Feature Extraction of Seafarers' Workload Based on EEG Signals

Jinglei Chen[1,2]
1. Intelligent Transport Systems Research Centre.
Wuhan University of Technology
Wuhan, China
2. National Engineering Research Centre for Water Transport Safety (WTSC)
Wuhan, China

Shiqi Fan[1,2,3]
1. Intelligent Transport Systems Research Centre.
Wuhan University of Technology
Wuhan, China
2. National Engineering Research Centre for Water Transport Safety (WTSC)
Wuhan, China
3. Liverpool Logistics, Offshore and Marine. Liverpool John Moores University
Liverpool, UK

Jinfen Zhang[1,2]
1. Intelligent Transport Systems Research Centre.
Wuhan University of Technology
Wuhan, China
2. National Engineering Research Centre for Water Transport Safety (WTSC)
Wuhan, China

Wuliu Tian [1,2]
1. Maritime college. Beibu Gulf University
Qinzhou, China
2. Qinzhou Maritime Navigation And Antifouling Key Laboratory, Beibu Gulf University
Qinzhou, China

Abstract*—Most of maritime accidents have been proved to be caused by human errors. In order to quantitatively analyze human factor of seafarers, we carried out the simulation test of ship operation. During the test, a brain instrument was used to collect Electroencephalogram (EEG) signals of the subjects.In the current research stage, EEG signals have been denoised by wavelet transform, and EEG features are extracted by finite impulse response(FIR) digital filter. The feature can be used as the feature vector of Support Vector Machine(SVM) classifier for training, and finally a classifier for workload recognition is established.

Keywords-Maritime safety; Human errors; Bridge simulator; Mental workload

I. Introduction

Recent years, with the rapid development of the economy and the needs of world trades, the demand for ship transportation has increased. As long as the shipping industry brings enormous economic benefits to society, it also carries many types of risk, some of which would result in different kinds of accidents. According to the statistics from the ministry of transport of China in [1], during 2018, there were 176 maritime traffic accidents in China, resulting in 237 fatalities or missing and 83 ships wreckages. Such fact reveals that there are still numerous problems in maritime transportation safety that need to be studied and addressed. It is meaningful to investigate maritime safety to reduce the loss.

In this regard, a great number of studies have been conducted to find the major cause of maritime accidents. Through the analysis of 174 typical cases collected by the maritime safety administration from 2000 to 2009 in [2], it is found that human error accounts for 74%, navigation environment accounts for 16%, ship fault accounts for 5% and other factors account for 5%. It reveals, except for a few accidents caused by bad weather and the ship's fault, most accidents are caused by human errors. Lots of researches have been performed to investigate the inherent principles behind human errors and try to reduce such effect. The traditional method to study the human factors of maritime accidents is to analysis the accident data or accident reports. Such approaches can identify the causes and process of the accidents from a macro perspective, but cannot identify the complicated relationship between human errors and their physical states (e.g. mental workload, fatigue, skills, etc.).

One of the most important objectives of human factors' study is to reduce human errors and enhance navigation safety from the perspective of the crew. Using physiological information to quantity human factors has become a popular method, like using a real-time Electroencephalogram (EEG)-based method to detect the potential danger during fatigue driving in [3], treating eye tracking as a useful method to evaluate and foster aviation pilots' self-awareness in [4]. The sensor device and signal processing method have been

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developing rapidly. Investigations of human factors based on physiological or psychological data have become an emerging subject. The main objects of human factors in maritime safety always compose the following aspects: emotion, fatigue, mental workload, and stress in [5-9]. Since workload can be understood as the response to a particular type of psychological stressor according to [10]. The mental workload factor of the crew is sensitive to working condition, especially in the case of unexpected emergencies, potentially workload problem is particularly acute. For example, man overboard, fire, multi-ships encounter, and rainstorm. Therefore, studying the mental workload associated with accidents would be beneficial to the train of seafarers and maritime safety.

