Research on Brain Load Prediction Based on Machine Learning for High-Speed Railway Dispatching

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Abstract. In this paper, based on a simulation experiment platform, multimodal physiological data of the operator during emergency scenario processing are collected and processed. Specifically, for the ECG signal acquired by the ECG sensor, the noise is eliminated by using the method of stationary wavelet transform, and then the R-wave labeling is performed by the differential algorithm to obtain the HRV waveform and extract the time-domain, frequency-domain and nonlinear related features; for the multi-channel brainwave signal acquired by the EEG test system, the electrode positioning, potential re-referencing, filtering and noise removal are firstly performed using the eeglab toolkit For the eye-movement data collected by the eye tracker, the subject's fixation behavior was extracted using the position-distance threshold algorithm, and the fixation frequency and mean fixation time were calculated, together with the mean and standard deviation data of the pupil's diameter, as the characteristics of the eye-movement dimension. In the process of regression prediction, a feature selection method based on entropy criterion was proposed in this paper. The results showed that the feature-selected dataset achieved better performance in the regression prediction of the SVR model compared with the original feature set.

Keywords: Brain Load · Machine learning · High-speed railway dispatching.

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1 Introduction

The improvement of train scheduling automation, on the one hand, reduces the daily operation of dispatchers, which makes them focus on the dynamic changes of the monitoring screen as long as possible; On the other hand, when an emergency occurs, dispatchers need to deal with the emergency quickly and correctly. In this process, the workload of dispatchers fluctuates continuously with the change of work content and work scene. Excessive or too little workload will have a certain negative impact [1]. Therefore, in order to reduce security incidents caused by human factors and improve the work effect of dispatchers, it is necessary to study the workload of dispatchers.

2 Related works

Currently, the commonly used workload evaluation methods are subjective evaluation method, task analysis method, physiological measurement method and complexity analysis method, etc. Hart et al. [2] used subjective evaluation method (NASA-TXL scale method) to categorize the influencing factors of workload into six categories, and assigned corresponding weights to weight the workload. The indicators of the physiological assessment method were divided into three major categories according to the functions of the physiological organs involved, namely, those related to the brain, heart, and eyes. [3–10]In an exploratory study of driver mental load, Shimizu et al. [11] used FMRI and FNIRS-related techniques to obtain data on drivers' brain physiological activity in relatively narrow traffic roads, and verified that cerebral blood flow is a physiological indicator for effective evaluation of brain mental load. Tattersall [12] found that the pilot's mental load increased with the increase of the flight task volume, but the LF frequency value in their heart rate variability power spectral density also decreased. Lee et al. [13] used Nocera et al. [14] designed a simulated driving game experiment, the results showed that there were significant differences in the distribution patterns of the test subjects' gaze points at different levels of mental load, and the concentration area of the gaze points shrank as the mental load continued to increase.

It can be seen that the railway field is limited by the invasive of physiological data collection equipment, and there is still room for in-depth research about it. In this paper, based on the high-speed railway dispatching simulation platform, the physiological data of dispatchers in the process of emergency disposal are collected, and the correlation model between physiological data and brain load is constructed to realize the detection and monitoring of brain load of dispatchers.

3 Research method

3.1 The experiment design

The test experiments are conducted based on the human factors engineering experiment system for dispatchers developed independently within the laboratory. The experiment system consists of scenario generation management system, dispatching command simulation system, and data acquisition and analysis system, which can provide functions such as normal and fault scenario generation and management, construction of human-machine interface and related environment for dispatchers, and acquisition and analysis of operational behavior and physiological parameters of the subjects. The graphic workstation, which is the subject's operating object, is also equipped with a desktop vertical radio microphone and a set of keyboard and mouse for interactive operation with the experimental system.

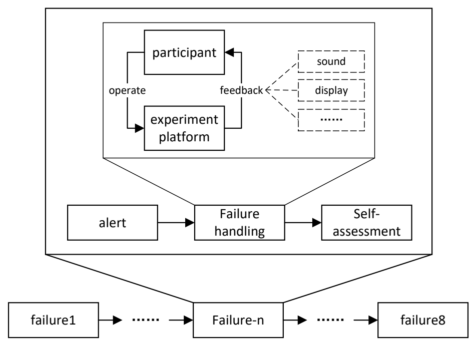


Fig. 1. The experimental process.

The experimental paradigm is shown in Fig. 1. The entire experiment contains a total of eight emergency scenarios, with 10 minutes between scenes for subjects to rest and adjust the experimental equipment. In the process of failure handling, the experimental platform will give corresponding display or voice feedback after the subject operates on the experimental platform. For example, after the subject calls the driver through the dispatcher's communication simulation subsystem and asks for confirmation of train-related conditions, the communication simulation subsystem will automatically play the corresponding reply voice. The data acquisition analysis marks the above feedback stimuli by recording time stamps and performs timeline alignment and synchronization on the collected physiological data such as ECG, EEG and eye movements. At the end of the disposition process, subjects filled out the NASA-TLX scale to make a self-assessment of the brain load for that contingency scenario.

