Drowsiness Detection Based on Wavelet Analysis of ECG and Pulse Signals

Aihua Zhang[1,2]
[1]College of Electrical and Information Engineering
Lanzhou University of Technology
Lanzhou, China

Fenghua Liu[1,2]
[2]Key Laboratory of Gansu Advanced Control for Industrial Processes
Lanzhou, China

Abstract—**The purpose of this study is to explore the impact of drowsiness state on ECG and pulse signals and seek a more convenient and effective method for detecting drowsiness. Different frequency bands of ECG and pulse signals are selected to calculate the wavelet packet energy and wavelet entropy based on wavelet analysis. The results show that the wavelet packet energy of ECG whose frequency ranges are from 7.8Hz to 23.4Hz and from 23.4Hz to 62.5Hz respectively, and the wavelet entropy of pulse signal whose frequency range is from 0.1Hz to 31.25Hz are significantly decreased (*p*<0.01) in the drowsiness state compared with that in the waking state. The accuracy rate of classification for these three features can reach 100% by using Support Vector Machines (SVM).**

Keywords-drowsiness detection; ECG; pulse signal; wavelet analysis; support vector machine (SVM)

I. INTRODUCTION

Drowsiness is a state which is accompanied by physical fatigue or mental fatigue. Drowsiness will greatly reduce the person's alertness, decision-making ability and memory [1], which may cause unimaginable consequences especial for many dangerous operation fields and high accuracy requirement working environment, such as driving, aerospace, surgical operation, and high-altitude-risk operations and so on. Therefore, it has important scientific significance and urgent practical needs to realize the accurate detection of drowsiness in real-time.

The research of drowsiness can be traced to the 1950s, mainly in the states of awake and drowsiness [2,3]. During the 1980s, with the frequent occurrence of accidents caused by the drowsiness, how to achieve objective detection of drowsiness is widely concerned by domestic and foreign scholars [4,5]. Currently, there are three main ways to realize the drowsiness detection: The first method is based on face detection. For example, eyelid movement, blink frequency and duration [6,7]. This method is non-contact without affecting the normal activities of subjects, but the accuracy is low, and it is easy to be influenced by environmental background as well as subjects behavior (turned down, bow, et al). The second method is on the base of biomarker detection. Some of the starch in saliva and some of the protein content in blood will change when people is in the sleepy state [8,9]. This method has high accuracy, but the analysis process is more complex and difficult to achieve real-time monitoring. The third one is on base of physiological signal detection, including EEG, ECG, pulse, EOG and EMG [10-13].

Because of the high precision of the method based on physiological signal detection and the rise of non-invasive electrode, the physiological signal has became the most widely method for drowsiness detection. Lin had distinguished the alert and drowsiness states with EEG power in alpha and theta bands [14]. Vinayak did bispectrum analysis of EEG for 42 patients, and found that S_B and ζ_{20} were significant difference in waking and drowsiness states [15]. However, the EEG acquisition will cause inconvenience to staff. Therefore, it has limitation in practical applications. In reference [16], the researchers used the R wave peak and the R-R interval of ECG to estimate fatigue. Li detected driver's drowsiness state by power spectral analysis of heart rate variability [17]. These studies are mainly based on the ECG amplitude signal (ECG signal) or heart rate signal (HRV signal), they located the R wave first and then did the correlation analysis, the results are easy to be affected by the positioning detection of R waves. In order to improve the computing speed and reduce interference of the signal frequency band without contribution, we divide ECG and pulse signals into three frequency bands with wavelet transform. Then the frequency band which is most relevant to the drowsiness state is found in hope of laying a foundation for drowsiness detection and assessment.

II. MATERIALS AND METHODS

A. Date acquisition

The self-assessment form of sub-health state (the score should be lower than 45 points) and the self-assessment form of Pittsburgh Sleep Quality Index (the score should be lower than 7 points) were used to select the appropriate subjects. In the study, fifteen male college students were selected as subjects. All of them were in good health, and had good sleep quality and nap habit. Insure that none of them had taken any drugs or drinks before the experiment which would affect the ECG and pulse signals. The EEG, ECG and fingertip pulse signals were acquired by the biological recorder MP150 with acquisition software called Acqknowledge4.0. The experiment of data collection was divided into two periods according to the body's normal circadian rhythm: The first period was between

This study was supported by grants (No. 30670529 and No. 11072099) from the National Natural Science Foundation of China

9:00 and 10:30, which was considered as the waking state, because subjects were in the most sober state during this period; the second was between 13:00 and 14:00 at the same day, which was treated as the drowsiness state. The sampling frequency was 1000Hz. After the experiment, the researchers determined the drowsiness state period by EEG according to the change of EEG by R&K sleep boundary standards (α rhythm is the main wave of EEG in the waking state, but in the drowsiness state α rhythm is below 50% and θ rhythm gradually increased) [18], then the ECG and pulse signals in the same period of time were selected for study.

