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EEG-based Human Factors Evaluation of Air Traffic Control Operators (ATCOs) for Optimal Training

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***Abstract*— To deal with the increasing demands in Air Traffic Control (ATC), new working place designs are proposed and developed that need novel human factors evaluation tools. In this paper, we propose a novel application of Electroencephalogram (EEG)-based emotion, workload, and stress recognition algorithms to investigate the optimal length of training for Air Traffic Control Officers (ATCOs) to learn working with three-dimensional (3D) display as a supplementary to the existing 2D display. We tested and applied the state-of-the-art EEG-based subject-dependent algorithms. The following experiment was carried out. Twelve ATCOs were recruited to take part in the experiment. The participants were in charge of the Terminal Control Area, providing navigation assistance to aircraft departing and approaching the airport using 2D and 3D displays. EEG data were recorded, and traditional human factors questionnaires were given to the participants after 15-minute, 60-minute, and 120-minute training. Different from the questionnaires, the EEG-based evaluation tools allow the recognition of emotions, workload, and stress with different temporal resolutions during the task performance by subjects. The results showed that 50-minute training could be enough for the ATCOs to learn the new display setting as they had relatively low stress and workload. The study demonstrated that there is a potential of applying the EEG-based human factors evaluation tools to assess novel system designs in addition to traditional questionnaire and feedback, which can be beneficial for future improvements and developments of the systems and interfaces.**

Keywords—Air traffic control, training, interface design, EEG, stress recognition, emotion recognition, workload recognition, human factors study

I. Introduction

Air Traffic Control (ATC) systems have been improved with the advancement in computer technology. However, with air traffic density expected to increase in the next 20 years [1], these systems need to be farther improved or replaced in order to keep up with the traffic demand. Currently, novel ATC system designs are proposed and developed. Such novel systems need to be well assessed before the implementation in real ATC systems in airports. Usually, the human factors experiments are done using traditional questionnaires that are filled after the task performance. However, novel Electroencephalogram (EEG)-based human factors evaluation tools allow us to recognize workload, emotion and stress during the ATC task performance with high temporal resolution [2]. The state-of-the-art algorithms of emotion, workload, and stress recognition from EEG were tested and applied to evaluate the ATC procedures in [2] in addition to the traditional questionnaires and showed promising results.

In the current stage, ATCOs monitor the movement of aircraft within the country's airspace via a 2D display, which shows a plan view of the approach sector with dots representing the aircraft in view. However, there is no vertical representation of the altitude the aircrafts are flying at [3]. Instead, the 2D display shows the altitude or Flight Level (FL) as a numerical value on each dot that is tagged to that particular aircraft. This bird's eye view of information could be messy during the peak hours, intensifying the stress on the ATCOs. It may increase the tendency for ATCOs to make errors, which could lead to severe consequences should there be a near miss. Thus, it is important to study the possibility of using additional 3D display in such procedure. In [4], it was proposed that 3D interface might be

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useful in Trajectory Based Operations (TBO), Holding Stack Management (HSM), Continuous Climb Operations (CCO), and Continuous Descent Operations (CDO) procedures. In [5], HSM, CCO, CDO, and TBO procedures were assessed in relation to the use of an additional 3D display and the positive results were received for HSM. For implementing new 3D interfaces at ATCO workplace, it is important to find out the time needed for learning to use additional 3D display. In this paper, we propose and implement an experiment where 12 ATCOs underwent two-hour training to use an additional 3D display based on real-life scenarios. The objective of the experiment is to determine the optimal training duration using novel EEG-based human factors evaluation tools such as human emotion, workload and stress recognition. The training durations of 30 minutes, 60 minutes, and 120 minutes are considered to find out the optimal training time in using the novel 3D display additionally to the 2D display. EEG is used to monitor the brain states of the ATCOs while they are learning to use the 2D+3D display. Traditional human factors questionnaires are also employed to get feedback from the ATCOs about the additional 3D display.

The paper is structured as follows. In Section II, related work is reviewed. In Section III, the experiment setting is introduced. In Section IV, the methodology is presented. Section V gives the results and finally Section VI concludes the paper.

II. Related Work

A. Current ATC Radar Display

A common ATC setup comprises two terminals, the Flight Radar Display (2D radar display) and the Flight Information Display. The Flight Radar Display (FRD) shows a plan view of the Flight Information Region (FIR) in which ATCOs have control over the aircraft flying within the region. Each aircraft is represented by a dot which displays the information such as aircraft call-sign, Flight Level (FL) at which they are flying, requested FL, aircraft speed and heading and expected runway (arrival) or departure routes (departure).

