The Discriminative Model of Mental Fatigue Based on Comprehensive Parameter Analysis

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***Abstract*—In order to establish a quantitative model to measure mental fatigue of the human body, subjects electroencephalog-ram (EEG), electrocardiogram (ECG), and galvanic skin response (GSR) are collected through the designed experimental method. Through optimized parameters setting, subjects states of mental fatigue are comprehensively analyzed and evaluated. Moreover, the entropy weight method is used for analyzing and verifying the above three kinds of data including EEG, ECG and GSR as well as comparing the data acquired from the subjects with various mental fatigue states. Thus, a parametric model is constructed to determine the degree of mental fatigue.**

Keywords-fatigue detection; mental fatigue; physiological and biochemical index; parameter model

I. Introduction

Faced with increasing working pressure and suddenly accelerating life tempo, people often suffer from brain fatigue, fatigue and weakness and frequent negative emotions in modern society, which does great harm to individual's physical and mental health, and affects his or her work and life. Studies have indicated that the main cause of the phenomenon is psychological fatigue, also known as mental fatigue, mainly caused by long hours of demanding cognitive activity and had implications for many aspects of daily life [1]. Mental fatigue was likely to exert a negative impact on people's cognitive capacity, causing poor work or behavior performance and more errors [2, 3]. Therefore, it is of great practical significance to be aware of the harm of continued work after fatigue and to study the criteria for the determination of mental fatigue. The fatigue detection index exploration makes a great difference to quantitatively measure the state of brain fatigue in order to avoid excessive use of the brain and reduce work faults. Furthermore, it can be applied to prevent relevant diseases due to excessive use of the brain.

II. Research Status of Mental Fatigue

A. The Definition of Mental Fatigue

Fatigue is a complex physiological and psychological phenomenon caused by prolonged or repeated stimulation. Engaging in tedious work, or heavily responsible work with great pressure, people tended to produce depression, distraction and other negative emotions by excessive mental or physical activity [4]. Accordingly, the concept of mental fatigue was put forward, which serves as a phenomenon featuring decline of man's working function and working capacity owing to long hours of mental work, lack of sleep, or disturbed circadian rhythm in the work or learning process [5]. As a gradual and accumulated process, mental fatigue was closely linked to the increasing inertia, reduction of alertness and work efficiency, and psychological barriers with general symptoms such as tiredness, emotional repression and vigor decline. Meanwhile, it was affected by numerous factors, such as nutrition, health condition, environment, body vitality and recuperation period [6].

B. Research Status of Mental Fatigue

EEG is one of the widely used indexes for evaluating changes of the central nervous system. According to the level of workload, mental fatigue was classified into Active Fatigue and Passive Fatigue by Desmond, etc [7]. Active Fatigue was mainly caused by subjective efforts to engage in the high workload for a long time [8] while Passive Fatigue often resulted from tedious work or lack of stimulation under the condition of low load [7]. On the basis of the experimental method, Saxby as well as other people [9] studied the driving fatigue to verify the rationality of fatigue classification featuring Active Fatigue and Passive Fatigue. Moreover, it was interpreted that Active Fatigue often experienced physical discomfort and other symptoms because of energy exhaustion while Passive Fatigue generally led to all sorts of adverse consequences such as decreased work engagement, confusion and distraction. With the help of 32 leads in the Neuroscan system, Liu Jianping [10] chose 13 leads (including Fp1, Fp2, F3, F4, A1, A2, C3, C4, P3, P4, Fz, Cz, Pz), adopted a method of combining Kernel Principal Component Analysis with Hidden Markov Model which allowed to effectively reduce the dimension of feature vectors to distinguish the two mental states, and improved classification and recognition accuracy. Through 32-lead polysomnograph, selecting 13 leads (Fp1, Fp2, F3, F4, T1, T2, C3, C4, P3, P4, O1, O2, Cz), Sibsambhu Kar [11] considered Shannon entropy, second order Renyi entropy, third order Renyi entropy, Tasllis wavelet entropy and generalized Escort-Tsallis entropy as fatigue indexes. The different fatigue degree can be evaluated by means of relative energy of α wave and energy ratio of $((\alpha+\beta)/\delta)$.

