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Comprehensive evaluation method for plateau driving fatigue based on psychophysiological indicators

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Abstract: To investigate the effects of plateau environments on driving fatigue, heart rate and electroencephalogram (EEG) signals were chosen as indicators to characterize driving fatigue. The study analyzed the variation in these indicators as drivers transitioned into fatigued stages. By examining the sample entropy of EEG signals and the heart rate variation coefficient, a complex indicator of driving fatigue (CIDF) was established using principal component analysis to overcome the limitations of single-indicator methods. According to the CIDF values, the driving fatigue states in plateau areas were subdivided into three categories, including alertness, mild fatigue, and severe fatigue, by cluster analysis. Optimal binning determined thresholds for different driving fatigue states, which were validated through variance analysis. The results indicate that the CIDF values effectively distinguish the driving fatigue states of drivers in plateau areas. The CIDF thresholds for the alertness and the mild fatigue states are 0.34 and 0.50, respectively. A CIDF value greater than 0.50 indicates that the driver is in a severe fatigue state.

Key words: plateau area; driving fatigue; driving simulation; psychophysiological indicators

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Driving fatigue is a significant factor in traffic accidents and casualties, accounting for approximately 20% of global traffic incidents, as reported by Horne et al.[1]. Research on driving fatigue has explored various aspects of this phenomenon. For instance, Zeng et al.[2] found that variations and complexities in a driver's autonomic nervous system show gender differences. Fang et al.[3] proposed a shared differential steering control method to mitigate the risk of vehicle instability caused by driver fatigue.

However, most studies focus on driving fatigue in plain areas, leaving a research gap regarding plateau environments. Compared to plain areas, plateau areas are characterized by low pressure, limited oxygen levels, monotonous landscapes, suboptimal road alignment, low traffic volume, and mixed traffic composition. These factors exacerbate the detrimental effects of driving fatigue on driver's cognitive and psychomotor abilities. For instance, 76% of drivers believe that driving on plateau highways induces more fatigue than driving on plain highways[4]. Wang et al.[5] analyzed a large number of traffic accidents on the Qinghai-Tibet Plateau and found that most accidents mainly occur in high-altitude areas with relatively flat roads, primarily involving individuals new to the plateau. The unique climatic conditions at high altitudes, including lack of oxygen, unclear road conditions, and driving fatigue, were identified as major contributing factors.

Considering the special impact of plateau environments on driving fatigue, studying the driving fatigue state of drivers in plateau areas is crucial. Previous research has often subjectively divided the driver's fatigue state based on experience. Lal et al.[6] classified the driving fatigue state by analyzing facial videos. Another method involves dividing the threshold of driving fatigue state according to the specific value of driving fatigue characterization parameters. Ting et al.[7] employed variance analysis to suggest that drivers enter a fatigue state after approximately 80 min of driving. Oron-Gilad and Ronen[8] proposed that drivers begin to feel fatigued after about 40 min based on psychophysiological data analysis.

Single-indicator methods have proven inadequate for effectively determining driving fatigue, prompting researchers to integrate multiple data sources for its identification. For example, Wang et al.[9] combined proposed electrooculogram (EOG) and electroencephalogram (EEG) data using fusion entropy analysis (sample entropy, approximate entropy, and spectral entropy) for driving fatigue detection. Zhang et al.[10] developed an automated system that identifies fatigue from EEG, electromyogram (EMG), and EOG signals.

In this study, driving simulation experiments were conducted in plateau areas to collect psychophysiological data from drivers. The sample entropy theory was employed to analyze these parameters. A comprehensive evaluation indicator for plateau driving fatigue based on psychophysio-

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logical indicators was established through principal component analysis. Cluster analysis was performed based on the comprehensive evaluation index to classify the fatigue states of drivers into different categories. The corresponding relationship between fatigue states and driving fatigue evaluation indicators was established, in addition to the psychophysiology-based fatigue threshold for plateau driving.

1 Materials and Methods

1.1 Experimental condition

The driving simulation experiment was carried out in Lhasa on the Qinghai-Tibet Plateau at an altitude of 3 650 m. To minimize the impact of circadian rhythms on EEG readings, the experiments were scheduled at 9:00 to 12:00 and 14:00 to 17:00, avoiding the period from 12:00 to 13:00 when EEG indicators can exhibit irregular fluctuations[11].