This representation of information can get very complicated when there is a high air traffic density with multiple dots flooding the screen. Furthermore, because the FRD displays the information in one view, it could be difficult to visualise aircraft flying over each other, such as during a holding stack or on parallel airways. The only information ATCOs can take reference from would be through the numerical value of the FL at which the aircraft is flying. In addition, it might be possible that ATCOs may get confused with the numbering of FL (1FL = 100ft), impeding their judgement. There have been studies indicating that ATCOs experience difficulties in visualising aircraft altitude behaviour as well as vertical separation with a single 2D display [6].

B. Three-dimensional Radar Display

The rising demand for aircrafts as a primary mode of transport is a compelling motivation for the aviation industry to increase the number of airplanes in operation at any one time. Consequently, air traffic controllers are required to become progressively efficient, not only in maintaining flight safety but also in the effectual guidance of orderly traffic flow. The cognitive capabilities of air traffic controllers would be challenged as they encounter more sophisticated instantaneous situations that necessitates swifter and more accurate decisions. It is imperative to ensure that the cognitive capacities of controllers are not exceeded in ATC duties [7], hence the need for more navigation aids such as decision support is growing. This however leads to an increasing amount of information necessary for controllers to perform their tasks which leads to an overloading of the conventional two-dimensional radar. Therefore, a potential remedy to overcome this problem would be through the use of a three-dimensional radar display [8].

Although use of 3D displays in current ATC operations are scarce, numerous studies have been conducted to determine the potential of a 3D display. For example, experiments were conducted to determine the effectiveness of a 3D display in performing trajectory operations of aircrafts in different weather conditions and terrains [9]. The use of a 3D virtual reality (VR) system for real-time visual representation of air traffic are currently undergoing further evaluation [10]. Furthermore, the Federal Aviation Authority (FAA) have also directed several studies regarding the use of 3D displays with novel NextGen tools [11].

C. Study for Optimizing ATC Training

Several researches have been conducted on optimizing the training efficiency of ATCOs by enabling learner-controlled task selection [12, 13]. Mental workload was measured by ratings from the subjects and used as an indicator of the training efficiency in [12]. In recent work [14], it also mentions that emotional stress could be used as an indirect indicator to assess the training. However, there is little work done on determining the optimal training length in ATC domain. Usually, fixed training duration is used [15]. To fill this gap, we investigate the optimal training length for ATCOs to manage a novel ATC system. Mental states such as workload, emotion, and stress are used as indicators to decide the duration of training.

III. Experiment

An experiment was carried out with ATCOs to determine the optimal training. EEG was recorded during the experiment to monitor the changes of brain states such as emotion, workload, and stress of the ATCOs while they were learning to use the additional 3D display.

A. Flight Plan

The flight plan comprises flight information of all planes in the training scenario, for instance, call sign, initial flight levels, designated runways, departing and arriving airport identifiers. To ensure realism, the required flight information was retrieved from Flightradar24, a live air traffic tracking website displaying the information of all flights in real time. However, to develop an appropriate scenario where the workload and mental effort experienced by the participants remain relatively constant throughout the two-hour scenario, flight schedules of each plane was slightly adjusted to maintain consistent air traffic density.

B. Additional 3D Radar Display

The 3D interface (shown in Fig. 1) possesses similar features to the conventional display, namely waypoint and flight labels as well as representation of restricted airspace.

The main function of the 3D radar display is the use of screen rotation, tilt and pan to allow for an oblique viewpoint of the airspace. Besides, the novel interface also boasts several new features which can be toggled on or off based on the controls located at the top left portion of the screen. For example, flights at different altitudes are required to adhere to different separation minima based on their speed and aircraft type. These are represented as coloured cylinders around each plane blipper. Another useful feature is the prediction of aircraft trajectories. The location of any aircrafts within the designated airspace can be represented through the use of trajectory prediction. Furthermore, an additional feature known as conflict prediction is available in the 3D interface. When an aircraft trespasses into the separation minima of another aircraft/s, the safety separation cylinder will flash red to alert the controller of a potential conflict scenario.

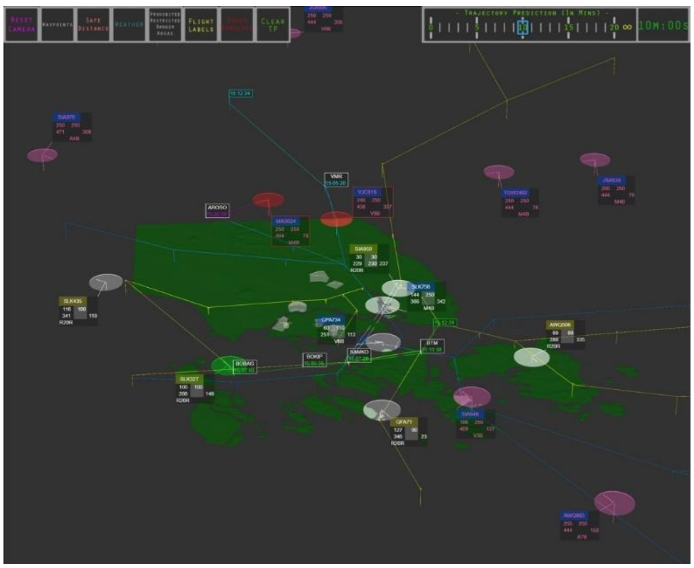

Fig. 1. 3D Flight Radar Display.

