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Mobile EEG-based Situation Awareness Recognition for Air Traffic Controllers

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***Abstract*—With the growing volume and complexity of air traffic, air traffic controllers (ATCOs) encounter heavier burden nowadays. Therefore, human factors study in air traffic control (ATC) is increasingly essential, paving the way to a safer air transportation system. In this paper, we conducted an ATC experiment, where Electroencephalogram (EEG) data were collected throughout the experiment. Compared to traditional questionnaires and psychological tests used in human factors study, the proposed novel EEG approach provides monitoring of situation awareness (SA) in a non-invasive and non-interruptive fashion. SA was represented as the response latency in situation-present assessment method (SPAM), which was predicted from EEG signals using three machine learning algorithms. Support vector regression obtained the lowest prediction error of 1.5 seconds, which is lower than 10% of the range of actual response latency. The results show that EEG is a promising approach forward in measuring situation awareness of ATCOs in both real-time and accurate manner.**

Keywords—Air traffic control, EEG, situation awareness, human factor study, neuroergonomics

I. INTRODUCTION

Today, air traffic controllers (ATCOs) play an important role in aviation safety. The nature of air traffic control is fast paced and requires high concentration where lapses in concentration can result in fatal accidents. By measuring human factors variables such as workload and situation awareness (SA) of an ATCO, preventive measures can be taken before errant human mental states lead to accidents. Currently, traditional methods to measure workload and SA are only done on a post-activity basis. For example, questionnaires such as NASA-TLX were used to assess the ATCO's workload experienced during the task [1]. However, by applying questionnaire, we can get the measurements only after the task is completed otherwise we have to interrupt the task performance to get feedback from the ATCO. A detection and measurement of human factors variables is needed in real time in experimental settings so we could continuously monitor the workload and SA without disturbing the ATCOs, and by getting real-time measurement we may be able in future to provide alarms to avoid fatal accidents. Here, Electroencephalogram (EEG)-based tools can be used to measure human factors variables such as mental workload and SA in real time. Compared with other methods, EEG possesses high time resolution, easy to set-up, and has an acceptable accuracy, which makes it suitable to be used in human factors study. In this paper, we proposed an EEG-based algorithm to assess SA.

The paper is organized as follows. Section II reviews the related work such as the usage of EEG in human factors study, EEG-based SA recognition, and the commonly used SPAM test which can measure workload and SA. Section III introduces the experiment used to collect EEG data. Section IV describes the proposed EEG-based SA recognition algorithm. Section V presents the results. Section VI concludes the paper.

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II. RELATED WORK

A. EEG in Human Factors Study

Traditionally, EEG is a medical imaging technique that reads scalp electrical activity generated by brain [2]. Recently, with availability of affordable wireless EEG devices, mobile neuroimaging techniques started to be used not only in medical applications but in neuroergonomics, human factors evaluation, neuromarketing, etc. EEG has a great potential and can be effective in measuring human factors such as SA and workload. In the case of measuring situation awareness, there have also been demonstrated encouraging results of correlating brain activities and the loss of situation awareness [3].

EEG is capable of measuring human factors in a manner that is non-intrusive while providing real-time data [2]. These features are highly desirable by many researchers [4]. Also while there are methods available to measure and detect various human factors independently, there is no single measurement instrument which can measure multiple human factors collectively. A large amount of money, time and effort can potentially be saved if a single experiment is able to produce data which reflect the effect of multiple human factors at once. In a real working environment, ATC task factors such as aircraft and airspace factors may affect various human factors issues of ATCOs rather than just affecting one independent and isolated human factor. Therefore, only by measuring all human factors at once, we can better understand the actual impact of aircraft and airspace factors on human factors in ATC. There are already attempts to apply the EEG-based technique in ATC area [5, 6]. Though they mainly focused on workload assessment in ATC area, it was shown that EEG has a great potential in human factors evaluation.

