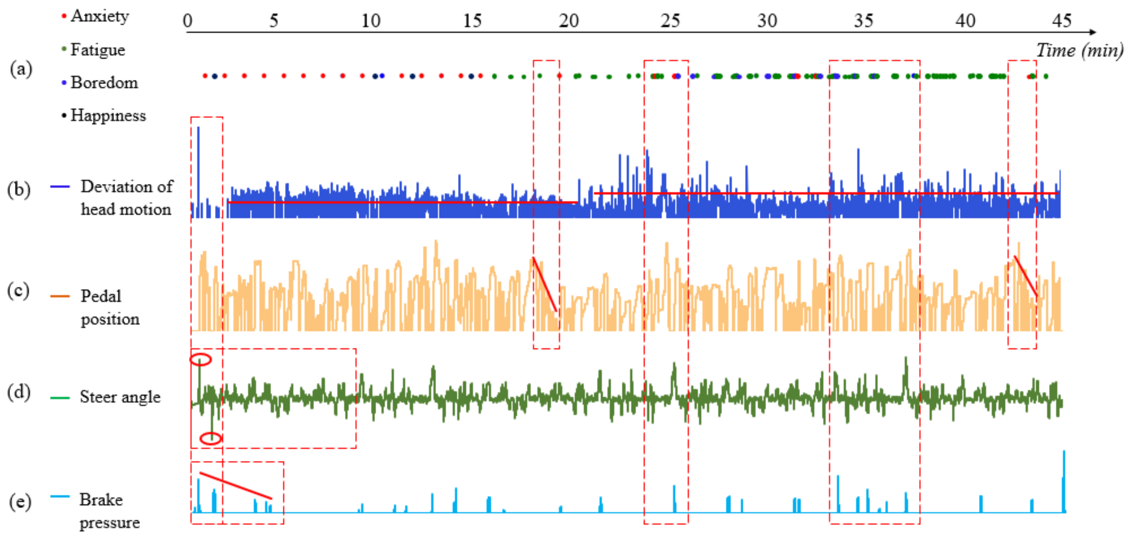


Figure 5-14. Comparison between mental states and driving data

00:33 - 00:38), the accelerator pedal position was notably higher. These observations underscore the importance of mitigating driver fatigue to minimize traffic accident risks.

- Emotions as indicators of operating status

The initial 2 minutes of the experiment showed significant variations in head motion, pedal position, steering angle, and brake pressure, indicating a heightened stress level in the driver. The steering angle exhibited two peaks within these first minutes, stabilizing afterward. Similarly, a gradual decrease in brake pressure was observed, suggesting reduced anxiety levels. Additionally, the periods 00:24 - 00:26 and 00:33 - 00:38, characterized by considerable variations in operating performance, imply that emotions like boredom and fatigue can escalate to impatience and potentially contribute to aggressive driving behaviors, colloquially termed road rage.

5.3.4. Conclusion

This chapter's research successfully quantified driver fatigue by analyzing the relationship between facial expressions determined through video analysis and mental states indicated by PANAS data. The comprehensive analysis of facial expressions revealed a pronounced correlation between these expressions and the psychological states of drivers. Beyond fatigue, the study effectively identified other mental states like happiness and anxiety, particularly in driving contexts. This result highlights the critical role of facial expression analysis in the real-time interpretation of drivers' mental states.

The outcomes open up promising prospects for assessing driver fatigue and other mental states using video recording technology. Furthermore, incorporating an AI model trained on extensive driving data and internal automotive conditions holds the potential to improve the accuracy and efficiency of these assessments. This research represents a significant advancement in the field by proposing an automated, innovative approach for processing and analyzing video data to evaluate facial states.

However, the research faced notable challenges. One primary concern is the variability in facial expressions across different drivers and under diverse conditions, which complicates the accuracy of facial recognition. Secondly, collecting images within vehicles poses significant privacy concerns, necessitating careful and ethical handling of such data. Addressing these challenges will require integrating additional sensor technologies in future studies.

5.4. Assessment of Fatigue State by Eye Movement Analysis

5.4.1. Research Objective

In light of the challenges delineated in Section 5.3, this section pivots towards refining the methodology for assessing driver fatigue, specifically emphasizing integrating auxiliary sensor technologies. This strategic incorporation of additional sensor modalities is poised to augment fatigue detection's accuracy and efficacy significantly.

5.4.2. Experimental Method

In Fiscal Year 2023, our research team significantly enhanced the sensor network established in the previous year by integrating sophisticated eye movement analysis techniques [5-6]. This expansion aimed to achieve a more granular and precise understanding of the physiological markers of driver fatigue. We equipped the vehicles with state-of-the-art eye monitoring equipment to ensure comprehensive data collection. This setup captured real-time biosignal data and synchronized it with the existing video footage and automotive performance metrics.

Figure 5-15 illustrates the detailed configuration of this enhanced sensor network. The upgraded sensor network incorporated a range of biosensors capable of capturing detailed physiological data, including heart rate variability, skin conductance, and advanced EEG metrics. These biosensors were carefully selected for their sensitivity and accuracy in detecting subtle changes in a driver's physiological state that may indicate fatigue. The integration of these sensors allowed for a multi-dimensional analysis of the drivers' physical responses under various driving conditions.

The experimental design also included two driving scenarios, the same as the conditions from Section 5.1. These scenarios ranged from high-stress situations, such as navigating through heavy traffic, to more controlled environments, like driving on a predetermined route. The data collected from these experiments were subjected to rigorous analysis utilizing advanced algorithms and data processing techniques. This approach allowed for extracting insights from complex biosignal data, enabling us to understand the nuanced relationships between different physiological markers and driver fatigue.