C. *Subjects*

Twelve Air Traffic Control Officers (ATCOs) with experience ranging from 1-8 years participated in the two-hour training session on the novel ATC three-dimensional radar display. As the participants have extensive experience with ATC operations, they are expected to have profound knowledge in the relevant protocols and be proficient in performing duties of a controller. Six out of the 12 ATCOs were males.

D. *EEG Recording*

A 14-channel Emotiv device [16] was used to record the EEG data. As the EEG-based brain state recognition algorithms are subject-dependent, calibration are needed before we can recognize the brain states during the ATC tasks. To induce the targeted emotions, sound clips from IADS [17] database are selected and used in the calibration process. For workload, the Stroop Color Test is used to evoke different levels of workload. More details about the calibration and the EEG-based brain states recognition algorithms can be found in our previous work [18] and [19]. After calibration, the ACTOs kept wearing the device and had their EEG recorded throughout the whole experiment.

E. *Questionnaire*

During the experiment, we have a series of questionnaires for the subjects to fill in, including intake questionnaire before the experiment and TRUST [20] questionnaires after 15-minute, 60-minute, and 120-minute training of using the additional 3D display. The intake questionnaire includes demography of the subject, ATC background, and consent form to attend this experiment. The TRUST questionnaire contains two parts: deception and trust between the subjects and the system. These are the traditional techniques used in the study of human factors.

F. *Procedure*

During the experiment, each subject went through the following procedure:

1. Briefing of the experiment.
2. Filling of the intake questionnaire and consent form.
3. Set-up and calibration of EEG-based emotion/workload recognition algorithm.
4. Participants underwent training program (interrupted after 15 minutes, 60 minutes, and 120 minutes). Questionnaires (TRUST) were given after the interruptions.

The experimental apparatus is as shown in Fig. 2, which consists of three separate screens: 3D radar display with a web camera to observe participants' behaviours (leftmost screen), conventional 2D display (centre screen), and the flight schedule display (rightmost screen). The EEG signal was recorded by the Emotiv device, which is wirelessly connected to the laptop as shown in the right of the ATCOs.

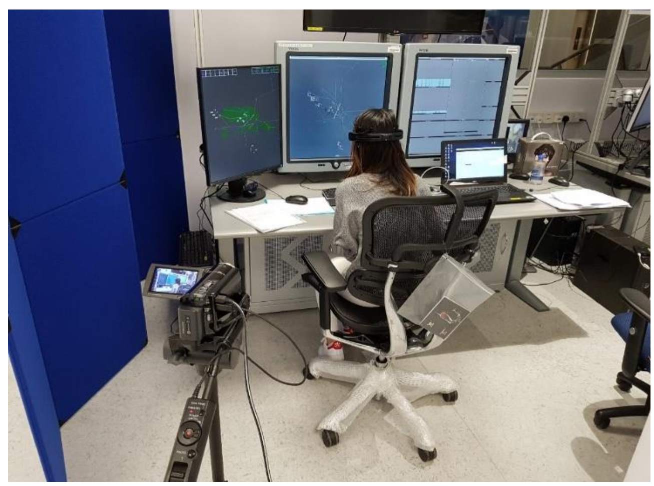

Fig. 2. Experiment scenario with ATCO.

IV. METHODS

A. *EEG-based Brain State Regcognition Algirithms*

In our previous work [18] and [19], subject-dependent algorithms for emotion and workload recognition from EEG signals were proposed. In work [21], a stress recognition algorithm is proposed based on the emotion and workload recognition algorithms. The idea is to combine the recognized emotion and workload results to get stress level as it has proven that stress is correlated with emotion and workload [22]. Finally, up to 8 levels of stress can be identified using EEG.

Successful emotion and workload recognition are crucial to the subsequent analysis, thus in this paper we further performed model selection by carrying out subject-dependent five-fold cross-validation using different features and classifiers on the labeled training data obtained during the calibration process. The model that yielded the best accuracy was selected for the subsequent processing. The averaged recognition accuracy across all subjects are presented in Table I and Table II for the emotion and workload recognition, respectively. As shown in the tables, the fractal dimension + 6 statistic features, in combination with a SVM [23] classifier, yield the best recognition accuracy for both emotion recognition and workload recognition. Additionally, the studies in [24, 25] have shown that the fractal dimension + 6 statistic features are among the most stable features even when no re-calibration is performed. We therefore use these models for the subsequent analysis of the ATCOs' cognitive performance.

