EEG-based Mental Workload and Stress Monitoring of Crew Members in Maritime Virtual Simulator

Wei Lun Lim[1], Yisi Liu[1], Salem Chandrasekaran Harihara Subramaniam[1], Serene Hui Ping Liew[2], Gopala Krishnan[2], Olga Sourina[1], Dimitrios Konovessis[3], Hock Eng Ang[4], Lipo Wang[5]

[1] Fraunhofer Singapore, Nanyang Technological University, Singapore
[2] Maritime Institute @ Singapore Polytechnic, Singapore
[3] Singapore Institute of Technology, Singapore
[4] School of Mechanical and Aerospace Engineering, [5] School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore
{wllim2,liuys,scharihara}@ntu.edu.sg, {liew_hui_ping, gopala_krishnan}@sp.edu.sg, eosourina@ntu.edu.sg, dimitrios.konovessis@singaporetech.edu.sg, mheang@ntu.edu.sg, elpwang@ntu.edu.sg

Abstract. Many studies have shown that most maritime accidents/incidents are attributed to human error as the initiating cause. Efforts have been made in study of human factors to improve safety in maritime transportation. Among the various techniques, Electroencephalography (EEG) has the key advantage of high time resolution, with the possibility to continuously monitor brain states including human mental workload, emotions, stress levels, etc. In this paper, we proposed a novel mental workload recognition algorithm using deep learning techniques and successfully applied it to monitor crew members in a maritime simulator. We designed and carried out an experiment to collect the EEG signals, which were used to study stress and distribution of mental workload among the crew members during collaboration tasks in the ship's bridge simulator. The experiment consisted of two parts. In part 1, the maritime trainees fulfilled the tasks with and without an experienced captain. The results of EEG analyses showed that 2 out of 3 subjects had less workload and stress when the experienced captain was present. In part 2, four maritime trainees cooperated with each other in the simulator. Each of them took on one of the following roles: officer on watch, captain, pilot, or steersman. Here, the trainee who acted as the captain had the highest stress and workload levels while the other three trainees experienced low workload and stress due to the shared work and responsibility. These results suggest that EEG is a promising evaluation tool applicable in human factors study for the maritime domain.

Keywords: EEG; human factors; neuroergonomics; maritime simulator; mental workload algorithm; stress; brain computer interfaces

1 Introduction

Over the years, various methods and techniques have been established to address human factors research to improve safety in maritime. Apart from conventional methods such as statistical analysis of accident data and questionnaires, bio-signals can be considered as novel tools to evaluate human factors. The Electroencephalogram (EEG) has several advantages over other bio-signals as the signal has high time-resolution with adequate accuracy. Mental workload, emotion and stress of the maritime trainees can be monitored using EEG when they perform tasks in a ship's bridge simulator. This allows the cause and effect of human errors to be studied.

In work [1], we did a case study of workload and stress levels of crew members during task performance in a virtual simulator, using state-of-art EEG-based workload and stress recognition algorithms. For this paper, we propose a novel mental workload recognition algorithm using deep learning techniques that improve classification accuracy compared to state-of-art algorithms, and subsequently apply it to monitor the crew members while they perform maritime tasks in a virtual simulator. We also describe an experiment with 7 maritime trainees that consists of 2 parts. In the first part of the experiment, we recorded EEG data from 3 trainees who performed the tasks in the simulator with and without an experienced captain. EEG signals of these three trainees were recorded. In the second part of the experiment, 4 trainees formed the crew in the ship's bridge simulator. Each trainee played one of the 4 roles: officer on watch, captain, pilot, or steersman. EEG signals of all 4 trainees were recorded. Workload, and stress levels of the trainees were recognized from the EEG signals in both parts of the experiment.

The paper is structured as follows. Section 2 reviews methodologies in maritime human factors study. Section 3 introduces EEG-based brain recognition algorithms. Section 4 describes the experiment, and Section 5 presents the experiment results. Finally, Section 6 concludes the paper.

2 Related Works

During routine work, the performance of an individual can be easily affected by one or many causes. In this paper, we aim to assess and evaluate workload and stress of individuals while they perform tasks to study the impact on crew performance. The results of this study may help prevent future accidents caused by human factors.

