Using Wireless dry EEG System to Detect Mental Workload during Mental Arithmetic

A Thesis

Presented to

the Faculty of the Department of Biomedical Engineering

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In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in Biomedical Engineering

by

Nesrine Aroua

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Abstract

Mental workload, the amount of cognitive resources invested during a task, is a crucial metric for performance. Determining the performance of an individual aids in the screening of candidates for, or detection of alertness during, a high-risk task. Three measures for assessing mental workload exist: subjective, performance, and physiological. Of the three, a physiological measure is the most direct type, which can be used to track mental workload as a subject performs tasks. One type of physiological measure is monitoring EEG signal variations. This study examined the efficacy of detecting mental workload in subjects performing mental arithmetic of increasing complexity using a wireless dry EEG system. The level of difficulty was confirmed by performance measures of accuracy in their responses, and the length of response times. The level of difficulty was correlated in most of the subjects to visually distinguishable patterns in time-frequency spectrograms between tasks and breaks within the alpha band (8-12 Hz). Subjects that exhibited more pronounced reduction in alpha band power as the level of difficulty increased achieved the highest response accuracy. Localization of mental activity was accomplished by discretely assessing alpha and theta band power in four brain lobes. Classification of low, medium, and high difficulty levels, as well as rest segments of the recorded EEG, was accomplished using a K-nearest neighbor classifier at an average accuracy of 91%. These findings validate the use of dry EEG as a valid technology that is capable of generating effective physiological measures for detecting mental workload levels.

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1. Introduction

a. Significance of Measuring Mental Workload

Neuroergonomics is an emerging science that investigates mental state while undergoing various tasks [1]. A focus of this interdisciplinary field is to understand how fundamental cognitive function can be utilized to design and optimize technology for brain machine interactions. Acquiring a better understanding of brain behavior positively impacts our society as it seeks to create a better and safer environment by improving productivity and diminishing human error [2]. Understanding this complex relationship involves the ability to discriminate between mental state levels, including fatigue, attention, task engagement and mental workload [3]. Mental workload has been studied extensively by various papers and journals as it represents a promising area of research in neuroergonomics.

Despite all the focus mental workload has received in the past four decades, a conventional definition has not been agreed upon. Instead, definitions vary from one research project to another, depending on the nature of the study [4]. Some authors define mental workload as the load generated when multiple activities are processed simultaneously [5]. Other authors define it as the correlation between activity detected in discrete-complex neuroanatomical sites to complex associations, ideas and actions [6]. Mental workload is most commonly evaluated and utilized as an index of the mental effort associated with the task difficulty level, where the task difficulty reflects the amount of the engaged cognitive resources [3].

The importance of measuring mental workload derives from the prevalence of undesired consequences due to excessive mental workload. Excessive mental workload, or

mental fatigue, may cause a response delay, which may lead to human errors and poor performance. Mental fatigue is typically characterized as inefficient information processing caused by overloading the working memory. Detection of low mental workload is also significant, since it can result in errors and undesired results due to lack of interest of the performer [7]. Thus, mental workload assessment by quantifying the engaged cognitive resources, in both excessive and low workload conditions, is crucial in evaluating and predicting operator performance [4].

Poor operator performance can lead to tragic consequences in various applications and industries. For instance, a surgeon's performance can be affected by high mental stress during an operation, which can compromise patient safety. Monitoring the mental workload during surgery may be a solution to reduce such stress related incidents before an error occurs [8]. Air traffic controllers are another group of operators that experience high levels of mental fatigue and the responsibility burden of ensuring the safety of hundreds of air travel passengers. This task requires an excessive amount of mental resources to keep the controller very alert and engaged. The ability to monitor the mental workload of the air traffic controller, provides a means to enhance performance and safety, which may reduce the chance of errors in the air traffic environment.

Research in mental workload assessment has gained a significant amount of attention as it is valuable in ensuring safety in areas that are directly associated to livelihood, such as medical practices. Several projects are also currently engaged in utilizing mental workload for development and optimization of human-computer interface as well [7]. Mental workload assessment can be classified into three categories: subjective, performance and physiological based measures. The subjective assessment is conducted

through a questionnaire where individuals provide their subjective judgement about the task [5]. The NASA Task Load Index (TLX), the Subjective Workload Assessment Technique (SWAT) and the Workload Profile (WP) are examples of subjective techniques used to assess the mental workload. Nasa TLX has been used extensively in evaluating the subjective mental workload of individuals in several studies such as air traffic control, vigilance tasks, surgical procedures and flight simulations. TLX contains a questionnaire composed of 6 questions where the individual rates different aspects of the task in each question such as the mental demand, physical demand and performance. It uses a 20-point visual analog scale to give the mental workload measurement [9]. Performance measures rely on direct measurement of performance during a particular task, by scoring how well the task was performed. The performance of the primary task can also be evaluated indirectly by adding a secondary task, where the performance of the latter becomes an indication of the individual available mental capacity [4].

Physiological measures assess cognitive workload of individuals based on their physiological responses to variations in task difficulties. Several researchers have studied cognitive workload using cardiac pulsation measures where they analyze heart rate variability (HRV) [10]. Other studies assessed oculomotor activity and blink intervals as an index of mental workload [10]. However, these assessments have been an indirect means of measuring mental workload, and are often influenced by ulterior factors. As such, direct measure of brain activity is becoming increasingly popular in this field. Different assessment methods, utilizing optical and electrophysiological based techniques, have been used to study the brain activity, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) [10].

EEG has gained significant popularity within the research community primarily since it conveniently provides a continuous record of the signal over time. Some hemodynamics based techniques, such as fMRI, may require complex systems that are not easily integrated into the working environment. In contrast, EEG systems are mobile and can perform more real-time data visualization, which facilitates a precise evaluation of the induced mental workload [10], [11]. Even more of an advantage is that, as previous research has proven, EEG systems are sensitivity to fluctuations in cognitive load due to different tasks and levels of difficulty [12]. EEG systems have the potential to be promising tools in investigating the mental workload induced by activities such as verbal memory tasks [11]. In addition, EEG studies have shown a correlation between the electrical activity and the process of encoding and retrieval of semantic or visuospatial information [13]. Detection of this process may be a reliable metric for measuring mental workload, particularly in response to a visual stimulus.

b. EEG Background

Hans Berger, a German psychiatrist, in 1924 was the first person to record an electroencephalogram signal on a human subject [14]. Electroencephalogram signals represent the electrical activity of the brain detected by placing electrodes on the scalp of a subject. The measured signal represents the spatial summation of postsynaptic potentials in a certain area encompassed by the electrode coverage. The recorded EEG is a measure of the voltage potential difference between a certain measurement electrode and a designated reference electrode. By the international 10-20 system, the measurement electrodes are placed in certain regions of the scalp and the reference electrode is placed

on the ear. The 10-20 configuration name describes the space between the electrodes, as illustrated in Figure 1 [15]. The number 10 indicates that the distance separating the inion and the most adjacent electrode and the distance separating the nasion and the most adjacent electrode in both cases is 10% of the total front back distance along the skull. The number 20 indicates that the distance between adjacent electrodes in the front back direction is 20% of the total front back distance along the skull and the distance between adjacent electrodes in the left right direction is 20% of the total left right distance along the skull [16].

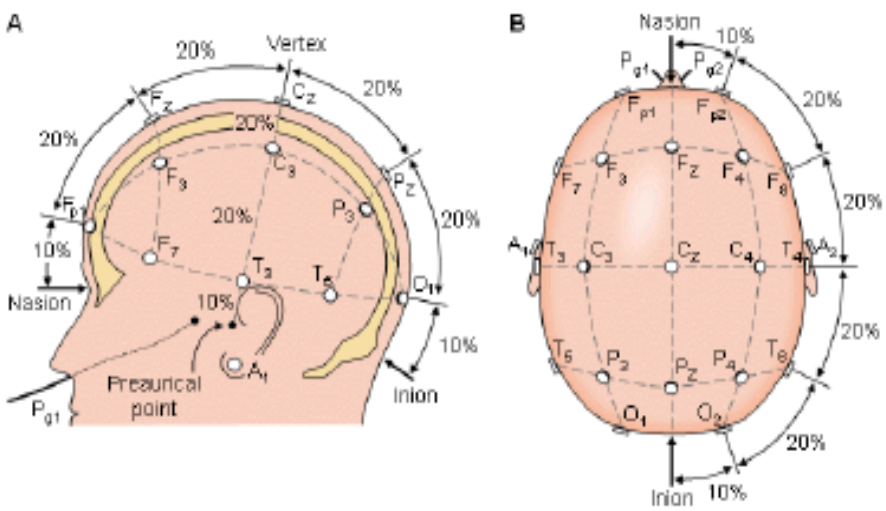

Figure 1: Standard International 10-20 System Configuration

The standard international 10-20 configuration localizes particular regions, or lobes, of the brain. The human brain is composed of 4 major lobes: Frontal, Temporal, Parietal and Occipital as seen in Figure 2 [15]. The brain is also divided into two hemispheres. The right hemisphere is mainly specialized to process musical and spatial recognition and the left hemisphere is mainly responsible for Mathematical skills and verbal processing [15].

