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Design of Driving Fatigue Detection System Based on Hybrid Measures Using Wavelet-packets Transform

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Abstract — **With the rapid development of urbanization and motorization in China, fatigue driving has become an increasingly serious road traffic problem. Driving fatigue affects drivers' alertness, decreasing an individual's ability to operate a vehicle safely and increasing the risk of human error that could lead to fatalities, which have been widely recognized as critical safety issues that cut across all modes in the transportation industry. In this paper, firstly, with a virtual driving system we developed, driving simulation experiments were designed to collect subjects' electroencephalogram (EEG) signals and mental fatigue data. To detect drivers' mental state in real time, wavelet-packets transform (WPT) was selected to extract continuous features; then, the subjective evaluation combined with video monitoring was used to evaluate driver's mental state in experiment accurately. At last, with fatigue feature as the input and fatigue state as the output, driving fatigue detection model can be constructed by classification methods. In this paper, Support Vector Machine (SVM) was used to build driving fatigue detection model to estimate mental fatigue state of EEG signal features, and the binary classification accuracy can be achieved up to 88.6207%.**

Index Terms -- **Driving fatigue, EEG, WPT, Stanford Sleepiness Scale, facial features, SVM.**

I. Introduction

Mental fatigue is a common phenomenon in our daily life, and is defined as a state of cortical deactivation, which reduces mental performance and decreases alertness [1]. According to a report of the American National Highway Safety Traffic Administration (NHSTA), driver's mental fatigue was believed to account for 20-30% of all traffic accidents [2]. The NHTSA conservatively estimates that 100, 000 police-reported crashes are caused by drowsy drivers each year. That is, about 1.5% of all crashes which is the reason why more and more researches are made to build automatic detectors of this dangerous state.

The history of drowsy-driver research can date back to the 1950s, beginning with studies on aircraft pilots [3]. In the 1990s, driver fatigue began to be recognized as a major concern to both automotive industry and public-safety agencies. So far, driving fatigue detection measures include subjective evaluation method and objective evaluation method. And objective evaluation method can be classified in terms of their specific techniques [4][5][6]. References [5] and [7] have summarized the detection techniques based on: 1) physiological signals, including pulse rate and EEG; 2) physical changes, including changes of head position, eye-closure rate, and eyelid movement; 3) driver–vehicle data, including steering angle, throttle/brake input, and speed. EEG signal contains abundant information and has the ability to reflect driver's mental status, which is the reason EEG signal is recognized as the most accurate, the objective method to detect driving fatigue.

Biomedical signals are especially useful to collect detailed information of the body's response during the drowsiness cycle. The information that they provide goes beyond the usual systems that just detect risky situations (degraded driving performance or visual symptoms of lack of attention), and can potentially anticipate the onset of sleepiness. The major drawback of the techniques based on biomedical signals are that they require placing sensors directly on the subject's body, although there are some attempts to record them indirectly, through non-intrusive systems that could be used in real vehicles [8].

An EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. In healthy adults, the amplitudes and frequencies of such signals change from one state of a human to another, such as wakefulness and sleep. The characteristics of the waves also change with age. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called α, θ, β, δ, and γ [9]. Different studies have been reported on driver drowsiness detection including methods identifying physiological associations between driver drowsiness/fatigue and the corresponding patterns of the electroencephalogram (EEG) (brain activity), electrooculogram (EOG) (eye movement), and electrocardiogram (ECG) (heart rate) signals [10][11][12][13][14]. Most of these studies reported that the physiological approach to drowsiness detection can provide very accurate results as strong correlation between these signals and the driver's cognitive state was found in many studies [15][16]. Specifically, many of these studies suggested that the change in the cognitive state can be associated with significant changes in the EEG frequency bands, such as delta (δ: 0~4 Hz), theta (θ: 4~8 Hz), alpha (α: 8~13Hz), and beta (β: 13~20 Hz) [17][18], or their combinations [19][20], and with changes in the eyelid parameters extracted from the EOG [21].

This paper is organized into the following sections: After

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a brief introduction on the background and motivation in Section I, Section II presents the EEG signal processing theory, which includes signal preprocessing, feature extraction and pattern classification, Section III presents the experimental design, which includes a detailed explanation of experimental device and objectives, driving simulation environment, and experimental process. Then, Section IV presents the driving fatigue detection model. The application of the driving fatigue detection model to detecting drowsy drivers was discussed in Section V. This will be followed by some detailed simulated experiments and the corresponding data. Section VI summarizes the study and provides future research ideas.

