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Analysis of Driver Fatigue Eye Movement Characteristics Under Intelligent Supervision Environment

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Abstract: Reducing drivers' improper driving behavior in transportation is an important condition for ensuring safety. In today's intelligent era, many passenger and freight companies are gradually using intelligent monitoring platforms to supervise the behavior and condition of drivers and vehicles. The intelligent supervision platform is beneficial for fatigue monitoring and improving driving safety. However, the research found that the number of alarms on the platform is too high, and the smart regulatory environment exhibits different operational characteristics compared to traditional driving environments. Therefore, based on the characteristics of driving behavior in the context of smart regulatory information interaction. It is very necessary to explore the influencing factors and development patterns of driving fatigue under the intelligent supervision environment. This article uses principal component analysis to identify sensitive indicators of driving fatigue eye movement characteristics in the context of intelligent supervision platforms, with the sensitive indicators being pupil diameter and blink frequency. This study helps to reveal the formation and variation rules of driver fatigue under the environmental conditions of intelligent supervision platforms, improving the accuracy and reliability of fatigue detection while driving.

Keywords: Intelligent monitoring environment; driving fatigue; eye movement characteristics; principal component analysis.

1. Introduction

During the driving process, the driver needs to maintain a high level of concentration throughout, gathering and processing information both inside and outside the vehicle. This high-stress operating state keeps the driver's central nervous system in a state of high activation. However, long periods of operation can lead to driver fatigue, and as the state of fatigue changes, it can also cause changes in physiological data and driving performance.

Due to the monotonous environment during driving, it is easy for the driver to experience visual fatigue. In order to intuitively and effectively reflect the state of visual fatigue, eye movement data has become an important indicator. Therefore, this article conducts research on the eye movement patterns of drivers when fatigued in an intelligent supervision environment to promote fatigue management for drivers under such conditions.

2. Research Review

In recent years, an increasing number of researchers have used methods such as eye tracking and facial recognition to make objective judgments about the fatigue state of drivers. Currently, researchers mainly use CNN algorithms [1-5], MTCNN algorithms [6-7], SSD network algorithms [8-9], HOG algorithms [9-10], and ASM algorithms [11-14] for face detection.

Wang Di[15] used an Adaboost cascade classifier for face detection and eye region segmentation, performing image preprocessing to reduce environmental interference, accurately locating the eyes through image processing and extracting eye feature parameters. Huang Z[16] extracted the blinking frequency, yawning frequency, and nodding frequency of drivers to create a fatigue detection sample library, and used the Naive Bayes algorithm to establish a model for classifying and judging the fatigue state of drivers. Wukun Liang [17] conducts a comprehensive assessment during driving by using the BFR (Blinking Frequency Ratio) algorithm and head pose algorithm: if the number of blinks exceeds the BFR threshold, posture collection is initiated, and a pre-trained head pose model is used for evaluation; if fatigue is detected, it alerts the driver. Dong BT[18] uses a single-shot scale-invariant face detector (S3FD) to detect faces in images, and then utilizes a face alignment network (FAN) to extract facial features. Wang XY[19] and others used the Dlib library to extract the coordinates of facial feature points, obtain the feature parameters of the driver's eyes and mouth, calculate the Euler angle parameters of head posture, and established a fatigue recognition model through an improved Multi-task Cascade Convolutional Neural Network (MTCNN). Xiao WC et al[20]. aimed to maximize the utilization of driver's facial feature information and temporal characteristics by establishing a Spatial Pyramid Fusion Multi-Scale Feature Output (SPP-MSFO) detection model, obtaining images of the facial region and calculating the aspect ratios of the left eye, right eye, and mouth based on the coordinates of key points, thereby forming a fatigue parameter matrix.

From the review of domestic and international research on driving fatigue, it can be seen that current studies on driving fatigue cover multiple aspects such as fatigue evaluation methods and fatigue evaluation indicators. These findings provide a foundation for the research presented in this paper. However, there are still some issues that need further research, as outlined below: Currently, there is a lot of literature on fatigue driving analysis both domestically and internationally. However, there has been no dedicated discussion on the characteristics of driver fatigue eye movements in the context of the latest intelligent supervision environment. Nevertheless, this research is of great significance for monitoring driving fatigue in the context of intelligent connected environments.

3. Research Methods

Principal Component Analysis (PCA) is a commonly used method for data dimensionality reduction and feature extraction. It transforms the original data into a set of new variables, which are linear combinations of the original data. Each new variable contains a portion of information from the original data, and the new variables are independent of each other. These new variables are called principal components. By selecting the first few principal components, it is possible to compress and reduce the dimensionality of the original data, making data analysis and visualization more convenient.

By the above method, the original high-dimensional data can be reduced to a few principal components. During this process, although the original feature space may be compromised, principal component analysis can yield principal components that contain the weight information of each original feature, thus still effectively reflecting the information of the original data. The corresponding principal components are arranged in order of the corresponding feature values from largest to smallest. Usually, the P (P≤0) principal components corresponding to the feature values with a cumulative contribution rate of over 85% or 95% can contain all the information of the original features. By using principal component analysis, redundant information in the original data can be eliminated, and the main components of the data can be extracted, allowing for a better understanding of the structure and patterns of the data.

4. Research Conclusion and Discussion

The research content of this paper is the driving fatigue characteristics under the supervision platform environment, so the principal component analysis data is the eye movement data of the driver in the experimental group, and the eye movement data is obtained by the laboratory simulation experiment.

