Electroencephalography Sample Entropy of Driver Passive Fatigue Threshold in Automated Driving

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Abstract

With the continuous improvement of automated vehicles, researchers have found that automated driving is more likely to cause insufficient mental workload for the driver, which induces passive fatigue and endangers traffic safety. To explore the impact of automation and scenario complexity on the passive fatigue of the driver, we developed a three-factor, 2 (automated driving, manual driving) × 2 (monotonic condition, engaging condition) × 6 (measurement stage: 1–6) mixed experiment. We collected electroencephalography (EEG), detection-response task (DRT) performance, and the subjective report scores of 48 drivers. We found that in automated driving under monotonic conditions, the topographic map's activation range of the drivers brain was the smallest in the six stages, and the mental workload of this group continued to maintain the lowest state at each stage; however, the subjectively reported fatigue level was significantly increased; thus, the driver experienced passive fatigue. After simulating a low-load scenario for 40 min, the power of the alpha of the driver's EEG indicators increased significantly, the accuracy of the detection reaction task decreased, and the reaction time became slower. The EEG sample's entropy value of the driver's passive fatigue was 0.243, and the judgement accuracy rate was 0.71. We proved that in automated driving under monotonic conditions, the driver is more prone to passive fatigue owing to insufficient mental workload.

1. Introduction

With the gradual improvement of vehicle automation, researchers have found that drivers free from driving tasks are more prone to under mental workload conditions1[1]. De Winter et al.[2] summarised 32 empirical studies on drivers' mental workload. They established that the mental workload of drivers under automated driving is reduced by 20.8% compared to manual driving. In both automatic and manual driving mode, the complex driving scenario has a cumulative effect on mental workload[3]. The driver needs to monitor the road continuously and the complex driving conditions still need high task requirements[4]. Therefore, this study quantifies the co-variation relationship between task demand and mental workload by creating traffic scenarios with different complexity levels.

Young et al.[5] further improved the relationship between task demand, mental workload, and operational performance based on previous studies. They divided three regions by the two red lines. The region to the left of the red line has low task requirements and arousal levels, and the operator has the remaining cognitive resources, called the reserve capacity region. The region on the right having higher task requirements is called the overload region. The region between the two red lines represents the optimal load region. These three regions are of great significance for driver workload monitoring and accident prediction.

In summary, we have selected two factors: driving mode (automated driving and manual driving) and driving scenario (monotonic condition, engaging condition), and put forward the following hypothesis:

Hypothesis 1

Driver's mental workload in automated driving under monotonic conditions is in the reserve capacity region.

Mental workload is closely related to driving fatigue. Hancock and Desmond[6] distinguished task-related fatigue into active and passive fatigue. Active fatigue is caused by tasks that require continuous coordination of perceptual activity. The fatigue caused by tasks requiring few perceptual activities and long-term monotonous reactions is called passive fatigue. May and Baldwin[7] further perfected this view and proposed that the key to dividing both fatigues depends on the mental workload. The fatigue induced by the underload was passive, and the fatigue caused by the overload was active. Previous research has unclear standards for the effectiveness of passive and active fatigue, and researchers generally classify them by creating driving scenarios with different complexity levels[8]; however the complexity of the condition is not the only criterion for defining active and passive fatigue. Oron-Gilad et al[9] believed that even monotonic conditions can induce active fatigue in novice and sleep-deprived drivers. Therefore, a simple road scenario cannot be used to determine the type of fatigue induced in this study. Owing to the increasing trend of alpha wave power in monotonic and complex scenarios[10,11,12], it is difficult to judge the type of fatigue using EEG. According to May and Baldwin[7], the key to distinguishing between active and passive fatigue is the mental workload. We can prove that passive fatigue induction was successful only when the experimental participants had a lower mental workload with accumulated fatigue.

This study measures the driver's mental workload and degree of fatigue simultaneously and tests the effectiveness of passive fatigue induction by comparing these two variables. Therefore, we proposed the following hypothesis:

Hypothesis 2

Compared with other driving conditions, the mental workload of drivers in automated driving under monotonous conditions should be the lowest, but the degree of fatigue is significantly increased, indicating that they are in a passive fatigue state.