II. EEG Signal Processing Method

A. Data Preprocessing

Human's EEG signal is a kind of weak electrical signal. Without processing, we will get EEG signals with a variety of noise interference. Signals recorded from electrodes will be mixed with noises such as: power frequency interference, blinks, eye movement artifact, ECG artifact, etc. Therefore, in order to meet the requirements of data analysis and processing, we should do noise reduction processing to original EEG signal at first.

The EEG signal acquisition devices are EMOTIV EPOC that can remove power frequency interference noise and ECG artifact automatically, so these noise signals will no longer be considered in EEG signal preprocessing section.

B. Feature Extraction

Biomedical signals usually consist of brief high-frequency components closely spaced in time, accompanied by long lasting, low frequency components closely spaced in frequency. Wavelets are considered appropriate for analyzing such signals as they exhibit good frequency resolution along with finite time resolution; the first to localize the low-frequency components and the second to resolve the high-frequency components [22].

The wavelet-packets transform (WPT) was introduced by Coifman [23] by generalizing link between multi-resolution approximations and wavelets. The WPT may be thought of as a tree of subspaces, with $\Omega_{0,0}$ representing the original signal space, i.e., the root node of the tree. In a general notation, the node $\Omega_{j,k}$, with j denoting the scale and k denoting the subband index within the scale, is decomposed into two orthogonal subspaces: an approximation space $\Omega_{j,k} \rightarrow \Omega_{j+1,2k}$ plus a detail space $\Omega_{j,k} \rightarrow \Omega_{j+1,2k+1}$. Divide the signal into three layers with wavelet packet decomposition, the subspaces are represented as figure 1. This is done by dividing the orthogonal basis $\{\phi_j(t-2^j k)\}_{k\in Z}$ of $\Omega_{j,k}$ into two new orthogonal bases $\{\phi_{j+1}(t-2^{j+1}k)\}_{k\in Z}$ of $\Omega_{j+1,2k}$ and $\{\psi_{j+1}(t-2^{j+1}k)\}_{k\in Z}$ of $\Omega_{j+1,2k+1}$, where $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are the scaling and wavelet functions, respectively, that are given in [24]as (1) and (2) shows:

$$\phi_{j,k}(t) = \frac{1}{\sqrt{|2^j|}}\phi(\frac{t-2^j k}{2^j}) \tag{1}$$

$$\psi_{j,k}(t) = \frac{1}{\sqrt{|2^j|}}\psi(\frac{t-2^j k}{2^j}) \tag{2}$$

Where, the dilation factor 2^j, also known as the scaling parameter, measures the degree of compression or scaling. The location parameter $2^j k$, also known as translation parameter, determines the time location of the wavelet.

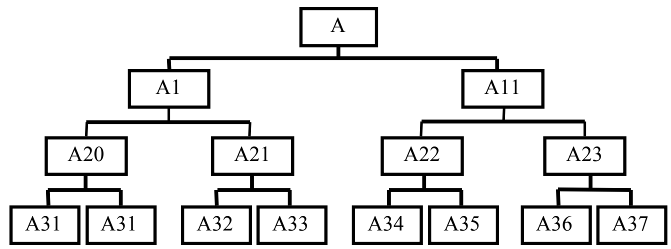

Fig.1. Signal 3-subspaces divided with wavelet packet decomposition.

There are many studies about how EEG signal will change when fatigue driving happens, and it's generally considered that slow wave gradually increase and fast wave gradually reduce when drivers' mental state change from clear-headed to fatigue. So the index of fatigue state F can be energy ratio of wave β and slow wave, as (3) shows:

$$F = \frac{E_\beta}{E_\alpha + E_\theta + E_\delta} \tag{3}$$

Since the size of wavelet packet decomposition coefficients show the strength of EEG signal, the application of expressing the sum of square of wavelet packet decomposition coefficient as energy of signals is reasonable. We assume d_j^q is the j^{th} level and the q^{th} node of wavelet packet decomposition coefficient, so the energy of reconstructing signal is as follow:

$$E_j^q = \sum_k (d_j^q(k))^2 \tag{4}$$

According to (3) and (4), the value of F can be obtained.

