Neuroscience Based Design: Fundamentals and Applications

Olga Sourina, Yisi Liu, Xiyuan Hou, Wei Lun Lim,Wolfgang Mueller-Wittig, Lipo Wang
Fraunhofer IDM@NTU
Nanyang Technological University
Singapore
{eosourina, liuys, houxy, wlim031, askwmwittig, elpwang}@ntu.edu.sg

Dimitrios Konovessis, Chun-Hsien Chen, Wei Tech Ang
School of Mechanical & Aerospace Engineering
Nanyang Technological University
Singapore
{dkonovessis, mchchen, wtang @ntu.edu.sg}

Abstract**—***Neuroscience-based or neuroscience-informed design is a new application area of Brain-Computer Interaction (BCI). It takes its roots in study of human well-being in architecture, human factors study in engineering and manufacturing including neuroergonomics. In traditional human factors studies and/or well-being study, mental workload, stress, and emotion are obtained through questionnaires that are administered upon completion of some task and/or the whole experiment. Recent advances in BCI research allow for using Electroencephalogram (EEG) based brain state recognition algorithms to assess the interaction between brain and human performance. We propose and develop an EEG-based system CogniMeter to monitor and analyze human factors measurements of newly designed software/hardware systems and/or working places. Machine learning techniques are applied to the EEG data to recognize levels of mental workload, stress and emotions during each task. The EEG is used as a tool to monitor and record the brain states of subjects during human factors study experiments. We describe two applications of CogniMeter system: human performance assessment in maritime simulator and EEG-based human factors evaluation in Air Traffic Control (ATC) workplace. By utilizing the proposed EEG-based system, true understanding of subjects working patterns can be obtained. Based on the analyses of the objective real time EEG-based data together with the subjective feedback from the subjects, we are able to reliably evaluate current systems/hardware and/or working place design and refine new concepts and design of future systems.*

Keywords-Neuroscience-based design; human factors; neuroergonomics, EEG; stress; mental workload; emotions

I. INTRODUCTION

Human factors study focuses on understanding of interactions among humans and other factors of a system including physical, cognitive and organizational/social aspects. On the other hand, neuroergonomics study the interaction between brain and human performance. Neuroscience-based design focuses on application of methods used in neuroergonomics and Brain-Computer Interaction (BCI) including Electroencephalogram (EEG)-based tools to design and assess software/hardware systems. Human stress, vigilance and mental workload levels, emotions during the interaction with software/hardware systems and well-being in the working place can be assessed. We proposed and developed an EEG-based system CogniMeter to monitor and analyze human factors measurements of newly designed systems, hardware and/or working places [1]. 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 or the whole experiment. However, this method only offers the evaluation of overall feelings of subjects during the task performance and/or after the experiment. Real-time EEG-based human factors evaluation of designed systems allows researchers to analyze the changes of subjects' brain states during the performance of various tasks. The data can be analyzed during or at any time interval. If we use 128Hz EEG Emotiv Epoc device, then the temporal resolution is 1/32 sec. Machine learning techniques are applied to the EEG data to recognize levels of mental workload, stress and emotions during each task. 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 from EEG together with the subjective feedback from the subjects using traditional questionnaire, we are able to reliably evaluate current systems/hardware and/or working place design and refine new concepts and design of future systems. In this paper, we describe application of CogniMeter system to assess workload of the cadets in maritime simulator and to evaluate human factors in Air Traffic Control (ATC) workplace experiment.

This paper is structured as follows: Section II introduces related works in human factors study, neuro-ergonomics, and reviews the current state of art in EEG-based emotion, mental workload and stress recognition algorithms. Section III describes proposed EEG-based tools integrated in the CogniMeter system. Two applications such as human performance assessment in maritime simulator and EEG-based human factors evaluation in ATC work place are presented in Section IV. Section V gives the conclusion.

978-1-5090-2303-5/16 $31.00 © 2016 IEEE
DOI 10.1109/CW.2016.52

II. RELATED WORK

A. Human Factors Study

Human factors research is defined as a discipline that focuses on understanding of interactions among humans and other factors of a system and the application of these understanding to optimize the human well-being and system performance [2]. It can be divided to three domains, namely physical (mainly related to physical activity such as the postures during working, movement, workplace layout, etc.), cognitive (mainly relevant with mental processing such as workload, stress while working, etc.), and organizational human factor (mainly focus on sociotechnical system such as team work, management, etc.) [2].

Human factors research contributes into various fields such as engineering, manufacturing, and biomechanics as it considers the interaction between human and machines, platforms or workspace, which leads to a more comfort and functional design.

The early application of human factors study can be traced back to 1980, when Denton [3] drew lines across the motorway to purposely distort the spatial geometry of the driver's perceptual system and successfully reduced the speed of motorbike and thus the number of fatal accidents. Besides the benefit of the human factors study to make the driving experience safer on the road, systems in cars are also being improved when human factors are investigated. An ongoing research of Intelligent Transportation Systems in car manufacturing [4] developed a cooperative adaptive cruise control system to enable different time gaps for human factors study; a workload detection system of driver is proposed in [5]. Other examples of human factors study are from medical area, where new virtual reality training simulations such as palpation of subsurface tumors are implemented and tested [6], and the effect of human factors in surgery performance are investigated [7]; from consumer products design area to meet the target of reducing the chance and errors in design and fulfill the end-users requirement [8]; from aviation domain where automation system are added as an extra help for air traffic controllers to release their workload [9]; from maritime area to correlate the mental workload, emotion of the crew and their performance onboard [10]; even from software engineering field, an attempt to include human factor into the software engineering lifecycle was made[11].