B. Date preprocessing

Human physiological signal is very weak. It is vulnerable to be affected by the following three kinds of noise during the acquisition process: Baseline drift, whose frequency is below 0.1Hz; Power frequency interference with frequency 50Hz; EMG interference with wide frequency range. The present study uses wavelet multi-resolution analysis to remove the noise of ECG and pulse signals because of its good time-frequency properties and flexibility. Through repeated tests, finally the wavelet function 'sym8' was used to decompose the original signal into 12 layers, then the approximate signal of the 12^{th} layer was considered as the baseline drift.

The original ECG signal is shown in Fig. 1(a). We decomposed the original signal into 12 layers. A_i(i=1,2,…,12) represents the reconstructed approximate signal of layer i, D_i(i=1,2,…,12) represents the reconstructed detail signal of layer i. After removing the baseline drift and high frequency interference the ECG signal is defined as $S=A_3-A_{12}$, and its frequency range is from 0.1Hz to 62.5Hz.Then the soft-threshold method is used to eliminate the frequency interference about 50Hz. The ECG signal after removing the noise is shown in Fig. 1(b).

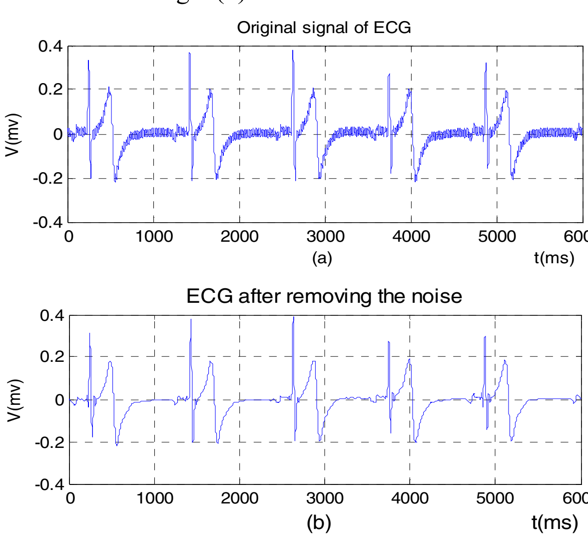


Figure 1. ECG preprocessing (a) Original signal of ECG; (b) ECG after removing the noise

The original pulse signal is shown in Fig. 2(a). The de-noising method is similar as that used for ECG. The pulse signal after removing the noise is defined as $L=A_4-A_{12}$, as shown in Fig. 2(b), its frequency range is from 0.1Hz to 31.25Hz. Because the pulse signal does not contain the 50Hz frequency interference, so there is no need on the second noise reduction.

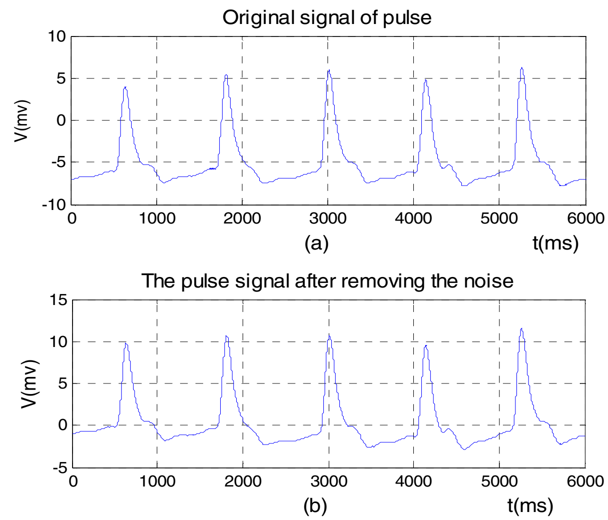


Figure 2. Pulse signal preprocessing (a) Original signal of pulse; (b) The pulse signal after removing the noise

