A Rapid Detection Platform for Mental Workload

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Abstract. In order to ensure safe production and solve the problem of time-consuming and labor-intensive for human mental workload detection, we have developed a fast detection platform for human mental workload. This platform can quickly detect the mental load of subjects by analyzing their voice data, physiological data, biochemical data and psychological data. The experimental results indicate that the platform could rapidly detect the mental workload, with an accuracy rate of over 75%.

Keywords: mental workload detection; speech voiceprint information; machine learning algorithm

1. Introduction

With the development of modern technology, more and more tasks require complex operations to be completed. In daily production and life, complex operations such as engineering construction, directional blasting, and driving are required; In high-precision jobs such as manned spaceflight, aircraft piloting, and submarine deep-sea operations, operators need to be highly focused and perform complex operations. In order to ensure safe production and the smooth completion of various tasks, it is necessary to conduct real-time monitoring of the mental load of operators, evaluate the mental load, and make adjustments to reasonably control the working time of operators. This is of great significance for the physical and mental health and safety of operators [1].

At present, commonly used methods for measuring mental load, include subjective measurement, physiological measurement and task measurement.

Subjective measurement method requires operators to judge and score the mental load exerted on them by the current work intensity [2, 3]. The advantage of this method is that it is simple to operate and easy to implement, which can directly reflect the individual's subjective feelings about the current level of mental load. However, this method has subjectivity in self-evaluation among participants and is easily influenced by individual differences and emotional states, resulting in inaccurate evaluation results.

Physiological measurement method reflects changes in the mental workload of operators through physiological indicators such as heart rate, electrooculography, electroencephalography (EEG) [4]. Among them, EEG signals are a type of bioelectric signal widely used in scientific research, which are collected by wearing EEG caps. However, due to the weak nature of EEG signals, they are easily affected by other physiological

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activities of the human body such as eye movements, muscle activity, electrocardiography, vascular waves, and tongue and throat movements [5]. Moreover, this data acquisition method is inevitably subject to external and device frequency interference.

The task measurement method uses the performance results of the operator at work, such as homework completion time, grade error rate, etc., as indicators to measure mental load. It reflects the operator's attention level and brain processing efficiency of information [6, 7]. The advantage of this method is that it is relatively objective and can reflect the cognitive load of the subjects based on specific behavioral indicators. However, its disadvantage is that the nature, difficulty, and individual differences of the tasks during the experimental process may affect the behavioral performance of the subjects, and the subjective assumptions of the observers may also affect the accuracy of the evaluation. Therefore, the use of behavioral performance as an indicator for evaluating mental load status needs further validation.

In this situation, it is urgent to develop rapid mental workload detection platform, which is small, portable, unaffected by environmental factors, and meets the requirements of non-contact and real-time detection. We developed a platform which can quickly detect the mental workload of operators using their voice information, physiological information, biochemical information and psychological information. This platform uses machine learning algorithms with a detection accuracy of over 75%.

2. Data and Method

2.1 Data

We collected speech voiceprint information, physiological indicators, biochemical indicators, and psychological questionnaire data from 15 subjects under different mental load conditions, as shown in table I.

TABLE I. MENTAL WORKLOAD DATA

No.	Mental Workload Data	
	First level indicator	***Secondary indicators***
1	voiceprint information	voice
2	physiological information	heart rate
		blood pressure
3	biochemical information	salivary cortisol
		Salivary norepinephrine
4	psychological information	self efficacy scale
		psychological resilience scale

2.2 Method

This article collected speech and voiceprint information, physiological indicators, biochemical indicators, and psychological questionnaire data from 15 testers under different mental load conditions. In the classification and modeling stage, machine learning algorithms such as logistic regression (LR), linear discriminant analysis (LDA), classi-

fication and regression tree (CART), and support vector machines (SVM) were compared, and finally SVM classification algorithm was adopted to establish a mental load classification model. It is possible to accurately classify mental workload in a shorter amount of time while maintaining classification accuracy. The classification accuracy has reached over 75%.