TABLE I. RECOGNITION ACCURACY (%) FOR THREE EMOTIONS (POSITIVE, NEUTRAL, AND NEGATIVE)

Feature	Classifier			
	LDA	*1-NN*	*SVM*	*Naïve Bayes*
6 Statistics [26]	66.11	62.41	69.07	62.22
36 HOC [27]	45.37	38.70	41.30	43.33
FD + 6 Statistics [28]	71.11	61.30	**72.22**	63.15
Hjorth [29, 30]	52.41	52.04	61.30	57.22
Signal Energy [30]	57.04	53.52	56.48	53.70
Spectral Band Power ($\delta + \theta + \alpha + \beta$) [31]	57.59	62.41	59.63	57.59

TABLE II. RECOGNITION ACCURACY FOR FOUR WORKLOAD LEVELS.

Feature	Classifier			
	LDA	*1-NN*	*SVM*	*Naïve Bayes*
6 Statistics [26]	61.90	61.96	70.77	54.64
36 HOC [27]	41.96	30.42	38.10	36.96
FD + 6 Statistics [28]	54.46	61.43	**74.23**	52.68
Hjorth [29, 30]	63.57	54.94	60.95	43.87
Signal Energy [30]	54.11	52.02	42.62	39.88
Spectral Band Power ($\delta + \theta + \alpha + \beta$) [31]	57.38	53.51	54.64	41.85

B. Hypotheses

The following hypotheses are tested based on the EEG-based brain state recognition results:

1. The participants experience the most negative emotions during the first 15 minutes of training, and more positive emotions comparing to the average emotional state of 1-hour training. The average emotion of the entire 2-hour training is more negative compared to the average of 1-hour training as the participants may feel less positive due to the long training hours.

2. The participants experience high workload during the first 15 minutes of training and lower workload when taking the average of the first 1 hour. The average workload across the entire 2-hour training is lower than the average for 15 minutes and for 1 hour as the participants are expected to fully manage the new 3D display after 2-hour training.

3. The participants experience a high stress level during the first 15 minutes of training, and a lower stress level during 60 minutes. When averaging across the entire 2-hour training, the lowest level of stress is expected as the participants may fully manage the new 3D display after 2-hour training.

For results from Trust questionnaire, we expect that

4. There is less trust presented at the beginning of the training of using the 3D display (after 15 minutes). The trust level increases gradually and reaches the maximum at the end of the experiment (after 120 minutes)

V. RESULTS

A. EEG-based Emotion Recognition

Firstly, the EEG-based emotion recognition results are averaged for every 5-minute interval per participant, then a mean emotion level is obtained across all 12 participants for 15-minute, 60-minute, and 120-minute training duration as shown in Fig. 3. Here, emotion scale ranges from 0 to 2, where each value 0, 1 and 2 represents positive, neutral and negative emotions respectively. Results obtained from the averaging of emotion values across the 12 participants indicate neutral emotions experienced throughout the 2-hour training. Relatively, the most negative emotions were experienced during the 15-minute time interval while the most positive emotions were obtained when considering the entire 2-hour training as shown in Fig. 3. These results imply that participants may have undesirable sentiments towards using a new system early on during the experiment before considerably adapting to it by the end of the experiment, leading to more positive feelings. This partially confirms Hypothesis 1 where it was stated that subjects would feel the most negative during the first 15 minutes of the experiment as they did not have enough time to adjust to the new 3D display.

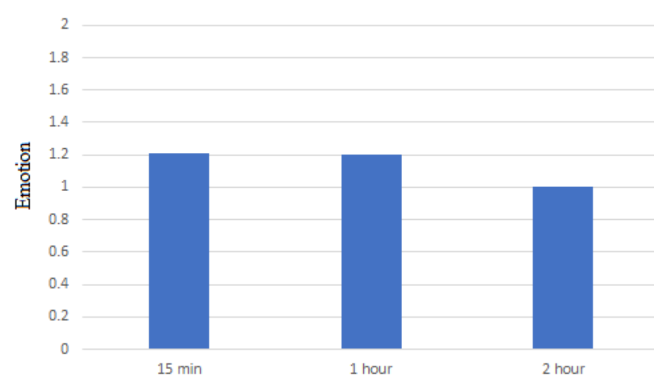

Fig. 3. EEG-based emotion recognition results.

A one-way repeated measures ANOVA was performed on the emotion data of all 12 participants during the 15-minutes, 60-minutes and 120-minutes intervals. The test with a Greenhouse-Geisser correction to account for non-sphericity of results indicates emotion values obtained across the three time intervals were not statistically significant ($p > 0.05$). This may suggest that emotions experienced by the ATCOs does not have a statistically significant difference over different training durations.