B. Neuroergonomics

Neuroergonomics study can be seen as one of the branches of human factors study. It investigates the interaction between the brain and human performance at all settings in everyday life [12]. For example, driving is one of the areas that neuroergonomics can make an impact. It was found in [13] that microsleeps detected from electroencephalogram (EEG) correlate with the declines in driving performance of drivers with sleep disorders. In [14] it was discovered that the parietal lobe activity, which is related with spatial processing in driving, decreases when the drivers listened to someone when driving. The knowledge of such interaction found by neuroergonomics can be applied to improve the work environments or to implement neuroadaptive interfaces for a better performance [15]. For example, an alert can be given to the distracted driver [16]. Neuroergonomics can also be used in design of new aviation systems where the designers may wish to come out with a system that balances the attractive information presentation and the performance of the primary flight task of the pilot. In such case, the neuroergonomic can provide fine details of the change in attention, mental workload of the pilot, which can be considered as a user feedback towards the new system. Moreover, [15] summarizes that brain-computer interface (BCI) and virtual reality (VR) are also related to neuroergonomics, as BCI can help human to interact with the environment via brain activity, e.g., using brain activity to trigger certain command in the game [17]. VR can simulate different situation where the brain states and work performance can be measured and correlated, e.g., the effect of neurofeedback on the surgical skill of trainee ophthalmic surgeons were verified in VR environment [18].

Currently, the technology in neuroergonomics research can be categorized into two groups. One measures cerebral hemodynamics, e.g., fMRI, positron emission tomography (PET). The other measures electromagnetic activity of the brain, e.g., EEG, ERP [15]. Though there is no ideal technique providing the best of spatial resolution, temporal resolution, and ease of use in the current stage, the EEG is one of the optimal choices since it has high temporal resolution, it is very easy to use, and has an acceptable spatial resolution. Mobility of EEG devices gives an important advantage over other devices in neuroergonomics. It is already proved that the spectral features from EEG can reflect the change in task difficulty and mental effort required [19-21]. Thus, in our work, we propose to use EEG-based tools to assess human performance and improve design of software/hardware and working places.

C. EEG-based Stress, Mental Workload and Emotion Recognition Algorithms

In the daily life, humans are involved in different situations that elicit emotions, stress, and workload. Traditionally, to identify these states, we may need self-reported feedback or physiological measurements that commonly are used in human factors study including neuroergonomics. However, the self-report comes with delay as it can be done only after the task completion. Physiological measurement, such as facial expressions, can be purposely pretended if the subject wants to hide his/her feelings. Bio-signals including Electro-encephalograms can be used to recognize emotions, stress, and workload. EEG-based brain state recognition is one of the emerging technologies as it can reflect the true feeling of the subjects with a high time resolution. EEG-based tools provide better accuracy of measurement than other biosignals (heart rate, skin conductivity, etc). EEG-based brain state recognition algorithms consist of two parts: feature extraction and classification. First, the EEG data are filtered and the features are extracted, then the data are classified. The classifier model is trained before brain state recognition using calibration for each subject in the case of subject dependent algorithms or using EEG databases in the case of subject-independent algorithms. Currently, subject-independent algorithms are used in applications as they have much higher accuracy than subject-independent ones.

Recently, more and more publications on EEG-based emotion recognition algorithms appeared. In [22], Hjorth parameters were extracted and fed into Support Vector Machine classifier. The best accuracy was obtained as 70% happy and sad emotions were recognized. In our previous work [23, 24]. The proposed features were fractal dimension, statistical, and higher order crossings features. In the classification step, the Support Vector Machine is used. The algorithm can recognize up to 8 emotions with the mean accuracy of 53.7% [23], and if only positive and negative emotions are recognized, the best accuracy is 92.03% [24]. In [25], a number of feature extraction methods were compared and different electrodes were tried to use. The conclusion was that the most promising features were the advanced one such as Higher Order Crossings, Fractal Dimensions, Higher Order Spectra, Hilbert-Huang Spectrum and the most promising locations were parietal and centro-parietal lobes. Unlike the other studies using stimuli such as pictures or sound clips to evoke emotions, [26] asked the subject to imagine positive or negative scene. The power spectrum of EEG rhythms was the features and the Filter-Bank Common Spatial Pattern method was used for doing the binary classification with the accuracy of 71.3%. This work confirmed that the EEG-based emotion recognition is not limited to certain type of stimuli.