3. A Rapid Platform for Mental Workload Detection

This platform has functions of user management, voice management, physiological/biochemical indicator management, psychological indicator management and mental load calculation.

3.1 User Management

Enter the administrator's username and password, click login to enter the system homepage. Click the arrow in the bottom right corner of the login page to switch to the user registration and login interface. After registration, users can log in to the system.

3.2 Voice Management

In the voice management module, voice files can be recorded, saved, played, queried, deleted, and feature value calculated, as shown in Fig.1-3.

Fig. 1. Voice recording

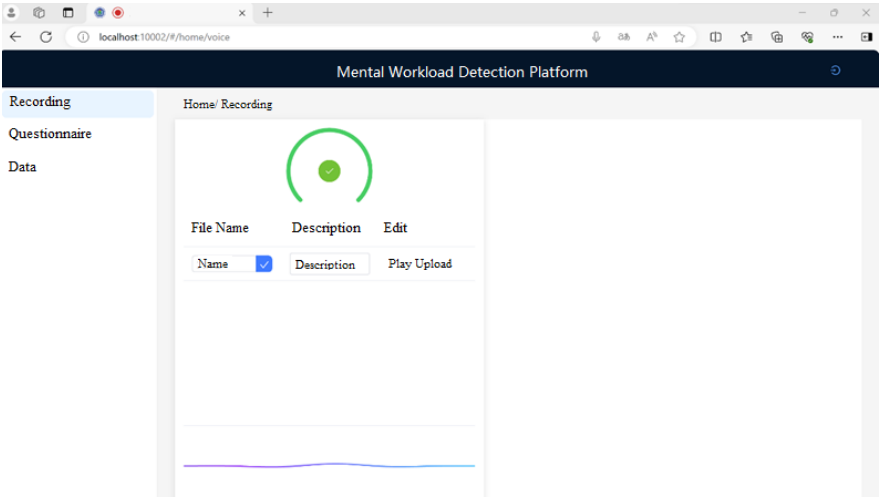

Fig. 2. Naming, playing, uploading, and deleting voice files

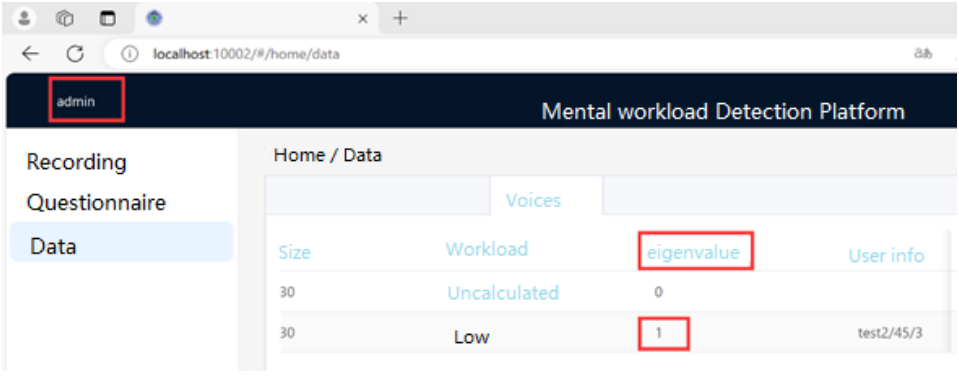

Fig. 3. Feature value calculation of voice files

3.3 Physiological Indicators Management

In the physiological indicator management module, physiological indicators can be entered, deleted, modified, queried, and data displayed, as shown in Fig.4-7.