2.1 Workload and Stress

In our research, we refer to the term 'workload' as cognitive workload. Workload can be defined as the mental resource required to process information to complete a task [2]. Stress, as often discussed by academics and scholars, also has various definitions. It is thought that stress correlates with mental consciousness and emotion within a person when the achievable capacity is exceeded [3]. Both workload and stress are important factors in maritime domain for safety during cruising [4-6].

2.2 Traditional Methodologies in Maritime Human Factors Study

Many studies were conducted by analyzing available reports and databases which are usually a joint effort between the maritime organization and the government's safety department. The data from these case studies are often used to identify underlying common factors [7].

However, researchers face a major challenge as there is no standardized system to classify the type of accidents. Accidents usually happen due to multiple factors, and it could be difficult to categorize them to gain meaningful insight. One of the major problems to overcome is to be able to identify the common factors of human errors. These underlying human factors can originate from the interactions between environment, people or technology. Preliminary findings have also shown that human errors can be due to poor performance or lack of situational awareness. Given the complexity when considering the possible factors, it is difficult to identify the actual error [4, 7].

Questionnaires are another commonly used traditional assessment method. For example, operator workload is usually assessed with the administration of a questionnaire, such as the NASA Task load index (NASA-TLX) [8] or the Subjective Workload Assessment Technique (SWAT) [9]. However, this method only provides a subjective assessment of an operator's personal workload which might not be reliable. Furthermore, administration of such questionnaires is usually done after the task, which adds to the subjectivity of the assessment and is not practical from an operational standpoint, where the goal is to assess operator workload as the task is being performed.

2.3 Bio-signal based Methodologies in Maritime Human Factors Study

To overcome the problems encountered by traditional methods in human factors study, different types of bio-signals can be applied. Among which, EEG is an electrophysiological method that reflects the electrical activity within the human brain. This method is noninvasive as the electrodes are placed on the scalp's surface. In addition, high precision of time measurement can be obtained by using an EEG device with a higher sampling rate. The EEG produces signals by reading the neuron undulations, commonly known as "brain waves". In the case of EEG-based assessment, various brain states can be identified with a classifier trained in advance. Thus, when the operator performs the task, the brain states of him/her will be recognized based on the trained model and not through any subjective assessment. Furthermore, the EEG device can be worn throughout the task and brain states can be assessed as the task is ongoing.

In this work, we shall monitor the workload and stress levels of maritime trainees using the EEG.

2.4 EEG-based Workload Recognition

Currently, EEG-based workload recognition algorithms that have the best accuracy are subject-dependent ones. Workload recognition generally involves the derivation of features, such as spectral power, from the EEG raw data and subsequently applying these derived features to train a classifier. For example in [10], the researchers utilized a fusion of spectral power and event related potential (ERP) features to train a Support Vector Machine (SVM) classifier and achieved an average 85.0% accuracy for classifying 2 levels of workload. Other studies have also proposed using the combination of features from various physiological measurements aside from EEG. In [11], a study on a combination of skin conductance, heart rate, pupil size, EEG spectral power, and ERP features to classify mental workload was carried out. The average reported accuracy was 91.0% for differentiating high and low mental workload. More recently, deep learning methods are also being studied to classify mental workload. Research in [12] applied a stacked-denoising autoencoder to study within and cross session EEG workload data. Average accuracy of 95.4% and 87.4% was reported for classifying 2 levels of workload for within and cross sessions respectively.

3 EEG-based Brain States Monitoring

3.1 Workload

In this paper, we proposed a novel subject-dependent mental workload recognition algorithm using deep learning techniques that outperforms state-of-art algorithms. Subject-dependent algorithms require calibration for each new subject. To calibrate 4 levels of workload, EEG data recorded during a Stroop color word test with 4 different levels of difficulty was used. Table 1 indicates the workload values: 0, 1, 2, 3 which corresponds to no workload, minimal workload, moderate workload and high workload respectively.

For the Stroop test, level 0 corresponds to the subject observing the screen but not performing any actions. Level 1 requires subjects to press the correct key in response to the color displayed on-screen. The ink color matches text displayed for this level. For example, the word “blue” is displayed with a blue color. In level 2, subjects are still required to press the correct key in response to the ink color displayed, but in this case, there is a mismatch between text and color displayed. For example, the word “blue” might be displayed with a yellow color, and the correct response would be to press the “yellow” answer key. Finally, for level 3, the task is same as in level 2 but with a time limit imposed. Subjects must respond within 1 second after the stimulus is displayed. The Stroop test interface can be viewed in Fig. 1. Each level lasts 1 minute.