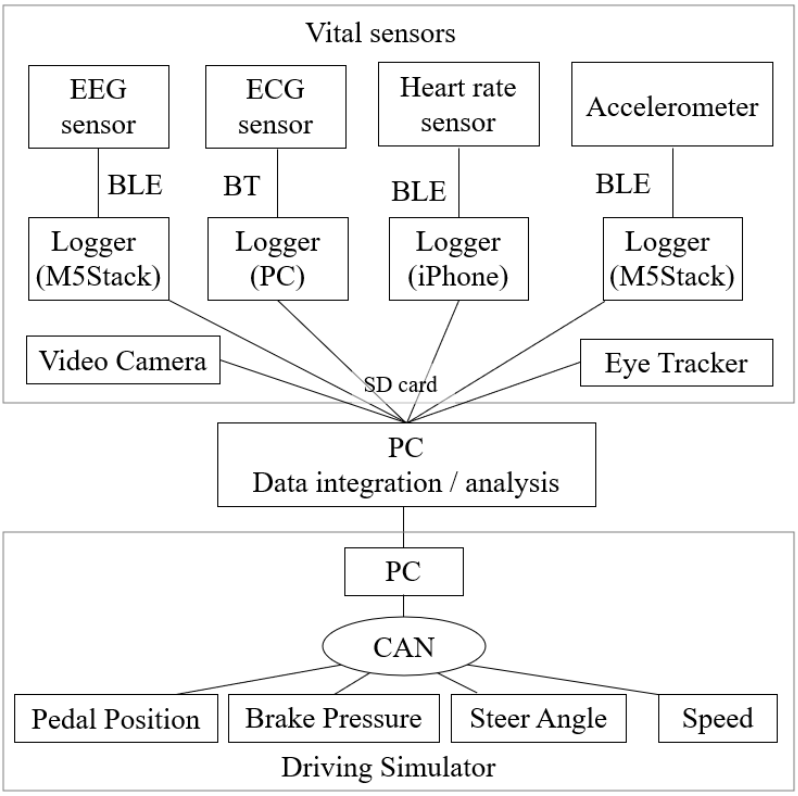


Figure 5-15. Diagram of sensor network implemented in FY2023

5.4.3 Result Analysis

(1) Estimation of fatigue based on driving data

Figure 5-16 delineates the correlation between the number of driving rounds completed and the duration of each round. A noteworthy trend emerges from the data: with the progression of multiple driving rounds, there was an approximate 20% increase in lap time. This pattern strongly indicates a diminution in driver concentration attributable to fatigue, manifesting as a reduction in overall driving speed.

Figure 5-17 graphically represents the relationship between ambient brightness levels and emotional changes as detected via EEG. The data illustrates a discernible decline in driver concentration correlating with the darkening of the roadway over successive driving rounds. This finding aligns with the trends observed in C1 driving data. In contrast, no significant decrease in attention levels was noted during driving sessions conducted in Paris. This differential outcome allows us to postulate that reduced lighting conditions adversely affect driver attentiveness, potentially exacerbating fatigue and diminishing concentration, particularly in nighttime driving contexts.

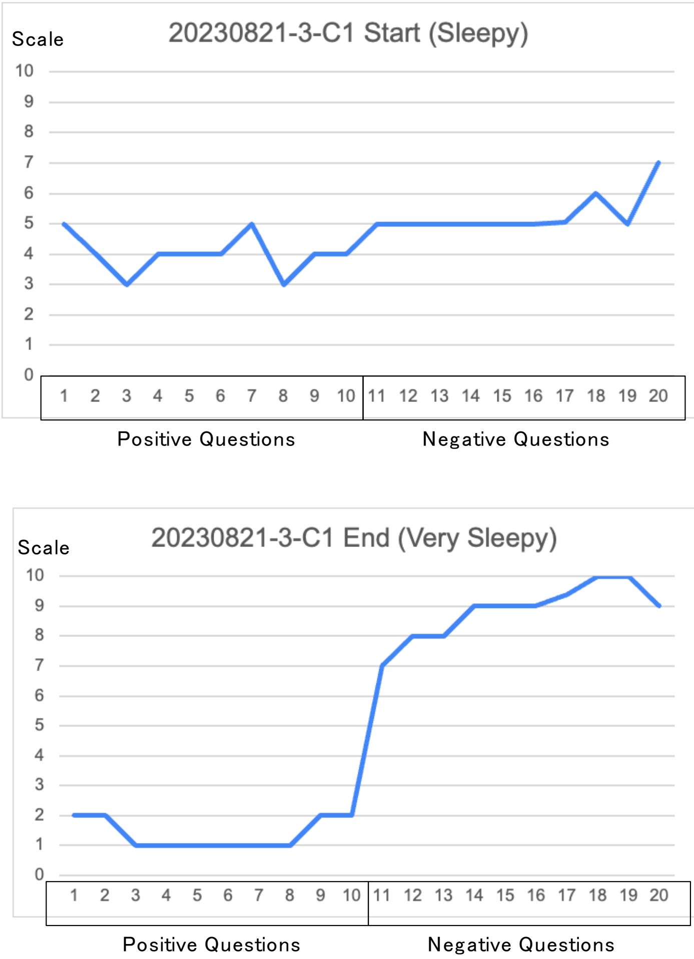


Figure 5-16. PANAS results before and after experiment

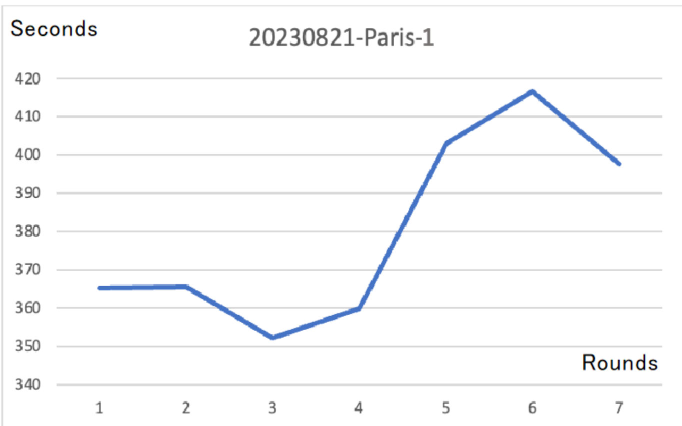


Figure 5-17. Driving time of rounds of Paris course

(2) Relation between facial expression and eye movement.

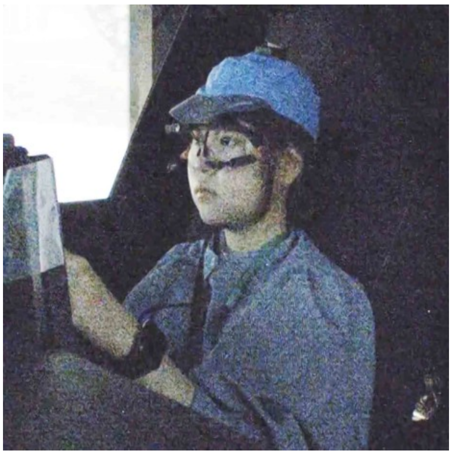
Our study thoroughly analyzed the interrelation between facial recognition technology and eye-tracking data, focusing on the incidence of eye closures. Figure 5-18 illustrates the classification of six distinct facial expression patterns identified during the experiment. These patterns have enabled us to deduce four primary emotional states: Neutral, Anxiety, Boredom, and Fatigue, emphasizing fatigue due to its relevance to driving-induced tiredness.