Figure 2: Lobes of Human Brain

c. EEG Frequency Bands

EEG signal is composed of a combination of waveforms that oscillate at different frequencies and amplitudes. The brain wave oscillations are directly reflective of the cognitive and physical states of the individual [1]. These brain waves have been categorized into five frequency ranges that have proven to be very useful in clinical studies: delta wave is characterized by a frequency interval of 0 to 4 Hz, theta wave is defined by a frequency range of 4 to 7 Hz, alpha wave falls in the frequency range of 8 to 12 Hz, beta band activity is characterized by oscillations at frequencies between 13 to 30 Hz and gamma rhythm is the wave with the highest frequency oscillating at 30 Hz or more. Delta waves are known as slow brain activities due to the low frequency at which they oscillate. They are predominantly found in deep sleep stages of normal adults. Theta rhythms are present during drowsiness and sleep stages, and are considered signs of abnormal

conditions if found in awake adults [16]. However, many studies have shown that theta rhythm is associated with cognitive and memory performance specifically [17] [18].

Alpha rhythms have been extensively studied as it is considered to be a major indicator of the cognitive state. EEG oscillations prevalent in the alpha band reflect a relaxed mental state of an awake adult and they are most noticeable in the occipital region [16]. This phenomenon is known as alpha synchronization which occurs during mental inactivity where clusters of neurons oscillate with the same phase and very similar frequency. This synchronicity blocks the processing of information [17]. When eyes become open and cognitive effort is applied alpha waves decrease and become suppressed as the effort is increased [16]. This phenomenon is known as alpha desynchronization where oscillators are no longer coupled as they start oscillating at different frequencies and amplitudes. Alpha desynchronization is believed to be associated with visual attention, cognitive and memory processes [17], [19].

Multiband counter-coupling has also been observed in such hyper mental activity states between alpha band desynchronization and theta band synchronization. Good cognitive and memory performance has been linked to a large theta event response synchronization (ERS) and a large alpha event response desynchronization (ERD) [17]. A more negative ERD reflects more power decrease in the alpha band which is believed to reflect an increased cortex excitability[20]. Beta band oscillations are associated with motor tasks where beta activity is detected during preparations and execution of movements [21][18]. Gamma band oscillations did not receive significant focus until the past few years, when gamma activity became associated with several processes, such as sensorimotor integration, attention and conscious awareness [18].

d. EEG Frequency Band Decomposition for Mental Workload Assessments

EEG frequency band decomposition, and in particular alpha and theta bands, has been the focus in the study of mental workload. Spectral markers within these bands can be extracted in order to investigate the workload and task difficulty variations [22]. Gevins and Smith investigated workload during tasks on sequential memorization of stimuli, and were able to distinguish between three different workload levels in alpha and theta band spectra [12]. Other researchers conducted their experiments using mental arithmetic tasks with increasing difficulty levels, and were also able to quantify changes in the alpha and beta band power across levels [7]. Due to its complex mental functions, mental arithmetic tasks have been extensively used by researchers [10].

Spectral analysis techniques used to detect, visualize, and quantify band power fluctuations vary across research projects. Fast Fourier Transform (FFT) is one of the most common tools applied in EEG data analysis and feature extraction. FFT is often used in the computation of the power spectral density of the EEG signal [23]. However FFT assumes that the underlying signal is stationary and applying FFT to long segments of a recording may not be appropriate since EEG is generally thought to be nonstationary [23], [11]. Short time Fourier Transform (STFT) is a modified application of FFT, which operates on fixed time windows, or samples of the data, instead of the entire EEG data. STFT enables time-frequency analysis, in which power fluctuations of certain bands can be detected over time, at a resolution specified by the user. [11].

In the case of mental workload investigation, the goal is to extract features of the signal at sufficiently small time window frames, since most aspects of cognitive

information processing occur quickly [11]. As such, STFT is a more suitable analysis tool, since it computes the frequency composition of the signal using a prescribed time window [23].

2. Experimental Design

a. Arithmetic for activation of mental workload

Mental arithmetic equations was chosen as the task for activation of mental workload. This task engages several cognitive functions including recognizing numbers, understanding verbal representation of numbers, assigning magnitudes to numerical quantities, reporting a numerical sum, and, in the particular case of this experiment, comparing it to a suggested answer [10]. As such, mental arithmetic can be expected to engage multiple lobes and specialized locations of the brain. The task was kept to mental arithmetic, instead of allowing subjects to physically solve the problem on a sheet of paper, in order to reduce EEG signal contamination by EMG. Activation of the motor cortex may also lead to a skew in the data away from mental workload when analyzing the averaged result across all channels.

b. Implementing Presentation software for arithmetic stimulus delivery

Presentation is a software application, developed by Neurobehavioral Systems, extensively used in psychological and neurobehavioral experiments. This technology delivers auditory and visual stimuli once a scenario is created and written using a custom programming language [24] [25]. Presentation records the response from almost any input device. In addition, it allows the transfer of information to other devices such as fMRI, eye trackers and EEG. This communication takes place through parallel and serial ports that ensures the process of sending and receiving multiple data strings simultaneously [26]. Presentation software is designed for precision on the order of milliseconds. As such, it

ensures the accuracy between the stimulus delivery and event logging, which allows for precise response monitoring [27].

i. Experimental Paradigm

The task is composed of six sets. Pairs of consecutive sets define a difficulty level such that set one and two define a low difficulty level, set three and four define a medium difficulty level and set five and six define a high difficulty level. Each set contains 10 equations involving the summation of two values within a 10 sec window. Equations in set one are composed of two one-digit values. In the subsequent sets, one of the two values is increased by one digit, such that set two contains a one- and two-digit summation, set three a two- and two-digit summation, and set four a two- and three-digit summation. Set five and six, however, both contain a three- and three-digit summation, with set six containing higher magnitude values. The primary reason for doing so was to avoid introducing exhaustion when subjects attempt to solve summations involving four-digit values, and to test how increasing the magnitude of the values alone can increase mental workload. In addition, preliminary experiments showed that most subjects could not solve summations involving four-digits within the allotted 10 sec per equation.

The experiment begins with a 30 second break, displayed in the screen as seen in Figure 3, which accounts for the baseline segment. Each set is then followed by a 30 sec break to provide the subject with a rest period. The purpose of the rest is to ensure that the subject does not get fatigued, in order to focus the experiment on observing mental workload rather than fatigue. Previous studies have shown that 30 sec should be a suitable break length to ensure an approximate return to baseline values [7].

Figure 3: Display of break set on the screen within Presentation software.

The equations are displayed on a computer screen, as seen in Figure 4, and a suggested answer for each is presented. Subjects mentally perform the summations, compare the result to the suggested answer and enter the response by tapping one of these following three letters on the keyboard: s, e and g. Letter e denotes an equal result to the suggested answer, letter s denotes a smaller result than the suggested answer and letter g denotes a greater response than the suggested answer. Presentation software stores the entered responses in a log file that can be accessed after the experiment to evaluate responses. The purpose of entering the response by tapping only one letter instead of several numbers, especially in the case of numbers containing several digits, is to minimize the amount of movement done by the subject and the ensuing motion artifacts into the recorded EEG signal.

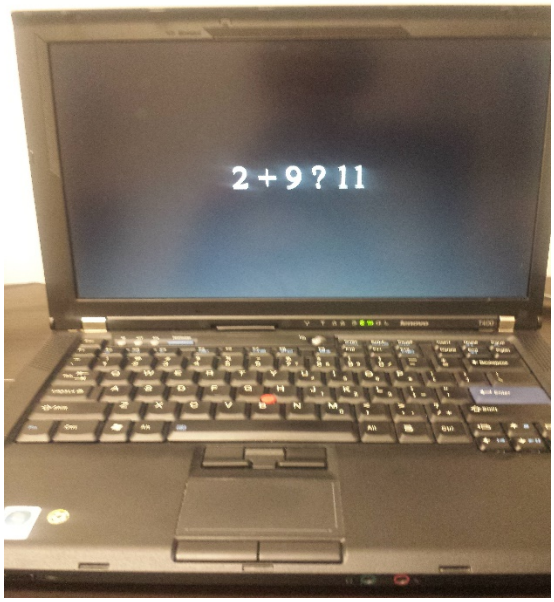

Figure 4: Display of equations on the screen within Presentation software.

c. Data Recording

i. Dry EEG System

Dry EEG systems have been developed to overcome the limitations attributed to the traditional EEG systems that used wet or gelled electrodes. Some EEG systems are wireless and, thus, do not need the wire connections to the system in order to transmit data. As a result, dry, wireless EEG systems are light, easy to apply on to subjects, inexpensive and do not require the application of gel on the scalp to ensure conductivity, which facilitate the ability for neuroscience studies outside the lab setting [28]. Wireless systems also enable mobility and allow subjects to be recorded under more natural conditions. Several studies seek to investigate brain activity in patients that might be in hospital beds. In these cases, dry EEG is a more suitable candidate to conduct the experiment. Besides, when participating in experiments, subjects, for example busy professionals such as surgeons, tend to be more willing to volunteer when the experiment set up is cleaner and less time

consuming. Based on its advantages, researchers started to incorporate dry EEG systems in their studies rather than the traditional wet electrode systems. However dry EEG sensors are far from becoming standard, especially in clinical settings. They need to be validated and their ability to collect high quality EEG signals needs to be confirmed [29].