B. EEG-based Workload Recognition

The average workload levels across all 12 participants for 15-minute, 60-minute, and 120-minute training duration are calculated the same way as emotions in Section A. The result is presented in Fig. 4. Here, the workload scale ranges from 0 to 3 with a stepwise of 1, where 0 indicating very low workload and 3 representing the highest level of workload. From Fig. 4, the highest workload level experienced was during the first 15 minutes of the experiments which then reduced significantly thereafter. It would be most likely due to the time taken for participants to be accustomed to a novel radar display system. With insufficient time to adapt to a new display, it would be expected that participants faced higher workload levels during the early portion of the experiment before getting used to the display. This observation agrees with the posited Hypothesis 2 as the subjects experienced the highest workload levels at the beginning and relatively lower workload during 60 minutes training. However, in conflicting to Hypothesis 2, the workload level experienced increased again when taking the entire 120 minutes into account, comparing to the results of 60 minutes. A possible reason could be fatigue that led to higher mental demand to complete the tasks. From the results, 60-minute training could be recommended as the optimal training duration.

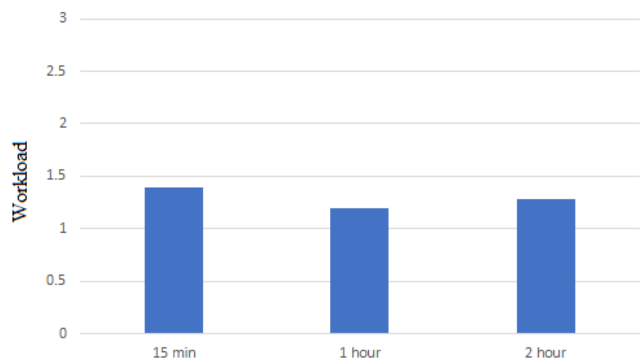

Fig. 4. EEG-based workload recognition results.

A one-way repeated-measures ANOVA revealed an insignificant difference between the mean workload levels during different training periods ($p>0.05$).

To further understand the results obtained, the workload results obtained via EEG was calculated over a 5-minute interval across all subjects and plotted in Fig. 6. As shown in the figure, the lowest workload was experienced when the training reached 50 minutes. The earlier supposition is refined that a further reduction to the training duration to 50 minutes could be suggested as the graph showed the lowest workload is obtained when the training reached 50 minutes.

C. EEG-based Stress Recognition

Similarly, the average stress results across all 12 participants for 15-minute, 60-minute, and 120-minute training duration is shown in Fig. 5. Here, the stress scale ranges from 0 to 3.5 with a stepwise of 0.5, where 0 indicating very low stress and 3.5 representing the highest level of stress. From Fig. 5, similar pattern is obtained for stress compared to workload, where the highest stress level experienced was during the first 15 minutes of the experiments and lower stress level was experienced during 60 minutes. However, different from workload results, the stress level kept decreasing insignificantly and reached the minimum at the end of the entire 120-minute training. As the stress recognition counts on both emotion and workload recognition results, this could be due to more positive emotion elicited at the end of the experiment. This observation agrees with the posited Hypothesis 3.

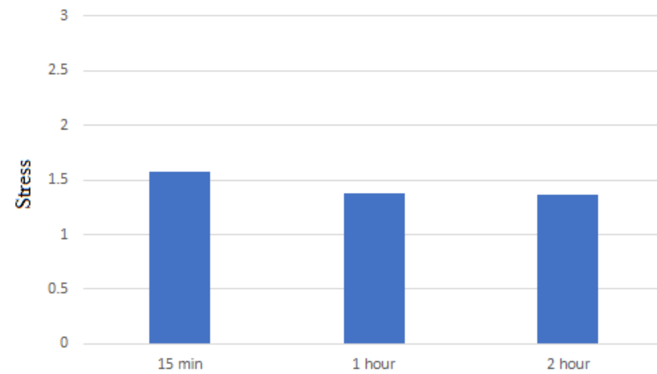

Fig. 5. EEG-based stress recognition results.

A one-way repeated measures ANOVA test was performed on the EEG-based stress results obtained for each participant. It indicates that stress experienced by ATCOs are significantly different among the training durations ($p<0.05$). Therefore, a paired samples t-test with a 95% confidence interval was also conducted to determine the significance of difference between two duration variables. It shows that the stress level experienced during 60 minutes of experiment was substantially less than that during the first 15 minutes which is aligned with the Hypothesis 3. There is no significant difference between 60 minutes and 120 minutes ($p > 0.05$). This may suggest that stress felt by the participants did not have considerable changes after the 1-hour.

Same as workload results, the stress results obtained via EEG was also calculated over a 5-minute interval across all subjects and plotted in Fig. 7. The trend of the changes of stress indicated that there is a low stress value of 1.37 when the training reaches 50 minutes. Thus, the recommendation of 50 minutes training concluded based on the workload results are further backed up by the stress results.

D. Trust Questionnaire Results

When reviewing the TRUST questionnaires, we noticed there is no significant changes of the TRUST questionnaire results over time. Thus Hypothesis 4 is not confirmed. However, one notable observation is the relationship between the ATCOs' trust of the innovative system and their corresponding emotion, workload, and stress.