Emotions and stress are correlated with each other as it was shown in a number of works, as stress can be categorized according to how it is generated: physical, mental and emotional [27]. In the emotional stress recognition works, most of them use the stimuli to evoke different emotions, e.g., images from International Affective Picture System database [27, 28], and videos [29]. In these studies, the recognition of emotional stress is more equal to the recognition of certain emotion, such as calm (considered as relaxed state), negative exciting (considered as stressed state). Different features were used in these work, including higher order spectra, second order spectrum, Fourier transform, normalized bispectrum and EEG band power in [27], asymmetry alpha rhythms pattern in [28], statistical features, Power Spectral Density and High Order Crossings [29], etc. In the classification step, well-known classifiers such as Elman classifier [27], K-NN [29] are used. An accuracy of 82.7% was obtained in [27] and 70.1% in [29] for two levels of emotional stress recognition. To recognize mental stress, [30] used Stroop test with congruent and incongruent stimulus to evoke relaxed and stressed states. The root mean square voltage in the beta, alpha, and theta bands were used as features while logistic regression classifier was used as a classifier. An accuracy of 73.96% was obtained to differentiate between relax and stress states. In our previous work [31], we employed fractal dimension and statistical features and Support Vector Machine. An accuracy of 67.06% for four levels of stress recognition was achieved.

Mental workload can be defined as a mental strain caused by an action or a task under certain operational conditions to respond to certain demand [32]. It is essential to measure the workload in order to calculate the mental cost of doing tasks so as to predict the performance of either the operator or system. For example, [33] attempted to use EEG to monitor the mental workload of the pilot and suggested this may make it possible to get feedback from the pilot towards the aircraft system. In [33], theta band power was found to increase when inflight mental calculations was needed. Our previous work also investigated the EEG-based mental workload recognition [34]. Fractal dimension features and statistical features were extracted and used as the input to SVM classifier. A mean accuracy of 80.09% was obtained for 4 levels of mental workload recognition. The proposed and implemented emotion, stress and mental workload recognition algorithms were integrated in the CogniMeter system.

III. CogniMeter

In this section, the details of the proposed brain states monitoring system CogniMeter are described. In the hardware part, the system supports EEG devices from different companies. For example, the wireless Emotiv EPOC device with 14 channels is applied in maritime [35], and air traffic control experiments[36] . It is a popular low-cost EEG device widely used for both research and entertainment. Emotiv EPOC has 14 channels located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 as shown in Fig. 1. In the software part, the workload [34], stress [31] and emotion [23, 24] recognition algorithms proposed in our previous work are implemented separately. Currently, subject-dependent algorithms are used as they give better accuracy than subject-independent algorithms. However, subject-dependent algorithms need calibration for each subject before being used in any applications. There are different calibration processes for workload, stress and emotion before real-time recognition or/and EEG recording for offline data processing. After calibration, the results of real-time recognition can be visualized on the meters for brain states monitoring.

A. Calibration

For workload calibration, SIMKAP simultaneous capacity test is applied to invoke different workload levels. In lower workload level, subjects need to complete a single task of matching numbers, letters and shapes. For a higher workload level, subjects require to perform multitasking like answering arithmetic questions, schedule checking and telephone searching. After each test, the subject fills a prompted questionnaire to rate workload level from 1 to 9, as shown in Fig. 2(a).

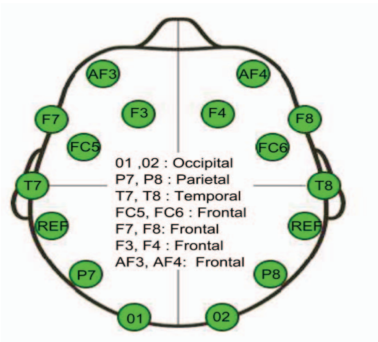


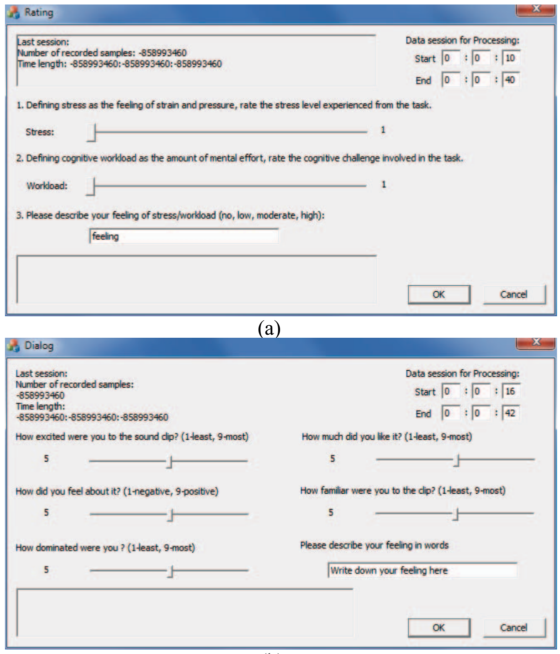
Figure 1. Location of 14 electrodes of Emotiv EEG device.