1.2 Participants

Young drivers, owing to their lack of driving experience and driving proficiency, are more susceptible to severe driving fatigue compared to skilled drivers. Therefore, this study focused on young drivers who are more vulnerable to fatigue issues in plateau areas.

Given the male-to-female driver ratio of approximately 7:3 among Chinese drivers, the study recruited 26 participants, including 18 male drivers and 8 female drivers. All participants were screened to ensure they had no sleep disorders, brain diseases, or injuries. They were also required to abstain from alcohol for 24 h and caffeine-containing beverages for 12 h before the experiment.

1.3 Materials

1.3.1 UC-win/Road modeling software

The UC-win/Road modeling software developed by Forum8 company in Japan was employed to establish the experimental road model. To accurately replicate plateau highway conditions, the model excluded additional traffic volume, ensuring an unrestricted vehicle flow while maintaining a uniform and monotonous landscape environment along both sides of the highway.

1.3.2 Eight-channel biofeedback instrument

To monitor the psychological and physiological changes in participants during driving, the study used an eight-channel biofeedback instrument produced by Thought Technology. This device converted the psychophysiological changes of the drivers into measurable indicators.

1.3.3 Driving simulator

This experiment adopted the UC-win/Road driving simulation cabin produced by Forum8. The physical structure and operation method of the simulation cabin closely mimic those of a real car, allowing for realistic driving simulation experiences.

1.4 Procedure

Before the experiment, staff checked and debugged the equipment to ensure the proper operation of the road simulation model. The experimental procedures and instructions were communicated to the participants, who were then allowed to adjust their seating posture, seat position, backrest angle, etc., according to their individual driving habits. A five-minute trial drive was conducted to familiarize participants with the operation methods and reduce potential interference. Each participant then engaged in 1 h of uninterrupted driving, striving to stay within the same lane. A quiet environment was maintained to minimize any impact on the drivers' psychophysiological states. After each experiment, the integrity and validity of the data were verified, and data storage was performed.

1.5 Data preprocessing

In practical applications, psychophysiological indicators are susceptible to internal and external environmental changes, resulting in interference indicators such as outliers and noise that can distort collected data and affect subsequent analysis, causing driving fatigue states to be unreliable. To address this, the moving window averaging method was used to remove outliers. Referring to previous studies[12], the time window length for cardiac psychophysiological indicator parameters was set to 15 s. In this study, each time window contained 120 samples, and outliers were detected and removed according to the "3σ principle." Linear interpolation was used to fill in the missing values after outlier removal. For over-sampled raw data, a Gaussian weighted moving average filter was applied to denoise the psychophysiological data.

1.6 Selection and analysis of psychophysiological indicators

1.6.1 EEG

The fatigue state of drivers is closely related to EEG indicators. However, using a single EEG indicator to determine fatigue states can lead to significant fluctuations, making it difficult to identify representative indicators. To improve accuracy, EEG indicator ratios were used to describe fatigue characteristics. This paper selected four EEG activities, namely α, β, θ, and δ waves. The EEG indicator ratio of θ and β waves ($R_{\theta/\beta}$) and that of α + θ waves and β waves ($R_{\alpha+\theta/\beta}$) were assessed as fatigue detection indicators.

EEG indicators comprise numerous coupling neurons, directly reflecting brain activity and exhibiting nonlinear characteristics. Linear analysis methods may lose valuable information from nonlinear data. Therefore, the sample entropy algorithm was employed to process the EEG indicators and their ratios. The algorithm for calculating sample entropy was implemented in Matlab R2021a to process the selected set of three indicators: $R_{\theta/\beta}$, $R_{\alpha+\theta/\beta}$ and R_{δ}.

1.6.2 ECG

Studies have found that with an increase in driving time and the onset of driving fatigue, drivers' heart rates gradually decrease[13]. To capture driving fatigue more accurately, this study introduced the concept of heart rate variability (HRV) as an indicator. HRV, obtained through time-domain analysis, serves as an electrocardiographic metric for evaluating driving fatigue.