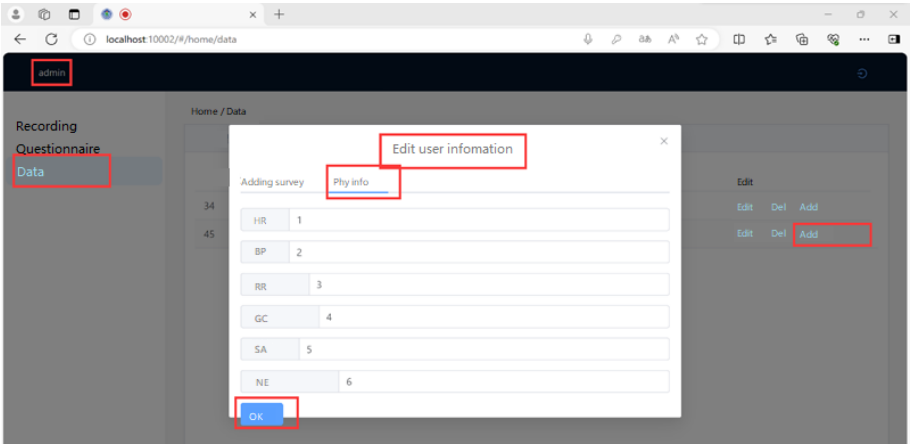

Fig. 4. Input physiological index

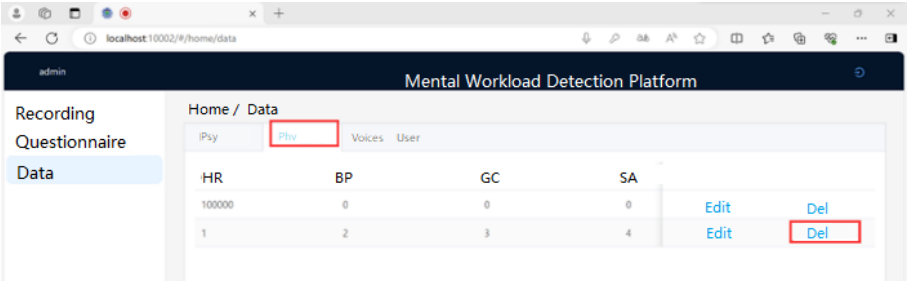

Fig. 5. Modification and deletion of physiological indicators

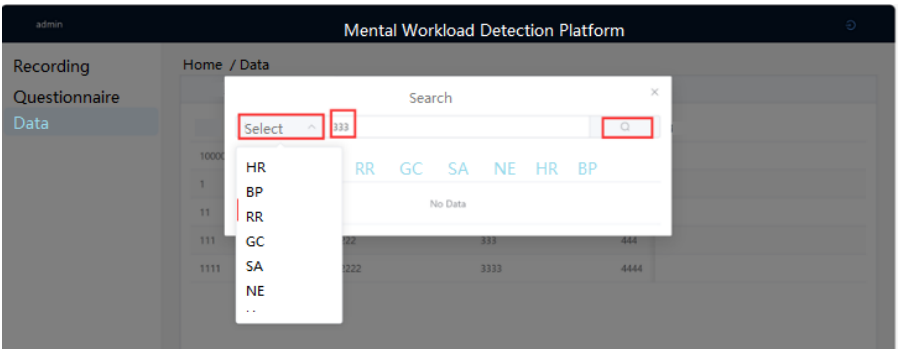

Fig. 6. Query of physiological indicators

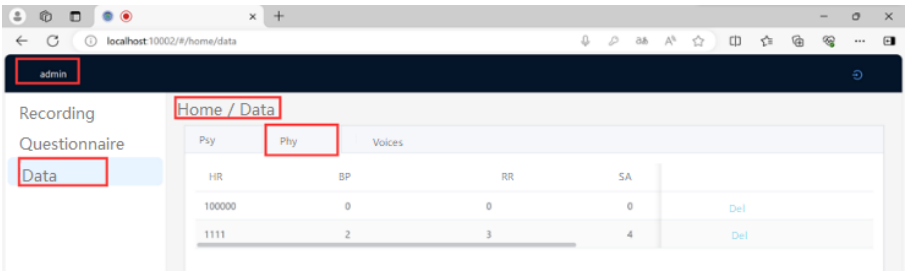

Fig. 7. Display of physiological indicators data

Psychological Indicator Management

In the psychological indicator management module, survey questionnaires can be set up, filled out, and displayed; Psychological indicators can be entered, modified, deleted, and queried, as shown in Fig.8-11.