C. Pattern Classification

A support vector machine (SVM) constructs a hyperplane or set of hyperplanes in a high-or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space [25].

SVM is good at dealing with sample data that are linear inseparable by Slack Variables and Kernel Function. The

SVM classifier is very concise and it need small amount of sample information, which makes it good to bring no trouble to storage and computing.

III. Design of Expeiment

A. Experimental Device

In this paper, we use wireless EEG scanners from EMOTIV. Based on the latest neurobiological science, EMOTIV developed the new Brain-computer Interaction (BCI) device EMOTIV EPOC. EMOTIV EPOC is a wireless helmet with a sampling frequency of 128HZ. EMOTIV EPOC has 14 sensors, and they are set to international standard positions, which are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. With these sensors, we can detect EEG signals, so as to control and affect other equipments with human thought, expression and emotion.

B. Experimental Objectives

We have fifteen subjects who are undergraduate students in school and they are all male aged between 20 to 24 years old. All subjects have no sleep problems and psychological problems. They get enough sleep before the experiment and they are forbidden to take coffee, tea and mental drugs or eat excitant food until the experiment is over.

C. Virtual Driving System

This environment is consisted of an automobile founded by a Physics Car module in VIRTOOLS and highways with surrounding scene by 3DS MAX. In respect that there is no requirement for the details of automotive body in the driving simulation system, we focus on making cars with real physical effect. Based on modifying the Physics Car module, we highlight four simulation wheels in VIRTOOLS, two wheels act as power output, and the other two wheels as control output of direction.

Fig.2. Virtual driving system for driving fatigue detection.

This paper turn potency dimension and rotation angle into floating point numbers from external devices. Because the transformation between them is a linear relationship, we can easily convert them to corresponding physical quantities in virtual driving model. In the model, the accelerator and brake are used to control the product of torque and rotational speed of the two rear wheels when rotating around concentric shaft. In other words, the accelerator and brake control the output power of the drive shaft of the two rear wheels. The steering wheel is used to control the angle of front wheel and rear wheel, implement of rotation to be achieved.

Therefore, this test environment provides an interactive, safe and realistic environment at very low cost, and the outcomes of this study should be highly applicable to real life driving safety research.

D. Driving Simulation Environment

In this paper, we use common game steering wheel and supporting pedals to simulate driving operation and two laptops were used, one to run virtual driving test program as a situational screen and capture video to record driver's facial information, the other one to run interface software of EMOTIV EPOC to collect EEG data. In the driving simulation experiment, subjects operate the driving simulation system to drive, and EMOTIV EPOC gathers EEG signals of the subjects at the same time.

Fig.3. Driving simulation environment which include EMOTIVE EPOC, steering wheel and two laptops to run specific software.

E. Experimental Process

We do the experiments in a close and sound insulation environment to get rid of external interference. During the two-day experiments, all subjects should eat normal and try to stay up. In order to obtain driving mental data under different physiological states, we conduct the experiment in six time points in two days as follows:

1) When getting up in the morning, the subject feels energetic and alert. We do the experiment at 9am.

2) The subject does mental works such as reading and learning until he feels tired and don't want to continue to complete the task. This process repeats until 3 pm. and that's when we perform the experiment.

3) The subject continues to do mental activity as described above and we conduct the experiment around 9 pm. The subjects need to stay up all night doing mental works.

4) Repeat the above 3 steps the next day.

After each break, every subject is supposed to fill in the Stanford Sleepiness Scale (Alertness Test) to evaluate his fatigue state. The Stanford Sleepiness Scale is a quick and easy way to assess how alert you are feeling by using the 7-point degree of sleepiness. We acquire data of each state for about 1 hours, 10 minutes simulation driving and rest for 5 minutes. Each subject will take a simulation driving 12 times a day. During the driving simulation process, we collect the driver's EEG signals.

Table 1 shows the time schedule for one time point, the other time point start at 3pm., 9pm. the same day, and 9 am., 3pm., 9pm. the next day. The experimental process is the same as that in Table 1.