The physiological data were segmented according to the event markers on the EEG signal, and a total of 120 sets of physiological data were obtained. AHP was used to determine the magnitude of the load induced by each feedback event within the scenario as a percentage of the overall contingency process, thus mapping the subjects' scale scores weighted to the score labels of each group of physiological data.

3.2 Feature extraction

Data pre-processing. The EEG data was preprocessed using the eeglab in matlab. (1) Electrode positioning. The channel electrode points are positioned using the standard channel position based on the international 10-20 system. (2) Filtering. Filter out 50Hz industrial frequency interference and use 0.1 30Hz bandpass filter to filter out high frequency band noise. (3) re-reference. Select the bilateral mastoid as the re-reference channel.

Discrete wavelet decomposition. The actual sampled signal is often discrete and finite interval, and the information processed by the computer can only be discrete, hence the introduction of the discrete wavelet transform. The spectrum of any signal can be fully partitioned by a series of wavelet functions and a scale function, decomposed into two parts: scale coefficients and wavelet coefficients.

In this experiment, based on the principle of discrete wavelet decomposition mentioned above, three bands of θ, α and β waves in the EEG signal are extracted as the object of study.

After each frequency band was obtained, its power was calculated separately. In this experiment, excluding the two reference electrodes, a total of 6 channels of EEG signals were acquired, and each channel was decomposed into 3 frequency bands, and a total of 18 power spectrum data were obtained as the characteristics of EEG signals.

Stationary wavelet denoising. In wavelet denoising, the multi-level high-frequency noise signal is under thresholding, and the processed detail signal is reconstructed with the approximation signal to obtain an estimate of the noise-contaminated signal. During the processing of ECG data, it was found that the denoised signal produced Gibbs oscillation phenomenon near the singularity point, as shown in Fig. 2(b). To suppress this phenomenon, the cancellation method of stationary wavelet transform is used.

The shape of the Daubechies wavelet family is similar to the QRS wave in ECG signals, and its energy spectrum is concentrated near the low frequency, so db5 in the Daubechies wavelet function family is chosen as the wavelet basis for the experiment in this paper. The results show that the stationary wavelet denoising significantly improves the Gibbs phenomenon at the singularities, as shown in Fig. 2(c).

In this experiment, the R-wave of ECG signal is labeled using the difference method to extract the heart rate variability, and the HRV data are correlated and calculated to obtain a total of 12 features in the time domain, frequency domain, and nonlinearity as the feature dimension of ECG.

3.3 Eye movement.

Fixation is a period of time during which the human eye is continuously focused on an object. The equipment cannot directly output the fixation position and

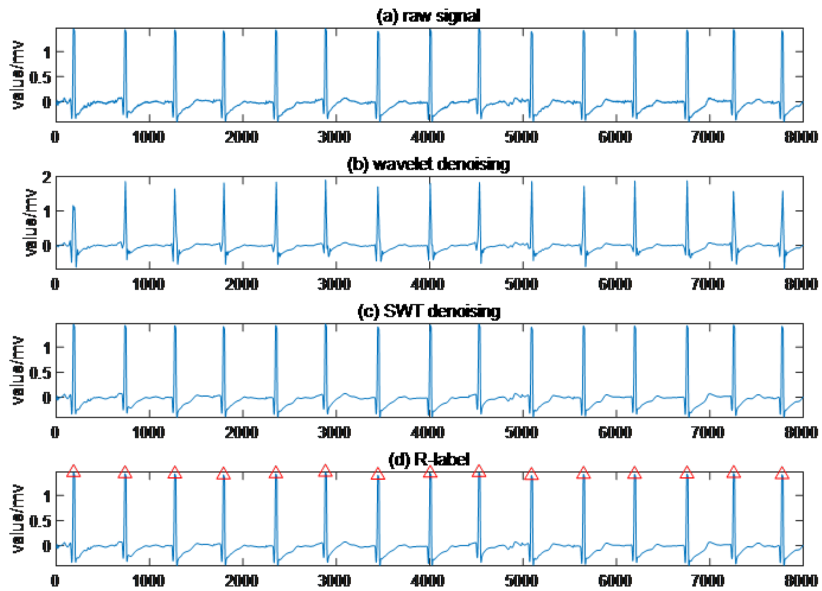


Fig. 2. ECG processing.

time, and an algorithm is needed to extract the fixation from the derived gaze point position and time. In this experiment, a position thresholding algorithm is used, and the points where the difference between the positions of two adjacent gaze points is greater than the threshold are recorded as the end point of the previous segment of fixation and the starting point of the next segment of fixation, respectively, from which the fixation segments are obtained. As shown in Fig. 3. The fixation segments with too short a duration were excluded, and the final fixation data of the subjects were obtained. Based on the fixation and pupil data, four features were extracted to form the feature dimension of eye movements.

