Developing a Mental Workload Model Using cEEGrid Technology

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INTRODUCTION

The purpose of the study is to examine the feasibility of cEEGrid technology to monitor the Mental Workload (MWL) of an operator during flight related tasks. Aviation has risks involved which can be extremely costly both fiscally and from a loss of life point of view. Pilots perform numerous and varying levels of difficulty tasks throughout a mission. The successfulness of a mission depends on the state of the aircraft and operator. If the operator is mentally underloaded they're in a complacent state; this ensues longer response times and the likelihood of noticing unexpected high risk events decreases. If the operator is mentally overloaded, performance degrades in one or more tasks. Optimizing the MWL state of the operator can increase safety and performance [7]. However, optimization of MWL cannot be done without monitoring the MWL of an operator reliably and accurately. There are three ways to monitor MWL: subjective measures, performance measures, and physiological measures. Subjective measures are based on rating scales, they are valid for the summary of quasi-static tasks but fail to measure different levels of MWL within a task without interruption. Performance based measures are commonly based on response times, accuracy, and success of a task. While performance measures provide continuous and reliable monitoring; source of MWL is lacked and the amount of MWL needed to attain a level of performance is unknown. Lastly, physiological measures can continuously monitor MWL but need performance and subjective measures for validation and can be intrusive. Current EEG cap configurations consist of up to 256 electrodes, the electrodes and wires are intrusive on the operator during flight operations and interfere with emergency ejection procedures. cEEGrid electrode arrays are flat, less invasive, and have shown reliable results compared to EEG caps [2]. Therefore, cEEGrids have potential utility in flight to monitor the state of the operator. However, the configuration has never been used to monitor MWL, therefore assessment is necessary.

OBJECTIVES

The objective is to collect EEG signals, performance metrics, and subjective ratings on single and dual tasks with several ranges of MWL. Once the data is collected, the subjective ratings are used as the ground truth value of MWL with the EEG signals and performance measures as the predictors. The model created will be applied on test trials for validation. Future studies may be able to use performance and the physiological signals together to determine MWL continuously and reliable across tasks with multiple levels of difficulty. Development of the tasks took 12 hours. Preparing the design of experiment took 2 hours. Collecting and the data took 2 hours. Analyzing the EEG signals took over 10 hours. Analyzing and preparing the performance metrics took 4 hours. Lastly, analyzing and preparing the performance, subjective, and EEG signals took over 12 hours.

MATERIALS & METHODS

In order to collect data on a broad range of MWL levels two tasks with multiple levels of difficulty were performed while wearing the cEEGrid technology. The two tasks selected for the experiment were: the Multi-Attribute Task Battery (MATB) [7] and an Audio task. MATB is performed on a touch screen tablet with a joystick attached. There are three components to MATB, System Monitoring, Tracking, and Resource Management, each part simulates an abstract flight-related component. The audio task consists of a random sequence of numbers played auditorily. Subjects are required to remember the number of times target numbers are heard during a trial. Each task had three levels of difficulty. A full factorial design with two replicates was used to determine run order. These tasks were chosen with Multiple Resource Theory (MRT) in mind. MRT postulates that the human mind has a limited resources for attention which are split into multiple cognitive resource pools [10]. These resources are determined by the input stimuli as well as the processing and responses required from a task. Performance of a task degrades when the demands of a task exceed the resource pool capabilities or when two or more tasks are using the same resource pool. These tasks exude different stimuli but have similar working memory processes. Therefore, adding the second task increases difficulty without completely interfering with the other task. Performance of the two tasks were recorded during each trial.

Two subjective rating scales were used in this experiment. The NASA Task Load IndeX (TLX) and the Bedford rating scale. The NASA TLX has shown reliable and valid correlations with the MWL in a task overall. The Bedford rating scale demonstrates the spare capacity available to accomplish a secondary task. The rating scales were performed after each run.

Figure 1. Subject wearing the cEEGrid Array [6]

The cEEGrids were worn throughout the experiment. The EEG signal is collected through the electrodes on the scalp as a time-series oscillation and defined by the frequency and amplitude of a wave. Once the experiment was complete, the EEG signal was processed and analyzed by the Fast Fourier Transform (FFT) in BrainVision Analyzer [3]. FFT transforms the signal in the time domain into the frequency domain to yield the spectral content of a signal within a trial. The spectral power for Alpha, Beta, and Theta frequencies for each trial was extracted for analysis. These frequencies have shown to be indicators of MWL in other experiments with EEG caps [1,9].

There were 18 trials of "Training" data and 4 trials of "Test data" interlaced between the training trials. Only one subject was used for data collection. The performance scores, spectral powers, and subjective ratings of the training trials were assessed in Eurequa [5] to develop a Linear Regression equation. The three equations with the highest R2 values were evaluated against the test trials.