TABLE 1 SCHEDULE OF THE EXPERIMENT FOR ONE TIME POINT

Time	Subject	Assignment
08:55~9:00	1	Adapt to the simulator and load the scene
09:00~09:10	1	Collect information in the process of simulation driving
09:10~09:15	1	Take a break and fill in the alertness test
09:15~09:25	1	Collect information in the process of simulation driving
09:25~09:30	1	Take a break and fill in the alertness test
09:30~09:40	1	Collect information in the process of simulation driving
09:40~09:45	1	Take a break and fill in the alertness test
09:45~09:55	1	Collect information in the process of simulation driving
09:55~10:00	1	Take a break and fill in the alertness test

IV. DRIVING FATIGUE DETECTION MODEL

This paper designs a driving fatigue detection model by driving simulation experiment. During experiments, we collect subject's EEG signals by EMOTIV EPOC and capture subject's facial expression features by video monitoring. By combining subject's facial features with his own subjective evaluation, we can conclude his fatigue state at that time. And by preprocessing and extracting the EEG signals, we can get subject's fatigue feature. In the end, with fatigue feature F as the input and fatigue state as the output, driving fatigue detection model was constructed by SVM.

Specific content of driving fatigue detection system is shown in Fig. 4.

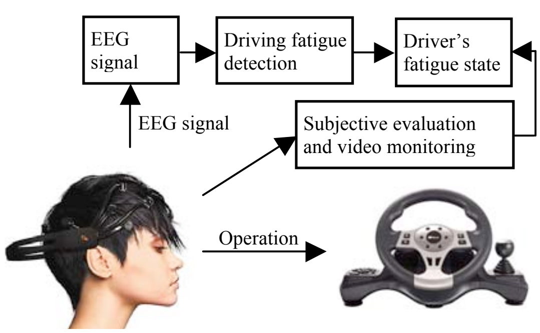

Fig. 4. Diagram of driving fatigue detection system. With driving fatigue detection model and EEG signals as input, we can get driver's fatigue state, so as to aid driving.

V. SIMULATION AND RESULTS

To begin with, the state of fatigue is evaluated by alertness test and facial expression monitoring. In consideration of veracity, only consistent data is used to build the model. When valuate fatigue state by recorded video, the evaluation criterion is rate of blinking, eyeball activity, head movements, yawning frequency, etc. Specific fatigue state evaluation standards are as shown in Table 2.

TABLE 2 FACIAL FEATURES OF DRIVER'S FATIGUE STATE

Fatigue State	Mark	Features Expression
Clear-minded	0	Eyes open normally, blink rapidly, eyeballs stay active, concentrate, head straight
Tired	1	Eyes tends to close, the vitality of eyeballs is falling, yawning, nod subconsciously, move head to resist fatigue
Fatigue	2	The trend of closing eyes is serious, closing eyes for a certain time, nod and head askew

During experiments, driver's fatigue states were evaluated with alertness test and facial features. Table 3 shows the experimental results of one group.

TABLE 3 DEGREE OF FATIGUE STATE

Time Point	Sleepiness Degree by Alertness Test	Fatigue Mark by Facial Features
1 2 3 4	1 1 4 4	0 0 0 0
5 6 7 8	2 2 4 4	0 0 1 1
9 10 11 12	1 2 5 5	0 1 1 2
13 14 15 16	6 6 7 7	1 2 2 2
17 18 19 20	2 4 7 7	1 1 2 2
21 22 23 24	4 5 6 7	1 1 2 2

The experiment carried out for two days, 12 times of simulation driving taking place in one day, and we have 24 time points in one experiment. As for the relation between sleepiness degree by alertness test and facial features mark, we define mark 0 equals to sleepiness degree 1 and 2, mark 1 equals to sleepiness degree 3 and 4, mark 2 equals to sleepiness degree 5 to 7. In this way, we can filter some of the time points to evaluate fatigue state more accurately.

In this paper, EEG signal preprocessing is divided into two steps. Firstly, we remove EEG signals that are clearly noises manually by EEGLAB. Then the signals are limited in the range from 0HZ to 30HZ by using Butterworth filter.

Then, we extract from the original EEG signals 4 kinds of rhythm waves by WPT method. Screening after many experiments, we choose wavelet typed db10 that is the most similar to EEG signals. The sampling frequency of EMOTIV EPOC is 128HZ. According to Shannon's sampling theorem, we can conclude that the bandwidth of our EEG signal is 64HZ. The 4 kinds of rhythm wave range from 0HZ to 30HZ, so we set decomposition layer of wavelet packet transform method 6 layers. After wavelet packet decomposition, we get 64 sub bands. Each node corresponds to a sub band of wavelet packet and their corresponding relation is as follows:

delta：1~4HZ ([6 1] [6 3] [6 2]);

theta：4~8HZ ([6 7] [6 6] [6 4] [6 5]);

alpha：8~13HZ ([6 15] [6 14] [6 12] [6 13] [6 8]);

beta：14~30HZ ([6 9] [6 11] [6 10] [6 30] [6 31] [6 28] [6 29] [6 24] [6 25] [6 27] [6 26] [6 16] [6 17] [6 19] [6 18] [6 23] [6 22]).