Various types of fatigue have various causes and intervention methods. Under automated driving, a mental workload that is too low can quickly induce passive fatigue in the driver, making it more difficult for them to take over the vehicle's control[13]. Körber et al.[8] found that drivers experienced fatigue in about 42 min based on the eye movement index, indicating that it took a specific time for drivers to develop a low mental workload from fatigue. Vogelpohl et al.[14] proved this by judging the time of fatigue in the condition of automatic driving by facial expression in 15–35 min. In this study, we hoped to collect the driver's EEG indicators and detection-response task (DRT) performance based on previous studies to clarify the precise time of passive fatigue. Consequently, we stated the following:

Hypothesis 3

Drivers' mental workload under reserve capacity region of approximately 40 min will induce the driver to experience passive fatigue.

During automation, the speed of drivers with passive fatigue became slower with regard to responding to takeover requests[14,15,16], and more frequent involvement in non-driving-related tasks occurs[17,18]. These indicators can sensitively reflect fatigue in practice; however, the driver's state is not sufficient to measure fatigue if it is to be monitored accurately and in real time. Researchers favour EEG indicators because of their accuracy and real-time performance19. Lal et al.[20] used the average EEG activity of waking state participants as the benchmark. They analysed the characteristics of changes in the participants' EEG in different fatigue stages and concluded that when the driver was fatigued, the delta and theta activity increased. In a simulated driving scenario, Jagannath and Balasubramanian[11] found that as the test participants' fatigue increased, alpha increased significantly, and theta decreased significantly; however, to accurately define a driver's passive fatigue state, a clearer definition standard is required. Thus, we compared and analysed the time-domain characteristics of EEG signals in different states and selected the sample entropy that characterises the signal's complexity as a passive indicator. Further, we used the receiver operating characteristic curve (ROC) analysis method to determine the driver's passive fatigue discrimination threshold, based on the entropy of the EEG samples. Thus, we proposed the following hypothesis.

Hypothesis 4

Based on the ROC curve method, the critical threshold of the EEG samples' entropy of the driver's passive fatigue and waking state can be calculated.

2. Methods

2.1 Experimental design

A three-factor, 2 (driving mode: autopilot and manual driving) × 2 (driving condition: monotonous and engaging conditions) × 6 (measurement stage: 1–6) experiment was designed for this study. The driving mode and driving conditions were the between-subject variables, and the driving stage was the within-subject variable.

2.2 Participants

From August to October 2020, we recruited 48 participants aged 20–35 years with no experience using automated vehicles (M = 24.83, SD = 2.81) and a driving history of 1–10 years (M = 2.94, SD = 2.06). All participants were randomly divided into groups. All participants were in good health with normal hearing and naked eyesight. After the experiment, a test fee of RMB 100 was given. This study was approved by the Ethics Committee of Liaoning Normal University and was performed in accordance with the approved guidelines and the Declaration of Helsinki. All the participants provided written informed consent before participating, and known their identifying images will publication in an online open-access.

2.3 Equipment

2.3.1. Driving simulator

The DRT is presented by a Xuan'ai QJ-3A1 (small) driving simulator with a viewing angle of 120°. It consists of an interactive visual system, a simulated cockpit, an electronic control system, customised software, auxiliary equipment, and exterior parts. It has functions such as video teaching, guided driving simulation exercises, interactive scene experience driving, and accident tendency assessment, as shown in Fig. 1.

The simulator can design the randomly appearing picture stimuli on the left and right sides as a detection-response task, with a time interval of 60 ± 40s. The reaction time from the appearance of the picture stimulus to the driver's braking was automatically recorded. After the experiment was completed, the number of trials that exceeded 2s during the reaction was recorded as an error to evaluate the driver's correct rate.

The driving modes and scenarios were generated using a driving simulator. In the automated driving mode, the driver does not need to operate the steering wheel and accelerator pedal, but only needs to take the brake response to the DRT. In the manual driving mode and the brake response to the DRT, the driver also needs to control the vehicle to drive along the established route. Engaging driving conditions included: cities, towns, tunnels, high-speed complex roads and multi-curved roads, which the driver used for one hour. The monotonous driving scene is a straight, monotonous highway with no buildings on either side.