To calibrate a classifier for 4 levels of workload recognition, two algorithms were tested using the EEG data from 18 subjects that was collected for workload calibration in the maritime experiment [13]. For classifier A, a SVM classifier was trained with a combination of fractal dimension (FD) and statistical features. The method follows the algorithm proposed in a separate study on multitasking workload

[14]. When applied on 4 levels of workload recognition from the 18 subjects, an average of 58.7% recognition accuracy was achieved from 5 folds cross validation on each subject. For two levels, an average of 83.2% recognition accuracy was achieved.

Table 1. Workload states.

Workload Level	State
0	No
1	Minimal
2	Moderate
3	High

Workload recognition was also studied using a novel approach. For classifier B, spectral data derived from the Fast Fourier Transform of the EEG raw data was first input to an Autoencoder to learn a feature representation, which was then combined with the statistical and FD features and trained with the SVM classifier. For this approach, an average accuracy of 79.9% was achieved from 5 folds cross validation on each subject for 4 levels of workload recognition. For two levels, this approach gave an average accuracy of 95.4%. The classifier calibration process can be viewed in Fig. 2. For both classifers, all 14 channels were used and the features were extracted using a sliding window of 4 seconds with 75% overlap. From the results, it shows that using deep learning technique in the algorithm is successful in improving classification accuracy.

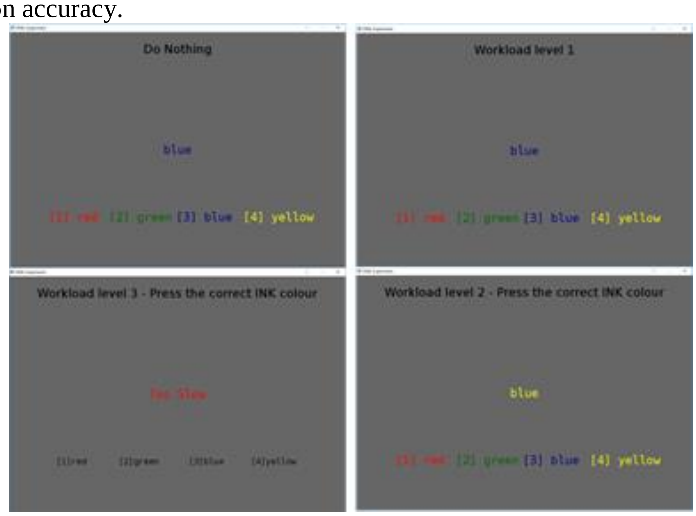

Fig. 1. Stroop test for 4 levels workload calibration. Clockwise from top left: Level 0, subjects are to observe the screen but not respond. Level 1, subjects are to respond by pressing the correct key corresponding to the ink color displayed. Level 2, same task as level 1 but with mismatch between word meaning and ink color. Level 3, same task as level 2 but with response time limit of 1 second imposed after stimulus display.

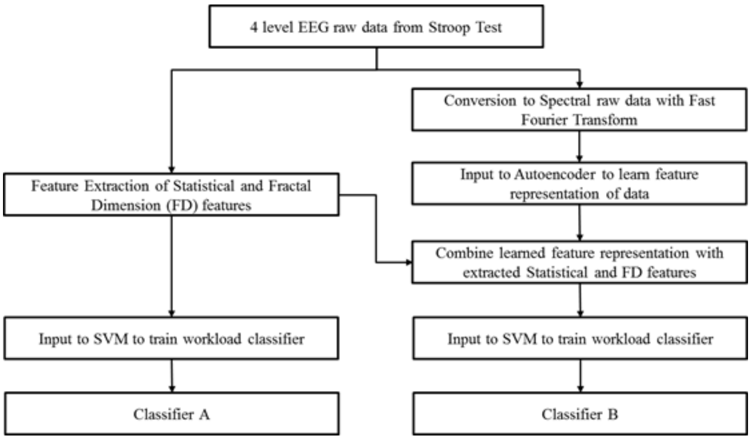

Fig. 2. Overall diagram for calibration procedure of 2 SVM classifiers used for 4 levels workload recognition from Stroop test.