B. EEG-based Situation Awareness (SA) Recognition

It was proposed in [7] that there are three levels of situation awareness. Level 1 situational awareness is having knowledge and perception of elements in an environment, level 2 is about comprehending the current situation as a mental image while level 3 is having the ability to predict future states of level 1 elements.

Recently researchers started to measure situation awareness according to the above-mentioned definitions using EEG technologies. This is done by attempting to map brain activity during loss of situation awareness to identify any co-activity in the visual and high-order regions of the brain and then relating it to influences on Level 1 situation awareness [3]. The results from the experiment were encouraging and they showed the evidence that loss of situation awareness was accompanied by concurrent engagement of visual regions and higher order regions associated with cognition. Regions with memory functions were also thought to be active as they also showed signs of activity during loss of situation awareness [3].

C. SPAM Test

Besides EEG-based techniques, there are traditional test-based situation awareness and workload measurements. Situation-present assessment method (SPAM) is one of the most commonly used methods [8] .

In SPAM, participants are required to respond to questions prompted based on the real-time information presented at the display. By administering SPAM in an experiment, we are able to obtain four parameters which are: (i) the percentage of correct response and (ii) the latency of the response (the time taken to answer the question) as situation awareness measures; (iii) time taken to be ready (mean ready latency); and (iv) number of ready response (percentage of ready response) as workload measures.

III. Experiment Design

To study SA of ATCOs during their tasks, we designed and carried out an experiment to collect EEG data and behavioral data.

A. Participants

There were a total of 36 participants (23 males and 13 females) with average age 30 years old, including 31 ATCOs from the Civil Aviation Authority of Singapore and Singapore Armed forces, and 5 college students with prior experience in radar training [9]. None of them has auditory deficit or any history of mental illness.

B. Task

The primary goal of the participants was to maintain aircraft separation and to control air traffic flow. Prior to the experiment, the participants attended a 1 hour briefing and training session. During the experiment, the participants were also encouraged to respond to specially designed Situation Awareness Probes administered using SPAM which allowed measure their workload and SA. There were 3 different conditions of conflict resolution aid (CRA), namely reliable, unreliable and manual [10]. Under each condition, the ATCOs performed the task for an hour with a total of 9 SA probes prompted to them at every 6 minutes interval.

C. Data Collection

In the experiment, workload and SA were measured using two methods: mobile EEG tools and SPAM as shown in Table I.

TABLE I. Collected Data

Human Factors Variables	**Measurement**	
Situation awareness	EEG	
Situation awareness	SPAM	
	Time taken to answer SA probe (Mean Response Latency)	Number of accurate response (Percentage of accurate answer)
Workload	SPAM	
	Time taken to be ready (Mean Ready Latency)	Number of ready response (Percentage of Ready Response)

The EEG data were recorded by Emotiv [11] with 14 channels. The sampling rate is 128 Hz.

IV. EEG-based Situation Awareness Recognition Algorithm

In this experiment, EEG signals are used to recognize SA, represented by the response latency that reflects the time required to answer the SA questions. The EEG data was first segmented according to the corresponding response time and then, the features were extracted from this data.

The features were then fed into three machine learning algorithms, including linear regression (LR), support vector regression (SVR) and extreme learning machine (ELM). For all algorithms, 70% of the data were used as training set. The recognition performance, such as root mean square error (RMSE) or Pearson correlation (CORR), is reported using the remaining 30% testing set. In this section, firstly, the features used are introduced, followed by three machine learning algorithms.

A. Extracting Features from EEG Signals

The EEG data were passed through a 2-42Hz bandpass filter since the major brain waves of human lie in this region [12]. To obtain useful information from raw EEG signals, several features are extracted from each segment, as shown in Table II.

Among the chosen features, mean and standard deviation are two of the most common features in EEG signal processing [13]. Power of the EEG signal in the alpha, beta and theta frequency bands was also extracted as brain activities in the alpha and theta bands were showed to be related to cognitive and memory performance and therefore workload [14-16]. Activities in the beta band were attributed to problem solving and active thoughts which are essential traits of SA [17]. These three frequency bands were also used in other studies related to mental workload [5, 6, 18]. Additionally, EEG signal data are irregular and nonlinear [19]. Therefore, to interpret the chaotic and random nature of EEG signals, sample entropy, approximate entropy, and Higuchi fractal dimension were chosen [20, 21]. The last feature chosen in autoregression coefficients which is widely used to characterize EEG signals [22]. The order of coefficients was 6 as recommended in [23, 24].