III. FEATURE EXTRACTION

60000 date points (one minute) are selected for feature extraction in waking and drowsiness states respectively. In order to enhance the computing speed and avoid unnecessary frequency signal which may affect the results of the study, the wavelet function 'db3' is used to decompose the ECG and pulse signals. Then the ECG and pulse signals whose frequency range are 0.1-7.8Hz, 7.8-23.4Hz and 23.4-62.5Hz respectively obtained. The wavelet packet energy and wavelet entropy are calculated for each sub-band and the signal after removing the noise in waking and drowsiness states (the frequency range of ECG is from 0.1Hz to 62.5Hz, the frequency range of pulse is from 0.1Hz to 31.25Hz). The specific steps are as following:

Step1：Decompose the de-noised ECG and pulse signals (S and L) into 7 layers using 'db3' wavelet function and extract signal characteristics about the first six nodes in layer 7, the frequency ranges of the first six nodes are shown in Tab. I.

TABLE I. FREQUENCY RANG OF THE FIRST SIX NODES IN LAYER 7

Node	**Frequency (Hz)**
(7,0)	0-3.9
(7,1)	3.9-7.8
(7,2)	7.8-11.7
(7,3)	11.7-15.6
(7,4)	15.6-19.5
(7,5)	19.5-23.4

Step2 : Calculate wavelet packet energy and wavelet entropy [19,20].

We suppose that the de-noised signal $S(n)$ or $L(n)$ is a signal with limited energy, n=60000. Decompose $S(n)$ or $L(n)$ into J layers using the wavelet packet (in this paper, J=7), W_j^p (j=0,1,…, J; p=0,1,…,2^j-1) means p sub-space of layer j. B_j^p denotes the set of orthogonal basis vectors of the subspace. The coefficient of wavelet packet in this sub-space can be defined as:

$$d_j^p = \{d_j^p(k) \mid k = 1,2,...,K_j^p\}$$

Wavelet packet basis functions are orthogonal to each other, so the energy of the signal subspace can be expressed as:

$$E_{j,p} = \sum_k |d_j^p(k)|^2 \tag{1}$$

The energy of the entire signal can be expressed as:

$$TE_j = \sum_p E_{j,p} \tag{2}$$

Probability for the wavelet packet energy in each subspace can be modified as:

$$P_{j,p} = E_{j,p} / TE_j \tag{3}$$

Similar to the Shannon entropy in information theory, the definition of the wavelet entropy is:

$$WE = -\sum_{p=0}^{2^j-1} P_{j,p} \ln P_{j,p} \tag{4}$$

In this article the wavelet packet energy in each band are calculated as follows:

$$\begin{gathered} E1 = E_{7,0} + E_{7,1} \\ E2 = E_{7,2} + E_{7,3} + E_{7,4} + E_{7,5} \\ E3 = TE_7 - E1 - E2 \end{gathered} \tag{5}$$

For ECG, $E1$ represents wavelet packet energy of 0.1-7.8Hz signal; $E2$ represents wavelet packet energy of 7.8-23.4Hz signal; $E3$ represents wavelet packet energy of 23.4-62.5Hz signal; TE_7 represents wavelet packet energy of 0.1-62.5Hz signal; WE represents wavelet packet energy of 0.1-62.5Hz signal. For pulse signal, $E3$ represents wavelet packet energy of 23.4-31.25Hz signal; TE_7 represents wavelet packet energy of 0.1-31.25Hz signal; WE represents wavelet packet energy of 0.1-31.25Hz signal, $E1$ and $E2$ are defined as the same as ECG.