3.2 Stress

In this paper, we recognize stress by combining the workload and emotion states. In our previous work [15], we proposed a subject-dependent algorithm for emotion recognition using sound clips from the IADS database [16] to evoke different emotions. A combination of FD and statistical features were used as input to train the SVM classifier. Once the classifier model is obtained, it can be used to identify the emotional state of the subject. All 14 channels were used in the algorithm, and the features were extracted using a sliding window of 4 seconds with 75% overlap. We showed in [15] that up to 8 emotions can be recognized with an accuracy of 69.53%.

In this work, 3 emotions, including positive, neutral, and negative are considered. The emotion labels and the corresponding numerical labels are presented in Table 2.

Table 2. Emotional states.

Emotion Level	State
0	Positive
1	Neutral
2	Negative

Stress has always been associated with one's emotional state and workload level as it is directly or indirectly influenced by both of them. Significant correlation has been found previously in [17]. Following the algorithm proposed in work [17], we combine the recognized emotional state and workload state to get the stress level, as shown in Table 3.

Table 3. Stress states.

Emotion Level	Workload Level	Stress Level	State
0	0	0	Low
1	0	0	Low
2	0	0.5	Medium Low
0	1	1	Moderate Low
1	1	1	Moderate Low
2	1	1.5	Medium
0	2	2	Medium High
1	2	2	Medium High
2	2	2.5	Moderate High
0	3	3	High
1	3	3	High
2	3	3.5	Very High

4 Experiment

We carried out a pilot experiment to study the relationship between maritime trainees' mental workload and stress levels, and their task performance when they shared duties on the bridge of a virtual simulator. The experiment consists of two parts. In the first part, trainees performed tasks with and without the presence of an experienced captain. The EEG of these trainees was recorded. In the second part, we recorded 4 maritime trainees' EEG while they cooperated with each other.

4.1 Simulator

The experiment was conducted within SMA's Integrated Simulation Centre (ISC), which houses five full mission ship's bridge simulators. Each simulator contains high-tech equipment such as True Motion radar, Automatic Radar Plotting Aid (ARPA), navigation controls, and electronic navigational aids display. A 180-degree field of view is provided by large-screen monitors, simulating a highly realistic environment.

4.2 Subject

In the simulator, each trainees was assigned the following roles: First, an Officer On Watch (OOW) who is tasked with the duties of watch keeping and navigation on the ship's bridge. He is also the representative of the ship's master and has full responsibility for a safe and smooth navigation of the ship. Second, a steersman, whose job is to steer the ship. Third, a captain who oversees the safe navigation of the ship while giving instructions to the rest of the crew. Lastly, a pilot who is a mariner with experience in the maneuvering of a vessel in congested areas or harbors and provides advice to the captain about navigation in an area.

As the experiment consists of two parts, we had two groups of subjects. The first part was carried out with 3 maritime trainees with and without an experienced captain in the simulator. When the experienced captain was absent, the trainees took over the duty of Officer on Watch (OOW), Pilot and captain. When the experienced captain was present, the trainees took over the duty of Officer on Watch (OOW) and Pilot. The EEG from the trainees whose role is OOW/Pilot/captain was recorded. The duty of steersman was taken by other trainees whose EEG data were not recorded.

The second set was carried out with 4 maritime trainees in the same simulator. Each of them took up a different role to simulate actual bridge watch-keeping duties. The EEG from all 4 trainees was recorded. Their respective roles were as follows: Trainee 1 - Officer On Watch; Trainee 2 – Steersman; Trainee 3 – Captain; Trainee 4 – Pilot.

4.3 Experiment Procedure

Before the start of the experiment, the subject was required to fill in an intake questionnaire. Next, the calibration for subject-dependent emotion and workload recognition were performed. As outlined in Sections 3.1 and 3.2, sound clips from IADS and the Stroop color word test were used for emotion and workload calibration. The Emotiv [18] device was used to record the raw EEG data when the maritime trainees were exposed to the stimuli and the obtained EEG data was used to train the classifier as described in Section 3.

After the calibration, the trainees were required to navigate the vessel in a simulator under pre-defined scenarios. Details of the vessel type and destination of voyage were given prior to the start of the exercise. The EEG data and video footage in the simulator was recorded in order to label the timelines of the EEG data with the corresponding significant events that occurred during the navigation.