In this paper, the approach to obtain the EEG signals of seafarers during operations is conducted, using a bridge simulator and the EEG device. Based on this, the EEG signals is preprocessed and workload feature is extracted.

II. LITERATURE REVIEW

A. EEG-based human factors study

It is cross-disciplinary research that using EEG signals to predict crew emotions, workload or stress. The visual and quantitative processing of human factors in maritime traffic is conducted using psychology and neuroscience, and then making the correlation analysis between human errors and accidents.

EEG signal is the spontaneous and rhythmic electrical activity of brain cells recorded by electrodes, which reflects the functional state of the brain macroscopically. The frequency range of the EEG signal is usually between 1-60 HZ. The weak bioelectricity generated by the human brain can be amplified and recorded by specific instruments to obtain the EEG signal. According to the study of the EEG signal, the correlations between crews' psychological and physiological state with navigation safety can be evaluated quantitatively.

After decades of research results in brain science, the neuroscience community and the international brainwave society divide brainwaves into four main categories according to brainwave frequency, which are α, β, θ and δ band. It has been found that the four types of brainwaves correspond to four different states of the brain in [6], as shown in TABLE I.

TABLE I. Major types of EEG

Type	Frequency	Chological concept
δ	0-4 Hz	Learing problems and poor sleep
θ	4-8 Hz	Hyperactivity or poor emotional awareness
α	8-12 Hz	Over-relaxed state or an inability to focus in high levels, higher stress levels in low levels
β	12-40 Hz	Inability to feel relaxed in high levels, poor cognitive ability and lack of attention in low levels
γ	40-100 Hz	Anxiety and stress in high levels, depression in low levels

In recent years, research on psychophysiological signals conducted in the maritime simulator has made progress. In [6], Fan et al. experimented with a maritime simulator and collected seafarers' EEG signals. The subjects took the test in the simulator, followed by the feedback questionnaire investigation. After correlation analyzing between seafarers' emotion and human errors. It revealed that seafarers' emotion from maritime operations affects their behavior, and negative emotion has a higher likelihood of contributing to human errors than positive emotion. In addition, less negative emotion is the most dangerous emotion state during navigation, followed by extreme positive emotion. Hou et al. [7-9] carried out a series of study and developed a system called CogniMeter, realizing the visual processing of crew's emotion, workload and pressure in the simulator environment. The system was then used to assess crew's capabilities. Maritime simulators continue to play a crucial role in the study of maritime traffic safety. With the comprehensive information in terms of hydrological and meteorological, as well as the events and other information, more and more complex scenarios can be simulated in the simulators. Consequently, the credibility of simulator-based tests has been improved gradually. It has become an important means of human factors' study.

In summary, it is essential to find out the influence of seafarers in maritime from the perspective of physiological behavior of seafarers, which contributes to an objective description of human performance and human errors in maritime accidents. This study is conducted to collect EEG signals of seafarers in the brideg simulation and extract the rhytm of the mental workload from EEG signals.

B. Mental workload identification

Although many studies have been conducted about the workload, the identification of workload reveals inconsistent. Generally speaking, the psychological workload of drivers refers to the significant relationship between human cognitive ability and efforts required to deal with the specific functions in [11-12]. They are primarily categorized into three categories, including cognitive workload, physiological workload and subjective workload in [13]. Due to the distinctions among individuals' personality, skills, and experience, there would be apparent differences in the cognitive level of individual workload. In specific studies, workloads are generally divided into two categories. One is objective workload, which is generally measured by a series of parameters, such as environment, traffic complexity, and visibility and task requirements. The other category is the physiological or psychological workload. The correlation between individual physiological and psychological responses and workload can be explored on the basis of measuring individual indicators, such as EEG.

It is found that θ band has the most significant relationship with the workload. According to the experiment in [14], as the increase of workload caused by increasing mental arithmetic tasks, the increase of the θ band power was detected at the same time. Similarly, in the experiment in [15], in different driving tasks, as workload increases, activities in the frontal θ band increase significantly. In another experiment in [16] which studied pilots' workload and fatigue, it was observed that in higher workload states, power increases in the θ band and power decreases in the α band. Similarly, this study aims to take advantage of the θ band to identify crew workload, then to analyze the correlation between workload and human errors.