2 Results and Discussion

2.1 Analysis of psychophysiological indicators

Research indicates that β waves dominate EEG patterns when the brain is in a state of wakefulness and alertness. As drivers experience fatigue and drowsiness, there is an increase in the amplitude of θ waves, signaling distraction and slower reaction times. In prolonged monotonous driving environments, drivers' attention levels decline, leading to increased α wave amplitudes. With further fatigue, the amplitudes of both α and θ waves slightly decrease, while δ waves gradually become the dominant EEG pattern[14-15]. Additionally, high-altitude environments exacerbate the psychophysiological burden on drivers, worsening as altitude rises[16]. Drivers in plateau areas exhibit obvious fatigue-related symptoms after just 1 h of continuous driving, whereas those in plain areas often require 2 to 3 h or more[17].

This study conducted an analysis to interpret the patterns of change in the extracted feature indicators to examine the relationship between various feature indicators and fatigue. Throughout the driving process in plateau areas, the drivers experienced transitions from alertness to fatigue. The sample entropy of EEG is expressed by SaEn. The waveforms of HRV and the sample entropy of θ and β waves (SaEn(θ/β), S_1), sample entropy of α + θ waves and β waves (SaEn(α + θ)/β), S_2), and sample entropy of δ waves(SaEn(δ), S_3) are shown in Fig. 1. The mean values of sample entropy were used to exhibit the amplitude changes of these indicators.

These four indicators exhibited a wave-like upward trend throughout the entire simulated driving experiment. This can be attributed to the self-adjusting ability of the human body in response to fatigue. After initially entering the fatigue state, drivers can temporarily alleviate fatigue through this self-adjustment. However, as driving time continues to increase, drivers quickly progress into a more serious fatigue state, at which point self-adjustment becomes less effective.

Based on the information shown in Fig. 1, the fatigue process of drivers can be initially divided into five stages: slow accumulation stage, mild fatigue, adjustment recovery, rapid accumulation, and severe fatigue. Specifically, as the driving time increases, the trends of HRV and sample entropy of $R_{\theta/\beta}$ and R_{δ} are generally consistent.

From 0 to 10 min, the drivers were in the slow accumulation stage. During this stage, the amplitudes of θ and δ waves increased, while the amplitude of β waves decreased. HRV also increased. The curves exhibited a gradual upward trend owing to the slow growth of fatigue.

From 10 to 20 min, drivers entered the mild fatigue stage. In this stage, the amplitudes of θ and δ waves were high, while the amplitude of β waves was low. HRV and sample entropy of $R_{\theta/\beta}$ and δ remained at relatively high levels and peaked around 15 min.

From 20 to 30 min, drivers entered the adjustment recovery stage. The self-adjusting ability of the human body came into play after the onset of fatigue, leading to a slight reduction in fatigue. The amplitudes of θ and δ waves decreased, while the amplitude of β waves increased. All indicators showed a decreasing trend during this stage, but their minimum values were still higher than the initial values. This indicates that although the body has some self-adjusting ability, it is difficult to fully recover to the alertness state.

From 30 to 40 min, the drivers entered the rapid accumulation stage. Fatigue grew rapidly during this stage, and the curve rose quickly to its peak.

After 40 min, drivers reached the severe fatigue stage. In this stage, δ waves became dominant, and the amplitudes of θ and β waves decreased. As a result, the sample entropy of $R_{\theta/\beta}$ showed a slight decrease compared to its peak value, while HRV and the sample entropy of δ wave remained at relatively high levels. The average values of these three indicators in the severe fatigue stage were higher than their peak values in the mild fatigue stage.

The overall trend of the sample entropy of the $R_{\alpha+\theta/\beta}$ curve was consistent with the other three indicators. However, it showed a delayed and slower peak during the slow accumulation and mild fatigue stages with fluctuations in its growth, as the amplitude of α waves primarily represents attention levels, which do not correspond directly to the level of fatigue but exhibit a certain lag. Additionally, the minimum value of the sample entropy of the $R_{\alpha+\theta/\beta}$ curve during the adjustment recovery stage was lower than the initial value. This may be attributed to the drivers' efforts to concentrate after feeling fatigued. Even though the fatigue level was higher compared to the initial stage, the drivers maintained a higher level of focus owing to the subjective initiative of the body. In the severe fatigue stage, there were fluctuations in the level of focus, indicating that drivers were still making efforts to maintain focus and counteract fatigue.