According to the study of human brain signal, we choose 4 leads that are most relevant to fatigue state, which are O1, O2, P7, and P8. Then, we can get 4 kinds of spontaneous rhythmic waves of EEG signals by reconstructing signals from wavelet packet node which are correspond to certain frequency band. We take average of EEG signals from the 4 leads, calculate the 4 kinds of rhythm, and represent part of the rhythm as Fig. 5 and Fig. 6.

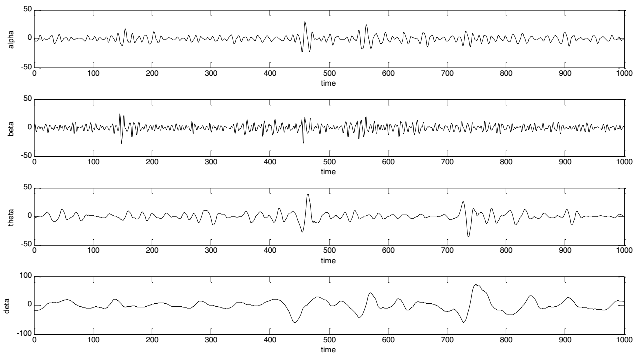

Fig. 5. Waveform graph of 4 kinds of rhythm when driver is clear-minded

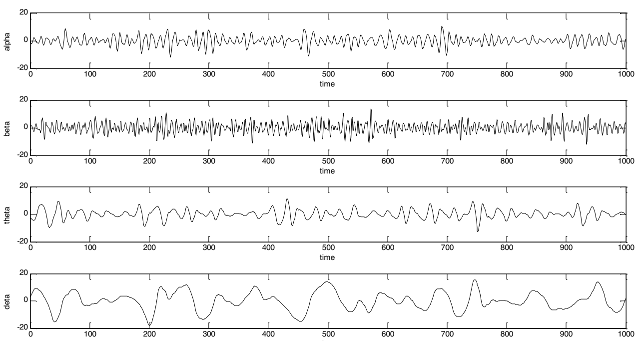

Fig. 6. Waveform graph of 4 kinds of rhythm when driver is in fatigue state

Compared with the 7-point degree of sleepiness in Alertness Test, mark 0 in Table 2 represents alertness degree 1 and 2, mark 1 stands for degree 3 and 4; mark 2 represents the left degree. With (3) and (4), we can calculate the numerical value of F, part of the data are shown in Fig 7.

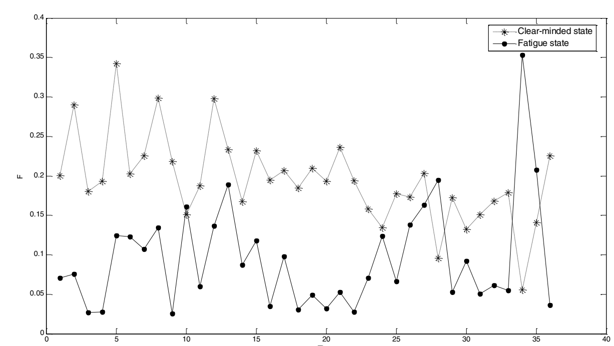

Fig. 7. The indexes of fatigue state F in a 10-minute simulation driving when the subject was clear-minded and fatigue. This paper chose 1500 sampling points as an elementary unit to calculate rhythmic waves. Some of the sampling points are deleted during EEG signal preprocessing part.

As we can see from Fig. 7, the value of F fluctuate with sampling point, but F in clear-minded state is larger than F in fatigue state overall.

According to Table 3, we delete the inconsistent time points. Using wavelet packet analysis method, we can get value F of the time point remaining. Specific situation is described as Fig. 8 and Fig. 9.