TABLE II. EEG FEATURES

Features	Remarks
Average	Average signal amplitude of each channel
Standard Deviation	Standard deviation of signal amplitude of each channel
Alpha Power (8-13Hz)	Power of the EEG signal in Alpha frequency band of each channel
Beta Power (13-30Hz)	Power of the EEG signal in Beta frequency band of each channel
Theta Power (4-8Hz)	Power of the EEG signal in theta frequency band of each channel
Band Power Ratio (Beta/Theta)	Ratio of Beta Power to Alpha Power of each channel
Band Power Ratio (Theta/Alpha)	Ratio of Theta Power to Alpha Power of each channel
Band Power Ratio (Theta/Beta)	Ratio of Theta Power to Beta Power of each channel
Approximate Entropy	Measure of regularity of EEG Signal of each channel
Sample Entropy	Similar to Approximate Entropy, but without Self-matching bias
Higuchi Fractal Dimension	Measure to describe the irregularity of EEG signal of each channel
Autoregression Coefficients	Coefficients of AR model (order of 6) of each channel

B. *Linear Regression*

Given the EEG features X with N rows and D columns indicating N EEG segments and D features, and the corresponding response latencies Y. Each segment corresponds to one latency value. Linear regression finds the linear coefficient W which minimizes the latency prediction error.

$$\underset{W}{\text{minimize}} \|XW - Y\|^2 + C\|W\|^2 \quad . \tag{1}$$

The hyperparameter C is a regularization parameter which controls the standard deviation of W. The optimal C was obtained by 5-fold cross validation, from a list 1 to 100 with stepwise of 1.

C. *Support Vector Regression*

Support vector regression automatically selects a set of support vectors from the training data. The kernel trick is applied in its dual form. The primal form is

$$\underset{W,b,\xi}{\text{minimize}} \|W\|^2 + C\sum_i \xi_i \quad , \tag{2}$$

subject to

$$\begin{gathered} y_i - W^T h(x_i) - b \leq \varepsilon + \xi_i \; ; \\ W^T h(x_i) + b - y_i \leq \varepsilon + \xi_i \; ; \\ \xi_i \geq 0 \; . \end{gathered}$$

where x_i is the input feature, y_i is the targeted label, $\|W\|^2$ is the Euclidean norm of coefficient W, b is bias, ε is the deviation from the target y_i, and ξ_i is the slack variable used in the soft margin loss function. The hyperparameters in SVR include the regularization parameter C, and a kernel scale γ which specifies the effective width of the Gaussian kernel. Five-fold cross validation was performed using C from 1 to 100 with stepwise 0.1 and γ was automatically determined by subsampling.

D. *Extreme Learning Machine for Regression*

Extreme Learning Machine is a neural network where the hidden weight $W \in \mathbb{R}^{D\times L}$ and bias $b \in \mathbb{R}^L$ do not need to be tuned [25]. In this case, W and b are generated from a uniform distribution between [-1,1] and then fixed. The hidden output is $H = \text{sigmoid}(XW + b)$. The hyperparameters in ELM include the number of hidden nodes L, and the regularization parameter C. Five-fold cross validation was performed using L from 238 to 350 with stepwise 1 and C from 0.01 to 1 with stepwise 0.01.

The output weight $\beta \in \mathbb{R}^{L\times K}$ is computed as

$$\underset{\beta}{\text{minimize}} \|H\beta - Y\|^2 + \frac{\|\beta\|^2}{C} \quad . \tag{3}$$

V. RESULTS AND DISCUSSION

With the EEG data collected from the experiment and the proposed SA recognition algorithm, in this section, we present the results using Linear Regression (LR), Support Vector Regression (SVR) and Extreme Learning Machine (ELM). The machine learning models were used to predict the SA Response Latency, in other words, the time taken to answer a SA query.