The correlation coefficient is calculated between the EEG-based emotion/workload/stress results and the ratings from TRUST (Table III). The EEG-base stress/workload recognition results and trust ratings indicated a negative correlation. In other words, this correlation indicates that with greater trust in an automated system, controllers consequently undergo less stress/workload during normal operations.

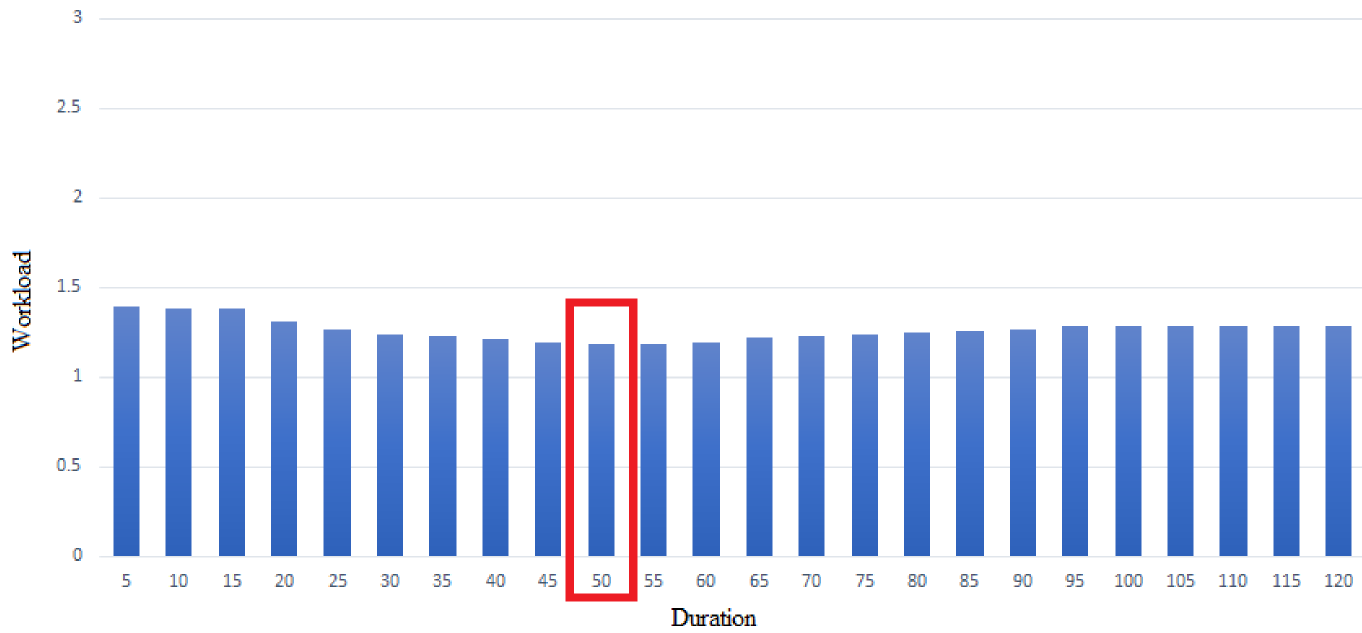

Fig. 6. EEG-based worklaod recognition results over 5-minute interval.