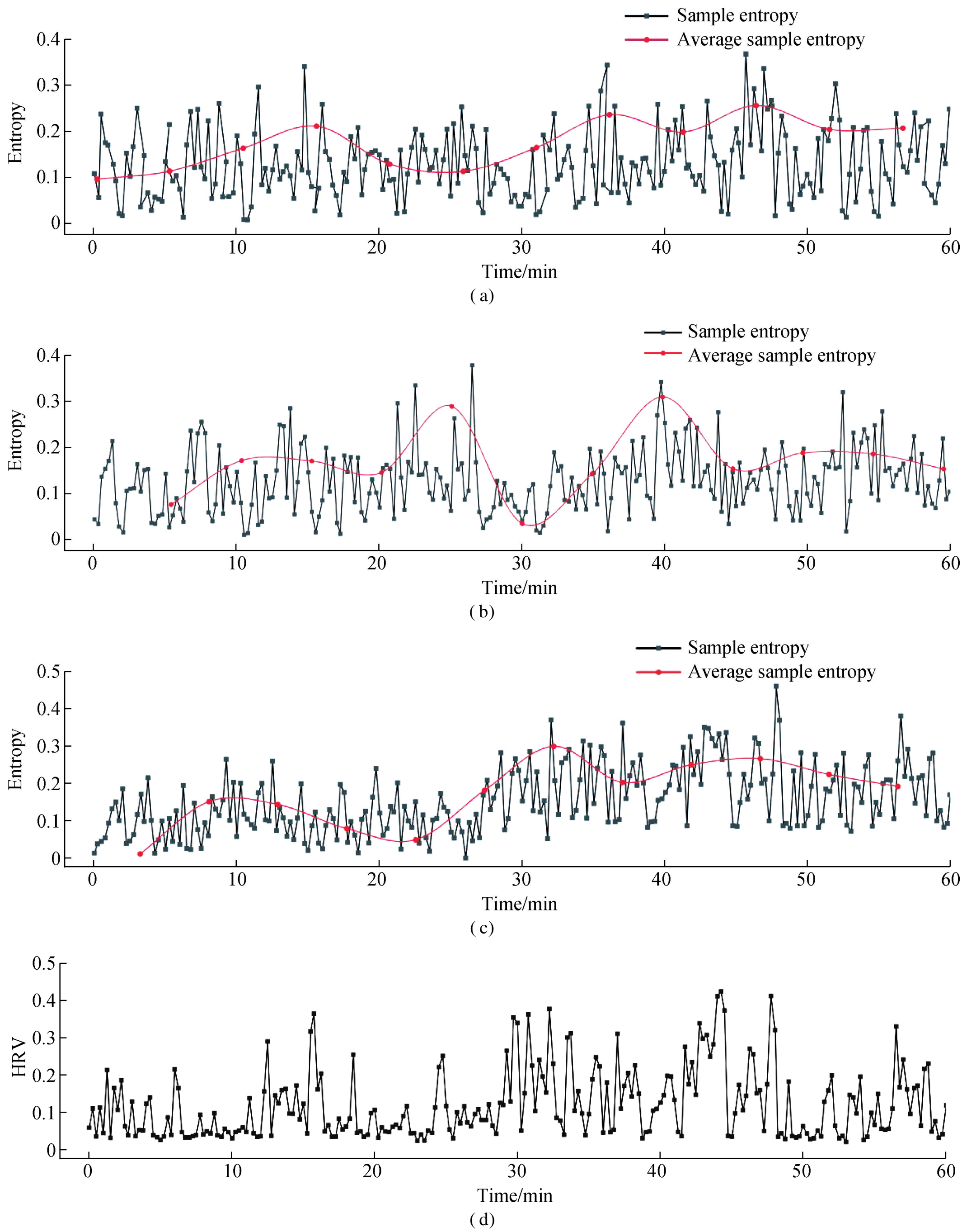

Fig. 1 Waveforms of indicators. (a) Sample entropy and average sample entropy of $R_{\theta/\beta}$; (b) Sample entropy and average sample entropy of $R_{\alpha+\theta/\beta}$; (c) Sample entropy and average sample entropy of R_{δ}; (d) HRV

2.2 Construction of comprehensive evaluation method

This study combined EEG and HRV to establish a complex indicator of driving fatigue (CIDF), representing the overall level of driving fatigue for drivers in plateau areas. Recognizing that the selected indicators might have certain correlations, principal component analysis (PCA) was used to eliminate the impact of redundant information on the indicator accuracy.