2.3.2. EEG

The eego™ mylab recording system recorded EEG data, and the 64-lead electrode cap was extended by the international 10–20 system. The scalp resistance of all electrode points was less than 10 kΩ, and the sampling frequency was 1 kHz. The CPz electrode was used as an online reference point, and the bilateral mastoid was selected for offline analysis. The collection of EEG signals is easily affected by the external environment; therefore, when conducting research, it is necessary to ensure that the participants are not affected by the outside world and do not perform actions unrelated to the research. Because driving activities involve the coordination and cooperation of various brain regions, no specific electrode points were selected, but data collected by all electrode points were analysed and processed, as shown in Fig. 2.

2.3.3. NASA-Task load index

The NASA-Task Load Index (NASA-TLX), developed by the National Aeronautics and Space Administration[21], has become an effective tool for subjectively assessing workload. The scale consists of six dimensions, each scoring from 0 to 10.

2.3.4. SOFI

The Swedish Occupational Fatigue Inventory-25 (SOFI), compiled by Ahsber et al.[22], consists of 25 questions divided into five dimensions: lack of energy, physical exertion, physical discomfort, lack of motivation, and drowsiness. There are five questions in each dimension, and each topic from 0 to 10 is divided into 11 levels: 0 represents a very small fatigue state level, and 10 represents an extremely large fatigue state level.\

2.4 Procedure

The experiment lasted for one hour. After participants arrived in the laboratory, they were asked to wash their hair, wear an EEG cap and eye tracker. Before starting the experiment, the participants were required to familiarise themselves with the driving simulator and practice three random DRT (approximately 5 min). Further, they were required to fill in the NASA-TLX and SOFI scales as pre-tests. After the experiment was officially started, the participants were asked to fill in the NASA-TLX every 10 min. During the filling, the driver pulled over and stopped recording the EEG and DRT data. After the experiment, the participants were required to fill in the NASA-TLX and SOFI post-tests.

3. Results

3.1 Subjective report

3.1.1. NASA-TLX

With the driving mode and scenario complexity as the between-subject variables, the measurement stage as the within-subject variable, and the cognitive load dimension score as the dependent variable, a repeated measures ANOVA was performed. The main effect of scenario complexity was significant [$F(1, 44) = 4.890$, $p = .046$, $\eta_p^2 = 0.088$]. Drivers in the engaging condition (4.96 ± 2.116) felt a higher psychological load than the simple scenario group (4.46 ± 2.000). The driving mode and stage's main effects were insignificant, as the interaction effects.

With the driving mode and scenario complexity as the between-subject variables, the measurement stage as the within-subject variable, and the frustration dimension score as the dependent variable, a repeated measures ANOVA was performed. The main effect of the measurement stage was significant [$F(1, 44) = 7.537$, $p = .009$, $\eta_p^2 = 0.146$]. As the measurement stage increased, the driver's degree of frustration also increased, as shown in Fig. 3. The main effects of the driving mode and scenario complexity were insignificant, and the interaction effects were also insignificant.

3.1.2. SOFI

The SOFI score was measured before and after the experiment as the dependent variable. A paired sample t-test was performed, and it was found that the scores of the five dimensions were significantly different, and the after score was higher than before. This shows that the one hour experiment successfully induced the participant' fatigue state, as shown in Table 1.

Table 1
Analysis of the difference between the five dimensions of the SOFI before and after the test

Dimension	Before	After	*t*	*p*
Lack of energy	1. 386 ± 1.887	3.390 ± 2.486	-4.851	0.000
Physical exertion	1.251 ± 1.401	1.907 ± 1.532	-2.495	0.017
Physical discomfort	1.209 ± 1.359	1.879 ± 1.461	-2.867	0.006
Lack of motivation	1.688 ± 1.800	3.237 ± 2.368	-4.387	0.000
sleepiness	1.688 ± 2.000	3.967 ± 2.789	-5.435	0.000

With scenario complexity as the independent variable and the SOFI score measured after the experiment as the dependent variable, the independent sample t-test was performed on the driver's scores on the five dimensions of the SOFI under different scenarios. The monotonic condition (2.076 ± 1.908) and the engaging condition (1.745 ± 1.083) showed significant differences in the scores on the physical exertion dimension, as shown in Table 2.