The dry EEG utilized for these experiments was the Quick-20, the latest model in mobile EEG technology made by the Cognionics. The system is comprised of 20 electrodes placed according to the standard 10-20 system [30]. The Quick-20 system can be seen in Figure 5 attached to a test subject during the adjustment phase of the experiment. This headset can be characterized as an octopus-like shape, where each electrode-terminated arm is elastic and engulfs the head of subjects with various head shapes and sizes. Two kinds of electrodes are attached to the end of each elastic arm of the headset: a set of electrodes that is in contact with the hair and a set that is in contact with the skin. Sensors that are in contact with the hair are designed differently, they are made of silver and carbon, an example of hair and skin electrodes are shown below in Figure 6 [30], [31]. Sensors that are in contact with bare skin, in the forehead region, are made of a hydrogel enclosed conductive membrane. Each electrode is attached to a pod which encompasses an amplifier that aims to enhance the signal quality while eliminating chances of inferences from other electronics [31].

Figure 5: Subject wearing the Cognionics Quick-20 dry EEG system.

Hair Skin

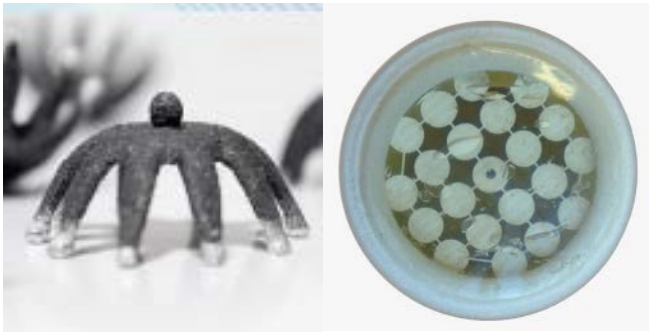

Figure 6: Hair and skin electrodes of the Quick-20 system.

The data captured by the EEG headset is wirelessly sent to a data acquisition software developed by Cognionics. Once the headset is on and the software is running, EEG signal for each channel is visualized on the screen as presented in Figure 7. For optimal signal quality, the software provides us with color coded map of channel locations, names and contact quality [32]. Red colored channels depict poor electrode scalp contact

while green colored channels reflect good contact. During the setup, rubbing hair electrodes to the scalp may be necessary to ensure good connection. Figure 8 describes the color coded map of channel locations of one subject before the beginning of the recording. Impedance is another characteristic based on which the scalp electrode contact can be judged. Impedance of each electrode is measured and displayed on the acquisition software in real time. The lower the impedance the better the electrode scalp contact, which can also be obtained by rubbing the electrodes against the scalp to enhance the contact between the two.

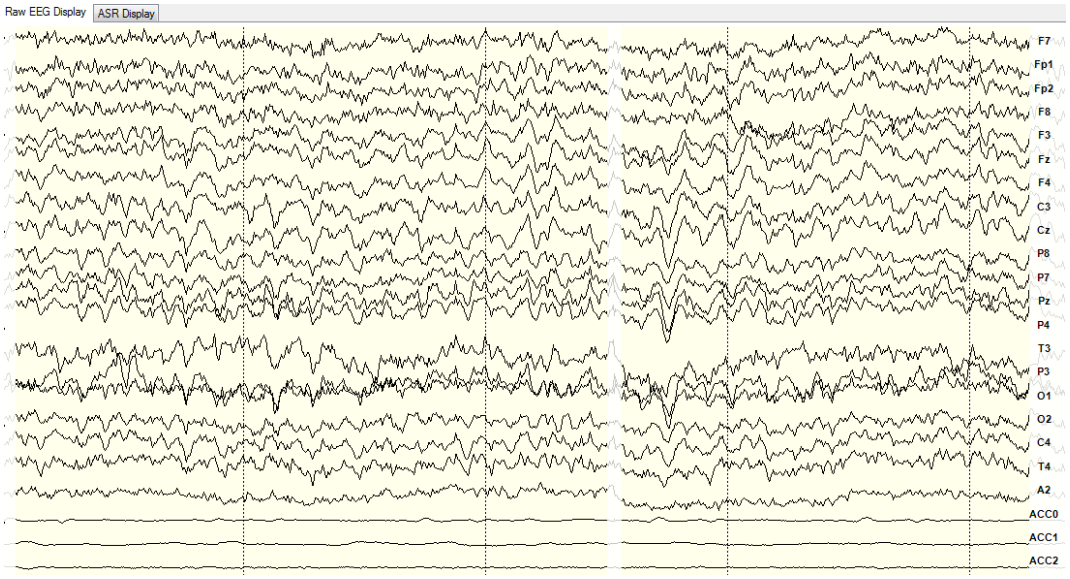

Figure 7: EEG data displayed by the Acquisition software.

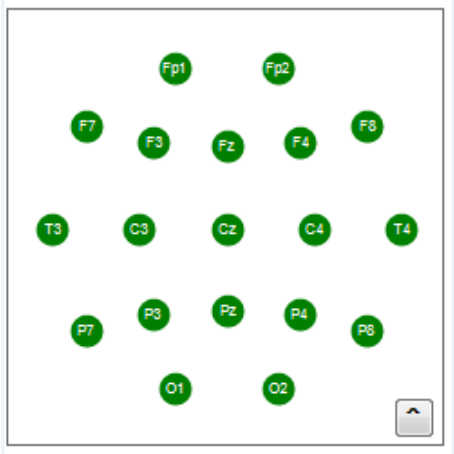

Figure 8: Green Channels that represent good electrode to scalp contact

Another advantage of the dry EEG system is its compatibility with a trigger box, also provided by Cognionics, that wirelessly sends time markers for events to ensure the reliability of the experiment [33]. Time markers are broadcasted with millisecond precision. They are captured by the EEG head set and are stored in a channel that can be visualized on the acquisition software. Trigger box, which is also compatible with and can be controlled by the Presentation software, is presented in Figure 9 [33]. The trigger channel can be conveniently visualized in MATLAB, as shown in Figure 9, where it was also used to determine response times and segment the data according to break and level sets.

The overall experimental setup, demonstrated by one of the subjects, is shown in Figure 10. In total, 12 volunteers were obtained, of which only 8 resulted in a usable data set free of prevalent and frequent motion artifacts, and glitches in the EEG recording. Due to the wireless transmission, the recorded data would occasionally suffer from recording lag or skipped results, which was visually assessed during the recording. In addition, since

the Quick-20 system is battery operated, glitches in the power in the system would also occasionally result in skipped data transmission.

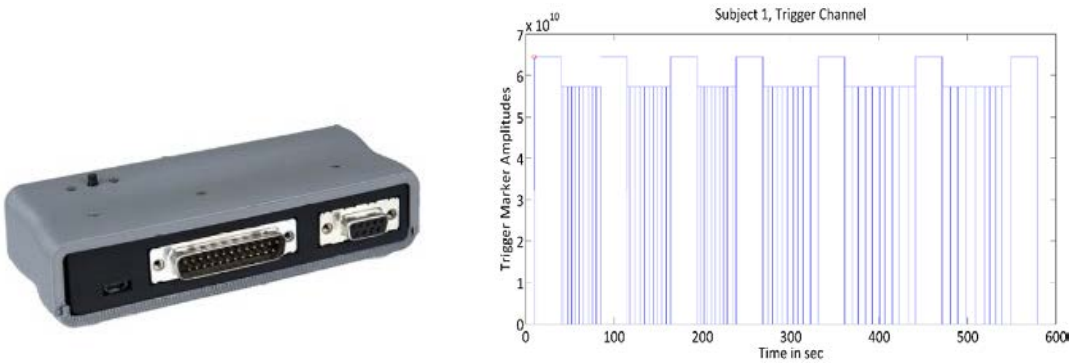

Figure 9: Wireless trigger box (left) used to deliver the onset and end of breaks and questions within each difficulty level of the experiment. The trigger markers can be visualized in MATLAB (right) and were used to calculate response times for each difficulty level.

Figure 10: Subject performing first set of the experiment.

