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Human Factors Evaluation in Maritime Virtual Simulators Using Mobile EEG-Based Neuroimaging

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Abstract. Neuro-ergonomics using mobile electroencephalogram (EEG)-based neuroimaging is a new area of Brain-Computer Interaction (BCI) applications. We propose and develop an EEG-based system to monitor and analyze human factors measurements in maritime simulators. The EEG is used as a tool to monitor and record the brain states of subjects during human factors study experiments. In traditional human factors studies, the data of mental workload, stress, and emotion are obtained through questionnaires that are administered upon completion of some task/tasks or the whole experiment. However, this method only offers the evaluation of overall feelings of subjects during the task performance in the simulators. Real-time EEG-based human factors evaluation in maritime virtual simulator allows researchers to analyze the changes of subjects' brain states during the performance of various navigational tasks under different environmental and collaborative scenarios. Machine learning techniques are applied to the EEG data to recognize levels of mental workload, stress and emotions. By utilizing the proposed EEG-based system, true understanding of subjects working pattern can be obtained. Based on the analyses of the objective real-time data together with the subjective feedback from the subjects, we are able to reliably evaluate human factors during experiments in simulator. We describe real-time algorithms of emotion recognition, mental workload, and stress recognition from EEG and its integration in the cadets/captains stress assessment systems. We design a simulator-based experiment to record EEG signals of cadets, from which we recognize the changes of their emotions, mental workload, and stress levels during the task performance. We recorded EEG of 12 participants using Emotiv device in maritime simulator. The participants went through four exercises (around 30 minutes per exercise) with 20-minutes break in between. The exercises were with increasing difficulty levels and shuffled to be given to the participants. Videos were taken to analyze the behavioral data of the participants and used to label EEG data. Emotion, workload and stress levels are calculated from EEG recording with the time resolution 1 sec. From the preliminary case study it can be seen that there is a correlation between the EEG-based emotion recognition results (in terms of timing and magnitude) and the events that were happening in the simulator.

Keywords. EEG, human factors, neuroergonomics, maritime simulator, mental workload, stress, emotion

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Introduction

In recent years, the rapid advancement in technology allowed greater improvement in the shipping industry in terms of vessel structural design, safety systems, comfort and also navigational systems. The ships and vessels today are created with many different kinds of technologies implanted to increase the overall performance, efficiency and safety [1]. Unfortunately, despite such efforts and evolution in the industry, maritime casualty rate still remains high and almost 80% of the shipping incidents cited human factors as the main cause [2]. As a result, scientists and researchers start to realize the need for deeper understanding in the field of human errors. Existing studies of the human factors mainly involved statistical analysis and breakdown of casual factors occurring at different parts of a chain of failures that gave rise to the final disastrous outcome. Recent research efforts attempted the inclusion of bio-signal measurements in the human factors study. For example, electroencephalogram (EEG), which has a high time resolution, revealed better accuracies in monitoring human effects such as stress and emotional levels [3].

In our research, we applied machine learning on EEG data to monitor brain states such as emotion, workload, and stress levels of the maritime trainees during an experiment in the maritime simulator. In the experiment, the trainees had four 30-min exercises with different difficulty levels. With the help of videos recorded in the simulator, we are able to label the demanding events of the exercises in the EEG data. In this paper, we present a case study on the emotional changes of one trainee during the exercise.

The paper is structured as follows. In Section 1, we give related work including the review on methods used in human factors study and EEG-based technique in human factors study. In Section 2, the EEG-based brain states recognition algorithms are introduced. In Section 3, the experiment is described. Section 4 presents the results of preliminary case study, and Section 5 concludes the paper.