A detailed timeline is provided in Figure 5-19, juxtaposing facial recognition results with those obtained from eye-tracking data. A noteworthy observation from this analysis is the substantial concurrence between periods characterized by the facial expression of fatigue and the occurrence of eye closures. This pattern suggests that eye-tracking technology is proficient in identifying drivers' emotional states, particularly fatigue.

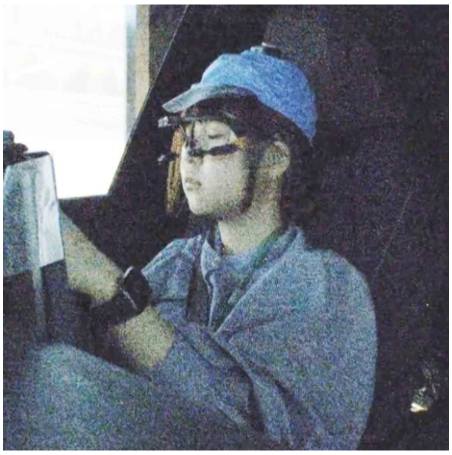
Moreover, Table 8-1 systematically enumerates the frequency of reported feelings of fatigue and the corresponding instances of eye closures, categorized into 5-minute intervals. As indicated by a low p-value (0.4) derived from the T-Test, the statistical analysis reinforces the robust correlation between eye movements and facial expressions. This finding substantiates our hypothesis that eye-tracking can effectively indicate driver emotion, especially in the context of fatigue detection.

(3) Relation between brainwave and eye movement.

Figure 5-20 graphically demonstrates the correlation between Gamma brainwave activity and eye blink frequency. The data analysis in Paris revealed a distinct pattern: a notable decrease in Gamma brainwave activity (below the threshold of 1.0E7) consistently correlated with a marked increase in eye blink frequency or complete eye closures. This phenomenon is graphically represented below the red line in Figure 5-18. The observed correlation suggests that fluctuations in Gamma brainwaves are a significant biomarker of fatigue, particularly indicative of sleepiness. This pattern was especially pronounced during the latter stages of the driving sessions, aligning with increased driver drowsiness. Furthermore, these findings highlight the efficacy of eye-tracking technology as a potent tool for real-time monitoring of driver behavior. By quantifying eye movements, eye tracking provides a robust method for assessing driver fatigue levels, contributing valuable insights into driver safety and performance during active driving scenarios.



(1)



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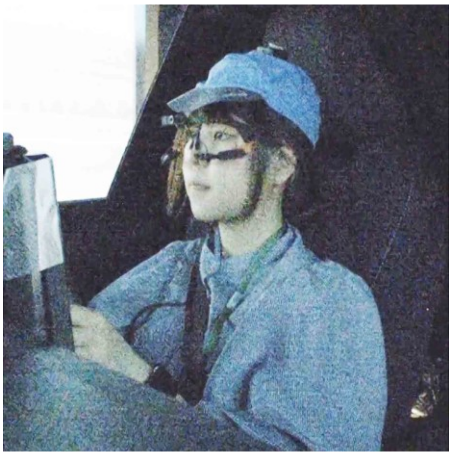

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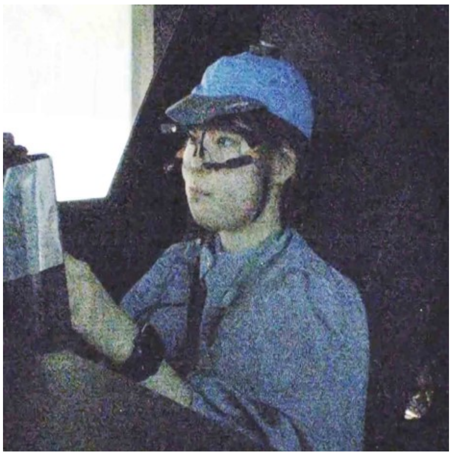

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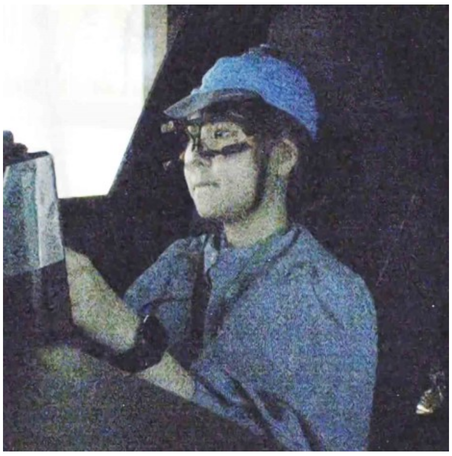


(5)

(6)

Figure 5-18. Classification results in FY2022

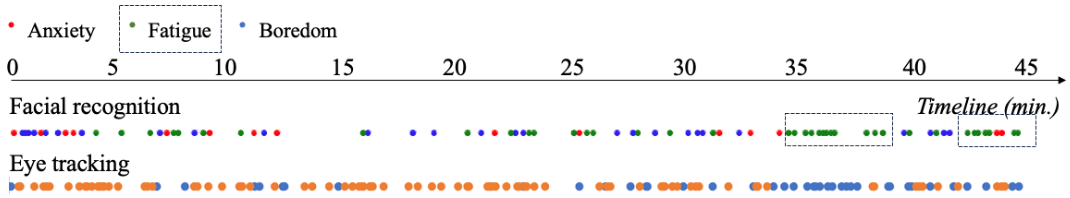
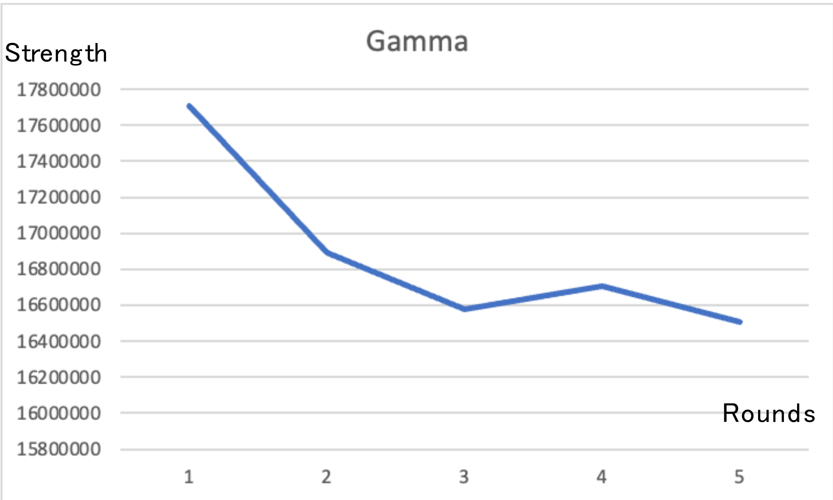