In this study, the EEG device was used to collect the EEG signal of seafarers when they participated in the examination in the simulator. The whole research can be divided into the following four steps: collecting EEG signals, denoising, extracting and recogniting feature, and classifying workload, shown as Fig. 1. This paper mainly described how to preprocess EEG signals. The presented work can be simplified with the help of toolbox, such as EEGLAB [17], Brainstorm [18], etc. The following data processing is completed in EEGLAB.

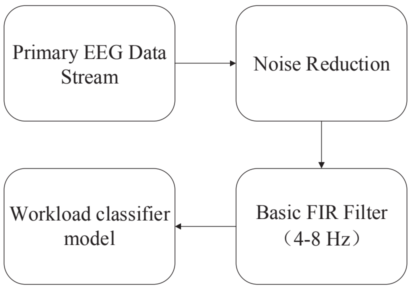


Figure 1. Pipeline of EEG data preprocessing

III. Methodology

A. Test subject selection

The test was based on 12 sailors aged between 26 and 38 from different companies. They were all males and they had 7.7 years of sailing experience on average. As a result, the relationship between their workload and errors during the voyage was more worthy of study than the inexperienced seafarers, which made the results of this test more convincing. Every subject were healthy with no brain injury, and they had not taken any drugs which would affect the recording of EEG signals before the experiment. They had no history of mental illness, either. All subjects were informed of the purpose and significance of the experiment beforehand, and they expressed their willingness to participate in the experiment and promised to cooperate with the completion of the experiment actively. All of them signed an agreement. During the trial, they could immediately terminate and withdrew from the trial when they changed their minds.

B. Test device selection

Traditional EEG technology usually uses wet electrode technology. Subjects have to be smeared with conducting medium before the research. If the test time is long, the performance of conducting medium will decline or disappear, resulting in distortion of the signals, thus affecting the quality of the signals. In addition, the traditional EEG system generally adopts wired communication mode, which is greatly restricted by the environment. And in this test, the mobility during the test was highly required. In conclusion, We chose NeuroSky Mindwave to conduct the test.

NeuroSky Mindwave is a common wireless single-channel (electrode) device that uses dry active sensor technology without the need for gel for electrode placement. This EEG device collected the signal at the position of FP1 (left front polar), and the reference was the left earlobe with the sample rate of 512 Hz.

C. Test protocol

The crew were required to simulate the voyage in specific scenarios wearing EEG device throughout the test. The test subjects operated in the ship simulator room, while the staff provided the subjects with navigation scenarios selected from the qualification examination database such as multi-ships encounter situation, poor visibility and emergency event in the separate control room. The staff would randomly change the scenarios in the ship simulator room, subjects needed to carry out the right and effective operation. At the same time, the staff would record what scenarios subjects encountered and when an emergency occurred as well as what operation subjects conducted. However the specific minutes of the task happened in the test is part of the exam database which is confidential and can not be opened to the public, so we could not show more details about this test.

In our test, there were subjects in the bridge simulator room to perform the test, and staffs in the control room to operate simulator. In the bridge simulator room, four people were playing four roles in the navigation test, seen in fig.2. However, only one of them, who acted as the captain, wore the EEG device and was studies in the test. Besides the subjects in the bridge, there was also an examiner to score the performance of subjects and a researcher to monitor and record the EEG signals of subjects. All scenarios and events were manifested by staffs in the other room, i.e. control room. The subjects in the test were supposed to navigate in the specific voyage along with the events occurred successively. Overall, 11 tests were efficiently collected, as 1 participant in the 12th test quitted the study before the test began.