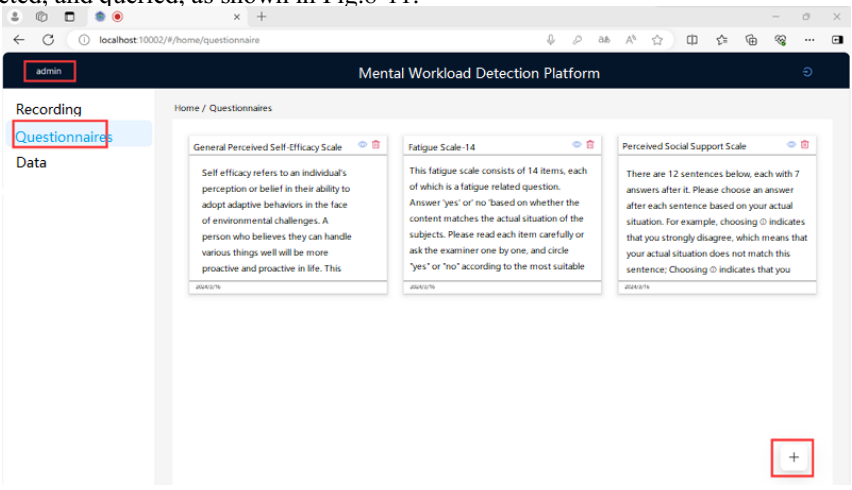

Fig. 8. Set up survey questionnaire

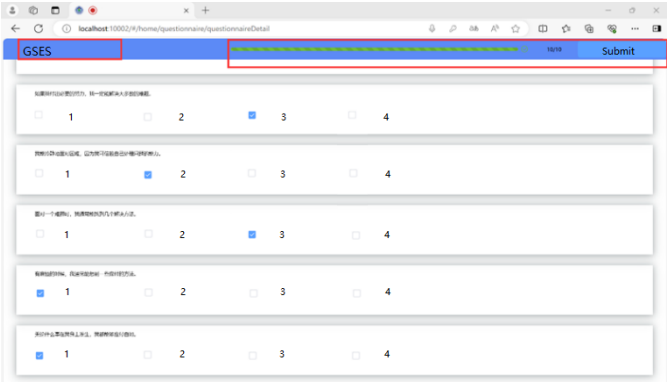

Fig. 9. Fill out the survey questionnaire

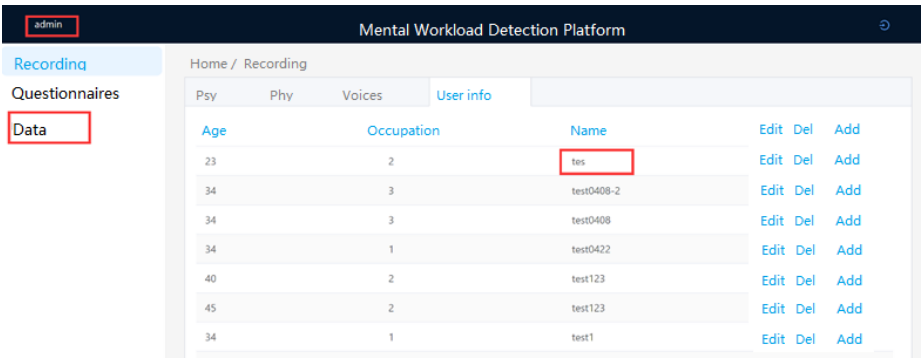

Fig. 10. Editing and deleting psychological indicators

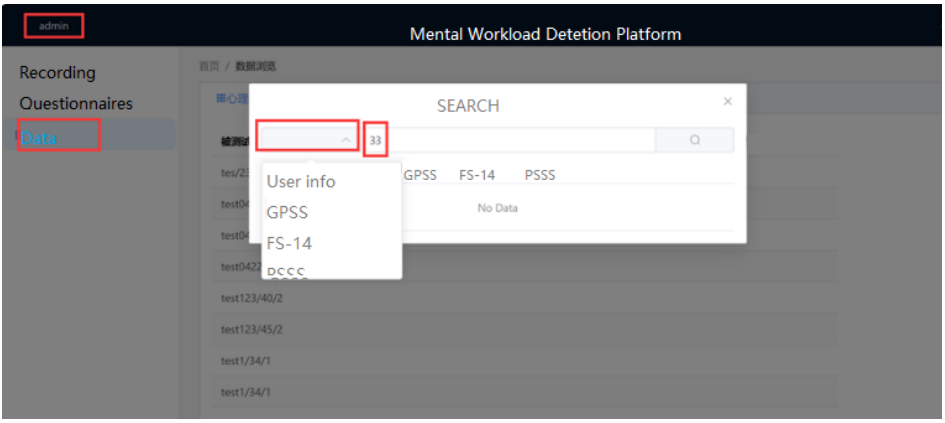

Fig. 11. Psychological index query

3.4 Mental Load Calculation

By using the subject's voiceprint information, physiological indicators, biochemical indicators, and psychological questionnaire data, and using machine learning algorithms, the subject's mental load can be calculated.

Click on 'Not Calculated' in the 'Mental Load' column to start calculating the mental load. After starting the calculation, cells that have