The HRV and sample entropy of $R_{\theta/\beta}$, $R_{\alpha+\theta/\beta}$ and R_{δ} were employed as evaluation indicators to characterize the complex program of information in time series. As analyzed earlier, these indicators increase with the deepening of driving fatigue, indicating a positive relationship. To ensure that HRV is comparable with EEG sample entropy values and to maintain comparability among different drivers with distinct heart rate variations, these four indicators were normalized. The normalized data were imported into SPSS software, where the PCA function was used to analyze the psychophysiological indicators (see Tables 1 and 2). Based on PCA results, this study selects the first, second, and third principal components to determine the weight coefficient of each sample entropy in the comprehensive index.

Table 1 Total variance

Component No.	Initial eigenvalue			Extraction sum of squared loadings		
	Total	Variance proportion	Accumulation/%	Total	Variance proportion	Accumulation/%
1	1.586	39.644	39.644	1.586	39.644	39.644
2	1.020	25.498	65.142	1.020	25.498	65.142
3	0.978	24.447	89.589	0.978	24.447	89.589
4	0.416	10.411	100.000			

Table 2 Component matrix

Indicator	Component No.		
	1	2	3
Sample entropy of $R_{\theta/\beta}$	0.888	0.021	0.050
Sample entropy of $R_{\alpha+\theta/\beta}$	0.887	−0.046	0.055
Sample entropy of R_{δ}	0.083	0.700	−0.709
HRV	−0.050	0.726	0.685

The principal components are described below. Y_1, Y_2, and Y_3 represent the three linear combinations; X_1 denotes the sample entropy value of $R_{\theta/\beta}$; X_2 indicates the sample entropy value of $R_{\alpha+\theta/\beta}$; X_3 is the sample entropy value of δ; H signifies HRV.

$$\left.\begin{aligned} Y_1 &= 0.705X_1 + 0.704X_2 + 0.066X_3 - 0.040H \\ Y_2 &= 0.021X_1 - 0.046X_2 + 0.693X_3 + 0.719H \\ Y_3 &= 0.040X_1 + 0.044X_2 - 0.563X_3 - 0.563H \end{aligned}\right\} \quad (1)$$

The CIDF (C) expression can be obtained by computing the weighted average of the index coefficients in the linear combinations of principal components, where the weights are determined based on the variance contribution rate of each principal component.

$$C = 0.329X_1 + 0.311X_2 + 0.094X_3 + 0.335H \quad (2)$$

As driving time increases, the level of driving fatigue among drivers in plateau areas gradually deepens, and the CIDF value increases. A higher CIDF value indicates a deeper level of fatigue experienced by the drivers.

2.3 Determination of driving fatigue threshold

To categorize the driving fatigue state using CIDF values, it is crucial to establish appropriate threshold values for CIDF across different fatigue states. This allows for a systematic and objective classification of the driver's fatigue level. Previous studies on driving fatigue have provided classifications for these states (see Table 3). Based on this, the study chose cluster numbers $K = 2, 3, 4, 5$ for analysis. K-means clustering analysis was performed on the fatigue degree scores (CIDF values) of typical sample data using SPSS software. The clustering effect was evaluated by calculating the contour coefficient (see Fig. 2).