For stress calibration, the Stroop color-word test is used to induce different levels of workload. The subjects perform the Stroop test with different levels, and the self-assessment for each level is done at the end of each section. In the easy level, the word's meaning is the same with the word's font color. In the medium level, the word's meaning is different with the word's font color to induce moderate stress. In the hard level, Stroop test requires the subject to react to the incongruent word within a limited time to induce higher stress. Each part of the Stroop test lasts for 1 minute, and the prompted questionnaire to evaluate the subject's mental stress level on the scale from 1 to 9 and to describe his/her feelings in words is as shown in Fig. 2(a).

For emotion calibration, several sound clips from IADS database [37] are selected as stimuli to evoke certain emotions. There are 15 seconds silence audio at the beginning of each sound clip to help the subject return to a neutral state. After playing the sound clip targeted to elicit one emotion for 30 seconds, the subject needs to fill a prompted questionnaire to evaluate and describe his/her experienced emotion when he/she was exposed to the sound clips. A 3D emotional model is used to define an emotion. The subject enters values on the scale from 1 to 9 of arousal (from calm to excited), valence (from negative to positive), and dominance (from low control to high control) dimension and describes the feelings by words as well as shown in Fig. 2(b).

B. Real-time Recognition and Monitoring

After calibration of a workload, stress and/or emotion, three classifier models are trained and applied for the corresponding brain state recognition. During real-time brain states monitoring, the results of the recognized workload, stress and emotions are sent to Node.js server which is updated every second. Fig. 3 shows CogniMeter interface developed in JavaScript and rendered in a Chrome browser. Workload and stress meters display the magnitude scale from 0 to max while the emotion meter represents emotions from positive to negative. In each meter, the color of the bar also represents the magnitude of values, which is green on the left, yellow on the middle, and red on the right.



(a)

(b)

Figure 2. Screenshots of calibration questionnaire interfaces: (a) stress and workload rating questionnaire; (b) emotion rating questionnaire.

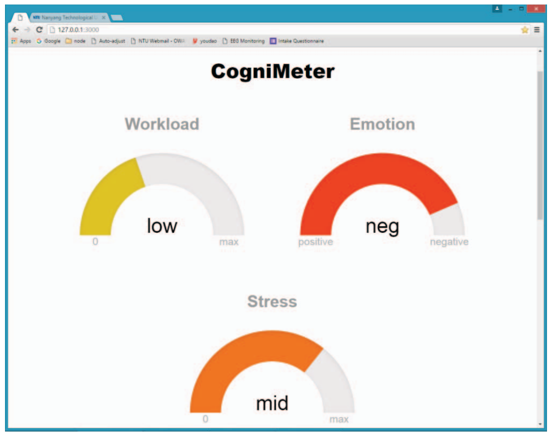


Figure 3. Screenshot of brain states monitoring system CogniMeter.

After a period of time of monitoring, a report can be generated to show the distribution of each brain states over the period of time. For example, Fig. 4 shows the distribution of mental workload (low, medium and high), emotion (positive and negative) and stress (low, medium low, medium, medium high, and high) during five minutes monitoring process. From Fig. 4, we can see that the workload is almost equally distributed in three levels (high 35%, medium 29%, and low 34%). Most of subject's emotions are positive 62% during the experiment. The stress level is medium 32% in most time of the experiment.

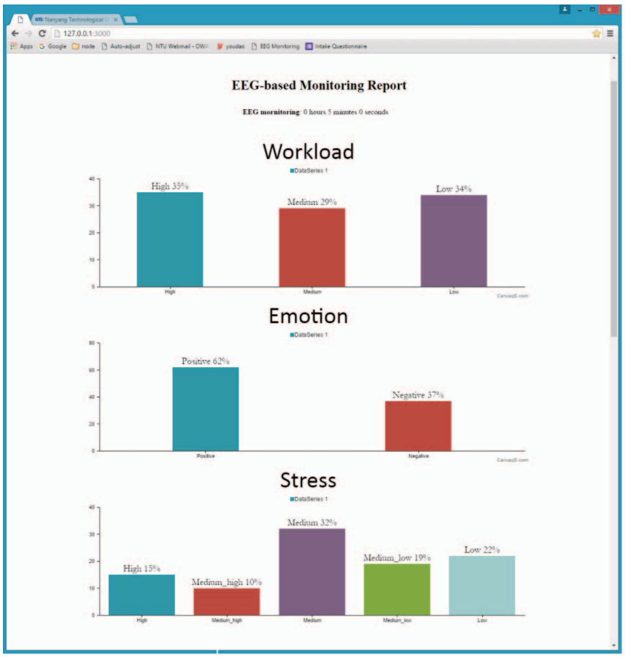


Figure 4. Screenshot of summary of workload, stress levels and emotions during 5 minutes monitoring.

The real-time EEG-based emotion, workload and stress visualization system CogniMeter is implemented with Visual Studio 2010 in C++. The proposed CogniMeter can be used to monitor and analyse human well-being and human performance related to different tasks in many applications. Here, we describe the following examples of use of the CogniMeter. First, a case study from the experiment in maritime virtual simulator to assess the cadet's performance during the navigation is described. Then, an experiment to assess new software in air-traffic control management system is given.