Figure 5-19. Comparison between facial expression and eye movement

Table 5-2. Frequency of fatigue expression and eye shut

	~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



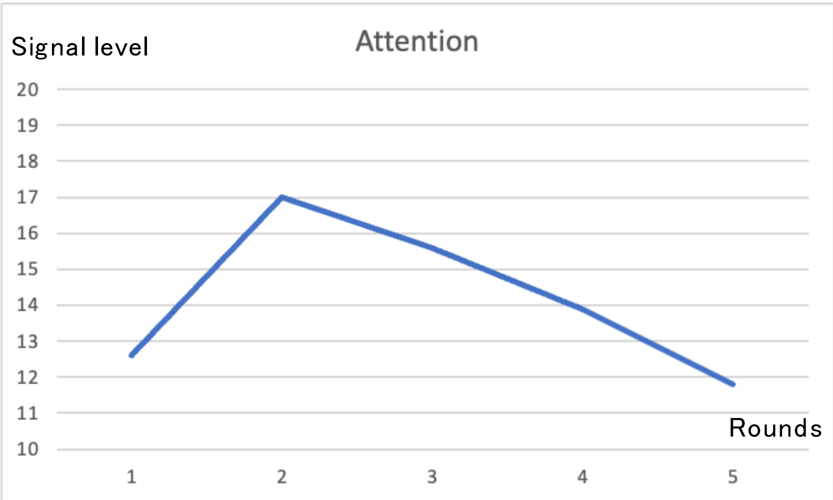


Figure 5-20 Variation of Gamma wave and attention ration

5.5. Assessment of Fatigue State by Topological Data Analysis

5.5.1. Research Objective

This study embarks on a detailed comparative analysis of electroencephalogram (EEG) data and other pertinent physiological metrics. Utilizing the ThinkGear Asic Module (TGAM), raw EEG data was captured at a frequency of 512 Hz, including aggregated values for distinct EEG frequency bands: Delta, Theta, Alpha, Beta, and Gamma, calculated on a per-second basis. However, the interpretation of the relationships among these EEG components is complex due to the inherently dynamic and variable nature of EEG signals. Additionally, the reliability of EEG data is often compromised by susceptibility to environmental noise and disturbances. Therefore, this research aims to devise methodologies to authenticate the validity and accuracy of EEG data amidst noise interference, develop robust data processing techniques to analyze brainwave interrelations, and ultimately enhance the assessment of driver fatigue by integrating additional, reliable, cost-effective and efficient sensor modalities [5-7].

5.5.2. Experimental Method

Given the complexities inherent in EEG data analysis, our study adopted an advanced methodology from topological data analysis: persistent homology. This technique, which finds its foundation in computational topology, excels in dissecting intricate data configurations and isolating salient features amidst chaotic datasets. Renowned for its ability to discern multi-scalar structures, persistent homology has been employed across various disciplines, including biology, data analytics, and image processing. This method calculates topological invariants, providing both a quantitative measure and a graphical interpretation of data architectures. The integration of persistent homology with machine learning algorithms enhances its efficacy in extracting features and training models, thereby offering a robust tool for comprehensive data analysis, both qualitative and quantitative.

Our research mainly concentrates on the Alpha, Beta, and Gamma frequency bands with significant mental state analysis implications. We compare datasets across varying drivers, days, and driving sessions to glean insights into mental status correlations.

The experimental framework engaged two female students from Chuo University, each with different driving experience levels. They navigated through diverse routes within the Tokyo Metropolitan Expressway and in Paris. Similar to the scenarios presented in Section 5.4, this variation in driving environments was intended to elicit a wide range of mental and physiological responses, thereby enabling a thorough investigation. These experiments were executed under standardized conditions over two days to maintain consistency and comparability.

5.5.3. Result Analysis

A persistence diagram representing the three-dimensional (3D) data of the Alpha, Beta, and Gamma bands is illustrated in Figure 5-21. A critical observation from this diagram is the alignment of most data points along the X=Y axis, with deviations from this line signifying distinct data features. Additionally, envelope curves in Figure 5-21 provide a macroscopic view of the data points' distribution. Notably, despite variances in driving skills, schedules, and dates, the envelope shapes for each lap showed similarities. This consistency hints at potential uniform changes occurring across laps.

Future research will explore the EEG data more comprehensively, particularly investigating the correlation between EEG dynamics and driver fatigue to deepen our understanding of neurophysiological responses in driving scenarios.