Table 3 Classification of driving fatigue states

Number of classes	Fatigue states
2	Awake, fatigue
3	Alertness, mild fatigue, severe fatigue
4	Awake, tired, fatigue, drowsiness
5	Alertness, slight fatigue, moderate fatigue, severe fatigue, extreme fatigue

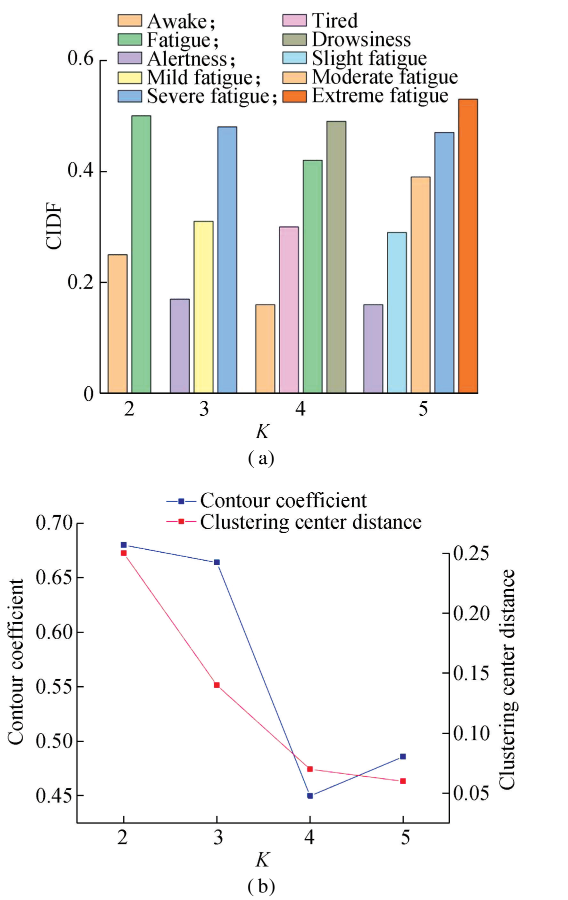

Fig. 2 Clustering results. (a) Clustering center; (b) Contour coefficient and clustering center distance

According to the clustering results, when K is 2 or 3, the contour coefficient of the clustering model is greater than 0.5, and the distance between the clustering centers is greater than 0.1, indicating good classification performance. Conversely, when K is set to 4 or 5, the contour coefficient of the clustering model is less than 0.5, and the minimum distance between the clustering centers is less than 0.1, resulting in higher dispersion within the model. Considering that the psychophysiological indicators exhibit significant fluctuations, a model with low contour coefficients and close clustering center distances would fail to effectively distinguish the data. To maintain satisfactory classification performance while providing detailed differentiation of driving fatigue states, this study determined the optimal number of clusters as $K = 3$. This categorization divides driving fatigue states into three categories: alertness, mild fatigue, and severe fatigue. The analysis results are listed in Table 4.

Table 4 Final clustering results

Cluster No.	CIDF	Number of cases
1	0.27	74
2	0.41	99
3	0.58	67

To determine the thresholds for driving fatigue, it was necessary to establish CIDF value ranges for different fatigue levels. The binning method was used to divide the data into several groups based on certain criteria. The data were binned under the condition of three cluster groups to classify the fatigue levels using SPSS (see Tables 5 and 6). The calculation for each bin is based on the condition that the lower limit is less than or equal to CIDF, and CIDF is less than or equal to the upper limit.

Table 5 Optimal bins

Cluster No.	Lower limit	Upper limit
1		0.34
2	0.34	0.50
3	0.50	

Table 6 Number of cases for each cluster

No.	Cluster 1	Cluster 2	Cluster 3	Total
1	74	0	0	74
2	0	99	0	99
3	0	0	67	67
4	74	99	67	240

Cluster 1 represents the alertness state, with a cluster center of 0.17 and a cluster interval of [0, 0.34). This cluster contains 74 data points, each representing a 15 s time window. Among these, 69 data points are located within the first 18.5 min, accounting for 93.2% of the total number of clusters. The fatigue state of drivers gradually changes with the increase in driving duration and does not exhibit significant fluctuations within a short period. From the clustering results, it is apparent that owing to the fluctuation in psychophysiological indicators, the three categories are not evenly distributed over time, with a few outliers present. When the proportion of samples in a certain fatigue state exceeds 90% within a certain time period, it can be considered that the drivers are in that fatigue state throughout the corresponding period. Therefore, it can be inferred that the drivers were in the alertness state during the first 18.5 min of driving.