IV. APPLICATION

A. *Human Performance Assessment in Maritime*

In [35], we described a case study from the results of stress recognition of crew in a ship's bridge simulator based assessment. In this paper, we present mental workload recognition of the crewmembers in the maritime virtual simulator. The experiment to collect the EEG data is briefly described as follows and more details are presented in [35]. 7 cadets were recruited to complete 4 exercises with increasing difficulty in the maritime simulator. A training session was done right before the exercise and it was used to calibrate the classifier for mental workload recognition. Four levels of workload ranging from low to high can be detected using the trained classifier. Then, the cadet executed the cruising exercise with mechanical emergencies or alarms, changing traffic conditions and weather conditions simulated. The cadets needed to wear the Emotiv device during the entire exercise, as shown in Fig. 5. The whole exercise was also recorded by video camera. This video is used to give time stamps of the demanding events of the exercise on the EEG data.

Figure 5. Cadet with EEG device in the simulator.

Using the EEG with time labels of the events, it is possible to get a complete understanding of the brain states changes during the experiment. A case study of one cadet is presented in Fig. 6-9. The y-axis denotes the recognized workload level, ranging from 1 (the lowest level) to 4 (the highest level), and the x-axis is the sample point number corresponding to the time. The solid line in the figures is the instantaneous workload level recognized from EEG and the dash line is the average over 1 minute. Let's consider the case study to see how mental workload recognition from EEG is used to assess the cadet performance. The following scenario was used in the experiment.

At time 4:17/257 (Hour: Minutes/sample point in the figure), a random alarm was given. From the workload recognized from EEG signal, a sharp spike was identified as shown in Fig. 6, which was a reading of the recognized level 3 (the highest workload) when the alarm was given, and once the alarm was turned off the workload values dropped back to the level 1 (the lowest workload).

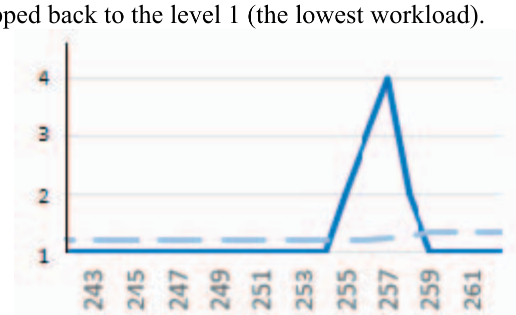


Figure 6. Mental workload level recognized from EEG when the alarm was given.

At time 5:30/330, the cadet altered the course to overtake. From the EEG results, an increase of mental workload was found, which indicated the recognized workload level was the highest when the overtaking was being conducted as shown in Fig. 7.

At 8:49/760, a fake fire alarm was given. The cadet went to assess the situation. From the EEG results, a continuously increasing workload was detected. The high workload was maintained for quite a while and was diminished after the cadet assessed the situation. The average workload also showed a steady increase as depicted in Fig. 8.

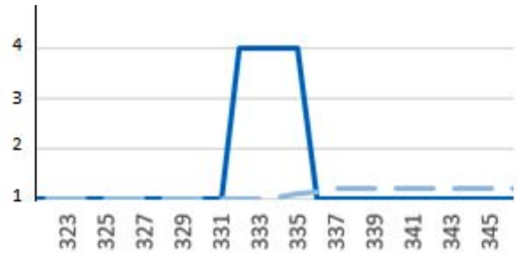


Figure 7. Workload level recognized from EEG when the cadet altered his course to overtake the ship.

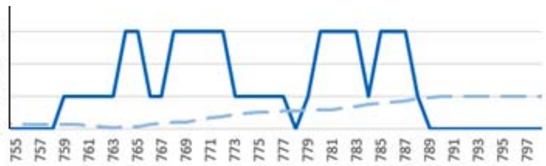


Figure 8. Workload level recognized from EEG when a fake fire alarm was given.

At time 19:30/1050, the cadet had a crossing ship situation and needed to watch the ship and to alter the course accordingly. Thus, the recognized workload level from EEG started to rise again, and as the cadet managed to complete the task, a medium-high workload was detected as shown in Fig. 9. When the cadet has normal cruise, the workload level keeps at the lowest level.

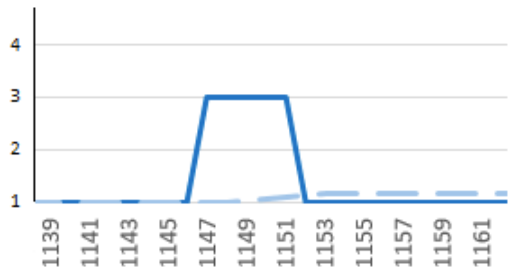


Figure 9. Workload level recognized from EEG when the cadet altered course to overtake.

From this case study, it can be seen that the EEG based mental workload level correlates with the timing of the corresponding demanding event in the maritime exercise and reflect amount of mental effort needed to attend the event.

B. *EEG-based Human Factors Evaluation in ATC Work Place*

In our previous work [36], we demostrated that there is a significant correlation between the EEG-based workload recognition and NASA Task Load Index (TLX) method results. Here, we extend this human factors study to evaluate the current Air Traffic Control (ATC) work place including interactive touch display and reliable/unreliable Conflict Resolution Aid (CRA). Fig. 10 shows an ATC simulator integrated with the interactive touch display (front) and conflict resolution aid (left).