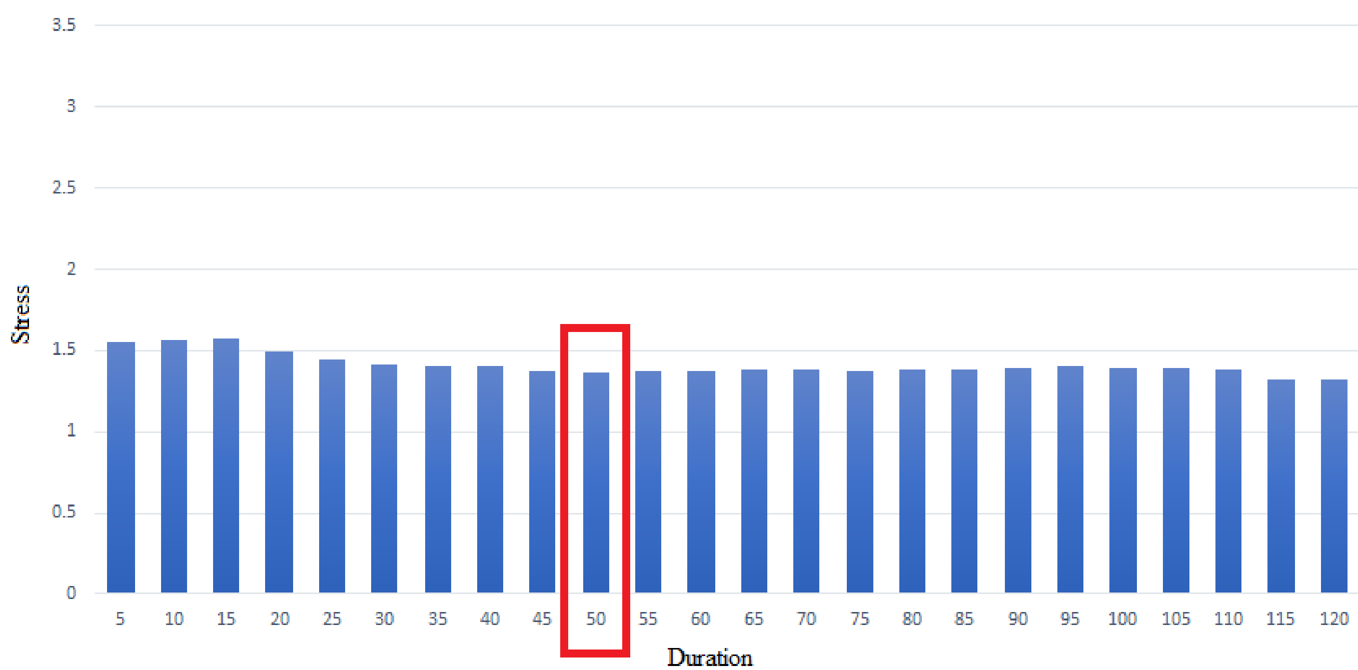

Fig. 7. EEG-based stress recognition results over 5-minute interval.

The correlation between emotion and trust follows the same trend except for the result for the 2-hour time interval. The results indicate that when the controllers have more faith in the system, they work with a more positive sentiment. The anomalous result for the last time interval could be due to the external counteractive effects such as fatigue, whereby controllers may have high trust in the system as they already manage the system but prolonged operation lead to stronger negative sentiments.

TABLE III. CORRELATION BETWEEN EEG-BASED STRESS/EMOTION RESULTS AND TRUST RATINGS

Duration	Correlation Coefficients	Stress (EEG)	Workload (EEG)	Emotion (EEG)
15 minutes	r	-0.73	-0.70	-0.35
60 minutes	r	-0.48	-0.44	-0.46
120 minutes	r	-0.45	-0.34	0.14

VI. CONCLUSION

In this paper, we examined the effects of using a supplementary three-dimensional (3D) radar display on the emotions, workload, and stress of ATCOs during a training session, and aim to figure out the optimal training time for managing the supplementary 3D display. Twelve ATCOs underwent a two-hour training simulation using a novel 3D display in addition to the traditional 2D display based on real-life scenarios. The reaction of the ATCOs to the training of using new system was measured by physiological methods (EEG) and subjective approaches (TRUST questionnaires). From the experimental results, it was observed that while emotions do not have a definitive impact on the training duration, workload and stress levels were significantly different among the training durations and the optimal training duration of 50 minutes is recommended with the criteria of low stress and workload level experienced as a basis. Furthermore, the correlation analysis indicates that if the ATOs have more faith in a novel system, their emotion could be more positive; stress and workload could be lower when they are learning to use this system. Conclusively, it was shown that the EEG data obtained provided a superior representation of the participants' mental state in terms of accuracy and reliability.

REFERENCES

[1] D. Scutt, "Global air travel could double to 7.2 billion passengers in 20 years," Available: https://www.businessinsider.com.au/global-air-travel-could-double-to-7-2-billion-passengers-in-20-years-2016-10.

[2] X. Hou *et al.*, "EEG-based Human Factors Evaluation of Conflict Resolution Aid and Tactile User Interface in Future Air Traffic Control Systems," in *Advances in Human Aspects of Transportation*: Springer, 2017, pp. 885-897.

[3] M. Göbel, J. Stallkamp, and J. Springer, "3-D Radar Display for Air-Traffic Control Tasks," in *Proceedings of the HFES European Chapter, Annual Meeting in Dortmund*, 1994, pp. 57-66.

[4] N. Masotti and F. Persiani, "On the history and prospects of three-dimensional human–computer interfaces for the provision of air traffic control services," *CEAS Aeronautical Journal*, vol. 7, no. 2, pp. 149-166, 2016.

[5] Y. Liu *et al.*, "Human Factors Evaluation of ATC Operational Procedures in Relation to Use of 3D Display," in *10th International Conference on Applied Human Factors and Ergonomics*, USA, 2019, in press.

[6] C. D. Wickens and N. R. C. P. o. H. F. i. A. T. C. Automation, *The future of air traffic control: human operators and automation*. National Academy Press, 1998.

[7] T. Prevot, J. R. Homola, L. H. Martin, J. S. Mercer, and C. D. Cabrall, "Toward automated air traffic control—investigating a fundamental paradigm shift in human/systems interaction," *International Journal of Human-Computer Interaction*, vol. 28, no. 2, pp. 77-98, 2012.