5 Results of the Experiment

As we had two parts in the experiment the results are presented in the following two sections: 1) Trainees with and without experienced captain and 2) Trainees collaboration with different roles.

5.1 Trainees with and without Experienced Captain

The states of workload and stress were averaged for the 3 subjects and summarized in Table 4. It shows that 2 out of 3 subjects (Sub 1 and 2) experienced less workload and stress when the duty is shared by the experienced captain.

Table 4. Stress states of the trainee with and without experienced captain.

	Sub 1		Sub 2		Sub 3	
	Without	With	Without	With	Without	With

	Captain	Captain	Captain	Captain	Captain	Captain
Average Workload Level	1.71	1.17	1.17	0.76	0.80	2.38
Average Stress Level	1.76	1.36	1.41	0.79	0.96	2.43

5.2 Trainees Collaboration with Different Roles

From the video footage, we observed that three significant events happened during the exercise: 1) at 14 seconds, the pilot gave instructions to the captain and asked to reduce the engine speed. The ship was trying to navigate away from a stationary vessel. All trainees were alerted. 2) At 847 seconds, OOW identified a nearby ro-ro vessel and cruise ship speed was identified as 6 knots. 3) At 1106 seconds, the trainees were discussing the voyage details. The brain states recognized from EEG signals for these three events are described and discussed in this Section.

Brain States for Event 1. For workload: High attention can be observed from 2s after the exercise started. The captain and pilot experienced the greatest degree of workload level while the steersman had 0 workload level throughout this event. The captain and pilot had a huge amount of responsibility to navigate the ship out of the congested area. The average workload level of the captain was the highest at 1.63, which was a moderate workload level compared to the rest of the crew members who had minimal workload levels. The results are summarized in Table 5.

For stress: As shown in Table 5, the captain and pilot had the highest stress levels while the steersman was at 0 stress level throughout this event. The captain's average stress level was 1.63, which suggests a low moderate stress level compared to the rest of the trainees who had a low stress level.

Table 5. Brain states for event 1.

		Workload		Stress	
Event 1	Activity during the event	At 14s	Average (1- 33 s)	At 14s	Average (1- 33 s)
OOW	Maintain watch-keeping duty and report to the pilot.	0	0.27	0	0.28
Steersman	On the helms. Reduce speed of ship, navigate away from the stationary vessel.	0	0	0	0
Captain	Receiving instructions from the pilot	1	1.63	1	1.63
Pilot	Giving orders and	0	0.50	0	0.55

	direction to the captain and OOW.

Brain States for Event 2. For workload: The OOW reported the cruising speed of the nearby vessel to the pilot and captain after checking the navigation panel. From Table 6, we can see that the workload level of the steersman and OOW appeared to be at 0 most of the time, indicating that there is almost no workload for them. In contrast, the pilot and captain experienced moderate to high level of workload. At 847s, the captain workload level was 3, indicating that he was having a high workload level when receiving instructions from the captain-instructor by phone. Meanwhile, we noticed that the workload level of the pilot was only at a high level from 837s to 850s when he was giving out orders. Thus, the average workload level of the pilot was 1.286 which was at the low to moderate workload level, while the captain had the highest average workload level at 2.571 among all trainees.

For stress: The results for Event 2 are presented in Table 6. It shows that the steersman and OOW had almost no stress throughout this event. At 847s, the captain's stress level was 3, indicating that he had high stress when receiving instructions from the captain-instructor. Meanwhile, it can be seen that the stress level of the pilot was only at a high level from 837s to 850s when he was giving out orders. The pilot's average stress level obtained was 1.333, which means that he had moderate stress while the captain had the highest average stress level at 2.571.

Table 6. Brain states for event 2.

		Workload		Stress	
Event 2	Activity during the event	At 847s	Average (837- 857 s)	At 847s	Average (837- 857 s)
OOW	OOW identified the nearby ro-ro vessel and cruise ship speed as 6 knots.	0	0.048	0	0.048
Steersman	On standby to navigate the ship.	0	0	0	0
Captain	Receiving instructions from the pilot.	3	2.571	3	2.571
Pilot	Giving orders and direction to the captain and OOW.	0	1.286	0	1.333

Brain States for Event 3. For workload: At 1106s, the OOW informed the captain and pilot about the route to be taken for overtaking the vessel ahead. From Table 7, the workload level was 3 for the OOW which could be due to processing the highly complex information to ensure safe voyage. The pilot was giving out advice to the captain after discussing the route to overtake the vessel. His average workload level remained minimal at 0.211. However, it is shown in Table 7 that the captain had the highest workload level compared to the rest of the crew at this particular time frame. The average workload level of the captain was 1.404 which is around minimal to moderate workload level.