1. Related work

Maritime industry is regarded to be a people industry and thus a significant percentage of accidents are attributed to human errors. It is reported that human errors contribute up to 89-96% of collisions and 75% of fires and explosions [4]. With an intention to support accident prevention and improve maritime safety by adequate training to the crew, human factors are identified and investigated [5]. Council has summarized the various human factors such as stress, workload and fatigue that could implicitly affect individual and team performance of maritime professionals [6]. Traditional approaches use standard questionnaires such as NASA Task Load Index (TLX) and Situation Present Awareness Method (SPAM) to study the direct influence of workload on personnel. TLX is a standard tool developed by NASA to estimate the perceived workload using a multi-dimensional rating scale by studying the variations in subjective workload between each type of tasks [7]. The relationship between situation awareness, workload and performance was studied in a cognitively oriented air traffic management simulator using SPAM technique [8]. A theory of situation awareness (SA) has been presented in relation to decision making ability in complex dynamic systems. The SA model was proposed based on a hierarchical arrangement of factors that influence decision making like workload, stress and memory [9]. However, reliance on questionnaires did not prove to be effective as they are just the perceived information by the participants and does not guarantee to be the actual mind state. Cook et al. had found that the participants were reluctant in declaring themselves to be stressed even though the pilotage was stressful [10].

Recently, research on psychophysiological measurements has become the top priority to study human factors [11-14]. An attempt to evaluate and improve the training process in a ship navigation simulator which used the registered eye movements to determine the decision making ability of the crew in an unexpected and sudden situation causing a collision [13]. A similar study on evaluation of flight training effectiveness was carried out in an actual and simulated aircraft to determine physical and mental workload by monitoring heart rate and its variability during basic flight tasks [11]. The application of Galvanic Skin Response as a cognitive load indicator was studied using a simulated traffic control management task [14]. Apart from simulator based human factors study, numerous research studies have been conducted in normal environment. Research has been conducted to study the relationship between pupil response and cognitive load levels using an eye tracking application for enhancement of training and adaptive learning. The gaze data from the eye tracker had not only be used to indicate cognitive workload but also to user attention and distraction for designing training materials [12].

Among various psychophysiological measurements used in human factors assessment, Koester et.al. shows that EEG gives more valid and reliable results than other subjective methodologies in maritime crew domain [15]. In this paper, we focus on various brain states such as emotion, workload, and stress. The states are monitored using EEG signals.

2. EEG-based brain state recognition

In our previous work [16], we presented an integrated brain states monitoring system called CogniMeters. This system can visualize the real-time brain states such as emotion, workload, and stress in the form of meters. The algorithms used for brain states recognition in this system are briefly described below. We apply the algorithm to identify the brain states in this paper.

2.1. EEG-based emotion recognition

A subject-dependent emotion recognition algorithm is proposed in our previous work [17]. Compared with subject-independent algorithm, subject-dependent one can obtain a higher accuracy but an individual calibration is needed for each subject. To obtain calibration data, sound clips from IADS [18] are selected as stimuli and played to the subjects. The EEG data are recorded at the same time.

In the feature extraction step, the Higuchi fractal dimension [19] and statistical features [20] are extracted from the raw EEG data. Then a Support Vector Machine (SVM) is trained using the calibration data which can be applied in recognition phase. In [17] , we showed that the accuracy of the proposed algorithm can be up to 69.53% for the recognition of 8 emotions, 84.41% for the recognition of 3 emotions, and 90.35% for the recognition of 2 emotions.

In this study, three emotions defined on valence dimension such as negative, neutral, and positive, are recognized.

2.2. EEG-based workload recognition

An EEG-based workload recognition algorithm was proposed and validated in our previous work [21]. Same as emotion recognition algorithm, FD and statistical features are extracted and SVM is the classifier. For 2 levels of mental workload, we showed an accuracy of 90.39% and 4 levels as 80.09% [21].

In this study, we focus on four levels of mental workload recognition. As the algorithm is subject-dependent, to train the SVM classifier, Stroop color test is used as the stimulus to elicit different levels of workload. For the elicitation of the lowest level of workload, the subjects need to do nothing but relax. For low workload, the subjects are required to do the test by choosing the correct answer that matches the ink color of the given word. Here the meaning of the word and the ink color are congruent. For moderate workload, the subjects need to select the choices that match the ink color. However, the meaning of the word and the ink color are incongruent. For high workload, the test is incongruent plus a response time limitation of 1 second. The EEG data are recorded when the subjects are exposed to the stimuli. Then FD and statistical features are extracted and used as the training data for the SVM classifier. For both emotion and workload recognition, SVM with polynomial kernel is used. The value of *gamma* for polynomial kernel was set to 1, *coef* was set to 1, order *d* was set to 5, and the *cost* was set to 1.