3. Data Analysis

a. Data Preprocessing

i. High Frequency Filtering

The first step of data preprocessing was to filter the signal in all channels to remove high frequency components of the EEG signal. Filtering was performed using a digital bandpass Butterworth filter defined by the following Matlab function:

[b,a]=butter(n_fi,Wn,),

where the inputs n_fi is the order of the filter and Wn is the cut-off frequency, and the outputs b and a are the transfer function coefficients returned by the butter function. A third order filter was used to filter the EEG signal. The bandpass filter was designed to filter EEG signal between 0.1 Hz to 40 Hz as it encompasses the frequency bands region of interest. These types of filters require the cut off frequencies to lie between 0 and 1 [34]. Thus, the desired frequencies were each divided by the Nyquist frequency of 250 Hz, which is half the sampling frequency of the Quick-20, and fed to the filter in the form of a vector.

The coefficients are then fed to a digital filtering function filtfit, and is defined as:

chfi(i,:)=filtfilt(b,a,chi(i,:)),

where chi(i) is the input of the function which contains the EEG signal in each channel i and chfi(i) is the output which contains the filtered EEG signal in each channel. Filtfit has an advantage over other filter functions as it performs the filtering in the forward and backward direction in order to eliminate any phase lag . After performing filtering in the EEG signal using these filters, all DC offsets and high frequency components were eliminated from the signal as shown in Figure 11. The top plot represents the raw EEG signal and the bottom plot represents the filtered signal. This signal is a segment form the

frontal channel F8 in subject 2 containing data from 350 seconds to 370 seconds of the whole recording.

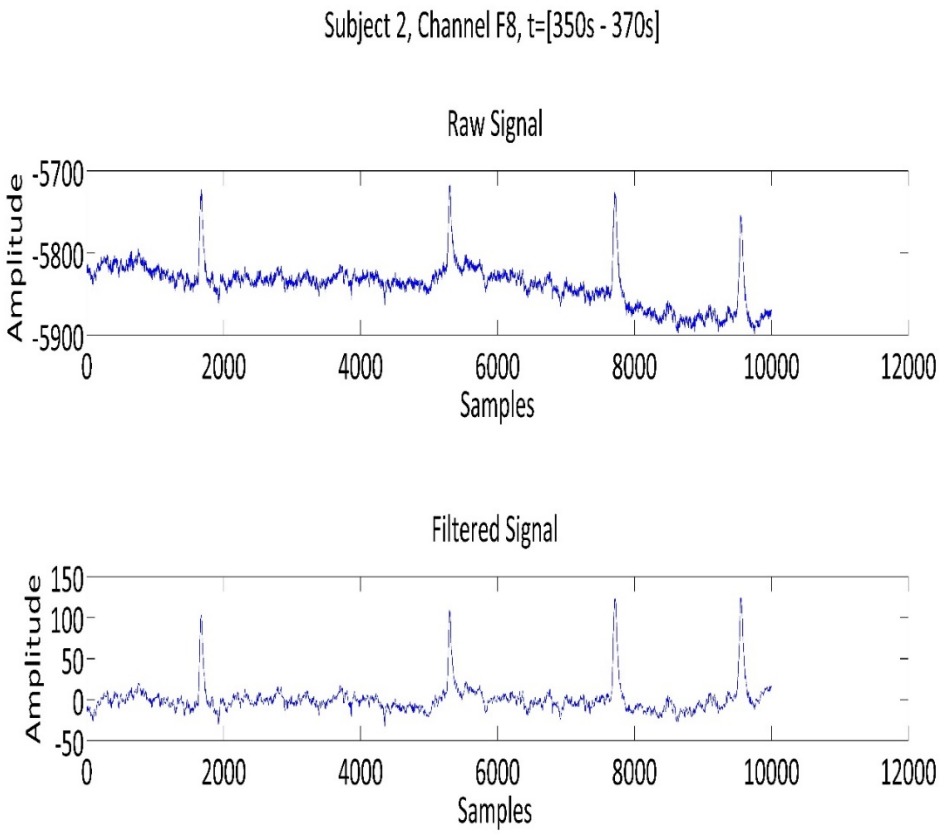

Figure 11: Comparison of the raw signal and the filtered signal showing reduction in the DC and high frequency EEG components.

ii. Ocular and Movement Artifacts Removal

Ocular and movement artifacts were removed by an automated artifact rejection technique known as Artifact Subspace Reconstruction (ASR). This technique is conveniently available as a plug-in for the MATLAB module EEGLAB [35]. It detects segments of EEG signal that contain artifacts using a sliding window principal component analysis. Whichever segment has a variance that exceeds a certain threshold is detected as an artifact. The threshold is set in accordance with the covariance of the calibration dataset

[36]. The calibration data set is constructed based on segments of EEG data that are detected by the algorithm and considered to be clean [35]. Segments of EEG data that are considered artifacts are reconstructed based the correlation structure that characterizes the calibration data [36]. After performing ASR on my filtered EEG data, ocular and movement artifacts were removed. This can be observed in Figure 12 where a segment of filtered EEG signal was superimposed with the same segment after performing ASR. Removal of ocular and movements artifacts, which are clearly visible in the filtered signal by high amplitude spikes, is noticeable on the cleaned signal. Movement artifacts vary in amplitude, yet, are still distinguishable from the majority of the true EEG signal. The EEG segment was extracted from channel F8 of subject 2 at t= 300 sec until t=375 sec.

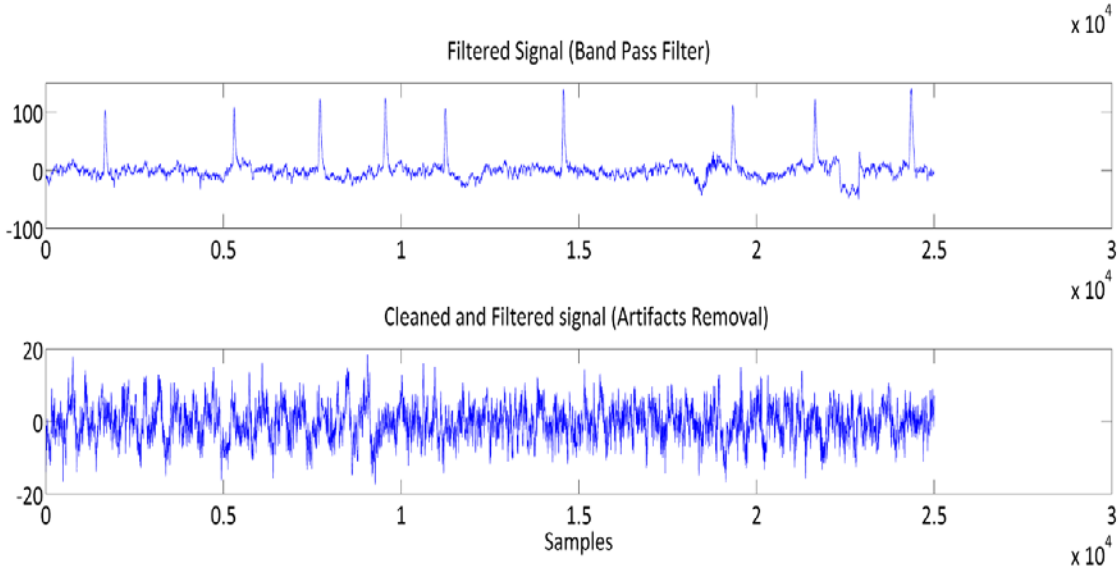

Figure 12: Superimposition of filtered and clean EEG signal after removal of ocular artifacts using ASR.

iii. Common Average Reference

Common average referencing (CAR) is performed to enhance signal to noise ratio [37]. This referencing technique consists of computing the mean of the signal of all the electrodes, and subtract it from every electrode. In my study, this averaging technique was performed using 19 channels where common noise contaminating the signal in all the electrodes was removed. The CAR formula is,

$$Ch^{CAR}(i)= Ch(i)-(\sum Ch(j))/19),$$

where Ch^{CAR} is the signal at the ith channel obtained after performing CAR.

a. Response Time and Accuracy for all Subjects

Response time for a complete level, from start of question one to end of question ten, was calculated using the trigger channel values. The initial trigger value, start of question one, was subtracted from the corresponding end trigger value, end of question ten, for each level. Average of response time for each level was calculated across subjects. Response accuracy was calculated by identifying the number of correct answers for each subject at each set and dividing it by the total number of questions the subject was able to answer.

b. Time Frequency Analysis

Time Frequency analysis is a technique that allows the visualization of the frequency content of the data as a function of time. This technique was applied to the data of several subjects at different channels using a built-in MATLAB function called

spectrogram. The obtained spectrograms were able to visualize the variation in frequency bands across the difficulty levels.

c. Event related desynchronization Analysis

Event related desynchronization (ERD) is defined as the percentage change in the average alpha power between a reference period that precedes a stimulus onset and a task period that follows it as seen in the equation [38],

$$\mathrm{ERD\%} = \frac{\mathrm{A-R}}{\mathrm{A}} * 100,$$

where A refers to the task/activity period and R refers to the reference period alpha power values.