A. *Results from Machine Learning Algorithms*

Based on the RMSE produced by the 3 models of machine learning as shown in Table III, SVR (Fig. 1) had the best result and is recommended to be adopted as the method of choice for the algorithm. The RMSE of the predicted SA response latency produced by SVR was 1.5s which outperformed LR and ELM.

TABLE III. RESULTS OF THE ALGORITHMS

Model	RSME	Correlation Coefficient
LR	5.1s	0.73
ELM	5.2s	0.68
SVR	1.5s	0.72

Using LR, as seen in Fig. 2, some of the predicted response time was negative which is illogical and could have contributed to the moderately high RMSE. As for ELM model, the predicted SA response latency had the worst performance out of the 3 models. The comparison between predicted response latency and actual one for ELM is shown in Fig. 3.

B. Correlation Analysis

We also analyze the correlation using EEG-based SA mean response latency and actual workload data obtained from SPAM test. As the workload data provided by SPAM have two parameters: mean ready latency and percentage of ready response, we got two combinations as shown in Table IV: mean ready latency (SPAM) of all subjects per question vs mean response latency (EEG) of all subjects per question; percentage of ready response (SPAM) of all subjects per question vs mean response latency (EEG) of all subjects per question. The hypothesis is that a negative correlation exists between workload and situation awareness, which is reflected by a positive correlation between mean ready latency (SPAM) and mean response latency (EEG) and a negative correlation between percentage of ready response (SPAM) and mean response latency (EEG). The mean ready latency (SPAM), percentage of ready response (SPAM), mean response latency (EEG), and mean response latency (EEG) were calculated as the average across the 9 questions in SPAM.

As the correlation coefficient is highly sensitive to any outliers [26], two extreme points were considered as outliers and removed when calculating the correlation between mean ready latency (SPAM) and mean response latency (EEG) as an additional step in the analysis. The calculated correlation coefficients are presented in Table IV. From the table, it is seen that a moderately strong linear relationship existed between mean ready latency (SPAM) and mean response latency (EEG), and percentage of ready response (SPAM) and mean response latency (EEG) had a significantly negative relationship ($p<0.05$). The results indicate that SA decreases when workload increases, which is consistent with our hypothesis.

TABLE IV. CORRELATION ANALYSIS

Workload Data	SA Data	Correlation Coefficient	p-values
Mean Ready Latency (SPAM)	Mean Response Latency (EEG)	0.53	0.22
Percentage of Ready Response (SPAM)	Mean Response Latency (EEG)	-0.73	0.03