2.3. EEG-based stress recognition

To obtain the levels of stress, we decided to combine the recognized emotion and workload results. As emotion recognition focuses on 3 states including positive, neutral, and negative, we assign numerical numbers to represent different emotions. Namely 0 denotes positive, 1 denotes neutral, and 2 denotes negative. For workload, same idea is applied. 0-3 is assigned to increasing workload levels. The details of the protocol to get stress level from emotion and workload are listed in Table 1.

Table 1. The protocol to get stress level from the combination of emotion and workload.

Brain States		
Emotion	**Workload**	**Stress**
0	0	0
1	0	0
2	0	0.5
0	1	1
1	1	1
2	1	1.5
0	2	2
1	2	2
2	2	2.5
0	3	3
1	3	3
2	3	3.5

3. Experiment

Over the course of 2 consecutive days, the experiment was conducted on 12 subjects who are cadet trainees from Maritime Institute @ Singapore Polytechnic. Each trainee was required to complete 4 bridge simulation exercises, with each exercise lasting about 30 minutes. By varying factors such as traffic condition, weather visibility, and occurrence of systematic alarms, these 4 exercises are designed to be of different difficulty levels.

Prior to each exercise, the trainees were briefed by an instructor. Although information such as type of vessel, initial location and final destination were given, there were no specific routes of advancement or specific instructions given to the trainees. Thereafter, each trainee was given the necessary navigational equipment such as parallel rulers and map, and the trainee proceed to their respective simulation room for preparation. Before the actual commencement of the simulation exercise, the trainees were allowed time to plan their route of advancement and to fill in a personal background questionnaire regarding their biography and sea service experience. Additionally, trainees had to go through a series of calibration tests where emotion and workload EEG data were collected to train the SVM classifiers. The Emotiv [22] device with 14 channels were used in the experiment to collect EEG data. During the exercise, the trainee performed their duties with the EEG device attached. EEG data and video footage of each exercise in the simulation room were recorded for synchronization and analysis purposes.

Upon completion of each exercise, the trainees were required to complete 2 sets of questionnaires which include Self-Assessment Manikin (SAM) to rate their emotion and workload/stress rating experienced over whole task.

4. Results and discussion

After collecting the data, we did a preliminary case study on one trainees' data. We manually synchronize the timestamps of the demanding events, which happened during the experiment, from the video to EEG results. The changes of emotion defined on valence dimension for different situations are plotted in Figure 1 to 5.

At the beginning of this exercise, the task was just navigation with minimal traffic and the mean value of emotion level over 12 min and 26 second is 1.31, which is close to neutral emotion level as label 1 is assigned to neutral state.

From 12:26 to 12:43, the trainee tried to stabilize the direction and sail between 2 vessels. The mean value of emotion level over this period is 1.33, which is slightly increased comparing with the beginning of the exercise. The detailed emotion changes are plotted in Figure 1. In the figure, the x axis denotes the time points and y axis shows different emotion level, namely 0 for positive, 1 for neutral, and 2 for negative. The solid curve represents the emotion levels at certain time point, the dash line is the linear trend of the intermittent emotional states. In Figure 1, the trend shows that the emotional state was gradually changed from neutral to negative during this period.

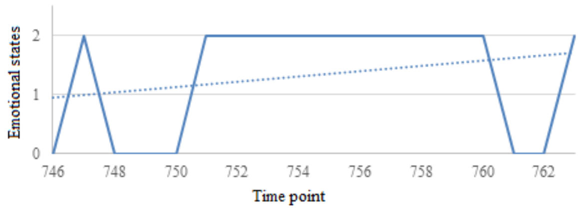

Figure 1. The emotional changes from 12:26 to 12:43

From 13:23 to 15:23, alarms and a lot commands were given to the trainee to adjust bearings. It was the toughest navigation of the entire exercise. As a reflection of the situation, the mean emotion level value increases to 1.60. This is closer to negative state and much higher than all the other period of the exercise. From Figure 2, we can see that the emotion states maintain at value 2 at most of the time, indicating negative emotion was detected.