i. Alpha Power Calculation

Alpha power was computed using the MATLAB function,

P = bandpower(X, Fs, FR),

where P is the returned power, X is the input signal, Fs is the sampling frequency and FR is the designated frequency range, which is, for alpha power calculations is 8-12 for the alpha range. Average Alpha power across all the channels was computed for every break and task interval for every subject. These obtained values were averaged across all the subjects and plotted in function of every break and difficulty level.

ii. Analysis on All Channels

ERD percentage was calculated at each difficulty level for each subject for all channels at once. ERD average across all subjects at each difficulty level was determined and plotted as a function of the difficulty level.

iii. Analysis on Specific Lobes

Channels attributed to a certain brain lobe were grouped together. A total of 4 lobes were obtained. Frontal lobe contained channels Fp1, Fp2, F7, F3, Fz, F4 and F8. Temporal lobe was composed of channel T3 and T4. Occipital lobe contained channel O1 and O2. Parietal lobe included channel P7, P3, Pz, P4, P8 C3, Cz and C4. ERD percentage was calculated for each lobe within each subject. ERD average across all subjects was computed and plotted as a function of difficulty level for each brain lobe.

iv. Analysis with Hemispheric Division

Channels belonging to left and right hemispheres were grouped accordingly. ERD percentage for each hemisphere in each difficulty level was computed in each subject. Average ERD values across all subjects was evaluated and plotted as a function of difficulty levels in each hemisphere.

d. Feature Extraction

Feature extraction was performed in the time domain. EEG signal was first decomposed into predefined frequency bands that are delta, theta, alpha, beta and gamma. Decomposition was achieved by using a Butterworth bandpass filter, where frequency range was specified for each frequency band. An analysis window for calculating each feature with length 0.5 sec was slid across the entire data in increments of 0.25 sec.

Extracted features provide information about the way EEG amplitude varies across different windows within trials. Amplitude variation can be assessed by common statistical

measure, such as root mean square, standard deviation, kurtosis and median absolute deviation. Root mean square is the square root of the mean value of the variance of the bandpass filtered EEG data over n samples at a fixed window time. Standard deviation is the square root of the variance. This feature indicates the spread of the data within the sample. Kurtosis describes the deviation of the distribution of the data from a normal distribution around the mean and serves as a measure of the degree of peaking of the data within the given window[39]. Median absolute deviation represents the mean of the absolute deviations of a set of data from the mean [40].

e. Classification

K-Nearest Neighbor (KNN) classifier was trained to discriminate 4 different workload levels. This non parametric classifier was chosen as it is known for its versatility and good performance. Classification is made based on the class of the k nearest neighbors. KNN predicts the test sample class by locating the nearest k neighbors from the training data, determining their classes and associating the dominant class to the sample being tested [41]. The higher the k chosen, the more accurate is the result, yet, at the cost computational power [41]. KNN was trained, for every subject, with 70% of data that comprises the extracted features and it was tested on 30% of the remaining data, with a k value of 5. Confusion matrix and classification accuracy were determined for every subject and were averaged to obtain a mean classification accuracy across all subjects.

4. Results

Mental workload is related to the difficulty level of the task as it represents the invested cognitive resources while performing a task [11]. Cognitive investment is expected to increase with an increase in difficulty. Assessment of mental workload of all subjects was conducted using two types of measures: Performance measure and Physiological Measure. Performance measure provides response times and accuracy of all subjects at each level. Physiological measure in our case is given by brain activation measured by EEG. Response time is expected to increase as the difficulty level increases. Response Accuracy is expected to be positively correlated with brain activation. Brain activation is located at areas of the brain that are engaged during task performance.

a. Performance Measure

i. Response Time across Subjects

The statistics of response times across all subjects for each difficulty level is shown in Figure 13. Interestingly, only a slight increase in response time distribution was obtained between level four and six. Overall the response time distributions follow a sigmoidal shape, with a threshold reached at ~70 seconds. The maximum possible response time would be 100 seconds for 10 questions, due to the 10 second time limit for each question. An increase in the response times is noted across the levels, correlating to the increase in difficulty. An increase in the difficulty of the task demands more invested cognitive resources thus higher mental workload [3]. Level one contains one to one digit additions, which represent the lowest arithmetic level of summation. Level two contains one to two digit additions, which, based on the response times in Figure 13, show only a slight increase

in difficulty. Level three and four contain two to two and two to three digit additions, respectively.

The largest increases in response times occurs at level three and four, attesting to the distinction in difficulty between single and double or triple digit arithmetic. Level five and six both consist of three to three digit additions, with only a slight difference between the two relating to the higher magnitude values used in level six. Interestingly, only a slight increase in response time distribution was obtained between level four and six.. The maximum possible response time would be 100 seconds for 10 questions, due to the 10 second time limit for each question.

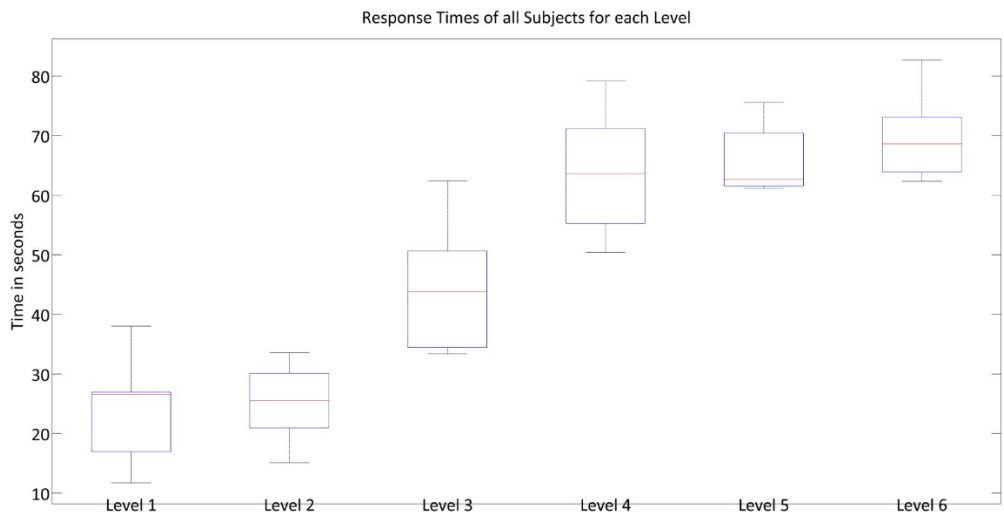

Figure 13: Response Time distribution of eight subjects across the increasing arithmetic difficult levels from one to six.

ii. Response Accuracy of Each subject

Response accuracy is the second performance measure used in the investigation of mental workload. Figure 14 shows response accuracy of every subject at every level along with average accuracy across levels. Subject 1 shows the highest average response accuracy, followed by subject 2. Subject 3 hold the third highest average response

accuracy. Subject 6 and 7 hold the least response accuracy with a score of zero at level 5. Response accuracy reduces across levels correlating to an increasing difficulty.

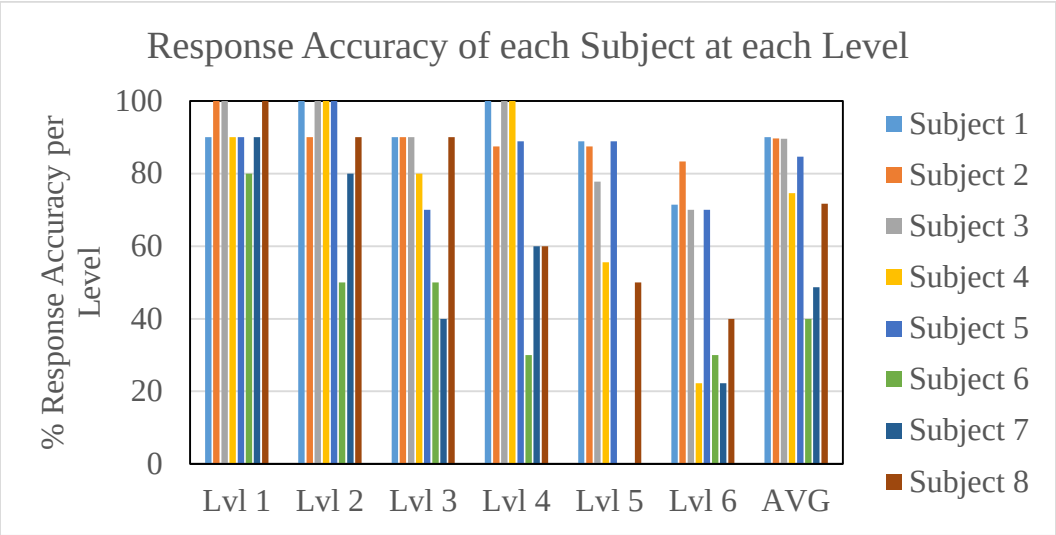

Figure 14: Response Accuracy of each Subject at each Level

b. Physiological Measure

i. Time Frequency Analysis

Fluctuations and patterns in mental activity can be visualized by performing time-frequency analysis on an EEG dataset. Time-frequency analysis is the calculation of frequency composition at discrete time windows throughout a dataset. Thus, if plotted in a 2 dimensional plot, it can reveal power fluctuations of certain frequency amplitudes over time. Figure 15 shows the frequency distribution of the filtered and cleaned EEG data in channel Pz of subject 1 that hold the highest average response accuracy. The graph was sectioned to conveniently identify break sections, marked with the letter B on top of the figure. The section in between breaks denote mental workload levels that increase in difficulty as time progresses. The power of the frequencies, shown as color intensities, has

higher magnitude in the frequency range of 8 and 12 Hz, representing the alpha band. A pattern is recognizable at the alpha band, showing higher intensity values at the break sections, and lower within the level sections.