Table 2
Analysis of the scenario complexity in SOFI after the experiment

Dimension	Monotonic	Engaging	*t*	*p*
Lack of energy	3. 752 ± 2.638	3.045 ± 2.339	0.930	0.556
Physical exertion	2.076 ± 1.908	1.745 ± 1.083	0.703	0.010
Physical discomfort	1.961 ± 1.599	1.800 ± 1.349	0.359	0.128
Lack of motivation	3.381 ± 2.464	3.100 ± 2.323	0.385	0.390
sleepiness	4.485 ± 2.899	3.472 ± 2.670	1.192	0.682

3.2 DRT performance

3.2.1. Reaction time of DRT

With the driving mode and scenario complexity as the between-subject variables, the measurement stage as the within-subject variable, and the reaction time of the DRT as the dependent variable, a repeated measures ANOVA was performed. The results indicated an insignificant main effect of scenario complexity [$F(1, 44) = 0.185$, $p = 0.996$, $\eta_p^2 = 0.004$] and driving mode [$F(1, 44) = 2.303$, $p = 0.136$, $\eta_p^2 = 0.336$]. There was a significant interaction between driving mode and measurement stage [$F(2, 88) = 3.851$, $p = .025$, $\eta_p^2 = 0.080$].

The simple effect test showed that the difference in the DRT reaction time caused by the driving mode was insignificant in stage 1 [$F(1, 44) = 0.000$, $p = 0.989$, $\eta_p^2 = 0.000$], stage 2 [$F(1, 44) = 2.631$, $p = 0.112$, $\eta_p^2 = 0.056$], stage 3[$F(1, 44) = 4.003$, $p = 0.052$, $\eta_p^2 = 0.083$], and stage 5 [$F(1, 44) = 0.297$, $p = 0.589$, $\eta_p^2 = 0.007$]; in stages 4 and 6, the difference in the DRT reaction time caused by the driving mode was significant [$F(1, 44) = 4.856$, $p = 0.033$, $\eta_p^2 = 0.099$; $F(1, 44) = 7.456$, $p = 0.009$, $\eta_p^2 = 0.145$], the reaction time of the driver during automated driving (1.768 ± 0.740; 1.735 ± 0.567) was higher than that of manual driving (1.406 ± 0.285; 1.383 ± 0.267), as shown in Fig. 4.

3.2.2. DRT accuracy

With the driving mode and scenario complexity as the between-subject variables, the measurement stage as the within-subject variable, and the DRT accuracy as the dependent variable, a repeated measures ANOVA was performed. The results indicated an insignificant main effect of scenario complexity [$F(1, 44) = 0.185$, $p = 0.996$, $\eta_p^2 = 0.004$] and driving mode [$F(1, 44) = 2.303$, $p = 0.136$, $\eta_p^2 = 0.336$]. There was a significant interaction between the driving mode and measurement stage [$F(2, 88) = 3.851$, $p = .025$, $\eta_p^2 = 0.080$].

The simple effect test showed that the difference in DRT accuracy caused by the driving mode was insignificant in stage 2 [$F(1, 44) = 0.281$, $p = 0.599$, $\eta_p^2 = 0.006$], stage 3[$F(1, 44) = 1.703$, $p = 0.198$, $\eta_p^2 = 0.036$], and stage 5 [$F(1, 44) = 0.243$, $p = 0.624$, $\eta_p^2 = 0.005$]; in stage 1,stages 4 and 6, the difference in DRT accuracy caused by the driving mode was significant [$F(1, 44) = 4.805$, $p = 0.049$, $\eta_p^2 = 0.082$]; $F(1, 44) = 4.468$, $p = 0.040$, $\eta_p^2 = 0.089$; $F(1, 44) = 6.491$, $p = 0.014$, $\eta_p^2 = 0.124$], the DRT accuracy of the driver in the automated driving of stage 4 and 5 (0.811 ± 0.256; 0.840 ± 0.204) is lower than that of the manual driving (0.934 ± 0.129; 0.954 ± 0.080), as shown in Fig. 5.

3.3 EEG

3.3.1. EEG data preprocessing

EEG data were pre-processed using EEGLAB, an open-source toolbox running in a MATLAB environment, and in-house MATLAB functions. Each participant's driving procedure was divided into six parts: each stage lasted almost 10 min and was preprocessed. Continuous EEG data were band-pass filtered between 0.5 Hz and 30 Hz, and the sampling rate decreased to 1000 Hz. EEG data were referenced to the average of both the mastoids (M1 and M2). Data portions contaminated by eye movements, electromyography (EMG), or any other non-physiological artifacts were corrected using the independent component analysis (ICA) algorithm. It should be noted that the EEG data of seven participants were excluded from further analysis due to extremely high noise or missing data.