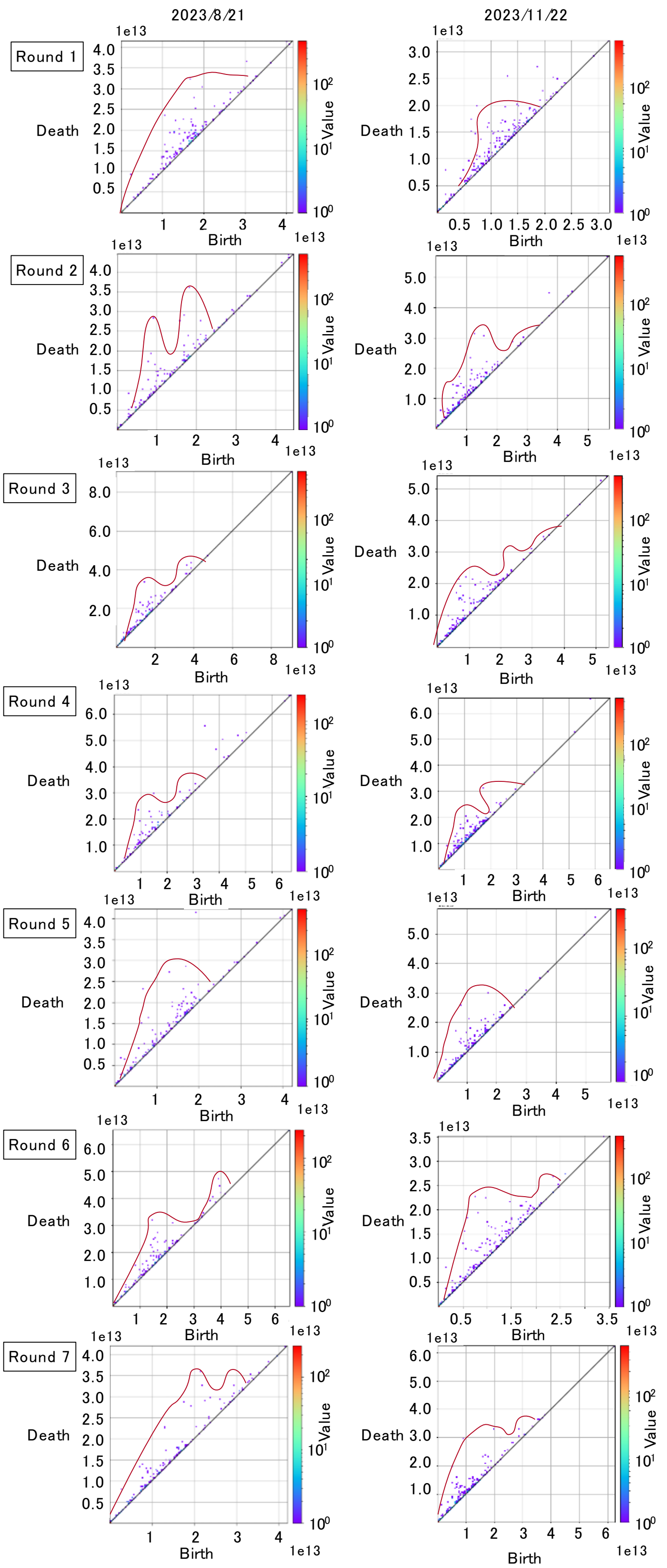


Figure 5-21. Persistent homology graph of brainwaves (Alpha, Beta, and Gamma)

Chapter 6

Conclusion and Future Work

In the contemporary epoch, characterized by an increasingly aged populace and a surge in vehicular incidents encompassing road rage and erratic driving, the prevalence of these occurrences has become a matter of significant concern. These incidents are frequently a manifestation of the drivers' psychological dispositions, underscoring the imperative need for mental health interventions to bolster vehicular safety. Notably, driver fatigue, a critical determinant in traffic accidents, epitomizes a deterioration in mental acuity, thereby impairing fundamental driving competencies such as attention, reaction time, and decision-making capabilities. This aspect assumes heightened importance in the transition toward autonomous vehicles. Presently, research and methodologies predominantly emphasize pre-driving relaxation techniques or reactive alerts to combat fatigue, conspicuously overlooking the ongoing evaluation of the driver's psychological state as a proactive vehicular safety measure. This oversight accentuates the necessity for more comprehensive safety methodologies within automotive contexts.

Our extensive research, spanning several years, has substantially contributed to understanding drivers' mental states, mainly focusing on fatigue and its ramifications for vehicular safety. The study evolved through various stages, augmenting our comprehension with increasing sophistication and intricacy.

The initial phase of our inquiry entailed the establishment of an extensive sensor network in tandem with a high-fidelity driving simulator. The Positive and Negative Affect Schedule (PANAS) was employed to authenticate the precision and dependability of the estimations derived from sensor data. Preliminary outcomes underscored the feasibility of utilizing bio-signal data to evaluate drivers' mental conditions.

We subsequently incorporated video cameras to address the challenges posed by the limited practicality of EEG and ECG sensors in experimental settings. This phase saw the integration of advanced facial recognition and body movement analytics into our sensor array, enriching our dataset and enhancing our insight into the interplay between physiological responses and distinct driving behaviors. This stage's analysis revealed intricate expressions of driver fatigue and other emotional states, demonstrating these technologies' potential for real-time driver surveillance.

Acknowledging the sensitivity associated with implementing video cameras within automotive vehicles and the variability of facial expressions among individuals, we augmented our approach with eye-tracking technology to monitor eye movements and directly estimate driver fatigue. The concluding phase of our study incorporated sophisticated eye movement analysis, which proved pivotal in establishing a robust correlation between eye movement patterns and driver fatigue. The amalgamation of this technology with our existing facial recognition and bio-signal data provided a more holistic perspective on driver fatigue.

Looking ahead, our research endeavors to integrate Controller Area Network (CAN) data and wearable sensor technologies, such as smartwatches, into our assessment framework. This fusion is anticipated to yield a more user-centric and comprehensive approach to monitoring drivers' emotional states and mental conditions. We also aim to refine our methodologies to surmount the identified challenges, mainly focusing on enhancing our system's usability and privacy aspects. The ultimate objective is to develop an all-encompassing, efficacious plan capable of real-time monitoring and intervention, thereby significantly contributing to the evolution of safety measures in the automotive sector. These forthcoming advancements hold the potential to engender safer driving conditions and ameliorate overall driver well-being.

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References

[1-1] Transport Department of Jharkhand, “Causes of Road Accidents,” [Online]. Available: https://jhtransport.gov.in/causes-of-road-accidents.html

[1-2] Tokyo University of Agriculture and Technology, “Near-Miss Incident Database Construction,” [Online]. Available: https://web.tuat.ac.jp/~smrc/oldSMRC/research.html

[1-3] N. Grugle, “Human Factors in Autonomous Vehicles,” [Online]. Available: https://www.americanbar.org/groups/tort_trial_insurance_practice/publications/tortsource/2019/fall/human-factors-autonomous-vehicles/

[1-4] T. K. Pernu, “The Five Marks of the Mental,” *Frontiers in Psychology*, vol. 8: p. 1084, July 2017, DOI: 10.3389/fpsyg.2017.01084.

[1-5] G. L. Clore and J. R. Huntsinger, “How emotions inform judgment and regulate thought,” *Trends in Cognitive Science*, vol. 11, pp. 393-399, Aug. 2007, DOI: 10.1016/j.tics.2007.08.005.