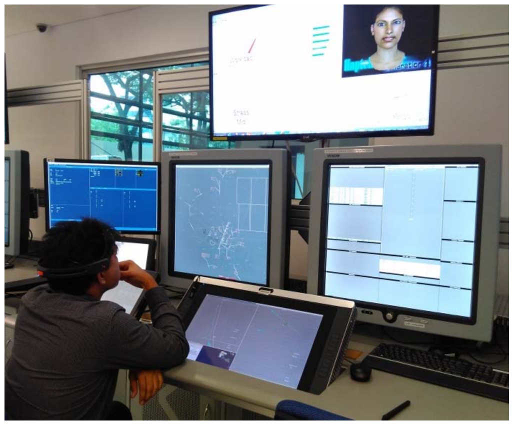


Figure 10. The air traffic control work place integrated with EEG-based brain states monitoring system.

Meanwhile, an Emotiv EEG device was used to collect brain signals. In this work place, a CRA display is integrated to support ATCOs in resolving conflict. The CRA is an automation aid that could advise air traffic controllers (ATCOs) on the resolution of a potential conflict about 2 minutes in advance. In addition, an interactive touch display is used to help ATCOs to understand the airspace situation. This display provides ATCOs with the information of aircraft speed profile, climb and descend rate along the time axes.

Three scenarios are designed in this experiment. EEG data are recorded throughout the whole experiment. Upon completion of each experiment scenario, the NASA-TLX questionnaire is used to measure mental workload of ATCOs. The results of the study will help to inspect the current workplace and propose further development design.

The data collected in the ATC work place is based on three groups (Non-Display, Display, and Trajectory Prediction) in the three CRA conditions (Manual, Reliable and Unreliable). In workload rating analysis, both NASA-TLX method and EEG-based recognition method were administered. We analyzed the relationship between mental workload calculated using traditional NASA-TLX method and the method used to label EEG data with different workload levels. It was found that the data are highly correlated in most of the simulations [36]. Thus, the EEG-based system can be used to recognize workload during each task performance at any time.

To get a deeper understanding of the workload experienced by ATCOs from different group and under different conditions, three-levels of EEG-based recognized workload were used for analysis. Each of the one-hour session was split into intervals of 5 minutes and the recognized workload level is defined as an average recognition results for each 5-minute interval.

To analyze the effects of automation aids on workload, the mean and standard error of the workload measured for different time intervals, all display modes and time intervals, and all CRA settings and time intervals are plotted in Fig. 11-13 respectively. In Fig. 11, it can be observed that the mean workload is relatively high at the start of the session and from the 20th minute to the 45th minute when all data are used regardless of the CRA and display settings. The significance value obtained from the mixed ANOVA test for time factor is 0.025, which means that ignoring the CRA setting and display mode, the workloads measured through the 12 time intervals are significantly different.

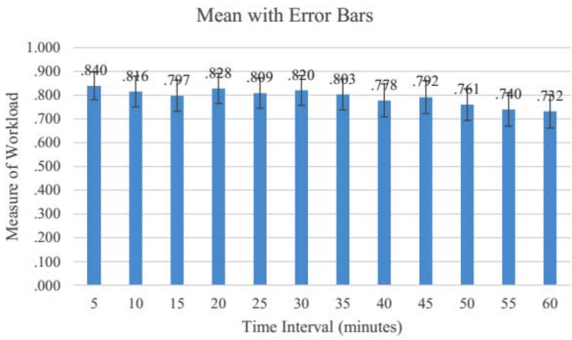


Figure 11. Measure of workload ignoring the CRA setting and display mode in 12 time intervals.

In Fig. 12, the mean workload measured is the highest under the trajectory prediction and similar for the display and non-display mode. In Fig. 13, the mean workload obtained from the interaction between CRA setting and time intervals is similar to the trend observed in Fig. 11 except that the mean workload at the start of the unreliable CRA setting is relatively low.

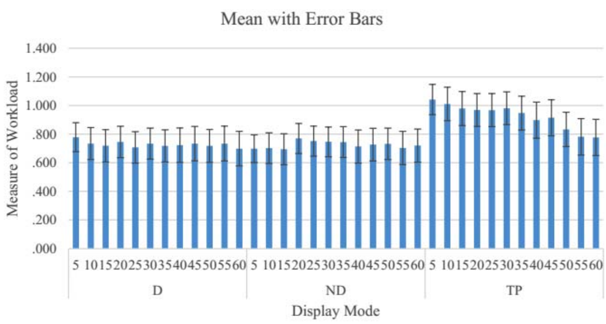


Figure 12. Measure of workload based on display mode Non-Display (ND), Display (D), and Trajectory Prediction (TP) in 12 time intervals.

EEG-based workload evaluation method enables the continuous measurement of the subject's workload, which allows for a more detailed analysis of experiment results obtained. From this ATC study, we conclude that the complexity of trajectory prediction has resulted in a higher workload compared to other display aids in all time points and the reliability of CRA has minimal effect on workload. Therefore, the trajectory prediction aid may need to be redesigned to meet the aim of reducing workload experienced by air traffic controllers.