3.3.2. Brain topography

The alpha (8–13 Hz) brain topography was divided into four levels and six stages (Figure 6). The brain topography map shows that the activation range of the autopilot simple scenario group is rectangular, more concentrated, and significantly smaller than the other three levels.

3.3.2. α power

With the driving mode and scenario complexity as the between-subject variables, the measurement stage as the within-subject variable, and the α power value as the dependent variable, a repeated measures ANOVA was performed. The results indicated an insignificant main effect of scenario complexity [$F(1, 37) = 0.223$, $p = 0.640$, $\eta_p^2 = 0.006$] and driving mode [$F(1, 37) = 3.192$, $p = 0.082$, $\eta_p^2 = 0.079$]. There was a significant interaction between the driving mode, scenario complexity, and measurement stage [$F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.112$].

The simple effect test shows that under complex scenarios, the differences in the driving modes in the six stages were insignificant. In the simple scenario, there was no significant difference in the power of the alpha power in stage 1 [$F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.026$], stage 2 [$F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.005$], stage 3 [$F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.018$], and stage 5 [$F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.04$]. In stages 4 and 6, the driving mode has a significant difference in the power of the alpha value [$F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.062$; $F(1, 37) = 4.651$, $p = .038$, $\eta_p^2 = 0.015$]. As shown in Fig. 7, in stages 4 and 6 of the simple scenario, the alpha value of the automatic driving group was significantly higher than that of the manual driving group.

3.3.3. Basic ROC curve-like electronic sample book judgement

A scatter diagram of the sample entropy of the EEG signals of 10 participants in the state of awake and passive fatigue is shown in Fig. 8.

There was a significant difference ($P = 0.031$) between the sample entropy of the EEG signals of the awake and passive fatigue states, which indicates that the sample entropy reflects the fatigue state of drivers and can be used as a discrimination index of passive fatigue.

To determine the judgement threshold of the entropy of passive fatigue EEG samples, the ROC curve based on the entropy of EEG samples were drawn according to the ROC curve analysis method, as shown in Fig. 9. The ordinate sensitivity indicates the probability of being correctly identified as sample II in sample II. The specificity of the abscissa indicates the likelihood of being incorrectly identified as sample II in sample I. According to the principle of threshold selection, selecting the feature point with the largest index in the upper left of y is the discrimination threshold. The y index corresponding to each discrimination threshold was calculated, and the feature point with the largest index (the red point in Fig. 9) was selected as the best critical point, corresponding to the EEG signal; the sample entropy was 0.243, sensitivity was 100%, and specificity was 60%. The area under the ROC curve was 0.71, indicating that the method was highly accurate.

4. Discussion

In this study, 48 drivers' subjective reports, reaction task performance, and EEG index were collected. The results verified the research hypothesis. In Sect. 3.1.1 and 3.3.1, we concluded that the driver's mental workload was in the reserve capacity region under automated driving and monotonic conditions. Thus, Hypothesis 1 is proved. In Sect. 3.1.2, we found that drivers with lower mental workload felt more fatigue, which proved Hypothesis 2. In Sect. 3.2 and 3.3, the specific time of passive fatigue induced by under load was discussed through real-time analysis of reaction task performance and EEG index, proved hypothesis 3. In Sect. 3.3.3, based on the sample entropy of the EEG, the threshold of passive fatigue was defined, proved hypothesis 4.

4.1 Driver's mental workload is insufficient under automated driving

The subjective report and the topographic map's activation area of the drivers brain showed that the mental workload of automated driving under monotonic conditions was significantly lower than that of the other three groups. The inherent driving force for the development of autonomous driving is that machines perform boring and monotonous work. Humans perform critical decisions, improve human-computer interaction efficiency, and reduce traffic accidents caused by improper operation of the driver; however, owing to the lack of technology, current autonomous driving has stagnated at a low level. Although the vehicle can perform simple control tasks, the driver still needs to be ready to take over control at all times and cannot engage in non-driving-related tasks. Many studies have found that drivers free from driving activities have a low mental workload [2]. Our study confirmed this through a multi-index comprehensive measurement platform. We further clarified the impact of driving scenarios on the driver's mental workload under autonomous driving conditions; in the automatic driving mode, monotonous scenarios would lower the mental workload.