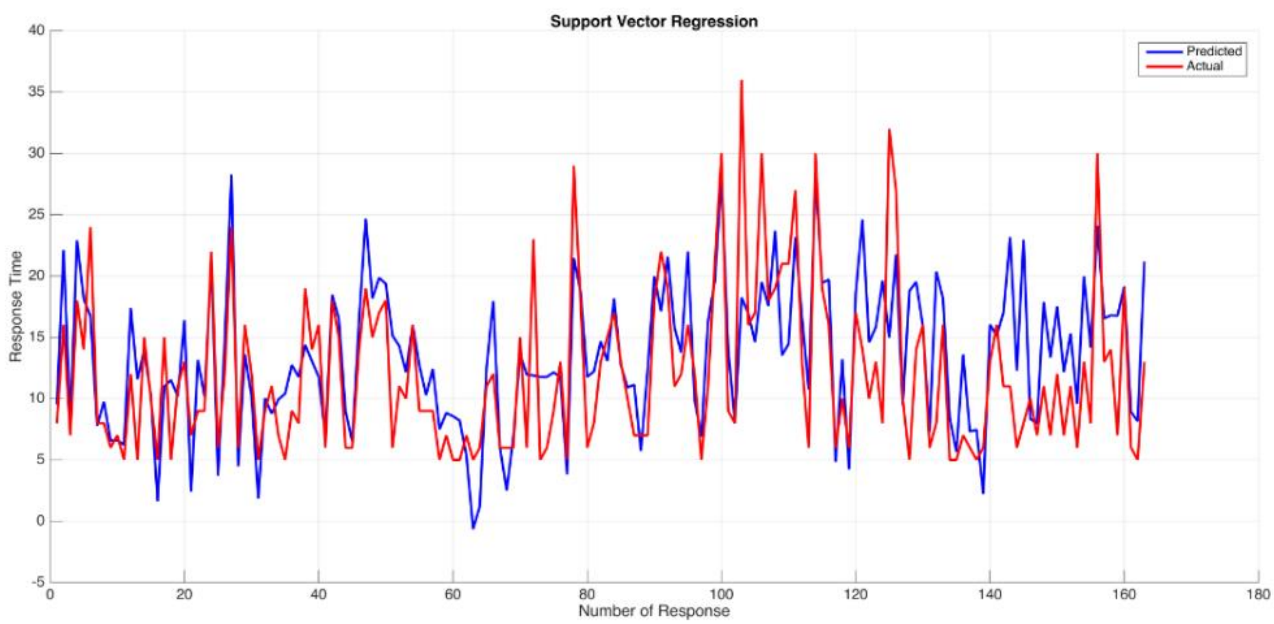

Fig. 1. Comparison of predicted and actual response latency by SVR.

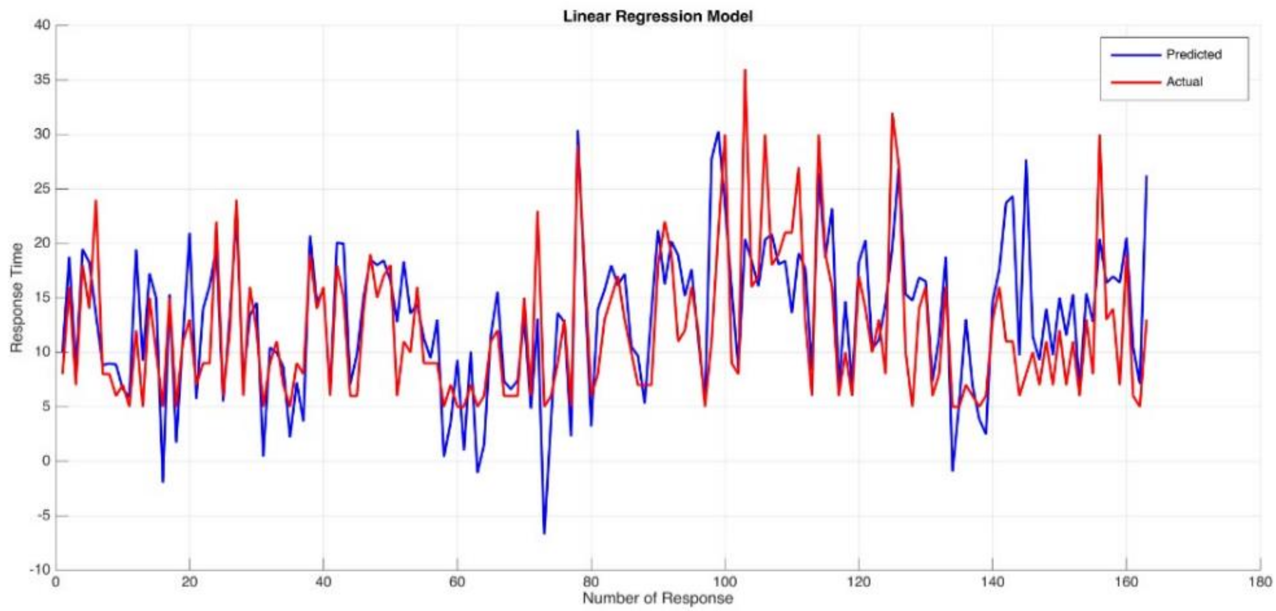

Fig. 2. Comparison of predicted and actual response latency by LR.