[1-6] Y. Kadoya, “Transportation Research Part F: Traffic Psychology and Behaviour,” [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1369847821001017?via%3Dihub/

[1-7] A. N. Stephens and J. A. Groeger, “Do emotional appraisals of traffic situations influence driver behaviour?,” *Department for Transport: Behavioural Research in Road Safety 2006 Sixteenth Seminar*, p. 49, 2006.

[1-8] ABS News, “Disconcerting' rise in road rage shootings resulting in death or injury, data shows,” [Online]. Available: https://abcnews.go.com/US/disconcerting-rise-road-rage-shootings-resulting-death-injury/story?id=78181165/

[1-9] Cabinet Office, “Countermeasures against Abusive Driving,” [Online]. Available: https://www8.cao.go.jp/koutu/taisaku/r01kou_haku/zenbun/genkyo/topics/topic_13.html

[1-10] Victoria News, “B.C. man gets 4 years in highway crash that killed 2 American tourists,” [Online]. Available: https://www.quesnelobserver.com/news/island-man-sentenced-to-4-years-for-dangerous-driving-causing-death-5822615/

[1-11] Healthline Media, “How to Treat and Prevent Mental Exhaustion,” [Online]. Available: https://www.healthline.com/health/mental-exhaustion/

[1-12] Federal Motor Carrier Safety Administration, “Regulatory Impact and Small Business Analysis for Hours of Service Options,” [Online]. Available: https://web.archive.org/web/20080126005807/http://www.fmcsa.dot.gov/rules-regulations/topics/hos/regulatory-impact-analysis.htm/

[1-13] Brake, “DRIVER FATIGUE,” [Online]. Available: https://www.brake.org.uk/get-involved/take-action/mybrake/knowledge-centre/driver-fatigue/

[1-14] United States Department of Transportation, “Drowsy Driving,” [Online]. Available: https://www.nhtsa.gov/risky-driving/drowsy-driving/

[1-15] European Road Safety Observatory, “Fatigue and crash risk,” [Online]. Available: https://road-safety.transport.ec.europa.eu/european-road-safety-observatory-staticcs-and-analysis- archive/fatigue/fatigue-and-crash-risk_en/

[1-16] K. Bengler, K. Dietmayer, B. Farber, M. Maurer, C. Stiller and H. Winner, “Three Decades of Driver Assistance Systems: Review and Future Perspectives,” *IEEE Intelligent Transportation Systems Magazine*, vol. 6, no. 4, pp. 6-22, Oct. 2014, DOI: 10.1109/MITS.2014.2336271.

[1-17] J. R. Crawford and J. D. Henry, “The Positive and Negative Affect Schedule (PANAS): Construct validity, measurement properties and normative data in a large non-clinical sample,” *British Journal of Clinical Psychology*, vol. 43, no. 3, pp. 245–265, Sep. 2004, DOI: 10.4306/pi.2010.7.3.163.

[1-18] M. Heideman, D. Johnson and C. Burrus, “Gauss and the history of the fast fourier transform,” *IEEE ASSP Magazine*, vol. 1, no. 4, pp. 14-21, Sep. 1985, DOI: 10.1109/MASSP.1984.1162257.

[1-19] S. Na, L. Xumin and G. Yong, "Research on k-means Clustering Algorithm: An Improved k-means Clustering Algorithm," *2010 Third International Symposium on Intelligent Information Technology and Security Informatics*, Jian, China, 2010, pp. 63-67, DOI: 10.1109/IITSI.2010.74.

[1-20] CAN in Automation, "History of CAN technology," [Online]. Available: https://www.can-cia.org/can-knowledge/can/can-history/

[2-1] I. Goldstein, "Intersubjective Properties by Which We Specify Pain, Pleasure, and Other Kinds of Mental States," *Philosophy*, vol. 75, no. 291, pp. 89–104, Jan. 2000, DOI: 10.1017/S0031819100000073.

[2-2] Stanford Encyclopedia of Philosophy, "Qualia: 2. Which Mental States Possess Qualia?," [Online]. Available: https://plato.stanford.edu/entries/qualia/#Which/

[2-3] Internet Encyclopedia of Philosophy, "Theories of Emotion," [Online]. Available: https://iep.utm.edu/theories-of-emotin/

[2-4] A. R. Damasio, "Emotion in the perspective of an integrated nervous system," *Brain Research Review*, vol. 26, no. 2–3, pp. 83–86, May 1998, DOI: 10.1016/S0165-0173(97)00064-7.

[2-5] Oxford Dictionary (Lexico), "Emotion," [Online]. Available: https://web.archive.org/web/20211009004612/https://www.lexico.com/definition/emotion/

[2-6] D. L. Schacter, D. T. Gilbert, D. M. Wegner and M. K. Nock, "Psychology," Worth Publication, p. 310, 2020.

[2-7] P. Jaak, "Affective neuroscience: the foundations of human and animal emotions," Oxford University Press, p. 9, 2005.

[2-8] C. Giovann, "From affect programs to dynamical discrete emotions," *Philosophical Psychology*, vol. 22, no. 4, pp. 407–425, Aug. 2009, DOI: 10.1080/09515080903153600.

[2-9] E. Paul, "Facial Expressions of Emotion: New Findings, New Questions," *Psychological Science*, vol. 3, no. 1, pp. 34–38, Jan. 1992, DOI: 10.1111/j.1467-9280.1992.tb00253.x.

[2-10] M. N. Shiota, "Ekman's theory of basic emotions," *The Sage encyclopedia of theory in psychology*, SAGE Publications, pp. 248–250, 2016.

[2-11] J. A. Russell, "Core affect and the psychological construction of emotion," *Psychological Review*, vol. 110, no. 1, pp. 145–172, Jan. 2003, DOI: 10.1037/00 33-295X.110.1.145.

[2-12] D. L. Schacter, D. T. Gilbert, D. M. Wegner and B. M. Hood, "Psychology," Worth Publishers, p. 189, 2011.

[2-13] A. M. Reitsema, "Emotion dynamics in children and adolescents: A meta-analytic and descriptive review," *Emotion*, vol. 22, no. 2, pp. 374–396, 2021, DOI: 10.1037 /emo0000970.

[2-14] H. M. Weiss and R. Cropanzano, "Affective Events Theory: A theoretical discussion of the structure, causes and consequences of affective experiences at work," *Research in organizational behavior: An annual series of analytical essays and critical reviews*, vol. 18, pp. 1–74, 1996.