4.1. Analysis of research results

First, it is necessary to determine whether the data meets the conditions for using principal component analysis. In this study, six original variables of eye movement data were used, including fixation time, fixation count, saccade count, average saccade speed, pupil diameter and blink count.In order to perform principal component analysis, these data need to be Z-standardized so that their mean is 0 and the standard deviation is 1.

Next, Bartlett 's sphericity test is needed to check whether there is a spherical skewness between the original variables, that is, whether there is multicollinearity. The test results are shown in Table 3-2, $p < 0.05$, indicating that there is a correlation between the original variables. The KMO value is 0.889, which is within the general appropriate range, indicating that it is suitable for principal component analysis.

Finally, two new comprehensive indicators were obtained by principal component analysis, which explained 59.27 % and 18.35 % of the variance of eye movement data respectively. The specific results are shown in Table 1, Table 2, Table 3and Figure 1.

Table 1. KMO and Bartlett test of eye tracking data

KMO sampling suitability quantity		.889
Bartlett sphericity test	Approximate chi-square	168.989
	degree of freedom	21
	significance	0.000

Table 2. Common factor variance of eye tracking data

	initial value	extraction
fixation time	1.000	0.723
the number of watch	1.000	0.755
Number of glances	1.000	0.756
average speed of saccades	1.000	0.736
pupil diameter	1.000	0.764
blink times	1.000	0.763

The common factor variance represents the degree to which the information contained in each variable can be represented by the extracted principal component, also known as ' common degree '.The ' initial value ' indicates that the demonstration information of each variable is 1, that is, 100 %.The ' extraction ' column indicates the degree to which the variance of the variable can be expressed by the principal component. It can be seen that the variance of the variable can be explained by the principal component by more than 70 %.

Table 3. Cumulative contribution rate of total variance of eye tracking data

	Initial eigenvalue			Extract the load sum of squares		
composition	total	variance proportion	accumulation%	total	variance proportion	accumulation%
1	4.132	59.265	59.265	4.132	59.265	59.265
2	1.322	18.349	77.614	1.322	18.349	77.614
3	.568	8.206	85.820			
4	.495	6.939	92.759			
5	.284	4.269	97.028			
6	.096	2.972	100.000			

Table 4. Eye tracking data component matrix

	composition	
	1	2
fixation time	0.715	0.454
the number of watch	0.619	0.413
Number of glances	0.743	0.471
average speed of saccades	0.474	0.223
pupil diameter	0.820	-0.353
blink times	-0.254	0.933

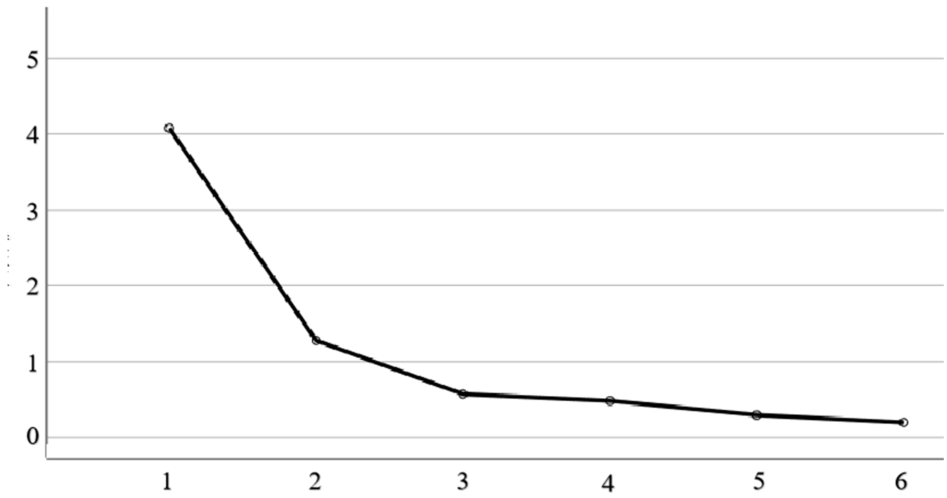

Figure 1. Eye movement data lithogram

According to the principal component analysis method, complex multidimensional data can be transformed into a few comprehensive indicators through dimensionality reduction, so as to better describe and explain the data. In this paper, after Z standardization and Bartlett spherical test of eye movement data, it is confirmed that the data are suitable for principal component analysis. According to the results of table3 , it can be seen that the cumulative variance contribution rate of the first two principal components is 77.614 %, so two principal components are extracted to represent the original variables. Figure 1 shows that the first two factors cover most of the information of the original variables. According to the component matrix table, it can be obtained that the index pupil diameter and blink times have higher loads on the first and second principal components, that is, the correlation is stronger. Based on the results of principal component analysis, the eye movement sensitivity index of driving fatigue under the intelligent supervision platform mainly chooses pupil diameter and blink times.

4.2. Discussion

In this paper, the principal component analysis method is used to determine the sensitive indicators of driving fatigue under the environment of intelligent supervision platform. However, due to the limitation of time and space, this paper mainly analyzes the main indicators of eye movement. In the later stage, this paper intends to carry out the characteristics analysis of ECG and vehicle behavior parameters, and will carry out fusion analysis, in order to carry out the driving characteristics and laws under the environment of intelligent supervision platform in a refined and systematic way, and lay a theoretical foundation for the management and early warning of driving fatigue under intelligent supervision.

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