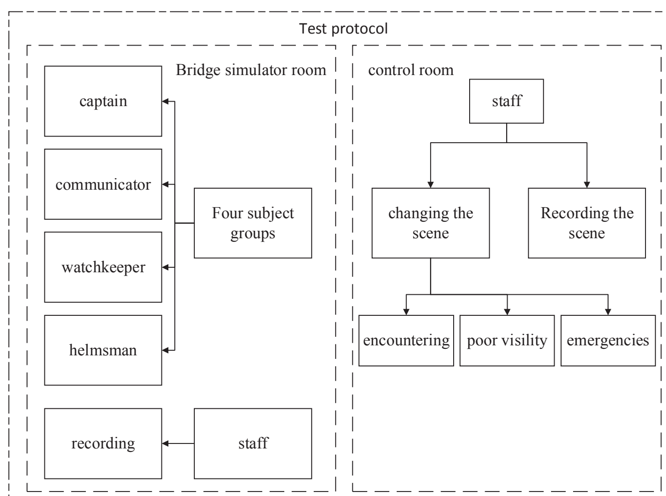


Figure 2. Test protocol

IV. Results

During the test, one of the crew members dropped out of the test for some reasons. The EEG data was collected from a total of 11 subjects.

A. *Primary EEG data*

The raw EEG signal waveform was obtained during the test. Fig. 3 presents a segment of original EEG signals. The x-axis represents the time, and the y-axis represents the magnitude. The line marked "h" represents the event or scenario encountered by the crew during the simulated voyage, which is recorded by the researcher in the bridge simulator. As can be seen from the waveform, the original EEG signals reveal significant spike signals, indicating that the EEG signals are interfered by activities such as blinks and muscle movements, resulting in a large number of artifacts.

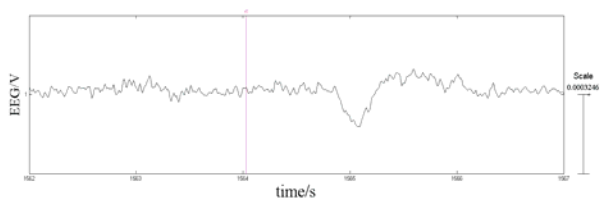


Figure 3. Primary EEG time domain (segment)

The power of each frequency EEG signals is available by carrying out fast Fourier transform on the original EEG signals, which is shown in Fig. 4. It reveals the power spectrum of EEG signals.

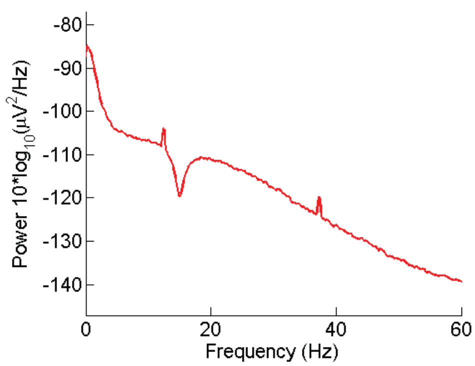


Figure 4. Primary EEG frequency domain (segment)

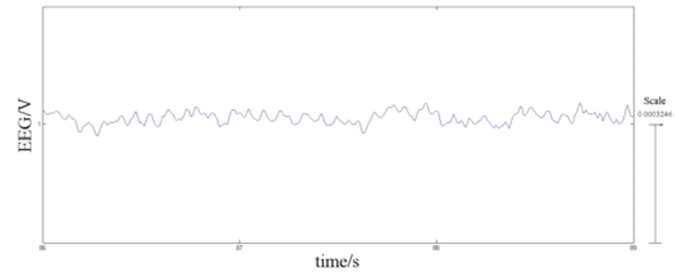
B. *Noise reduction*

Generally speaking, the EEG signal is sensitive to the noise. Before the analyze, the noise of raw EEG signals should be eliminated to avoid the data distortion. The denoising process was divided into two parts.