[2-15] X. Wang and Y. Zeng, "Organizational Capability Model: Toward Improving Organizational Performance," *Journal of Integrated Design and Process Science*, vol. 21, pp. 1-20, Oct. 2017, DOI: 10.3233/jid-2017-0005.

[2-16] Dorset Research & Development Support Unit, "Emotional Expression," [Online]. Available: https://web.archive.org/web/20070630090007/http://www.emotional processing.org.uk/Emotion%20concepts/Emotional%20expression.htm

[2-17] U. Hess and P. Thibault, "Darwin and emotion expression," *American Psychogist*, vol. 64, no. 2, p. 120, 2009, DOI:10.1037/a0013386.

[2-18] E. Paul, "Basic Emotions," *Handbook of Cognition and Emotion*, pp. 45–60, 1999.

[2-19] D. Matsumoto, D. Keltner, M. N. Shiota, M. O'Sullivan and M. Frank, “Facial Expressions of Emotions,” *Handbook of Emotion*, pp. 211–234, 2008.

[2-20] P. Ekman and W. V. Friesen, “Constants across cultures in the face and emotion,” *Journal of Personality and Social Psychology*, vol. 17, no. 2, pp. 124–29, 1971, DOI: 10.1037/h0030377.

[2-21] P. Maisel, E. Baum and N. Donner-Banzhoff, “Fatigue as the chief complaint-Epidemiology, causes, diagnosis, and treatment,” *Deutsches Arzteblatt International*, Aug. 2021, DOI: 10.3238/arztebl.m2021.0192.

[2-22] M. R. Zielinski, D. M. Systrom and N. R. Rose, “Fatigue, Sleep, and Autoimmune and Related Disorders,” *Frontiers in Immunology*, vol. 10, p. 1827, 2019, DOI: 10.3389/fimmu.2019.01827.

[2-23] A. Crawford, “FATIGUE AND DRIVING,” *Ergonomics*, vol.4, no. 2, pp. 143-154, 1961, DOI: 10.1080/00140136108930515.

[2-24] J. E. Shackman and S. D. Pollak, “Experiential influences on multimodal perception of emotion,” *Child Development*, vol. 76, pp. 1116–26, 2005, DOI: 10.1 111/j.1467-8624.2005.00901.x.

[2-25] J. Hughlings-Jackson, “On affectations of speech from diseases of the brain,” *Brain*, vol. 38, pp. 107–74, 1915, DOI: 10.1093/brain/2.2.203.

[2-26] L. F. Barrett, B. Mesquita and M. Gendron, “Context in Emotion Perception,” *Current Directions in Psychological Research*, vol. 20, no. 5, pp. 286–290, 2011, DOI: 10.1177/0963721411422.

[2-27] A. A. Alian and K. H. Shelley, “Photoplethysmography,” *Best Practice & Research Clinical Anaesthesiology*, vol. 28, no. 4, pp. 395-406, 2014, DOI: 10.1016/ j.bpa.2014.08.006.

[2-28] N. Dael, M. Mortillaro and K. R. Scherer, “Emotion expression in body action and posture,” *Emotion*, vol. 12, no. 5, pp. 1085–1101, 2012, DOI: 10.1037/a0025737.

[2-29] A. T. Beck, C. H. Ward, M. Mendelson, J. Mock and J. Erbaugh, "An inventory for measuring depression," *Archives of General Psychiatry*, vol. 4, pp. 561-571, 1961, DOI: 10.1001/archpsyc.1961.01710120031004.

[2-30] C. D. Spielberger, F. Gonzalez-Reigosa, A. Martinez-Urrutia, L. F. S. Natalicio and D. S. Natalicio, "State-Trait Anxiety Inventory," *Interamerican journal of psychology*, vol. 5, pp. 3-4, 1971, DOI: 10.1002/9780470479216.corpsy0943.

[2-31] J. P. Bernstein and M. Calamia, "Dimensions of driving-related emotions and behaviors: An exploratory factor analysis of common self-report measures," *Accident Analysis & Prevention*, vol. 124, pp. 85-91, DOI: 10.1016/ j.aap.2019.01 004.

[2-32] C. Bankar, A. Bhide, A. Kulkarni, C. Ghube and M. Bedekar, "Driving Control Using Emotion Analysis Via EEG," *IEEE Pune Section Conference*, Pune, India, 2018, pp. 1-7, DOI: 10.1109/PUNECON.2018.8745412.

[2-33] P. W. Huang, C. H. Hsieh, M. C. Liang, C. Tsou and S. Y. Lee, "ECG monitoring and emotion stabilization system with a physiological information platform for drivers," *2015 International Symposium on Bioelectronics and Bioinformatics*, Beijing, China, 2015, pp. 180-183, DOI: 10.1109/ISBB.2015.7344953.

[2-34] H. Xiao, W. Li, G. Zeng, Y. Wu, J. Xue, J. Zhang, C. Li and G. Guo, "On-Road Driver Emotion Recognition Using Facial Expression," *Applied Sciences*, vol. 12, no. 2, p. 807, 2022, DOI: 10.3390/app12020807.

[2-35] K. Zaman, Z. Sun, S. M. Shah, M. Shoaib, L. Pei and A. Hussain, "Driver Emotions Recognition Based on Improved Faster R-CNN and Neural Architectural Search Network," *Symmetry*, vol, 14, no. 4, p. 687, 2022, DOI: 10.3390/sym14040687.

[2-36] L. O. Chua and T. Roska, "The CNN paradigm," *IEEE Transactions on Circuits and Systems- Fundamental Theory and Applications*, vol. 40, no. 3, pp. 147-156, 1993, DOI: 10.1109/81.222795.

[2-37] Z. Kowalczuk, M. Czubenko and T. Merta, “Emotion monitoring system for drivers,” *IFAC-PapersOnLine*, vol. 52, no. 8, pp. 200-205, Jan. 1993, DOI: 10.1016/j.ifacol.2019.08.071.

[2-38] G. Rebolledo-Mendez, A. Reyes, S. Paszkowicz, M. C. Domingo and L. Skrypchuk, “Developing a body sensor network to detect emotions during driving,” *IEEE transactions on intelligent transportation systems*, vol. 15, no. 4, pp. 1850-1854, 2014, DOI: 10.1109/TITS.2014.2335151.