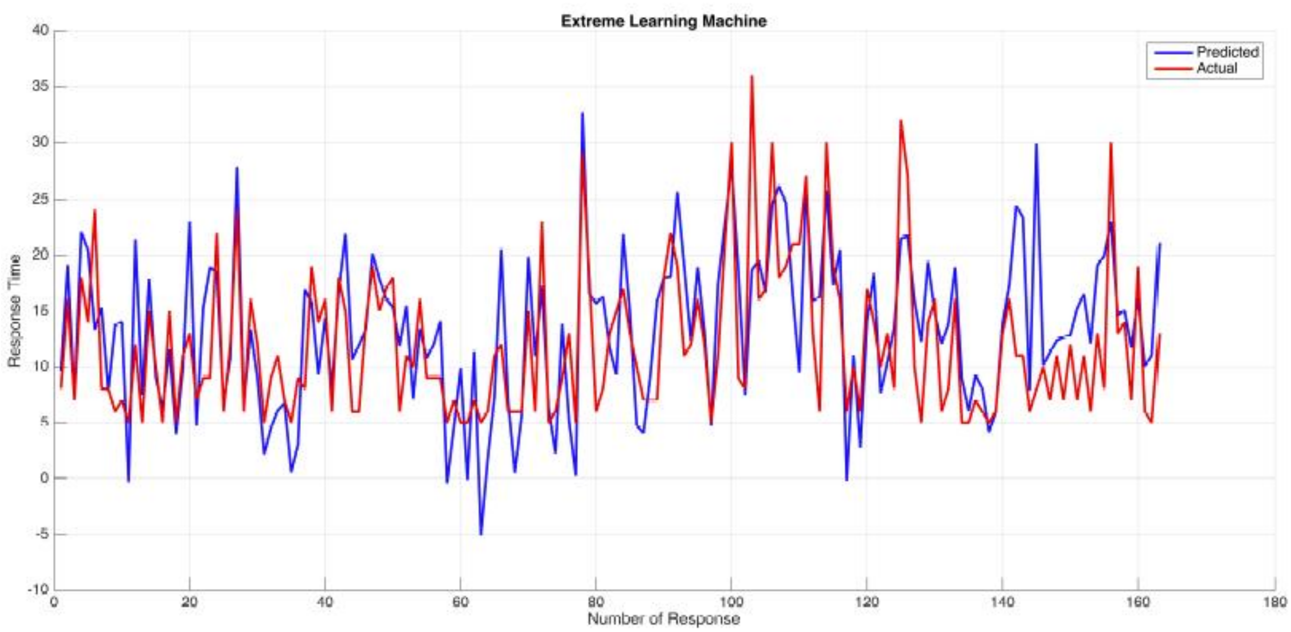

Fig. 3. Comparison of predicted and actual response latency by ELM.

VI. Conclusion

It is important that steps are taken to understand how human factors are affected by the tasks of ATCOs and then methods can be devised to detect the unwanted lapses to correct them before it snowballs into an avoidable accident.

The current methods available to measure the human factors such as subjective measures based on questionnaires are limited in their validity due to them being done post-trial. The responses are also subjected to personal bias of different individuals and hence a method which measures everyone on a common basis is needed. EEG is able to provide us with continuous real-time analysis of human factors in a non-invasive and non-interruptive manner. The available works mostly focus on offline processing and workload detection. In our paper, we proposed a novel method to measure real-time SA by predicting the response latency using SVR, which was proved to be the best model compared to ELM and LR. The algorithm has a RMSE of 1.5s, which is below 10% of the range of actual response latency (31s). Based on the real-time SA monitoring, alarm could be given to ATCOs to avoid fatal accidents. The results of data analyses also confirmed negative relationship between workload and SA.

To conclude, EEG is a promising approach in measuring human factors in real-time. In the next step, we are going to convert the estimated response latency to a scaled rating allowing objective quantification of SA level of an ATCO in real time.

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