Cluster 2 represents a mild fatigue state, with a cluster center of 0.31 and a cluster interval of [0.34, 0.50). This cluster contains 99 data points, of which 93 are located between 18.5 min and 43.25 min, accounting for 93.9% of the total number of clusters. Therefore, it can be judged that the drivers entered the mild fatigue state after 18.5 min of continuous driving, and the mild fatigue state persisted until 43.25 min.

Cluster 3 represents the severe fatigue state, with a cluster center of 0.48 and a cluster interval of [0.50, +∞). This cluster contains 67 data points, with 65 of them located from 18.5 min to 43.25 min, accounting for 97.0% of the total number of clusters. Therefore, it can be judged that the drivers entered severe fatigue after 43.25 min of continuous driving.

Based on the comprehensive evaluation of psychophysiological indicators, the fatigue thresholds are determined as follows: 0.34 for mild fatigue and 0.50 for severe fatigue. It can be concluded that drivers entered the mild fatigue state after 18.5 min of continuous driving and the severe fatigue state after 43.25 min. The distribution characteristics of the sample data are illustrated using a box plot, with CIDF values under different driving fatigue states depicted accordingly (see Figs. 3 and 4).

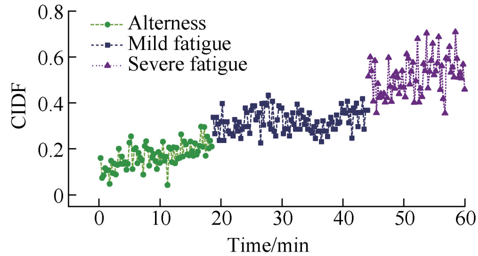

Fig. 3 Driving fatigue state classification

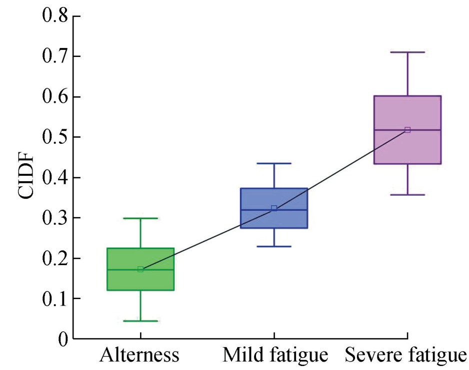

Fig. 4 Classification box plot

2.4 Analysis of variance

One-way analysis of variance (ANOVA) is a statistical method that can be used to investigate whether different levels of a control variable significantly affect an observed variable. In this study, ANOVA is suitable for studying the classification of driving fatigue based on CIDF values. In ANOVA, the p-value represents the probability of obtaining observed differences between groups if the null hypothesis is true. A smaller p-value suggests that the observed differences are less likely to be attributed to random factors, providing evidence to reject the null hypothesis. The F-value represents the F-statistic in ANOVA, which is used to test whether there are significant differences among the means of one or more groups of samples. A larger F-value indicates a greater ratio of between-group differences to within-group differences, thereby increasing the likelihood of rejecting the null hypothesis.

Through the Kolmogorov-Smirnov test, it was found that the CIDF values exhibit characteristics of a normal distribution ($p = 0.198 > 0.05$). The variability in CIDF data across different levels of driving fatigue does not show significant differences ($p = 0.082 > 0.05$), indicating that the assumption of variance homogeneity is satisfied (see Table 7).

Table 7 ANOVA driving fatigue classifications

Fatigue state	Alertness	Mild fatigue	Severe fatigue
Sample size	74	99	67
Mean	0.173 2	0.324 3	0.518 3
SD	0.052 83	0.048 92	0.084 14
P_1	0.198	0.198	0.198
P_2	0.082	0.082	0.082
P	543.6	543.6	543.6
F	0.000	0.000	0.000

Note: P_1 represents the p-value in the Kolmogorov-Smirnov test; P_2 represents the p-value in the variance homogeneity test.

Given that the CIDF values satisfy the assumptions of normal distribution and variance homogeneity, one-way ANOVA was conducted on the data. The results indicate that the CIDF values under different fatigue states are significantly different, suggesting that the clustering analysis of CIDF values can effectively classify the driving fatigue states. To obtain a fatigue threshold universally applicable to all highland drivers, a mathematical analysis was conducted to determine the points at which each driver enters different fatigue states (see Table 8).