4.2 Mental workload is an essential basis for judging the type of driver fatigue

Oron-Gilad et al.[9] proposed that workload level is a function of driver suitability and situational requirements; however, most current studies involving passive fatigue rely only on the one-way dimension of driving situational needs to define low-load conditions. The driver's initial suitability was ignored, making it impossible to guarantee experimental validity induced by passive fatigue. According to the definition of passive fatigue by May and Baldwin[7], the key to distinguishing between active and passive fatigue is the mental workload. We can prove that passive fatigue induction is successful only when the experimental participants have a lower mental workload with accumulated fatigue.

In this study, the participants' mental workload and fatigue state were measured simultaneously. The trends of the two variables were compared to clarify the effectiveness of the passive fatigue induction of drivers in automated driving under monotonic conditions. In this study's subjective report, the driver's mental workload in the monotonic state was lower than that in the engaging condition. The drivers in the simple scenarios experienced more fatigue. This shows that the drivers' fatigue in this study belongs to the passive fatigue state. The subjective report further found that the driver was in physical exertion at this time, mainly including fatigue symptoms such as breathing heavily, out of breath, experiencing the taste of blood, sweating, and palpitations. This result reminds us that the user experience of autonomous driving function's needs to be urgently improved in a simple situation. In the future, researchers should continue to explore the regulation and improvement of drivers' passive fatigue, develop multiple forms of vigilance maintenance tasks, and maintain the driver's mental load level in the optimal load zone to avoid the generation of passive fatigue symptoms.

4.3 Time node and EEG threshold of driver's passive fatigue

As the subjective report is only filled out before and after the experiment, the precise time of passive fatigue cannot be determined. Through further analysis of the data, it was found that in automated driving under monotonic conditions, the EEG indicators and the performance of the detection response task were significantly different with manual driving under monotonic at about 40 minutes. Therefore, we believe that the driver will experience passive fatigue in the simple scenario of automatic driving, the time point should be around 40 minutes. However, the time required to induce passive fatigue differs under various scenarios. Thus, time cannot be used as the gold standard for evaluating passive fatigue.

It is necessary to quantify the physiological characteristics of a driver's passive fatigue. After clarifying the occurrence time of passive fatigue, we analysed the entropy values of the EEG samples of the drivers in the passive fatigue state and the normal state of 10 drivers in the automated driving under monotonic conditions and found that as the degree of passive fatigue increased, the entropy value of the samples also gradually increased. Using the ROC curve method, the threshold of passive fatigue discrimination based on the EEG sample entropy was 0.243. The determination of the threshold further clarifies the occurrence time and physiological characteristics of passive fatigue and improves the passive fatigue theory of Hancock and Desmond[6].

4.4 Self-regulation of driver's passive fatigue

Finally, whether it is the performance of DRT or the driver's EEG indicators, at a stage after the emergence of passive fatigue, the differences caused by passive fatigue disappeared; this seems to be a type of regression. We believe that this regression occurs because the driver adapts to the fatigue state through subjective regulation. The driver's regulation can be divided into two types: self-regulation and external regulation. In self-regulation, the driver adjusts the cognitive strategy, optimises the processing mode, makes psychological efforts, actively adjusts the low mental workload, and improves the passive fatigue state. In external regulation, drivers participate in external activities more frequently, seeking an increase in task demands. At present, many studies have proved the existence of external regulation, and Naujoks and Totzke[23] found that under autonomous driving conditions, drivers with a lower mental workload will participate more frequently in non-driving-related tasks. This seems to be a behaviour characteristic of the driver's regulation of mental workload; however, research on the self-regulation of drivers is still rare. Future research can further explore the self-regulation of drivers' passive fatigue, such as the timing of regulation, the fluctuation law of regulation, and whether regulation is a conscious strategy or an unconscious automatic adaptation process.

5. Limitations

First, this study did not find a quantitative indicator of mental effort to prove the existence of driver self-regulation. We believe that mental effort refers to the extra effort required to maintain stable performance when the driver experiences passive fatigue. Waard[24] called this state-related effort. In addition to developing a wealth of external control tasks, future research should focus on drivers' self-regulation. Second, the length of the experiment designed in this study is too short, proving that the passive fatigue group driver is still different from other groups in the sixth stage after the regulation. It is impossible to explore whether the driver's self-regulation has elastic fluctuations. Future research should extend the duration of the experiment to explore whether there is a limit to the passive fatigue control scope. Third, the complex manual driving scene did not induce the driver's active fatigue state; therefore, Hancock and Desmond's[6] fatigue theory is still not comprehensive. Future studies can set up a high task demand group to explore the neural mechanism of active fatigue induced by overload.