[8] N.-T. Dang, H.-H. Le, M. Tavanti, and V. Duong, "A multidisciplinary framework for empirical analysis of the applicability of 3D stereoscopic in Air Traffic Control," in *Computational Intelligence in Robotics and Automation, 2003. Proceedings. 2003 IEEE International Symposium on*, 2003, vol. 2, pp. 811-816: IEEE.

[9] P. A. May, M. Campbell, and C. D. Wickens, "Perspective displays for air traffic control: Display of terrain and weather," *Air Traffic Control Quarterly*, vol. 3, no. 1, pp. 1-17, 1995.

[10] M. Lange, J. Hjalmarsson, M. Cooper, A. Ynnerman, and V. Duong, "3d visualization and 3d and voice interaction in air traffic management," in *The Annual SIGRAD Conference. Special Theme-Real-Time Simulations. Conference Proceedings from SIGRAD2003*, 2003, no. 010, pp. 17-22: Linköping University Electronic Press.

[11] Federal Aviation Adminstration, "System Wide Information Management (SWIM),"Available: https://www.faa.gov/air_traffic/technology/swim/.

[12] R. J. C. M. Salden, F. Paas, N. J. Broers, and J. J. G. van Merriënboer, "Mental Effort and Performance as Determinants for the Dynamic Selection of Learning Tasks in Air Traffic Control Training," *Instructional Science*, vol. 32, no. 1, pp. 153-172, Jan 2004.

[13] R. J. C. M. Salden, F. Paas, and J. J. G. van Merriënboer, "Personalised adaptive task selection in air traffic control: Effects on training efficiency and transfer," *Learning and Instruction*, vol. 16, no. 4, pp. 350-362, Aug 2006.

[14] K. Surkov and R. Babenko, "Integral assessment method results of preparation air traffic controller," *2019*, adaptive learning systems; air traffic control controller; fuzzy sets; linguistic variables; evaluation criteria; training no. 1(34), p. 6, May 2019.

[15] D. Brudnicki, K. Chastain, and B. Ethier, "Application of Advanced Technologies for Training the Next Generation of Air Traffic Controllers," *MITRE Corporation*, 2006.

[16] Emotiv. Available: http://www.emotiv.com

[17] 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.

[18] Y. Liu and O. Sourina, "Real-Time Subject-Dependent EEG-Based Emotion Recognition Algorithm," in *Transactions on Computational Science XXIII*, vol. 8490(Lecture Notes in Computer Science: Springer Berlin Heidelberg, 2014, pp. 199-223.

[19] 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.

[20] J.-Y. Jian, A. M. Bisantz, and C. G. Drury, "Foundations for an empirically determined scale of trust in automated systems," *International Journal of Cognitive Ergonomics*, vol. 4, no. 1, pp. 53-71, 2000.

[21] Y. Liu *et al.*, "EEG-based Mental Workload and Stress Recognition of Crew Members in Maritime Virtual Simulator: A Case Study," in *Cyberworlds (CW), 2017 International Conference on*, 2017, pp. 64-71: IEEE.

[22] 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.

[23] C.-C. Chang and C.-J. Lin, "LIBSVM: a library for support vector machines," *ACM transactions on intelligent systems and technology (TIST)*, vol. 2, no. 3, p. 27, 2011.

[24] Z. Lan, O. Sourina, L. Wang, and Y. Liu, "Stability of features in real-time EEG-based emotion recognition algorithm," in *Cyberworlds (CW), 2014 International Conference on*, 2014, pp. 137-144: IEEE.

[25] Z. Lan, O. Sourina, L. Wang, and Y. Liu, "Real-time EEG-based emotion monitoring using stable features," *The Visual Computer*, vol. 32, no. 3, pp. 347-358, 2016.

[26] R. W. Picard, E. Vyzas, and J. Healey, "Toward machine emotional intelligence: Analysis of affective physiological state," *IEEE transactions on pattern analysis and machine intelligence*, vol. 23, no. 10, pp. 1175-1191, 2001.

[27] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186-197, 2010.

[28] Y. Liu and O. Sourina, "Real-Time Subject-Dependent EEG-Based Emotion Recognition Algorithm," in *Transactions on Computational Science XXIII*: Springer, 2014, pp. 199-223.

[29] B. Hjorth, "EEG analysis based on time domain properties," *Electroencephalography and clinical neurophysiology,* vol. 29, no. 3, pp. 306-310, 1970.

[30] F. Feradov and T. Ganchev, "Ranking of EEG time-domain features on the negative emotions recognition task," *Annual Journal of Electronics,* vol. 9, pp. 26-29, 2015.

[31] K. Ishino and M. Hagiwara, "A feeling estimation system using a simple electroencephalograph," in *IEEE International Conference on Systems, Man and Cybernetics*, 2003, vol. 5, pp. 4204-4209 vol.5.