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With the help of 32 leads in the Neuroscan system, Liu Jianping [12] selected 11 leads and extracted two kinds of complexity measures including basic scale entropy and permutation entropy of EEG before and after continuous long hours of mental work, drawing a conclusion that the basic scale entropy and the permutation entropy are capable of effectively reflecting change characteristics of EEG complexity before and after fatigue. By means of 25 leads in the PL-EEG Wavepoint system, Zhang Chong [13] carried out power spectrum analysis on EEG under two kinds of fatigue states, and extracted three sorts of characteristic parameters of the relative power, gravity frequency and the power spectrum entropy from each EEG rhythm. Thus, a conclusion was drawn that the three characteristic parameters sensitively reflect the transformation of physiological mental fatigue. Making use of 16 leads of a NicoletOne wearable device, Li Wei [14] calculated 12 characteristic parameters of energy ratio. Grey correlation degree analysis was adopted for measuring the best index of fatigue, and kernel principal component analysis played an important role in reducing the number of electrodes. Hence, on the basis of the EEG data of Fp2 lead and 01 lead, a fatigue assessment model was established. With the help of 64 leads in the Neuroscan ESI-128 system, Liu Hongjun [15] proposed a fatigue analysis method of EEG based on sparse representation for classification, which is capable of efficiently identifying the fatigue state with 90% accuracy. According to Wang Fuwang [16], portable Emotive equipment, F7 lead and F8 lead were selected and used. The α wave was extracted by wavelet packet transform to calculate its relative power spectrum. Finally, the EEG characteristics can be used to detect people's changes of the fatigue state.

III. THE RESEARCH PURPOSE OF MENTAL FATIGUE

Before Mental fatigue is likely to exert an ill impact on people's health, which often contributes to some symptoms such as physical breakdown, inattention, confusion, depression, low work efficiency and more errors at the same time. It not only reduces the efficiency of learning and work, but also has a certain effect on mental health. Long-term mental fatigue usually brings about depression, boredom, distraction and exhaustion to people, and even leads to mental diseases. Hence, it is of significant necessity to carry on the research on mental fatigue.

Research based on the EEG physiological signal characteristics is the mainstream research direction at present. The physiological signal characteristics were used for examining brain fatigue with high accuracy [17, 18] because the relatively objective physiological characteristics were able to directly reflect physiological characteristics changes of the human body, especially brain fatigue estimation based on EEG. Compared with other signals, EEG reflected the fatigue state of the brain, which were known as the most reliable and accurate indexes for fatigue detection and were widely recognized by medical and scientific communities [19, 20]. As a result, a new comprehensive analysis is conducted on EEG, ECG, and GSR to determine the state of brain fatigue by the application of a new comprehensive parameter analysis method in the experiment.

IV. DESIGN AND IMPLEMENTATION OF MENTAL FATIGUE MEASUREMENT EXPERIMENT

A. *Experimental Design*

The experimental methods in the study are designed and improved according to the generation mechanism of brain fatigue, and the brain is most prone to fatigue when it meets the following two conditions: firstly, carrying out simple and humdrum repetitive operation for a long time and secondly, going on work with high pressure for a long time.

According to the above principles, the specific experimental program is as follows: experimental subjects are involved in a mixed memory span test experiment for 50 minutes through a memory span tester (its initial figure is 3 digits). The experimental principle of the memory span test is that the experimental subjects need to remember the random number (starting from 3-digit number, then, 4-digit, 5-digit number and so on, and keeping sustained increase) on the screen. After numbers appears, the experimental subjects are expected to repeat the numbers in positive or reverse order respectively. And then the experimental subjects are asked to press the numbers on the small numeric keyboard as required. The experiment continues to be carried out until the experimental subjects offer a wrong answer. If the answer is wrong, the experiment will be started over and the cycle goes endlessly.

Before and after the experiment, the experimental subjects' EEG, ECG and GSR are recorded for 5 minutes respectively by BioCapture software on the BioCapture instrument with 250Hz of frequency in use.

B. *Introduction of Experimental Instruments*

(1) BioRadio-wireless data acquisition system

The wireless data acquisition system is capable of displaying, recording, and analyzing real-time physiological signals by adopting complicated wireless and miniaturized technologies. BioRadio physiological data acquisition system allows free movement of the data collection side which gathers data through the software installed on the computer. The wearable data collection end of BioRadio acquires the physiological signals by the sensor installed on the human body. The physiological signals are amplified, sampled and digitized, eventually transmitted to the computer terminal through Bluetooth wireless technology and are recorded. The physiological signals can be obtained and recorded by BioRadio matched with a variety of sensors in a frequency of 2.4-2.484GHz of Bluetooth band and within the range of about 100 feet. The physiological signals can be recorded in a frequency of 250Hz-5kHz of signal band, including electroencephalogram (EEG), electrocardiogram (ECG), electromyography (EMG), and electrooculogram (EOG).