For stress: At 1106s, the OOW and captain had high stress at level 3 as shown in Table 7. While the pilot was giving out advice to the captain to overtake the vessel, his average stress level remained minimal at 0.360. Similar to the OOW, the captain had the highest stress level as 3 during this particular time frame. By comparing the average stress levels, the captain had the highest stress level at 1.404 which means medium stress level.

Table 7. Brain states for event 3.

		Workload		Stress	
Event 3	Activity during the event	At 1106s	Average (1080-1136s)	At 1106s	Average (1080-1136s)
OOW	OOW identified the nearby ro-ro vessel and cruise ship speed as 6 knots.	3	0.351	3	0.368
Steersman	On standby to navigate the ship.	0	0	0	0
Captain	Receiving instructions from the pilot.	3	1.404	3	1.404
Pilot	Giving orders and direction to the captain and OOW.	0	0.211	0	0.360

Overall Brain States. For workload: To summarize the workload levels experienced by the trainees, the average workload levels are calculated throughout the entire experiment session. During all three events, the captain had the highest average workload which is 1.71 as shown in the Fig. 3. Meanwhile, the rest of the crew had low workload levels, 0.45 for OOW, 0.01 for steersman, and 0.82 for pilot. The captain had the highest workload as he was required to give out orders to the crew and assume responsibility for the ship. As expected, the steersman, who had the easiest task to perform among the trainees, experienced the lowest workload level.

For stress: The captain and pilot had the highest average stress during the entire session which was 1.097 and 0.918 respectively as shown in Fig. 4. Meanwhile, the rest of the crew had lower stress levels, 0.493 for OOW and 0.023 for steersman. The reason for higher stress is that the captain had to give orders to the crew for most of the time, and both the captain and pilot are in a position of higher responsibility. Among all trainees, the steersman had the lowest stress level at 0.023 as he just needed to follow the orders.

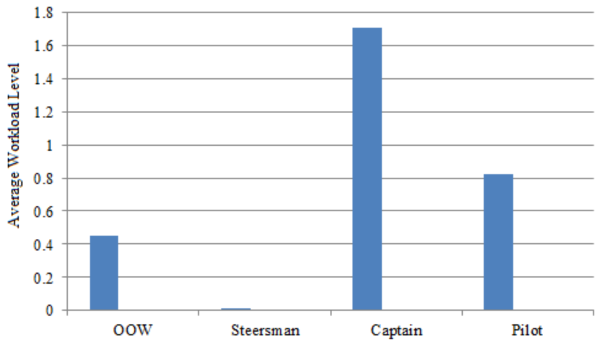

Fig. 3. Overall workload level for the entire exercise.

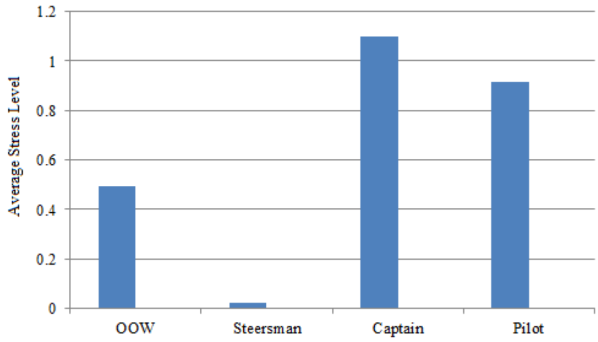

Fig. 4. Overall stress level for the entire exercise.

6 Conclusion

In this paper, we designed and implemented an experiment to study workload and stress levels of crew members when they were performing the tasks in a maritime virtual simulator. To improve the accuracy of the experiment data analyses we proposed a novel EEG-based mental workload recognition algorithm using deep learning and applied it to identify the workload and stress of maritime trainees. We designed and carried out the experiment which consists of 2 parts. EEG data from 3 trainees were recorded in the first part that was carried out with and without the experienced captain. 2 out of 3 trainees showed less workload and stress when there was a captain to share their work. In the second part, EEG data was recorded from 4 trainees who collaborated with each other and acted as office on watch, steersman, pilot, and captain. The results show that the trainee who played the role of the captain experienced the highest workload and stress levels compared to the others, while the steersman had the lowest workload and stress. These findings are consistent with the complexity levels of their roles. Both parts of the experiment support the use of EEG signals in monitoring the brain states of maritime trainees. In the next step of our project, the proposed experiment design will be implemented with real crews of maritime companies.