A decrease in the power of alpha band is known as desynchronization in the alpha band. The desynchronization between a break and a proceeding level becomes more prominent as the difficult level increases. Level 6 which is considered to comprise the most difficult questions represents the biggest desynchronization correlating with highest level of cortical activity. Figure 16 shows the spectrogram of subject 4, having 4th highest average response accuracy, of channel Pz. Similar pattern is identified where there is an increase in alpha desynchronization correlating with difficulty level. However the desynchronization in alpha band is not as prominent as it is in subject 1. Figure 17 shows the spectrogram of channel Pz of subject 6 whose response accuracy is lowest. The desynchronization in alpha band between levels in barely noticeable.

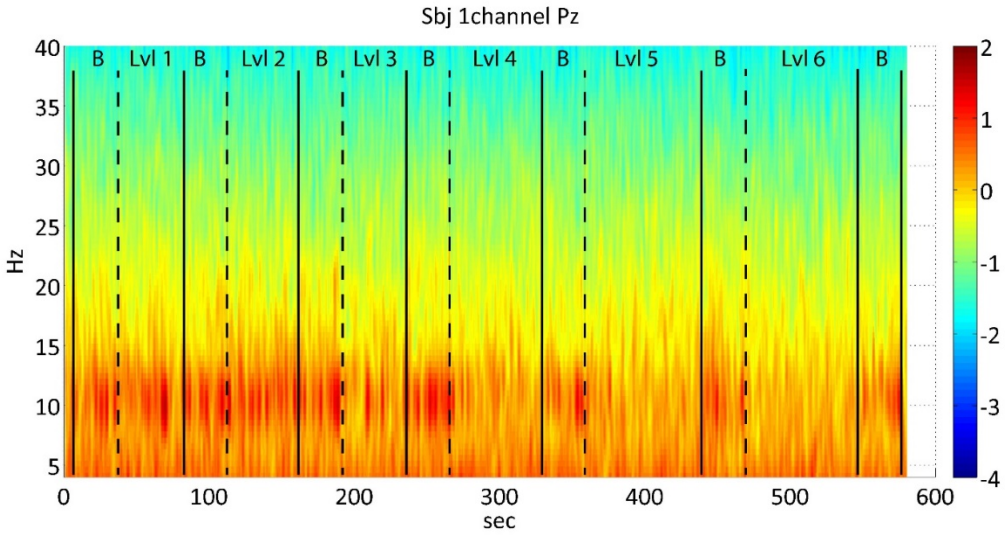

Figure 15: Spectrogram visualizing the frequency composition across levels in channel Pz of Subject 1.

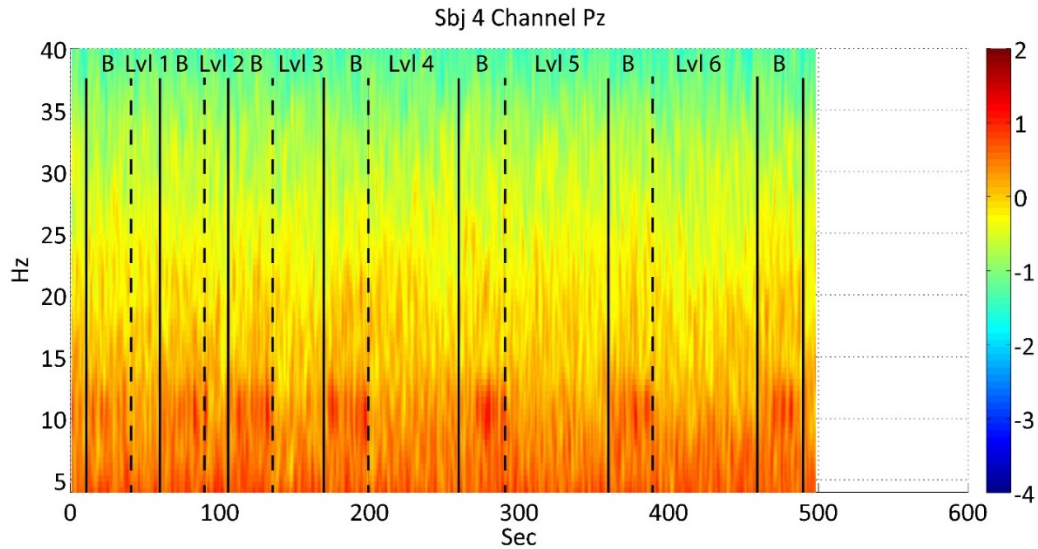

Figure 16: Spectrogram visualizing the frequency composition across levels in channel Pz of Subject 4.

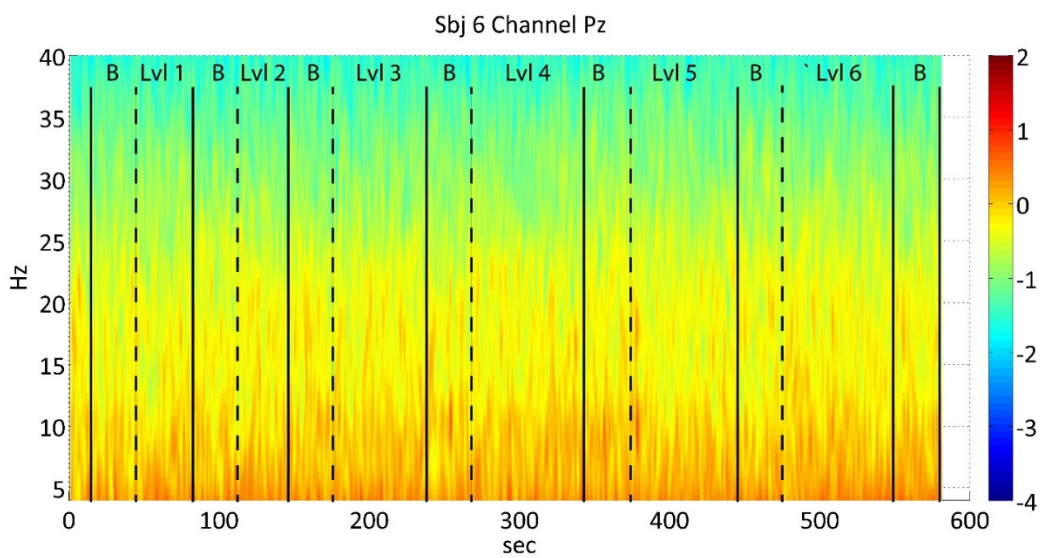

Figure 17: Spectrogram visualizing the frequency composition across levels in channel Pz of Subject 6.

ii. Alpha Power Calculations

Spectrograms are the ideal tool to qualitatively visualize the change in the power of frequency bands across time or tasks in one channel. However, computing the power of

specific bands results in more precise and quantitative information about the power fluctuation of these bands in all channels. Power of a frequency band can also be averaged across a certain amount of channels, such a channel subset that correlates to a particular brain region or lobe. With the help of the MATLAB function bandpower, alpha band power was computed for every subject in every break and difficulty level across all channels. Figure 18 shows normalized average of computed alpha power across all subjects.

A decrease in alpha power is noted across level 3 to level 6. This alpha desynchronization correlates to an increase in difficulty and mental workload. Level 1 through level 2 show a similar amount of alpha power, reflecting a similarity in the difficulty level. The highest amount of alpha power are observed during break sections. This amount increases across breaks reflecting the greater need for relaxation of the subjects after a level. Error bars within the figure represent the variance between the subjects. A greater variance in alpha power between subjects is observed during break sections. Variance within levels is noticeable but less than in the break sections. A Student t-test was performed to assess the significance between the alpha power in level 1 and level 6. A p-value of 0.114 was obtained, which, although the lowest p-value comparison between all levels, denotes the lack of a statistical difference between the data in each level. However the trend of decreasing alpha power with increasing task difficulty is obvious by inspection of Figure 18.