Figure 1. Schematic diagram of BioRadio wireless data acquisition system

(2) Memory Span Tester

The tester is composed of a controller, a keyboard input box and the like. The panel to be tested is provided with a large 1-digit Nixie tube for displaying memory materials, and answer information is input to the keyboard. Especially the main test panel is equipped with a six-digit Nixie tube to display scores, errors, digits and time in real time.

(3) Main Technical Indexes

First, memory material: numbers from 0 to 9 are randomly combined into three to sixteen-digit groups, and there are four diverse groups of numbers in the same group. Moreover, there are two sets of codes in total.

Second, display mode of the memory material: the numbers are shown on the large Nixie tube for 0.7 second respectively in sequence.

Third, response mode: there are normal answer and converse answer.

Fourth, display mode of test results: the results are shown on the six-digit Nixie tube, and the tester can automatically count scores, errors, digits and time. If the fourteen digit groups have been tested or the experimental subjects make eight consecutive mistakes, the tester will buzzes to remind the main test panel to record the test result.

Fifth, time range: from 0 to 99 minutes and 59 seconds.

Figure 2. Schematic diagram of memory span tester

C. Specific Steps of Experiment

Firstly, experimental subjects' EEG, ECG and GSR in a calm state are recorded for 5 minutes by the BioCapture software before the experiment.

Secondly, the experimental subjects participants in the mixed memory span test for 50 minutes through the memory span tester. The experimental principle of the test is that the experimental subjects need to remember the random number (starting from 3-digit number, then 4-digit number, 5-digit number, and keeping continuous increase) on the screen. After the numbers appear, the experimental subjects are required to repeat the numbers in positive and reverse order. And then the experimental objects are asked to press the numbers on the small digital keyboard as required. The experiment continues to be carried out until the experimental subjects offer a wrong answer. If the answer is wrong, the experiment will be started over, and the cycle goes endlessly.

50 minutes later, the experimental subjects' EEG, ECG and GSR are also recorded after the experiment, according to the method implemented before the experiment.

Schematic Diagram of Experimental Measurement Points:

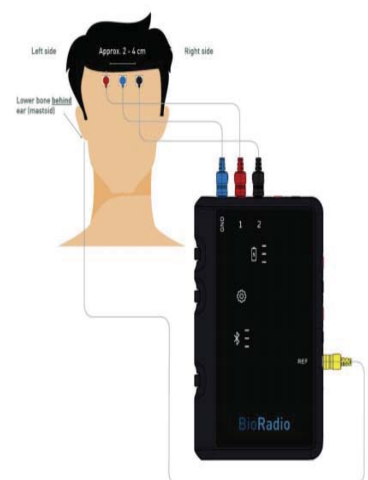

Figure 3. Schematic diagram of EEG and GSR measurement points

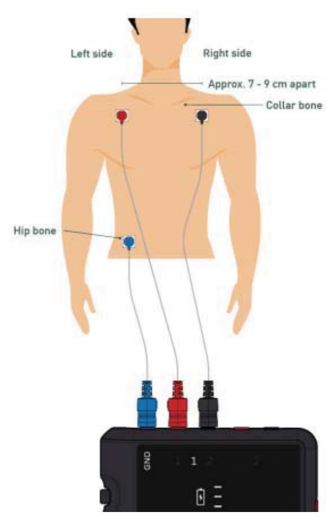

Figure 4. Schematic diagram of ECG measurement points

V. ANALYSIS OF EXPERIMENT DATA

A. Analysis Method of Experiment Data

The entropy weight method is adopted to analyze the data in the experiment because the entropy weight method meets the demands of the processing principle of the experiment data based on the variability of the same type of data before and after the experiment. According to the variation degree of each index, it calculates the entropy weight of each index with the help of information entropy, and then modifies the weight of each index through the entropy weight, thereby acquiring a relatively objective index weight.

The Principle of the Entropy Weight Method

The principle of the entropy weight method lies in quantification and totalization of information in each unit to be evaluated in evaluation. The entropy weight method weights every factor, which allows to simplify the evaluation process.