From Fig. 8, Fig. 9, and Table 3, we can find F change with fatigue state. There is a trend that F decreases with the increase of fatigue state. As it's generally considered that slow wave gradually increase and fast wave gradually reduce when drivers' mental state change from clear-minded to fatigue, F will decrease with fatigue degree deepens. Therefore, the value of F can detect driving fatigue.

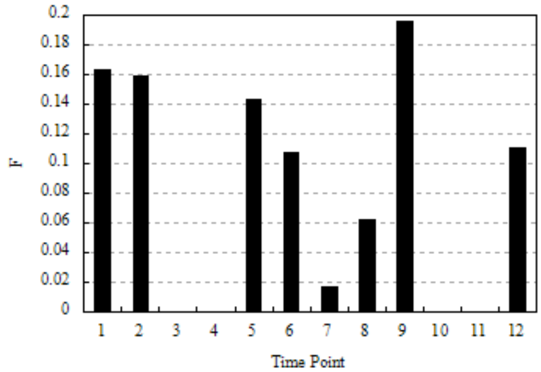

Fig. 8. The value of F at each time point (First 12 time points).

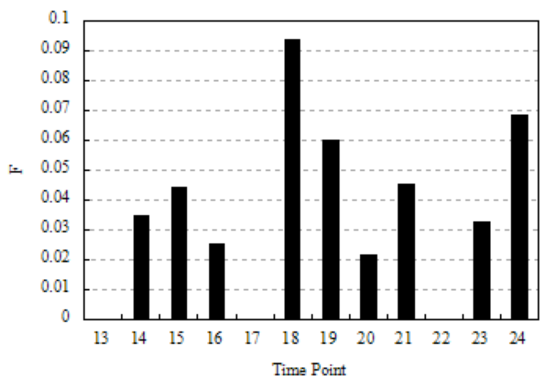

Fig. 9. The value of F at each time point (Last 12 time points).

Using feature extraction method, we get the fatigue feature. With video monitoring and subjective assessment, we get driver's mental state at that time. So we can build driving fatigue detection model by sorting technique. In practice application, with EEG signals as input, we can get driver's fatigue state, so as to aid driving.

In order to test the validity of the fatigue feature, this paper divided fatigue state into two categories, which is clear-minded state and fatigue state, and classifies the EEG data with SVM algorithm. The average classification accuracy is up to 88.6207%, and the classification results show the driving fatigue detection model is accurate.

VI. Conclusion

In this paper, we analyzed the driving fatigue detection system based on EEG recognition in detail, and feature extraction method of EEG signals is our focus. We built the driving fatigue detection system and verified our model by the driving simulation experimental data. The main research results in this paper are as follows:

1) Fatigue feature F will decrease with fatigue degree deepens on condition that the experiment and the processing of EEG data are precise.

2) A driving simulation system was set up to avoid boring and inaccuracy when sit for measuring EEG signals which makes the subject more focused.

3) This paper combined the subjective evaluation section with video monitoring to judge driver's status, which makes driving fatigue detection more accurate.

4) With the fatigue features this paper proposed, driving fatigue detection in real-time is possible. In practice applications, we have to know one's fatigue value range in advance so as to understand what the fatigue degree of the current F stands for.

Brain-Computer Interface technology is complex and involves many research fields, and there is still a long way to go in a wide range of practical application. The driver's data did not reach a certain size and only representative indexes chosen in this paper were analyzed. The driving fatigue detection model was not accurate and there were some limitations in the model. Therefore, some following aspects are needed for the further research:

1) We should integrate a variety of driving operational information to build a more reliable and fatigue driving model;

2) We should do researches on fatigue characteristics of EEG signal and improve the reliability of fatigue detection technology;

3) We should compile the corresponding simulated driving system and the brain electrical signal processing PC interface, so as to realize the real-time detection of driver's fatigue states.

Obtaining reliable data on fatigue-related crashes is challenging. Fatigue, however, can be managed, and effectively managing fatigue will result in a significant reduction in related risk and improve safety. Driving fatigue detection system will benefit the realization of non-contact fatigue warning technology and it has great guiding significances in improving driving safety.

References

[1] Lal, S.K.L., Craig, A. A critical review of the psychophysiology of driver fatigue, Biol. Psychol., 2001, 55, 173-194.

[2] L. Evans. Traffic Safety. Bloomfield Hills, MI: Sci. Serving Soc., 2004.