In the future, road traffic should remain in the driver-based mode with machines as the supplementary mode. While self-driving vehicles create a relaxed driving environment for drivers, it is also effortless to maintain their mental workload at a lower level. An insufficient mental workload of approximately 40 min induces a passive fatigue state of the driver, which causes performance degradation and affects traffic safety. Ensuring the driver's workload level is stable and slow or avoiding passive fatigue is an intricate problem that traffic psychology must solve.

6. Conclusion

Based on a comprehensive measurement of 48 drivers, we discussed the impact of driving patterns and scenarios on drivers' mental workload. During passive fatigue, the driver's EEG indicators verified the existence of the reserve capacity region, and proposed criteria for the effectiveness of passive fatigue induction and improved the driver's passive fatigue theory by defining the time and critical threshold of passive fatigue. The following conclusions were drawn: a) in automated driving under monotonic conditions, the driver's mental workload is in the reserve capacity region; b) when the driver is in a low-load state for approximately 40 min, passive fatigue occurs; and c) when the driver's EEG sample's entropy value is above 0.243, the driver is in a passive fatigue state.

Declarations

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Declaration of Interest

We have no conflicts of interest to declare.

Author contributions

J.M. conceived the study and designed the experiments. Testing and data collection were performed by Y.Z.; Y.Z. and C.Z. performed the data analysis and interpretation under the supervision of J.M.; Y.Z. and J.M. wrote the main manuscript text; R.C. reviewed the manuscript and all authors approved the final version of the manuscript for submission.

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Figures

Figure 1

Automated driving scenario in the Sunheart QJ-3A1 Driving Simulator (small)

Figure 2

Automated driving scenario in the Sunheart QJ-3A1 Driving Simulator (small)

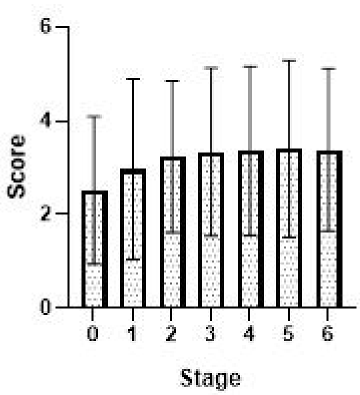

Figure 3

Changes in the dimension of driver frustration in six stages

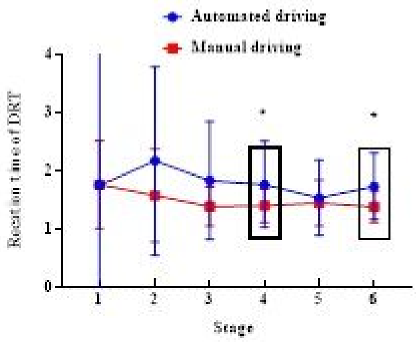

Figure 4

Influence of driving mode on the reaction time of the detection reaction task in the six stages (Note: *p< .05)

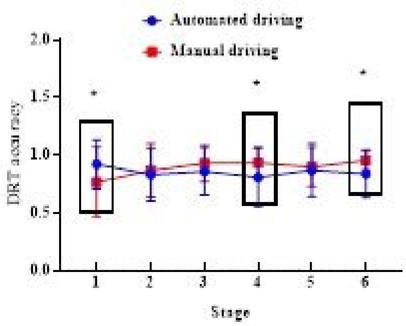

Figure 5

The influence of driving mode on the DRT accuracy in the six stages (Note: *p< .05)