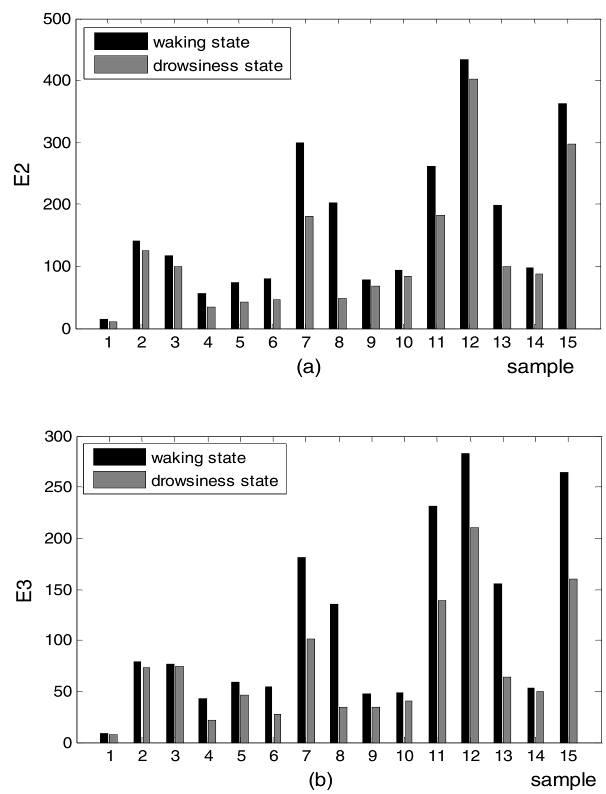
IV. RESULT

We did t-test for $E1$, $E2$, $E3$, TE_7 and WE for both ECG and pulse signals which were extracted from 15 subjects in waking and drowsiness states, the results are shown in Tab. II.

TABLE II. t-TEST RESULTS OF ECG AND PULSE CHARACTERISTICS IN TWO STATES

	Features	***p***
ECG	$E1$	0.1205
	$E2$	0.0015
	$E3$	0.0015
	TE_7	0.0015
	WE	0.4950
Pulse	$E1$	0.1518
	$E2$	0.0947
	$E3$	0.0523
	TE_7	0.1480
	WE	6.7915×10^{-4}

The results show that $E2$, $E3$ and TE_7 of ECG and WE of pulse signal changed significantly ($p<0.01$), the rest of the characteristic parameters had no obvious changes ($p>0.05$). For ECG, $E2$ and $E3$ had the same t-test results as TE_7 (p=0.0015). Fig. 3 shows the column charts of $E2$, $E3$ and TE_7 in waking and drowsiness states.



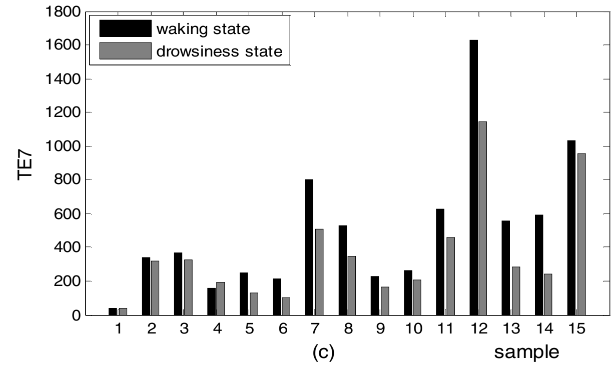


Figure 3. The column chart of ECG characteristics (a) ECG wavelet packet energy whose frequency is 7.8-23.4Hz (b) ECG wavelet packet energy whose frequency is 23.4-62.5Hz (c) The total wavelet packet energy of ECG

It can be seen from the Fig. 3(a) and Fig. 3(b), both $E2$ and $E3$ declined in the drowsiness state compared with the waking state for all samples. In Fig. 3(c), the total wavelet packet energy (TE_7) decreased except the fourth sample. For the fourth sample, the total wavelet packet energy might be impacted by P / T wave or the rest of the frequency bands. So it did not change significantly. The results had demonstrated that $E2$ and $E3$ can reflect drowsiness state better compared with TE_7.

In addition, in the drowsiness state, the wavelet entropy of pulse signal in all samples decreased, as shown in Fig. 4. The t-test was carried for wavelet entropy in the two states, the p value was 6.7915×10^{-4}. This indicated that the wavelet entropy of pulse signal changed significantly in the drowsiness state, and it could be used as indicator of drowsiness detection.

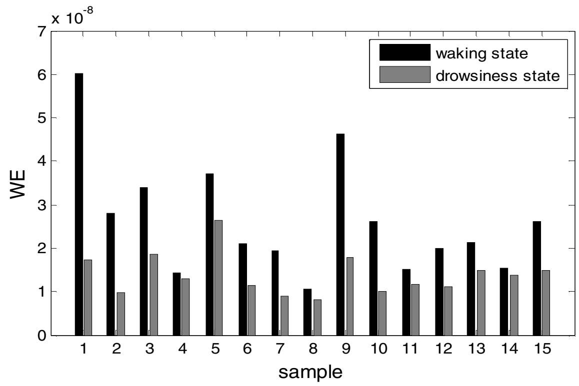


Figure 4. Column chart of pulse wavelet entropy

In this paper, $E2$, $E3$ and TE_7 of ECG and WE of the pulse signal were treated as the feature vectors. The SVM was used to classify these features. The classification results were shown in Tab. III.