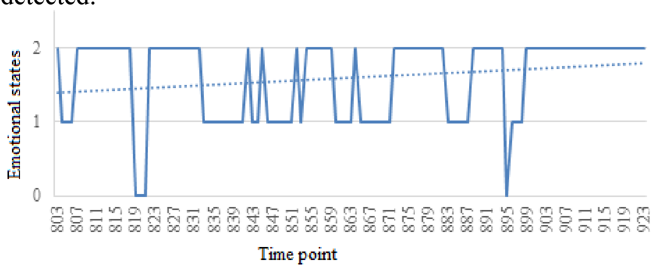

Figure 2. The emotional changes from 13:23 to 15:23

Figure 3 illustrates the emotional change from 14:00 to 14:20. It shows that the emotion values reduced from the 14:00 to 14:10 as only two spikes of negative emotion was observed. However from 14:10, the trainee had to steer away more from another vessel, thus negative emotion started to appear more frequently and it stayed for a while. The average emotion over these twenty seconds is 1.43, which is closer to neutral than the previous event in Figure 2.

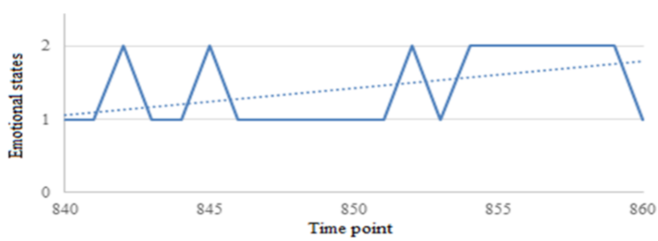

Figure 3. The emotional changes from 14:00 to 14:20

From 16:48 to 19:58, the trainee was overtaking the vessel and finally passed it from its starboard side. The emotion in most of the time is negative as shown in Figure 4. The average emotion value is 1.54, which is closer to negative emotion. However, an interesting phenomenon is that the trend line shows a deceasing pattern which may be due to the completion of passing the vessel nearby at the end.

From 19:58 to the end, the trainee was cruising to final destination with minimal traffic thus the mean emotion level value decrease to 1.38 which is very close to neutral state. From the curve (Figure 5), it can be seen that there are more neutral states detected.

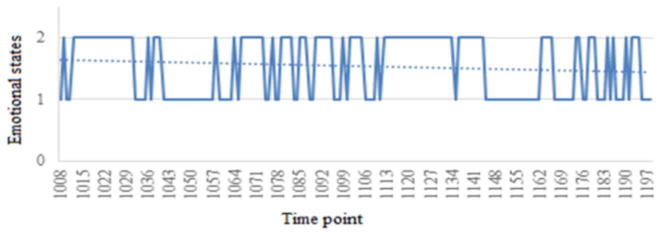

Figure 4. The emotional changes from 16:48 to 19:58

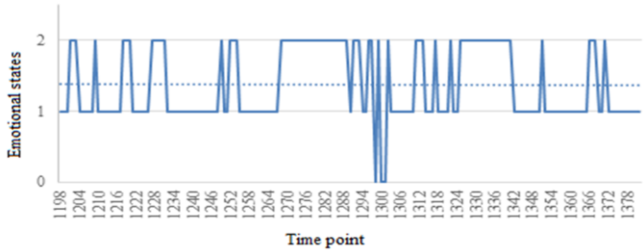

Figure 5. The emotional changes from19:58 to the end of exercise

Although in this section we present the results of only one subject, it gives positive support to the use of EEG technique in maritime human factors study.

5. Conclusion

In this paper, we introduce the EEG-based brain states recognition algorithms which can continuously identify the ongoing states such as emotion, workload, and stress. An experiment was carried out to collect the EEG data when the maritime trainees were performing different exercises in the simulator. We present an initial case study to investigate the emotional response to demanding events during the exercise. The results show that EEG-based recognition can accurately reflect the demanding events. Different from the traditional human factors study like use of surveys or interviews, the proposed EEG-based method allow researchers capture the detailed changes of emotion, stress, and mental workload levels in maritime simulator, and in future during maritime simulator-based assessments. Thus, human factors can be studied in maritime virtual simulators using EEG-based mobile neuroimaging tools to analyze the causes of human errors and failures in different scenarios. In the next step, we will analyze more data together with workload and stress levels identified, and link the brain states with the performance of the trainee.

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