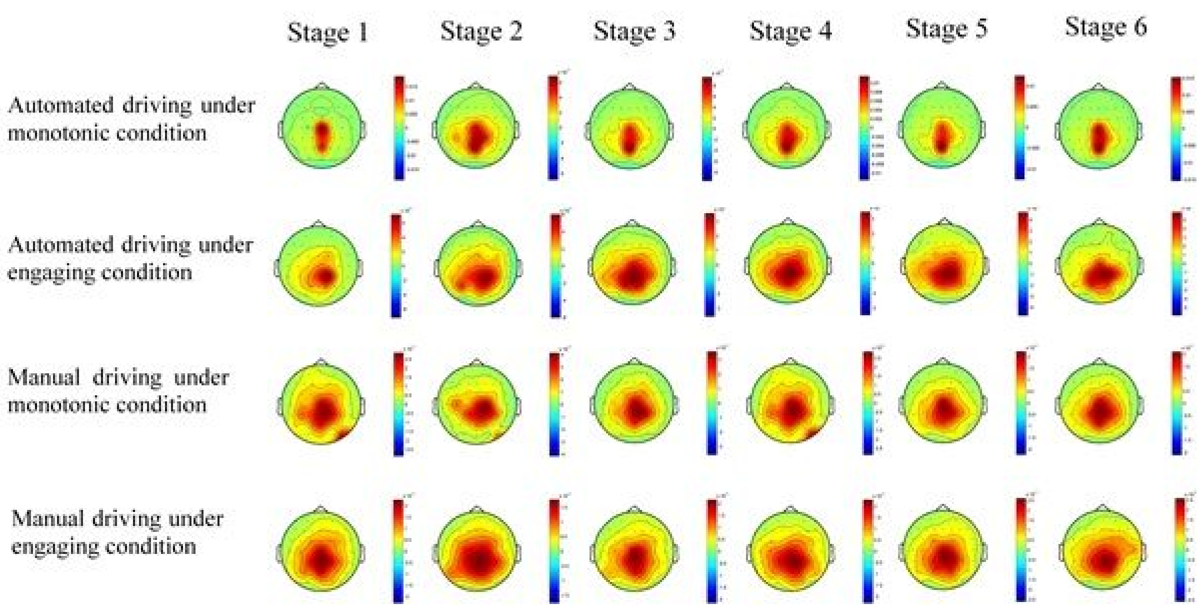

Figure 6

Map of the alpha wave brain of the driver

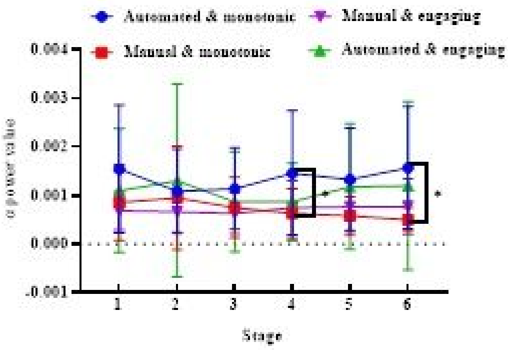

Figure 7

Interaction of driving modes, driving scenarios and stages on α power (Note: *p< .05)

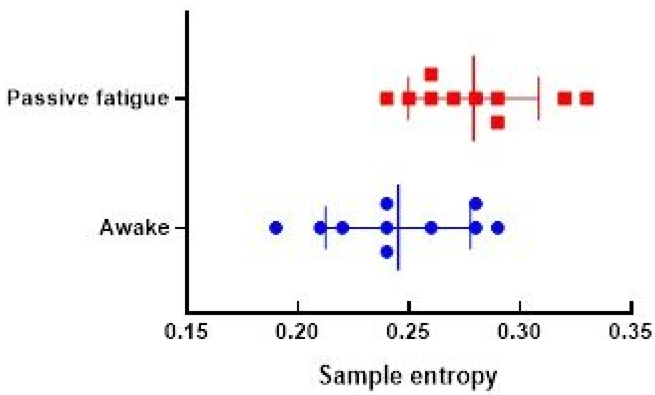

Figure 8

Scatter plot before and after passive fatigue

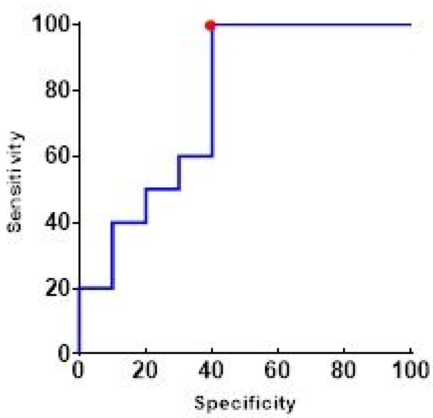

Figure 9

ROC curve of EEG sample entropy