Set the number of data was n_0 and n_1 separately in waking and drowsiness states. In this paper, $n_0= n_1=15$, the number of sample data was N, $N=2\times n_0=30$, the number of circuit training was m, $m=n_0=15$. We selected k date as test set randomly, $k=N/m=2$ (Equivalent to improve the leave-one, retain two data as test set each time), and defined l as training data, $l=N-k=28$. For 15 times training cycles, the number of training data was $(N-k)\times m=420$, the number of testing data was $k\times m=30$, this method could improve the disadvantage of the small sample. The selected RBF kernel function was:

$$K(x_i, x_j) = \exp[-(\frac{1}{2\sigma^2} \| x_i - x_j \|^2)] \tag{6}$$

For two classification tasks, the training set was defined as: $\{(x_1,y_1),(x_2,y_2),\ldots,(x_N,y_N)|x_i \in R^n, y_i \in \{1,2\}, i=1,2,\ldots,N\}$. In which, x_i was defined as the input vector, y_i could be considered as the type of signs, corresponding to waking and drowsiness state. Through the grid optimization, the penalty factor C and kernel parameter σ was set to 0.25 and 0.0625. The decision-making function can be defined as:

$$g(x) = \sum_{i=1}^{N} \lambda_i y_i K x_i^T x + b \tag{7}$$

In equation (7), b is the threshold of classification, λ_i is the Lagrange multiplier, the general form of discriminate output of the classifier is defined as: $q(x) = \{\begin{matrix} 1, g(x) \ge 0 \\ 2, g(x) < 0 \end{matrix}$, $q(x)$ is the category of a feature belongs to [21].

TABLE III. CLASSIFICATION RESULTS OF SVM

Features	TE_7	E2	E3	WE
SVM(%)	96.6667	100	100	100

(TE_7: the total wavelet packet energy of ECG, $E2$: the wavelet packet energy of ECG whose frequency is 7.8-23.4Hz, $E3$: the wavelet packet energy of ECG whose frequency is 23.4-62.5Hz, WE: the wavelet packet energy of pulse signal)

The results showed that these four features in waking and drowsiness states could be clearly distinguished, and the recognition rate of $E2$ and $E3$ could reach up to 100%, which were higher than TE_7. Therefore, selecting interested frequency band signal for feature extraction not only improved the calculation speed, but also improved the detection accuracy.

V. DISCUSSION AND CONCLUSION

In this study, we extracted features of ECG and pulse signal from 15 subjects and analyzed them. The results showed that the wavelet packet energy of ECG whose frequency are 7.8-23.4Hz and 23.4-62.5Hz could better reflect the drowsiness state than the total wavelet packet energy of ECG, because the QRS complex is mainly concentrated in these two bands, and drowsiness can lead to QRS changes, the total energy of wavelet packet may be impacted by P/T wave or other frequency band signal. Accordingly, select interested frequency band signal for drowsiness detection not only improve the calculation speed, but also can improve the detection accuracy. In addition, the wavelet entropy of pulse signal was significantly lower in the drowsiness state. Wavelet entropy is a measure of the signal level of uncertainty or confusion. The entropy is smaller, the signal changes more law. Therefore, the wavelet entropy of pulse signal can also serve as indicator of drowsiness detection. The accuracy rate of classification for these three kinds of features can reach 100% by using SVM. Wavelet packet energy of ECG and wavelet entropy of pulse signal can be calculated directly by using wavelet transform, without detected R-wave of ECG or P-wave of pulse signal, significant saving the processing time. The number of sample involved in this paper is limited. Therefore, there is a certain gap for the practical application and the division of the band is not detailed enough. In future research, we will add more samples and find more effective methods for drowsiness detection and identification. Drowsiness detection has important scientific significance and urgent practical needs in the field of fatigue operations.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China under grant 30670529 and 11072099.