not been calculated will become animations for transitions. After the calculation is completed, the animation ends and the cells automatically display the level of mental load, as shown in Fig.12-13.

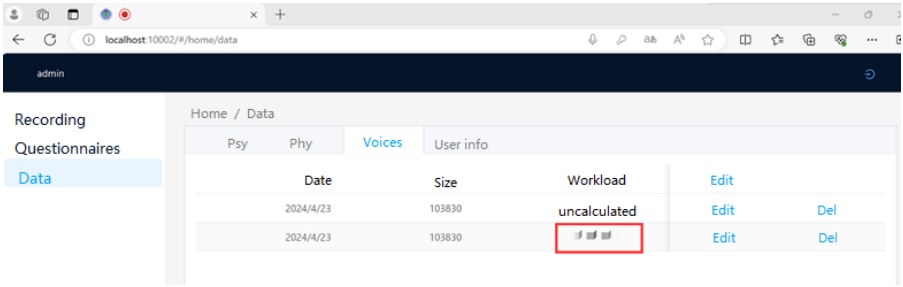

Fig. 12. Mental load calculation

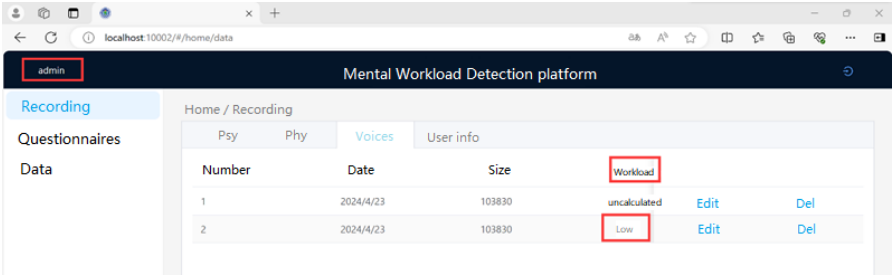

Fig. 13. Calculation results of mental workload

4. Conclusion

In this paper, we developed a platform which can quickly detect the mental workload of operators using their voice information, physiological information, biochemical information and psychological information. This platform uses machine learning algorithms with a detection accuracy of over 75%.

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