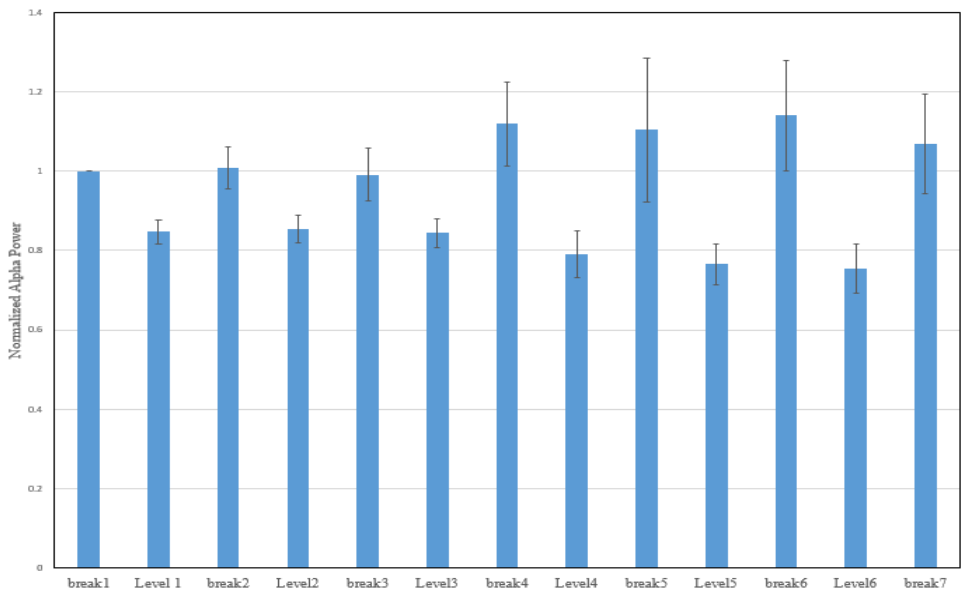

Figure 18: Normalized average alpha power for all subjects across all channels in each experimental segment of break and task level.

ii. ERD% Calculations

A more useful tool to investigate the brain activity is to compute the ERD% of interest. ERD stands for event related desynchronization which occurs when there is a decrease in alpha power. ERD has been referred as the electrophysiological correlate to cortical activity [38]. Increased cortical activity is correlated to an increase in mental workload

Averaged ERD% for all subjects across all channels for each arithmetic level was calculated as shown in Figure 19. The plot of average ERD% follows a decreasing sigmoidal shape where ERD value at each level is negative which depicts a decrease in alpha power at each level with respect to the baseline. ERD starts at -15% at level one and reaches -25% at level six. A decrease in ERD% across the levels correlates with an increase in difficulty, as was the case for normalized alpha power averages across the levels above. Similarly to Figure 13 and Figure 18, level one and two showed similar levels of difficult,

evident by response time level and ERD%, and the largest change occurred between levels three and four. Error bars reflect the variance in the ERD% between the subjects. The variance between subjects grew as the level increased, attributed to the inter-subject variability in response to mental arithmetic.

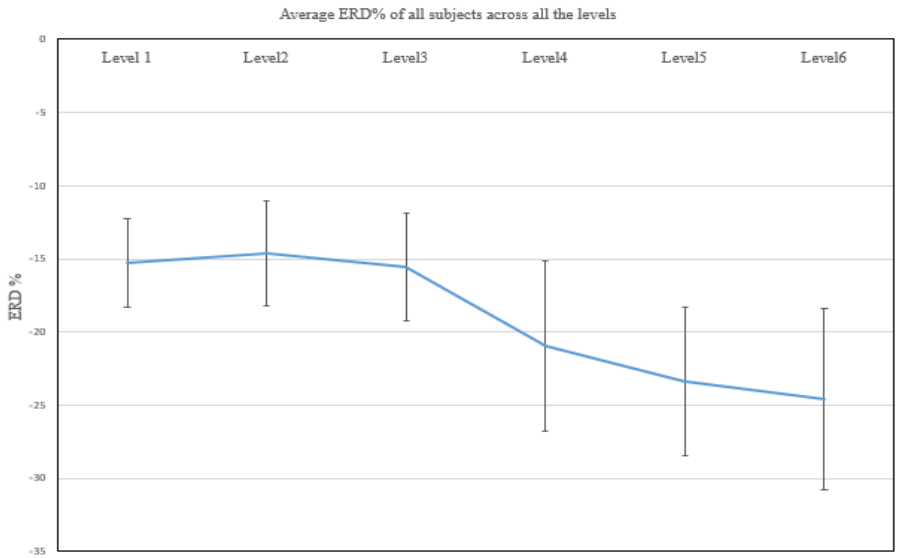

Figure 19: Average ERD% of all subjects across all channels.

Obtaining ERD for a select number of channels located at a certain region is more informative than calculating ERD across all channels. Region specific ERD depicts the cortical activity within that area, which helps in identifying cortical region roles during tasks. Figure 20 shows the average ERD% for all subjects at each level in four discrete lobes. The fronto-parietal lobe and occipital lobe depict a decrease in ERD% across the levels correlating to an increase in difficulty and mental workload within these regions. In fact, the lowest ERD% achieved is at the fronto-parietal and occipital lobe reaching up to -29% at the last three difficulty levels. Prefrontal and temporal do not follow a similar

pattern of desynchronization as the fronto-parietal and occipital lobes. Prefrontal lobe is the only lobe that shows alpha synchronization for the majority of the subjects, which is detected primarily at level two and three. The temporal lobe predominantly shows desynchronization at every level, however ERD% does not show a steady decreasing trend, such as that found in the fronto-parietal and occipital lobe. Thus, temporal and prefrontal lobe activity cannot be correlated to the task difficulty and mental workload.

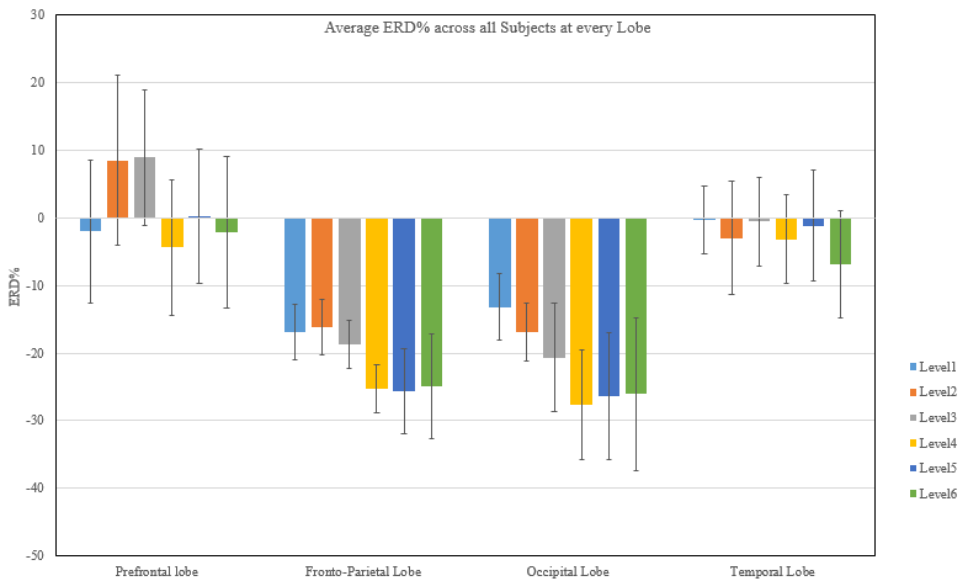

Figure 20: Alpha ERD% for each Level in four discrete brain lobes.

iv. Theta Event Related Synchronization Calculations

Event Related Synchronization (ERS) represents a measure of the increase in the power of theta band between active tasks and a reference period. An increase in prefrontal Theta band ERS has been linked to an increase in working memory load and attention demand [42]. ERS% in theta band was calculated using the same procedure in calculating ERD% where power in theta band was used instead of the alpha band. Figure 21 shows the

average ERS% for all subjects in the same four lobes chosen for ERD% calculations. Prefrontal lobe depicts an increase in ERS% from level one across level three and then from level four across level six. A decrease of about 5% is noted between level three and level four. Highest ERS of 50% is noted at level 6 whereas an ERS of 15% is noted at level one. This increase across levels is correlated by an increase in difficulty. ERS% changes in the rest of the lobes did not have a specific trend, ERS% in fronto-parietal, occipital and temporal lobe could not be correlated with an increase in difficulty.