REFERENCES

[1] J. Krajewski, A. Batliner, and M. Golz, “Acoustic sleepiness detection: Framework and validation of a speech-adapted pattern recognition approach,” Behav. Res. Methods., vol. 41, pp. 795-804, January 2009.

[2] M. A. Carskadon, W. C. Dement, and M. M. Mitler, “Guidelines for the multiple sleep latency test (MSLT): a standard measure of sleepiness,” Sleep, vol. 9, pp. 519-524, 1986.

[3] R. J. Cole, D. F. Kripke, and W. Gruen, “Automatic sleep/wake identification from wrist activity,” Sleep, vol. 15, pp. 461-469, 1992.

[4] M. Vennelle, H. M. Engleman, and N. J. Douglas, “Sleepiness and sleep-related accidents in commercial bus drivers,” Sleep Breath, vol. 14, pp. 39-42, 2010.

[5] B. V. Willem and M. Z. David, “Preventing drowsiness accidents by an alertness maintenance device,” Accident Analy. Prev., vol. 31, pp. 199-211, May 1999.

[6] S. Vitabile, A. D. Paola, and F. Sorbello, “A real-time non-intrusive FPGA-based drowsiness detection system,” J. Ambient Intell. Human Comput., vol. 2, pp. 251-262, March 2011.

[7] D. H. Liu, P. Su, and Y. Q. Xiao, “Drowsiness detection based on eyelid movement,” Educ. Technol. Comput. Sci., vol. 2, pp. 49-52, April 2010.

[8] S. T. Harding, M. Sorenson, and L. Jason, “The associations between basal salivary cortisol and illness symptomatology in chronic fatigue syndrome,” J. Appl. Biobehav. Res., vol. 13, pp. 157-180, July 2008.

[9] J. Banasik, H. Williams, and M. Haberman, “Effect of lyengar yoga practice on fatigue and diurnal salivary cortisol concentration in breast cancer survivors,” J. Am. Acad. Nurse Prac., vol. 23, pp. 135-142, March 2011.

[10] Y. Lin, H. Leng, and G. Yang, “An Intelligent Noninvasive Sensor for Driver Pulse Wave Measurement,” IEEE Sens. J., vol. 7, pp. 790-799, May 2007.

[11] B. L. Lu, J. W. Fu, and L. C. Shi, “A Survey on EEG-based Vigilance Analysis and Estimation,” Chinese J. Biomed. Eng., vol. 28, pp. 590-595, 2009.

[12] R. K. Sinha, “Artificial Neural Network and Wavelet Based Automated Detection of Sleep Spindles, REM Sleep and Wake States,” J. Med. Syst., vol. 32, pp. 291-299, February 2008.

[13] M. Akin, M. B. Kurt, and N. Sezgin, “Estimating vigilance level by using EEG and EMG signals,” Neural Comput. Appl., vol. 17, pp. 227-236, May 2007.

[14] C. T. Lin, “An EEG-based subject and session-independent drowsiness detection,” Neural Networks, vol. 1, pp. 3448-3454, 2008.

[15] V. Swarnkar, U. Abeyratne, and C. Hukins, “Objective measure of sleepiness and sleep latency via bispectrum analysis of EEG,” Med. Biol. Eng. Comput., vol. 48, pp. 1203-1213, November 2010.

[16] B. Yilmaz, M. H. Asyali, and E. Arikan, “Sleep stage and obstructive apneaic epoch classification using single-lead ECG,” BioMed. Eng., vol. 9, pp. 39-52, 2010.

[17] Z. Y. Li and K. M. Jiao, “Car drivers driving in the process of heart rate variability power spectral analysis,” J. Biomed. Eng., vol. 22, pp. 574-576, 2003.

[18] W. O. Tatum, A. M. Husain, and S. R. Benbadis, Handbook of EEG Interpretation, New York: Demos Medical Publishing, 2007.

[19] G. S. Zhong, J. Li, and K. Zhao, “Structural safety criteria for blasting vibration based on wavelet packet energy spectra,” Min. Sci. Tech, vol. 21, pp. 35-40, January 2011.

[20] S. Mallat, “A Wavelet Tour of Signal Processing,” Beijing: China Machine Press, 2002.

[21] C. Zhang, C. X. Zheng, and X. L. Yu, “Evaluation of mental fatigue based on multipsychophysiological parameters and kernel learning algorithms,” Chinese Sci. Bull., vol. 53, pp. 1835-1847, June 2008.