[3] D. McRuer and D. H. Weir. Theory of manual vehicular control, Ergonomics, 1969, 12(4): 599–633.

[4] N. Wright, B. Stone, T. Horberry, and N. Reed. A review of in-vehicle sleepiness detection devices, Trans. Res. Lab., Berkshire, U.K., 2007. Tech. Rep. PPR.

[5] M. Kaneda, H. Iizuka, H. Ueno, M. Hiramatsu, M. Taguchi, and M. Tsukino. Development of a drowsiness warning system, the 14th Int. Tech. Conf. on Enhanced Safety Vehicles, Munich, Germany, 1994, Paper 94-S3-O-08.

[6] Q. Wang, J. Yang, M. Ren, and Y. Zheng. Driver fatigue detection: A survey, in Proc. 6th World Congress on Intelligent Control and Automation, Dalian, China, Jun. 21–23, 2006, 8587–8591.

[7] J. Yang. Analysis and detection of driver fatigue caused by sleep deprivation, Ph.D. dissertation, Dept. Aeronaut. Astronaut., MIT, Cambridge, MA, 2007.

[8] LEE H.B., CHOI J.M., KIM J.S., ET AL. Nonintrusive bio-signal measurement system in a vehicle, in Proc. of 29th Annual Int. Conf. IEEE EMBS Cite Internationale, Lyon, France, 23 – 6 August 2007.

[9] Chambayil B, Singla R, Jha R. EEG Eye Blink Classification using neural network, in Proc. of the World Congress on Engineering. 2010, 1: 2-5.

[10] I. D. Brown. Car driving and fatigue, Triangle Sandoz J. Med. Serv., 1967, 8: 131–277.

[11] M. H. Chase. Brain electrical activity and sensory processing during waking and sleep states, in Principles and Practice of Sleep Medicine, New York: Saunders, 2000, 93–111.

[12] E. I. Dureman and C. Boden. Fatigue in simulated car driving, Ergonomics, 1972, 15: 299–308.

[13] S. K. L. Lal and A. Craig. Critical review of the psychophysiology of driver fatigue, Biol. Psychol., 2001, 55: 173–194.

[14] E. Zilberg, Z. M. Xu, D. Burton, M. Karrar, and S. Lal. Statistical validation of physiological indicators for noninvasive and hybrid drowsiness detection system, African J. Inf. Commun. Technol., 2009, 5(2): 75–83.

[15] M. H. Chase. Brain electrical activity and sensory processing during waking and sleep states, in Principles and Practice of Sleep Medicine, New York: Saunders, 2000, 93–111.

[16] Q. Ji, Z. Zhu, and P. Lan. Real-time nonintrusive monitoring and prediction of driver fatigue, IEEE Trans. Veh. Technol., 2004, 53(4): 1052–1068.

[17] S. K. L. Lal and A. Craig. Psychological effects associated with drowsiness: Driver fatigue and electroencephalography, Int. J. Psychophysiol., 2001, 55: 183–189.

[18] T. Akerstedt, G. Kecklund, and A. Knutsson. Manifest sleepiness and the spectral content of the EEG during shift work, Sleep, 1991, 14(3): 221–225.

[19] K. A. Brookhuis and D. Waard. The use of psychophysiology to assess driver status, Ergonomics, 1993, 39(9): 1099–1110.

[20] Jap B T, Lal S, Fischer P, et al. Using EEG spectral components to assess algorithms for detecting fatigue, Expert Systems with Applications, 2009, 36(2): 2352-2359.

[21] H. Shuyan and Z. Gangtie. Driver drowsiness detection with eyelid related parameters by Support Vector Machine, Expert Syst. Appl., 2009. 36: 7651–7658.

[22] M. Akay. Wavelet applications in medicine, IEEE Spectrum, 1997, 34(5): 50–56.

[23] R. R. Coifman,Y. Meyer, S. Quake, andV.Wickerhauser. Wavelet analysis and Signal processing, Wavelets and Their Applications. Sudbury, MA: Jones and Barlett, 1992, 153–178.

[24] S. Mallat. A Wavelet Tour of Signal Processing: The Sparse Way. New York: Academic, 2009.

[25] Blankertz B, Tomioka R, Lemm S, et al. Optimizing spatial filters for robust EEG single-trial analysis, IEEE Signal Processing Magazine, 2008, 25(1): 41-56.