Table 8 ANOVA of classification of all samples

Fatigue state	Mild fatigue threshold	Severe fatigue threshold	Time to enter mild fatigue	Time to enter severe fatigue
Range	[0.31, 0.39]	[0.46, 0.55]	[13.75, 34.50]	[40.50, 54.00]
Mean	0.344 2	0.516 9	21.37	41.48
SD	0.026 10	0.016 19	4.97	3.65
P_3	0.077	0.077	0.200	0.200
P_2	0.723	0.723	0.034	0.034
P	566	566		
F	0.000	0.000		

Note: P_3 represents the p-value in the Shapiro-Wilk test.

According to Table 8, the Shapiro-Wilk test reveals that both the fatigue thresholds and the times to enter the fatigue state follow a normal distribution ($p > 0.05$ for both). For the variance homogeneity test of thresholds, there is no significant difference in the variability in the two thresholds ($p > 0.05$), satisfying the assumption of variance homogeneity and allowing the use of one-way ANOVA. However, the times to enter two fatigue states do not meet the assumption of variance homogeneity.

A one-way ANOVA conducted on the driving fatigue thresholds of 26 drivers revealed a significant difference between the mild and severe fatigue thresholds obtained through K-means clustering analysis ($p = 556$, $F = 0.000$). Both thresholds exhibited a standard deviation smaller than 0.03, indicating minimal data dispersion. The fatigue thresholds among the 26 drivers were highly consistent, with average values of 0.34 for the mild fatigue threshold and 0.50 for the severe fatigue threshold, effectively categorizing each driver's fatigue state.

By contrast, the standard deviations of the times to enter different fatigue states were large, indicating substantial data scattering. This variability is attributed to various factors, such as individual physical conditions, meaning each driver reaches mild and severe fatigue states at different specific times. Consequently, it is impractical to use these time values alone to accurately categorize the driver's fatigue state owing to the high degree of variability.

3 Conclusions

1) This study focused on investigating driving fatigue in the unique low-pressure and low-oxygen environment of plateau areas. The sample entropy of EEG signals and HRV were selected as psychophysiological indicators to characterize driving fatigue states. By analyzing the correlation between these psychophysiological signals and driving fatigue status, the study identified these indicators as effective measures of driving fatigue.

2) A comprehensive evaluation indicator, CIDF, was developed based on psychophysiology to effectively evaluate and manage fatigue-related risks in plateau areas. This approach overcomes the limitations of single-indicator methods.

3) Clustering analysis and optimal binning techniques were applied to determine driving fatigue thresholds in plateau areas. This resulted in the establishment of a driving fatigue threshold where a value of 0.34 represents mild fatigue, and 0.50 indicates severe fatigue. Consequently, the fatigue state is divided into three stages: alertness, mild fatigue, and severe fatigue.

4) Despite the findings, there are some deficiencies and limitations. Driving fatigue can be influenced by various factors, such as road alignment, temperature, driver gender, and experience. Considering factors such as safety and fatigue resistance, the participants in this study were mainly young drivers. Future research can further explore the driving fatigue detection model and propose more systematic approaches to effectively mitigate driving fatigue.

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基于心生理指标的高原驾驶疲劳综合评价方法

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摘要: 为研究高原环境对驾驶疲劳的影响,选取脑电信号与心率作为驾驶疲劳表征指标,分析驾驶员进入疲劳状态全过程的指标变化规律. 基于脑电信号样本熵和心率变异系数,利用主成分分析方法建立驾驶疲劳综合评价指标(CIDF),以克服单一指标方法的局限性. 根据 CIDF 值,采用聚类分析方法,将高原环境下驾驶疲劳状态细分为清醒、轻度疲劳和重度疲劳 3 种状态. 使用最优分箱确定高原地区不同驾驶疲劳状态下的阈值,并利用方差分析方法进行验证. 结果表明,根据 CIDF 值可对高原地区驾驶员疲劳状态进行有效划分. 清醒和轻度疲劳状态下的 CIDF 阈值分别为 0.34 和 0.50,CIDF 值大于 0.50 则表示驾驶员处于重度疲劳状态.

关键词: 高原地区;驾驶疲劳;驾驶模拟;心生理指标
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