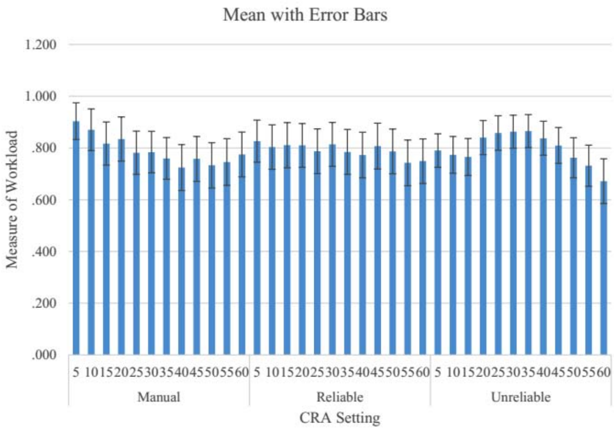


Figure 13. Measure of workload based on the CRA settings Manual, Reliable and Unreliable in 12 time intervals.

V. Conclusion

In this paper, we discuss application of EEG-based mental workload, stress and emotion recognition algorithms in human factors study and neuroergonomics. Neuroscience-based design is a new application area of human BCI. The implemented CogniMeter system allows for monitoring and analyzing EEG recordings to recognize mental workload, stress levels and emotions and assess design of software/hardware and/or working place based on human performance. Currently, subject-dependent algorithms are used, and calibration of each algorithm for each subject is needed that requires additional time before the algorithms application. Two applications of CogniMeter system are described: human performance assessment in maritime simulator and EEG-based human factors evaluation in ATC work place. The results of workload recognition from EEG comply with traditional method such as NASA Task Load Index (TLX) workload assessment results using the questionnaire. The advantage of EEG application is the possibility to recognize emotion, stress, and mental workload at any time during the task performance or experiment.

Acknowledgment

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its international Research Centers in Singapore Funding Initiative, by Singapore Maritime Institute and by Civil Aviation Authority of Singapore (CAAS) and Air Traffic Management Research Institute (ATMRI) Project ATMRI: 2014-R5-CHEN.

References

[1] X. Hou, Y. Liu, O. Sourina, and W. Mueller-Wittig, "CogniMeter: EEG-based Emotion, Mental Workload and Stress Visual

Monitoring," in *International Conference on Cyberworlds* 2015, pp. 1-10.

[2] I. E. Association. *Definition and Domains of Ergonomics*. Available: http://www.iea.cc/whats/index.html

[3] G. G. Denton, "The influence of visual pattern on perceived speed," *Perception,* vol. 9, pp. 393-402, 1980.

[4] F. Bu, H.-S. Tan, and J. Huang, "Design and field testing of a cooperative adaptive cruise control system," in *American Control Conference (ACC)*, 2010, pp. 4616-4621.

[5] Y. Yang, H. Sun, T. Liu, G.-B. Huang, and O. Sourina, "Driver workload detection in on-road driving environment using machine learning," in *Proceedings of ELM-2014 Volume 2*, ed: Springer, 2015, pp. 389-398.

[6] M. Dinsmore, N. Langrana, G. Burdea, and J. Ladeji, "Virtual reality training simulation for palpation of subsurface tumors," in *Virtual Reality Annual International Symposium, 1997., IEEE 1997*, 1997, pp. 54-60.

[7] M. R. de Leval, J. Carthey, D. J. Wright, V. T. Farewell, and J. T. Reason, "Human factors and cardiac surgery: A multicenter study," *The Journal of Thoracic and Cardiovascular Surgery,* vol. 119, pp. 661-672, 4// 2000.

[8] N. A. Stanton, *Human factors in consumer products*: CRC Press, 1997.

[9] M. Endsley, R. Sollenberger, and E. Stein, "The use of predictive displays for aiding controller situation awareness," presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 1999.

[10] Y. Liu, X. Hou, O. Sourina, D. Konovessis, and G. Krishnan, "Human factor study for maritime simulator-based assessment of cadets," in *Proceedings of the 35th International Conference on Ocean, Offshore and Arctic Engineering (OMAE)*, 2016.

[11] N. Bevan and M. Azuma, "Quality in use: Incorporating human factors into the software engineering lifecycle," in *Software Engineering Standards Symposium and Forum, 1997. Emerging International Standards. ISESS 97., Third IEEE International*, 1997, pp. 169-179.

[12] R. Parasuraman, "Neuroergonomics: Research and practice," *Theoretical Issues in Ergonomics Science,* vol. 4, pp. 5-20, 2003.

[13] A. Paul, L. N. Boyle, J. Tippin, and M. Rizzo, "Variability of driving performance during microsleeps," in *Proceedings of the Third International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*, 2005, pp. 433-440.

[14] M. A. Just, T. A. Keller, and J. Cynkar, "A decrease in brain activation associated with driving when listening to someone speak," *Brain research,* vol. 1205, pp. 70-80, 2008.