At first, the original data matrix can be determined as

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nm} \end{bmatrix}_{n\times m} \qquad (1)$$

Normalization is conducted on the matrix, wherein the ratios between the column vectors y_{ij} in Y matrix and the sum of all elements in the matrix are considered as the normalized result. The formula is as follows:

$$z_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \quad (j = 1,2,\cdots,m) \qquad (2)$$

where z_{ij} is an element in the normalized matrix. The operation formula is as follows in the determination of entropy weight values of evaluation indexes.

$$H(y_j) = -k\sum_{i=1}^{n} z_{ij} \ln z_{ij} \quad (j = 1,2,\cdots,m) \qquad (3)$$

where k is the adjustment coefficient, wherein $k = 1/\ln n$ and z_{ij} is the standardized value of the j^{th} index in the i^{th} evaluation unit.

The entropy values of the evaluation indexes are transformed into the weight values.

$$S = 1 - H(y_j); W = \sum_{j=1}^{\mathbf{m}} S; \mathbf{d}_j = S\times W \quad (j = 1,2,\cdots,m) \qquad (4)$$

where $0 \le d_j \le 1$ $\sum_{j=1}^{m} d_j = 1$ and the weight coefficient vector: $d = \left(d_1, d_2, \cdots, d_m\right)^T$.

B. Data Analysis

In the BioCapture software, EEG original data is processed with bandpass-inversechebyshev filter and then is exported. The average value of data in Fp1 and Fp2 channel are filled into the Table 1. ECG original data is processed with bandpass-inversechebyshev filter and then is exported. The average values of the data of the Fp1 and Fp2 channel are filled into the Table 1. GSR original data is processed with bandpass-inversechebyshev filter and then is exported. The average values of the data of the Fp1 and Fp2 channel are filled into the Table 1.