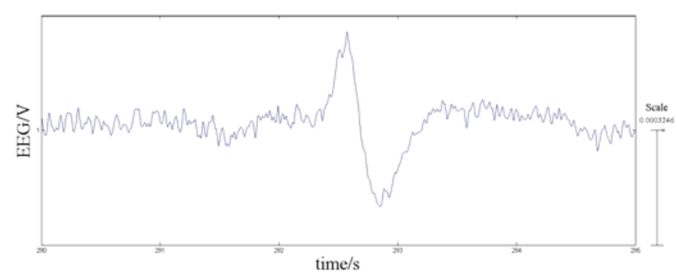
1) Manually remove artifacts: In the process of EEG signal acquisition, artifacts generated by the human body's physiological activities, such as ocular activities, muscular activities and heartbeat, are difficult to be avoided.

It can be seen in [19] that different artifacts have special waveforms. For example, the signal which is fluctuating up and down once a time at a short period of second of rhythm is likely to be the wink. The signal which is regularly fluctuating in a short time of rhythm is likely to be the heartbeat. The signal which is jumbled is likely to be the muscle movement. These artifact components can ben manually labeled and removed.

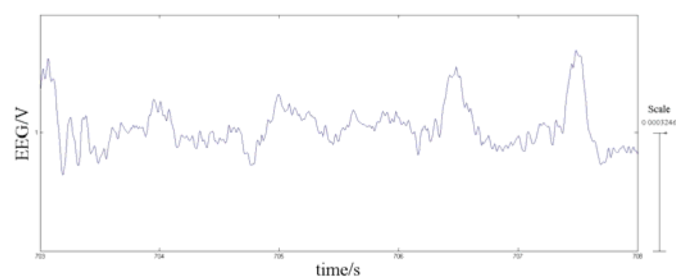
Through identification, the time-domain waveforms of pure and some typical artifact components in EEG signal we collected are shown in Fig. 5.



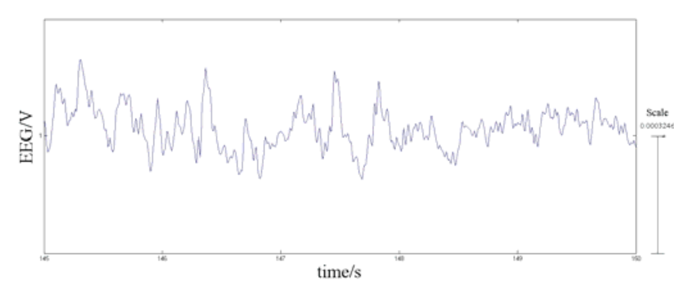
(a) Pure EEG data



(b) eye movement artifact



(c) heartbeat artifact



(d) muscle artifact

Figure 5. waveform of artifacts

2) wavelet transform: Besides artifact signals, there are many interference signals caused by other instruments and environment. The most common interference is power frequency interference caused by other electrical equipment.

A common method to denoise a non-stationary signal is wavelet transform. Wavelet transform is a time-frequency analysis method which emerged in the 1980s. The window of the wavelet transform can be adaptively adjusted according to the frequency, so it has multi-resolution characteristics.

Because wavelet transform has the capacity to have higher frequency resolution and lower time resolution in the low-frequency part, as well as lower frequency resolution and higher time resolution in the high-frequency part, it is known for "mathematical microscope".

The key of wavelet denoising lies in the selection of wavelet basis and threshold. What we should do is to compare the effect of different wavelet basis, like Haar, Daubechies, Symlets, and Morlet, the effect of different level of the wavelet decomposition, and the effect of different threshold rule, as rigrsure, sgtwolog, heursure, and minimaxi.

Then select the combination of wavelet basis, level, and threshold rule which make waveform smoother without distortion.

Db8 wavelet was selected in this paper after comparing the filtering effect of different combinations of bases and thresholds in the model, where 3 level wavelet decomposition presented the best effect. Fig.6 shows the waveform of 1,000 points from the EEG data before and after processing.