3.4 Regression prediction

Feature Selection. Each feature has a different degree of influence on the brain load prediction. In order to improve feature sensitivity, improve prediction accuracy and model generalization ability, the entropy criterion is used to select the feature set to choose the appropriate and important information.

The entropy measure based on the similarity between objects is constructed to evaluate the importance of the original feature set, so as to filter out the important feature subset.

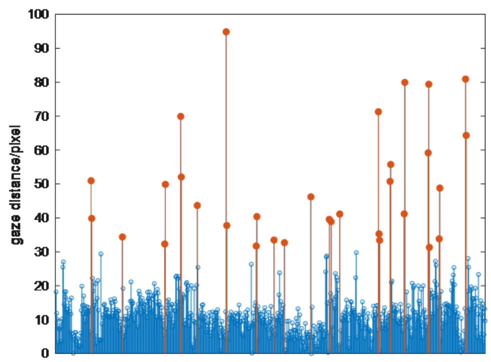


Fig. 3. Fixation extract.

Regression method. In the experiment, the SVR model of scikit-learn machine learning toolkit is selected for regression prediction of brain load of high-speed railway dispatchers. Meanwhile, a ten-fold cross-validation method is used to avoid model overfitting as much as possible.

To compare the prediction accuracy between different regression models, linear regression, random forest regression and SVR regression models with default parameters were trained using the data set before feature selection was performed. The prediction results are shown in Table 1.

Table 1. Error of different model results.

	RMSE	MAE	R^2
Liner regression	53.4744	6.5340	0.6524
Random forest regression	57.506	5.57	0.6262
SVR	10.0921	4.4622	0.7495

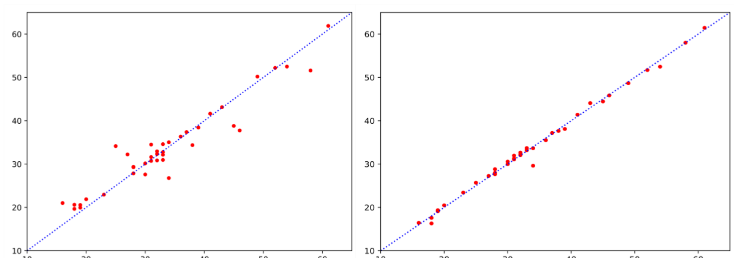
Among them, the RMSE of the linear regression and random forest models were 53.4744 and 57.506 respectively, which were much larger than the RMSE of the SVR model; the MAE of the three models were not very different, but the MAE of the SVR model was the smallest among the three; in terms of R^2 value, the SVR model only reached 0.7495, but it was higher than the R^2 of the linear regression and random forest models values. This shows that the SVR model predicts better than the linear regression and random forest regression models on the original data set.

To verify the effectiveness of the above feature selection methods, the SVR model was used for regression prediction based on the original dataset, and the dataset after entropy criterion feature selection, respectively. During the model training, the kernel function is the default rbf Gaussian kernel function, the kernel width parameter gamma of Gaussian kernel is set to 0.1, and the penalty coefficient c is set to 150. the prediction results are shown in Table 2.

Table 2. Error without\with feature selection.

	RMSE	MAE	R^2
Before	9.1602	2.0949	0.7728
After	0.8235	0.5611	0.9280

Compared with the whole features, after entropy criterion feature selection, the R^2 of regression prediction results improved to 0.928, and RMSE and MAE decreased accordingly. The regression results are plotted with the measured value as the independent variable and the predicted value as the dependent variable. As shown in Fig. 4(a) and Fig. 4(b). It can be found that the agreement between the predicted and measured values is significantly improved after feature selection, indicating that the prediction accuracy of the regression model after feature selection is significantly improved and can meet the actual prediction needs.



(a) before feature selection (b) after feature selection

Fig. 4. Predicted values to actual values.

4 Conclusion

In this experiment, a brain load prediction method based on multi-physiological features is proposed for the high-speed railway dispatching under emergency scenarios. Three independent signal processing and feature extraction channels are constructed in this paper for three types of physiological signals, which can be well adapted to the respective data characteristics of different physiological parameters.

However, there are still shortcomings in this experimental study. First, due to the objective conditions, the number of subjects in this experiment is limited, and the randomness of the sample is insufficient. Second, the parameters of the SVR algorithm in this paper are not intelligently optimized, and there is still room for research and improvement.

Next, the model parameters with the best effect will be found with intelligent optimization algorithm. Meanwhile, the feature set can be used as a part of pending variables to participate in the process of SVR intelligent tuning.

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