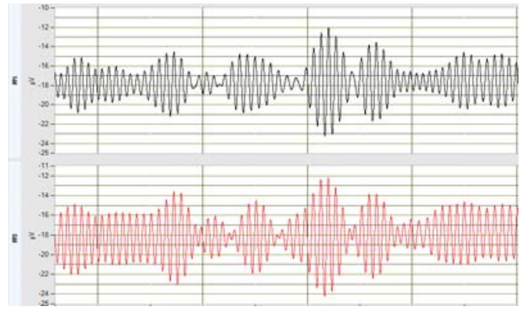

Figure 5. EEG before the test

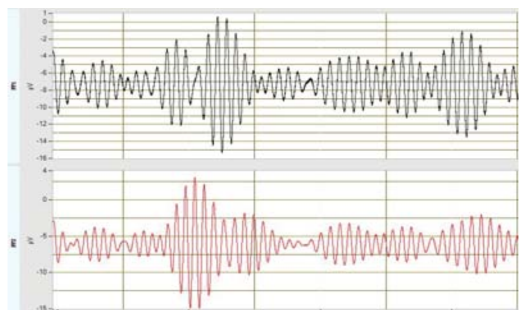

Figure 6. EEG after the test

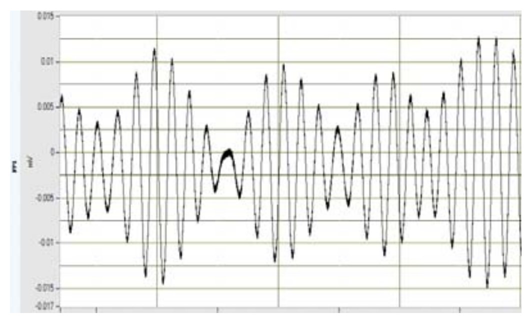

Figure 7. ECG before the test

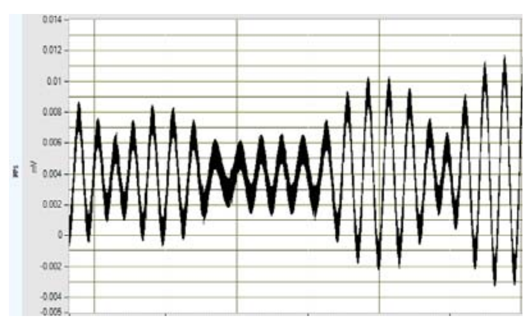

Figure 8. ECG after the test

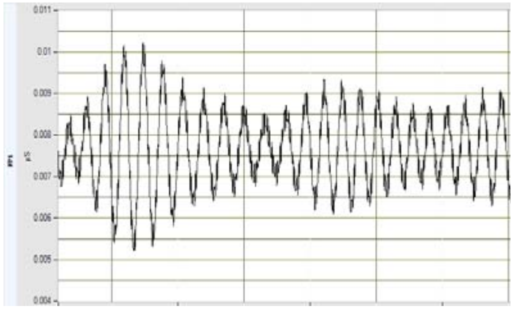

Figure 9. GSR before the test

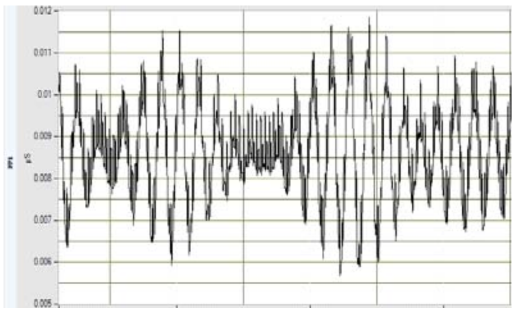

Figure 10. GSR after the test

TABLE I. RESULTS ANALYSIS OF EEG, ECG AND GSR BEFORE AND AFTER THE EXPERIMENT

	EEG/μv	*ECG/mv*	*GSR/μs*
Before the experiment	-17.65	-0.0007	0.0077
After the experiment	-7.31	0.004	0.0086
Variation	10.34	0.0047	0.0009

Before and after the experiment, three groups of data of the subjects are averaged. Mean variation of EEG is 10.34μv and mean variation of ECG is 0.0047mv. Mean variation of GSR is 0.0009μs.

According to the entropy weight method, matrixing processing is conducted on the three groups of data at first, wherein $Y = \{10.34, 0.0047, 0.0009\}$. Normalization processing is conducted on the Y matrix, thereby obtaining the matrix $Z_{ij} = \{0.99945, 0.00045, 0.0001\}$. Then the entropy weight values of the evaluation indexes are determined according to the following formula:

$$H(y_j) = -k\sum_{i=1}^{n} z_{ij} \ln z_{ij} \quad (j = 1,2,\cdots,m) \tag{5}$$

Obtain $H(y_j) = \{0.00006, 0.0044, 0.0054\}$. According to the following formula,

$$d_j = (1 - H_j) / \sum_{j=1}^{m} (1 - H_j) \quad (j = 1,2,\cdots,m) \tag{6}$$

Obtain $d_j = \{0.3343, 0.3331, 0.3326\}$.

Therefore, a fatigue detection model can be constructed on the basis of the above analysis:

$$P = 0.3343 \times E + 0.3331 \times C + 0.3326 \times S \tag{7}$$

Thereof, P stands for the fatigue value, E for EEG variation, C for ECG variation and S for GSR variation.

C. *Model Verification*

According to the above model, 4 sets of verification experiments are carried out with the following results:

TABLE II. THE RESULTS OF THE 4 SETS OF VERIFICATION EXPERIMENTS

Variable Quantity			**Model Parameter**	**Subjective State of Fatigue**	**The State of Fatigue Judged According to the Model**
EEG/μv	*ECG/μv*	*GSR/μs*			
4.6	1.3	0.0006	1.53841259	Mild Fatigue	Mild Fatigue
10.34	4.7	0.0009	3.45852691	Mild Fatigue	Mild Fatigue
11.11	7.8	0.0017	3.71557202	Moderate Fatigue	Moderate Fatigue
11.94	8.8	0.0020	3.99513848	Moderate Fatigue	Moderate Fatigue

Through the verification experiment, the fatigue values calculated by the model under diverse fatigue conditions are quite different. They are judged to be mild fatigue in the range of 0-3.45852691 and be moderate fatigue in the range of 3.45852691-3.99523826. By comparatively analyzing the two columns of the subjective state of fatigue and the state of fatigue judged according to the model, the fatigue state determined by the model indexes is correct within a large range.

D. *Conclusion*

The paper has comprehensively analyzed mental fatigue state by collecting and comparatively analyzing EEG, ECG and GSR. It calculates the entropy weight of each index with the help of the information entropy, and then modifies the weight of each index through the entropy weight, thereby obtaining a relatively objective index weight. Thus, the model capable of conducting fatigue determination through number values is built. Through the collection of data values of EEG, ECG and GSR under different states in the experiment, the degree of mental fatigue can be accurately detected by the calculation of the variability of the data.

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