RESULTS

All Alpha, Beta, and Theta spectral power for all electrode channels were used as variables for prediction. System Monitoring, Resource Management, and Tracking performance scores were normalized on a 10 point scale. The NASA TLX rating was used as the response variable. Several equations were tested with the train and test data. The equation with the lowest Percent Error was:

$$MWL_{TLX} = 54.2 + System + 16ThetaL_8 + 9ThetaR_4 - 5.98AlphaL_7 - 8.89ThetaR_9$$

The NASA TLX score from the experiment and the workload score developed from the Linear Regression model are compared by trial in figure 2 and by the test data in figure 3.

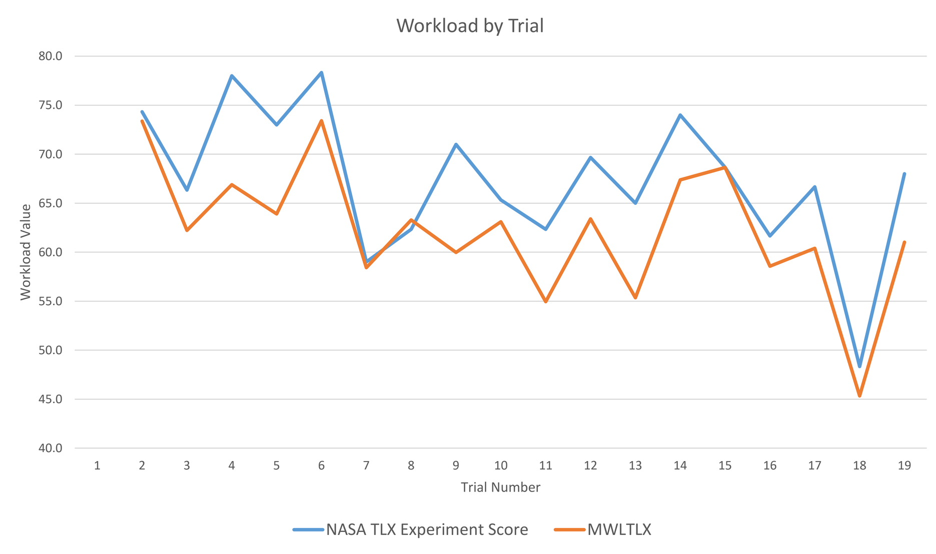

Figure 2. Workload Comparisons for Train Trials

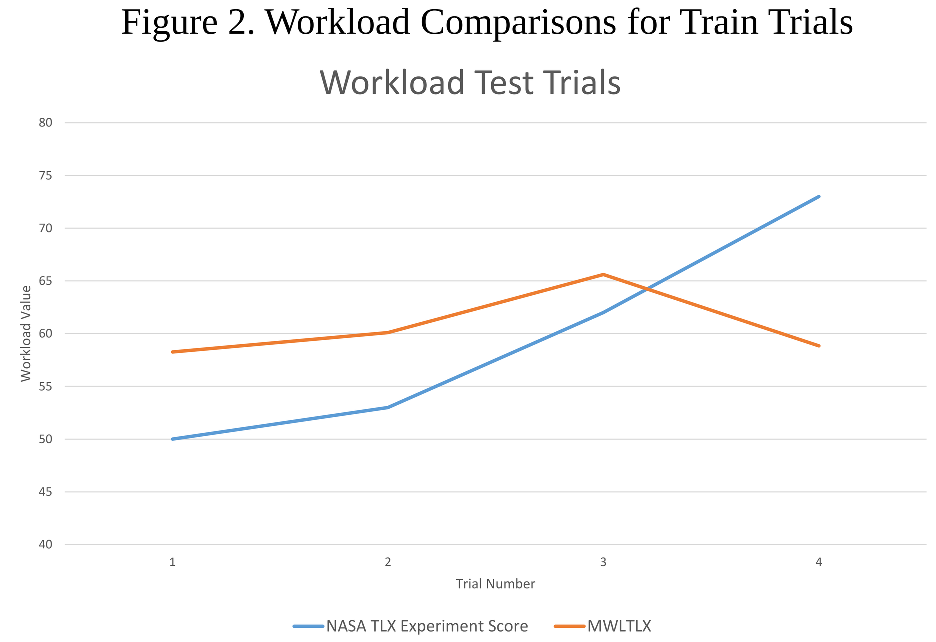

Figure 3.Workload Comparison for Test trials

Ultimately, the equation had an R^2 value of 0.80. There were equations with higher R^2 values but they tended to overfit the data and had higher percent errors for the test data. The equation chosen yields a 14% error on the test trial data.

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CONCLUSIONS

This research has laid the foundation for using cEEGrid technology to classify MWL levels. The test trials somewhat validated the potential use of performance and physiological measures to build a Linear Regression equation. However, this project only used one subject and observed two static tasks and no verbal responses. The MWL model may change for different tasks and across subjects. Further testing would need to occur to validate other forms of task demands.

In the future, this model may be usable for MWL of short segments trials with quasi-static expected workload. Moreover, nonlinear analysis of the EEG signals may yield continuous 'live' workload classification of changing levels.

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