The proposed algorithms and methods can be applied far beyond the maritime domain. The EEG-based human factors evaluation tools can be used for human-machine interaction assessment in the automotive industry, air-traffic control systems, user interfaces, game industry, neuromarketing, etc.

Acknowledgment

This research is supported by Singapore Maritime Institute and by the National Research Foundation, Prime Minister's Office, Singapore under its International Research Centres in Singapore Funding Initiative. We would like to acknowledge the final year project students of School of MAE of Nanyang Technological University and personally Lee Jian Wei for his contribution in this work.

References

1. Liu, Y., et al.: EEG-based Mental Workload and Stress Recognition of Crew Members in Maritime Virtual Simulator: A Case Study in International Conference on Cyberworlds Chester (2017), in print, pp1-8.
2. Berka, C., et al.: EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. Aviation, space, and environmental medicine. **78**(5): p. B231-B244 (2007).
3. Folkman, S.: Stress: appraisal and coping. Springer (2013).
4. Hetherington, C., R. Flin, and K. Mearns: Safety in shipping: The human element. Journal of safety research. **37**(4): p. 401-411 (2006).
5. Arenius, M., G. Athanassiou, and O. Sträter: Systemic assessment of the effect of mental stress and strain on performance in a maritime ship-handling simulator. IFAC Proceedings Volumes. **43**(13): p. 43-46 (2010).
6. Lützhöft, M.H. and S.W. Dekker: On your watch: automation on the bridge. Journal of Navigation. **55**(01): p. 83-96 (2002).
7. Baker, C.C. and A.K. Seah: Maritime accidents and human performance: the statistical trail. in MarTech Conference, Singapore. (2004).
8. Hart, S.G. and L.E. Staveland: Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research, in Advances in Psychology, P.A. Hancock and N. Meshkati, Editors, North-Holland. p. 139-183 (1988).
9. Reid, G.B. and T.E. Nygren: The subjective workload assessment technique: A scaling procedure for measuring mental workload. Advances in psychology. **52**: p. 185-218 (1988).

10. Brouwer, A.-M., et al.: Estimating workload using EEG spectral power and ERPs in the n-back task. Journal of neural engineering. **9**(4): p. 045008 (2012).
11. Hogervorst, M.A., A.-M. Brouwer, and J.B. van Erp: Combining and comparing EEG, peripheral physiology and eye-related measures for the assessment of mental workload. Frontiers in neuroscience. **8** (2014).
12. Yin, Z. and J. Zhang: Cross-session classification of mental workload levels using EEG and an adaptive deep learning model. Biomedical Signal Processing and Control. **33**: p. 30-47 (2017).
13. Liu, Y., et al.: Human Factors Evaluation in Maritime Virtual Simulators Using Mobile EEG-Based Neuroimaging. in Transdisciplinary Engineering: a Paradigm Shift: Proceedings of the 24th ISPE Inc. International Conference on Transdisciplinary Engineering, July 10-14 2017. IOS Press (2017).
14. W. L. Lim, et al.: EEG-based Mental Workload Recognition Related to Multitasking. in Proceeding of the Int Conf on Information, Communications and Signal Processing (ICICS). (2015).
15. Liu, Y. and O. Sourina: Real-Time Subject-Dependent EEG-Based Emotion Recognition Algorithm, in Transactions on Computational Science XXIII, M. Gavrilova, et al., Editors, Springer Berlin Heidelberg. p. 199-223 (2014).
16. Bradley M. M. and L. P.J.: The International Affective Digitized Sounds (2nd Edition; IADS-2): Affective ratings of sounds and instruction manual, University of Florida: Gainesville (2007).
17. Hou, X., et al.: CogniMeter: EEG-based Emotion, Mental Workload and Stress Visual Monitoring. in International Conference on Cyberworlds (2015).
18. Emotiv: http://www.emotiv.com. Available from: http://www.emotiv.com.