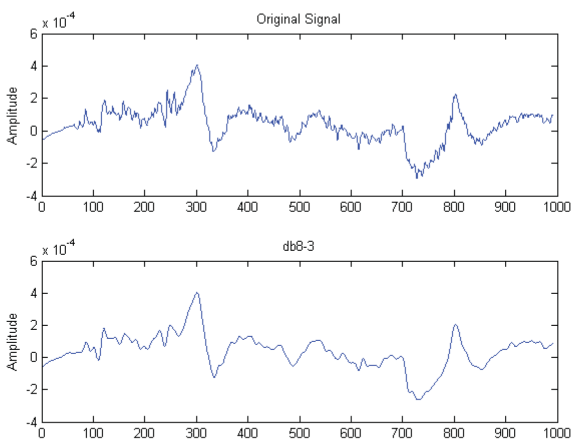


Figure 6. EEG data before and after processing

C. *Feature extraction of EEG data*

There are two common methods to detect EEG rhythm (δ, θ, α, β). The first one is based on wavelet packet, another one is using the filter. Both of them are valid methods to finish the research. In this study, we just choose the latter one. But we will extract EEG rhythm using wavelet packet in the next research and compare the effort of these two methods.

A filter is a frequency selection device that allows a particular frequency component of a signal to pass and attenuate other frequency components. In this study, what we need to extract is the 4-8 Hz frequency which is related to mental workload according to TABLE I. The high-pass frequency is set as 4 Hz, which means signals above 4 Hz can pass normally, while low-frequency signals below 4 Hz are blocked. Similarly, the low-pass frequency is set to 8Hz, which means signals below 8Hz can pass normally, while high-frequency signals above 8Hz are blocked.

The filter can be divided into analog filter and digital filter according to the type of signals. We chose digital filter because the digital filter has more advantages in precision and stability. Digital filter can be divided into IIR (infinite impulse response) filter and FIR (finite impulse response) filter. Compared with IIR filter, FIR filter is easy to achieve strict linear phase characteristics while ensuring amplitude characteristics. The most important reason is that FIR filter has no feedback loop, which means there is no instability problem, the precise linear phase is guaranteed while the amplitude characteristic can be determined arbitrarily.

After extracting EEG rhythm according to TABLE I. The waveform of time domain can be obtained. Fig 7 and Fig.8 shows θ band's waveform and the frequency response of the obtained phase and amplitude.

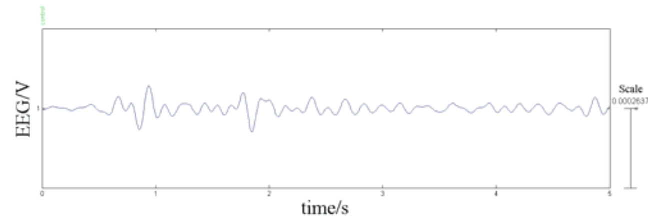


Figure 7. Waveform of θ band

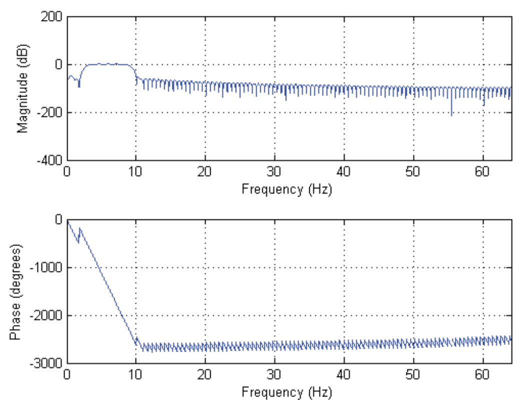


Figure 8. Frequency response of θ band

V. CONCLUSION AND FUTURE WORK

In order to quantitatively analyze the influence of human factors on maritime safety, this study conducted an experiment based on a maritime simulator to collect EEG data of seafarers. In this paper, some preliminary noise reduction and feature extraction processing have been carried out. However, there is no comparative study to validate the proposed methodology. Furthermore, we will contibue to more methods to compare with this method. Moreover, the correlation between human errors and workload will be analyzed in the next step. In this way, it helps a profound understanding of human errors of maritime accidents, as well as seafarers training considering mental workload.

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