[2-39] S. D. Nadai, M. D'Inca, F. Parodi, M. Benza, A. Trotta, E. Zero, L. Zero and R. Sacile, “Enhancing safety of transport by road by on-line monitoring of driver emotions,” *11th System of Systems Engineering Conference (SoSE)*, Kongsberg, Norway, 2016, pp. 1-4, DOI: 10.1109/SYSOSE.2016.7542941.

[3-1] H. Cai, Y. Lin and R. R. Mourant, “Study on driver emotion in driver-vehicle-environment systems using multiple networked driving simulators,” *In Proceeding of the Driving Simulation Conference,* North America, 2007, pp. 1-9.

[3-2] K. Steinhauser, F. Leist, K. Maier, V. Michel, N. Pärsch, P. Rigley, F. Wurm and M. Steinhauser, “Effects of emotions on driving behavior,” *Transportation research part F: traffic psychology and behaviour*, vol. 59, pp. 150-163, 2018, DOI: 10.1016/j.trf.2018.08.012.

[3-3] Ansible Motion, “This is why driving simulators are so useful,” [Online]. Available: https://www.ansiblemotion.com/ansible-motion-automotive-driver-in-the-loop-simulation- news/this-is-why-driving-simulators-are-so-useful/

[3-4] WitMotion, “WT901BLECL,” [Online]. Available: https://www.wit- motion.com/9-axis/wt901blecl-mpu9250-high-precision.html

[3-5] Bluetooth SIG , “Bluetooth Core Specification Version 5.0 Feature Enhancements,” [Online]. Available: https://www.bluetooth.com/bluetooth-resources/bluetooth-5-go-faster-go-further/

[3-6] M5Stack, “M5Stack: The Innovator of Modular IoT Development Platform,” [Online]. Available: https://m5stack.com/

[3-7] Mindsall Inc., “Mindsall EEG Headband,” [Online]. Available: https://mindsall.com/projects/

[3-8] Apple Inc., “Watch - Apple,” [Online]. Available: https://www.apple.com/watch/

[3-9] Pupil Labs, “Pupil Core,” [Online]. Available: https://pupil- labs.com/products/

[4-1] C. Gunnar, “Topology and data,” *AMS Bulletin*, vol. 46, no. 2, pp. 255–308, 2009, DOI:10.1090/S0273-0979-09-01249-X.

[4-2] G. Kusano, Y. Hiraoka and K. Fukumizu, “Persistence weighted Gaussian kernel for topological data analysis,” *In Proceedings of the 33rd International Conference on International Conference on Machine Learning*, PMLR, 2016, pp. 2004-2013, DOI: 10.48550/arXiv.1601.01741.

[4-3] I. Obayashi, “HomCloud,” [Online]. Available: https://homcloud.dev/index.en.html

[4-4] M. David, “Chapter 20. An Example Inference Task: Clustering,” *Information Theory, Inference and Learning Algorithms*, Cambridge University Press, pp. 284–292, 2003.

[4-5] OpenCV team, “OpenCV - Open Computer Vision Library,” [Online]. Available: https://opencv. org/

[4-6] Google Inc., “MediaPipe-Face Mesh,” [Online]. Available: https://google.github.io/MediaPipe/solutions/face_mesh.html

[4-7] T. Özseven and M. Düğenci, “Face recognition by distance and slope between facial landmarks,” *2017 International Artificial Intelligence and Data Processing Symposium (IDAP)*, pp. 1-4, 2017, DOI: 10.1109/IDAP.2017.8090258.

[4-8] L. LIU and M.T. ÖZSU, “Mean Average Precision,” *Encyclopedia of Database Systems*, MA: Springer, pp. 1703-1703, 2009, DOI: 10.1007/978-0-387-39940-9_482.

[4-9] Y. Qiu and Y. Wan, “Facial Expression Recognition based on Landmarks,” *2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Chengdu, China, Dec. 2019, pp. 1356-1360, DOI: 10.1109/IAEAC47372.2019.8997580.

[4-10] A. Yaman, A. Aneesa and T. Maen., “Real-Time Machine Learning-Based Driver Drowsiness Detection Using Visual Features,” *Journal of Imaging*, vol. 9, p. 91, 2023, DOI: 10.3390/jimaging9050091.

[4-11] Python Software Foundation, “scikit-learn,” [Online]. Available: https://pypi.org/project/scikit-learn/

[4-12] P. C. Kendall, “Treating anxiety disorders in children: results of a randomized clinical trial,” *Consult Clin Psychol*, vol. 62, no. 1, 100-10, Feb. 1994, DOI: 10.1037/0022-006x.62.1.100.

[5-1] Eclipse Foundation, “SUMO,” [Online]. Available: https://eclipse.dev/sumo/

[5-2] H. Yoshimoto, A. Ito, “Emotion estimation of a car driver,” IEICE TL2020-18, vol. 120, no. 427, pp. 1-6, 2021.

[5-3] J. Luo, H. Yoshimoto, Y. Okaniwa, Y. Hiramatsu, M. Hasegawa and A. Ito, “Estimating and Visualizing Drivers' Emotions Using the Internet of Digital Reality,” *Infocommunications Journal*, vol. 15, pp. 11-19, 2023, DOI:10.36244/ICJ.2023.6.2.

[5-4] J. Luo, H. Yoshimoto, Y. Okaniwa, Y. Hiramatsu, A. Ito and M. Hasegawa, “Emotion monitoring sensor network using a drive recorder,” *2023 IEEE 15th International Symposium on Autonomous Decentralized System (ISADS)*, Mexico City, Mexico, 2023, pp. 1-8, DOI: 10.1109/ISADS56919.2023.10092139.

[5-5] Y. Okaniwa, H. Yoshimoto, J. Luo, Y. Hiramatsu, A. Ito and M. Hasegawa, “Implementing a face detection camera in emotion monitoring sensor network,” NWS-29-2, pp. 27-32, 2022.

[5-6] J. Luo, Y. Okaniwa, N. Yamazaki, Y. Hiramatsu, M. Hasegawa and A. Ito, "Measuring Driver's Emotion," *2023 Eleventh International Symposium on Computing and Networking Workshops*, Matsue, Japan, 2023, pp. 1-6.

[5-7] J. Luo, Y. Okaniwa, N. Yamazaki, Y. Hiramatsu, M. Hasegawa and A. Ito, "Cognitive Aspect of Emotion Estimation of a Driver," *Infocommunications Journal, Special Issue on Cognitive Aspects of Virtual Reality*, 2024. (Accepted)