[15] R. Parasuraman and M. Rizzo, *Neuroergonomics: The brain at work*: Oxford University Press, 2006.

[16] C. Spence, "Drive safely with neuroergonomics," *Psychologist,* vol. 25, pp. 664-667, 2012.

[17] Y. Liu, X. Hou, O. Sourina, and O. Bazanova, "Individual Theta/Beta Based Algorithm for Neurofeedback Games to Improve Cognitive Abilities," in *Transactions on Computational Science XXVI: Special Issue on Cyberworlds and Cybersecurity*, Heidelberg: Springer Berlin Heidelberg, 2016, pp. 57-73.

[18] T. Ros, M. J. Moseley, P. A. Bloom, L. Benjamin, L. A. Parkinson, and J. H. Gruzelier, "Optimizing microsurgical skills with EEG neurofeedback," *BMC neuroscience,* vol. 10, p. 87, 2009.

[19] A. Gevins, M. E. Smith, H. Leong, L. McEvoy, S. Whitfield, R. Du, and G. Rush, "Monitoring working memory load during computer-based tasks with EEG pattern recognition methods," *Human Factors: The Journal of the Human Factors and Ergonomics Society,* vol. 40, pp. 79-91, 1998.

[20] A. Gundel and G. F. Wilson, "Topographical changes in the ongoing EEG related to the difficulty of mental tasks," *Brain Topography,* vol. 5, pp. 17-25, 1992.

[21] A. Gevins and M. E. Smith, "Electroencephalography (EEG) in neuroergonomics," *Neuroergonomics: The brain at work,* pp. 15-31, 2006.

[22] R. M. Mehmood and H. J. Lee, "EEG based emotion recognition from human brain using hjorth parameters and SVM," *Int. J. Bio-Sci. Bio-Technol.,* vol. 7, pp. 23-32, 2015.

[23] Y. Liu and O. Sourina, "Real-time Subject-dependent EEG-based Emotion Recognition Algorithm," *Transactions on Computational Science XXIII,* Vol 8490, pp 199-223*,* 2014.

[24] Z. Lan, O. Sourina, L. Wang, and Y. Liu, "Real-time EEG-based emotion monitoring using stable features," *The Visual Computer,* 32(3), pp 347-358, 2016.

[25] R. Jenke, A. Peer, and M. Buss, "Feature extraction and selection for emotion recognition from EEG," *IEEE Transactions on Affective Computing,* vol. 5, pp. 327-339, 2014.

[26] C. A. Kothe, S. Makeig, and J. A. Onton, "Emotion recognition from EEG during self-paced emotional imagery," in *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*, 2013, pp. 855-858.

[27] S. A. Hosseini and M. A. Khalilzadeh, "Emotional stress recognition system using EEG and psychophysiological signals: Using new labelling process of EEG signals in emotional stress state," in *2010 International Conference on Biomedical Engineering and Computer Science*, 2010, pp. 1-6.

[28] A. G. Pomer-Escher, M. D. P. de Souza, and T. F. Bastos Filho, "Methodology for analysis of stress level based on asymmetry patterns of alpha rhythms in EEG signals," in *5th ISSNIP-IEEE Biosignals and Biorobotics Conference (2014): Biosignals and Robotics for Better and Safer Living (BRC)*, 2014, pp. 1-5.

[29] T. F. Bastos-Filho, A. Ferreira, A. C. Atencio, S. Arjunan, and D. Kumar, "Evaluation of feature extraction techniques in emotional state recognition," in *Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on*, 2012, pp. 1-6.

[30] T. K. Calibo, J. A. Blanco, and S. L. Firebaugh, "Cognitive stress recognition," in *2013 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2013, pp. 1471-1475.

[31] X. Hou, Y. Liu, O. Sourina, T. Y. R. Eileen, L. Wang, and W. Mueller-Wittig, "EEG based Stress Monitoring," in *IEEE International Conference on in Systems, Man and Cybernetics (SMC)*, 2015, pp. 3110-3115.

[32] B. Cain, "A review of the mental workload literature," DTIC Document2007.

[33] T. C. Hankins and G. F. Wilson, "A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight," *Aviation, space, and environmental medicine,* vol. 69, pp. 360-367, 1998.

[34] W. L. Lim, O. Sourina, L. Wang, and Y. Liu, "EEG-based Mental Workload Recognition Related to Multitasking," in *Proceeding of the Int Conf on Information, Communications and Signal Processing (ICICS)*, 2015, pp. 1-4.

[35] Y. Liu, X. Hou, O. Sourina, D. Konovessis, G. Krishnan, and N. E. Sánchez, "Human Factors Evaluation in Maritime Simulator-based Assessment: a Case Study," in *6th International Maritime Conference on Design for Safety*, accept, 2016.

[36] X. Hou, F. Trapsilawati, Y. Liu, O. Sourina, C. Chen, W. Mueller-Wittig, and W. T. Ang, "EEG-based Human Factors Evaluation of Conflict Resolution Aid and Tactile User Interface in Future Air Traffic Control Systems," in *7th International Conference on Applied Human Factors and Ergonomics,* accepted, 2016.

[37] 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, Gainesville2007.