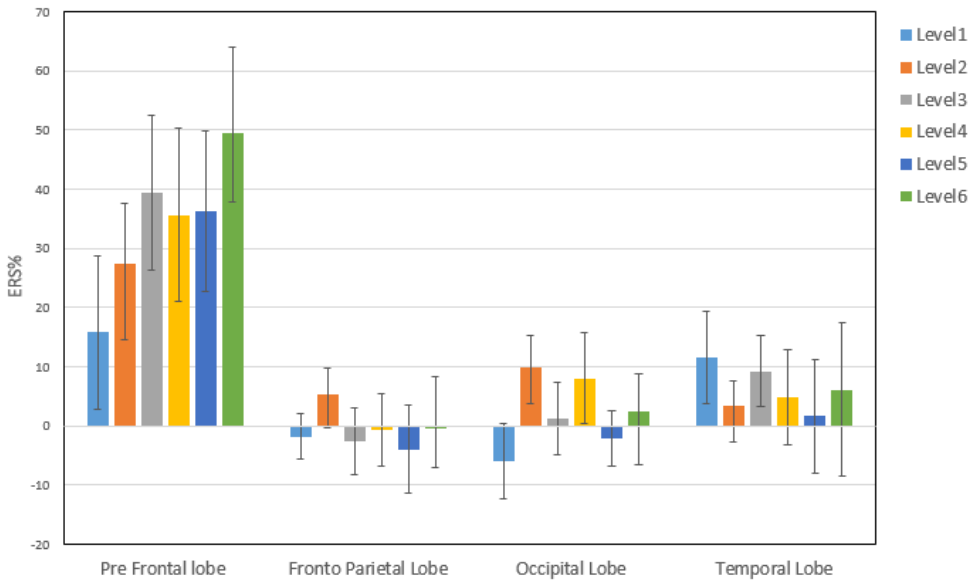

Figure 21: Theta ERS% across all subjects in four discrete brain lobes.

v. Subgroup Analysis based on Performance Measure

The highest performance, determined by calculating response accuracy, was obtained by four of the eight subjects: subject one through three and five. The subject accuracies were around 90% for all four, whereas that of the others was at or below 70%. Physiological measure was performed on these four subjects to investigate mental

workload and its correlation with increasing difficulty. Greater correlation is expected within the subject subset, since these subjects performed well, which may reflect a greater amount of cognitive investment across the levels.

ERD changes were computed in the alpha band across these four subjects at each lobe. Figure 22 shows a steadier decreasing trend of ERD% in the fronto-parietal and occipital lobes correlating with increase in difficulty and mental workload. Prefrontal and temporal lobes show a decreasing trend only from level three to level six. The biggest desynchronization is reached in the occipital lobe at level six with an ERD% value of -41%. Desynchronization in the alpha band was more pronounced in the case of the four selected subjects, suggesting a correlation to the performance and response accuracy.

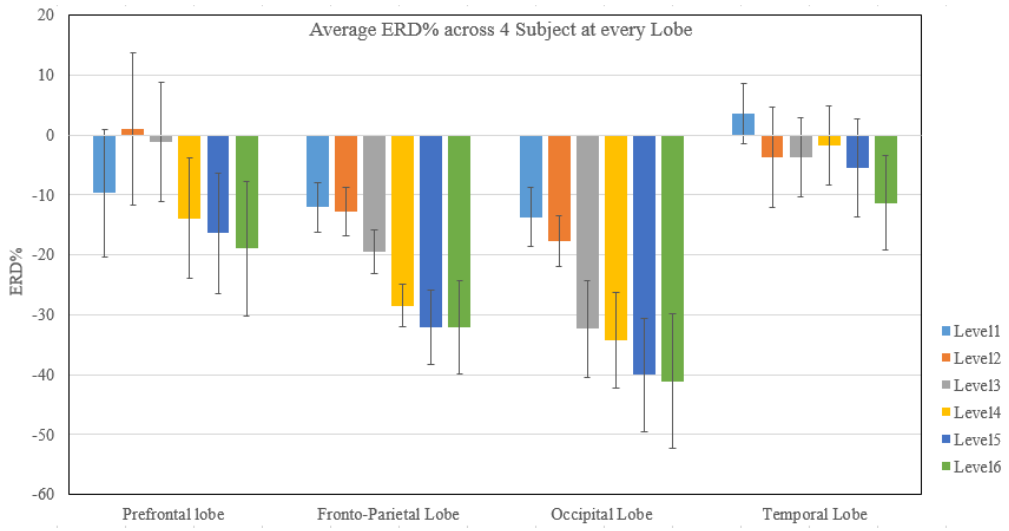

Figure 22: Average ERD% for a subset of subjects (n=4) at four discrete lobes.

Changes in the ERS% were computed for each level across the four selected subjects. Figure 23 shows an increasing trend from level one to level four at the prefrontal lobe and from level one to level three at the occipital lobe correlating with the difficulty

level. The fronto-parietal and temporal lobes do not reflect any trend across the levels. The highest amount of synchronization is detected at level six at the pre-frontal cortex. Theta synchronization was more pronounced in this subgroup correlating with response accuracy.

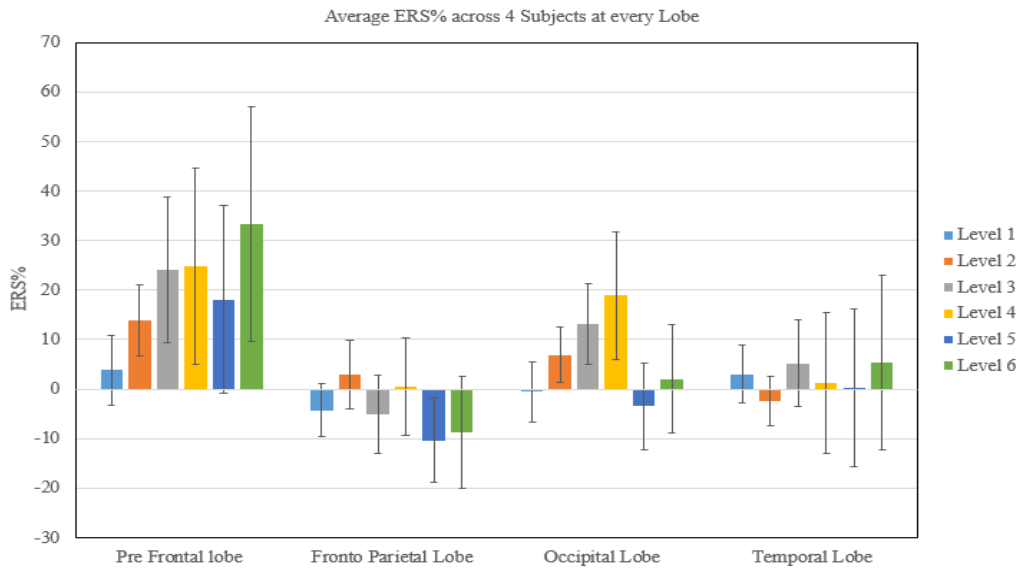

Figure 23: Average ERS% for a subset of subjects (n=4) at four discrete lobes.

d. Classification

Classification aims to discriminate between four classes. The first class was the class associated with low mental workload (MWL1), which contained level one and two. The second class was associated with a medium workload (MWL2), which contained level three and four. The third class was associated with high mental workload (MWL3), which contained level five and six. Class four represented the break sections (Rest).

The KNN classifier was trained to distinguish between these four classes. A total number of 380 features form 19 channels for 2019 time windows were extracted. Of these, 70% were fed into the classifier and 30% were used to test the classifier. After running

KNN with a k value of 5 on the sub group, an average accuracy value of 90.81% was obtained. Table 1 shows the average confusion matrix of the four selected subject subset, which tabulates the four different classes to be distinguished versus the class assigned to the samples being tested. The second column corresponds to samples belonging to class one and classified as either class one through four. The third, fourth, and fifth column correspond to samples belonging to class two, three, and the rest, respectively. The diagonal values reflect the accuracy of classification for each class. Summing these numerical values yields the overall accuracy.

Table 1. Classification Confusion Matrix.

	LMW	MMW	HMW	Break
LMW	98	3	2	10
MMW	1	116	5	7
HMW	1	2	180	6
Break	6	5	8	235

5. Discussion

Mental workload can be defined as the cognitive resources invested in performing a certain task. However, mental workload is capable of reflecting more than the difficulty level of the task, as it reflects certain characteristics of the task performer. By analyzing and correlating mental workload assessment obtained by several measures the expertise of the performer may be determined. Along with their expertise, or capabilities, their motivation and their physical and emotional state while performing the task can also be assessed [29]. In this analysis, response times was the first performance measure of mental workload to be calculated. Averaged response time across the subjects shows an increasing trend across the sets, with increasing level difficulty. This trend proves that incremental increases in the complexity of the arithmetic problem can be correlated to increasing levels of difficulty, and can, thus, stimulate higher levels of workload.

Level 5 and 6 consisted of summations of two 3-digit figures that required more time to solve. These two levels had a very close average response of 60 seconds. Level 1 and 2 represented the simplest task which consisted of adding two 1 digit figures at level 1 and then 1 digit figure to 2 digit figure at level 2. Average response time for these two levels was close and had a median of approximately 29 seconds, half the response time of level 5 and 6. This signifies the contrast in effort required by the subject at low and high mental workloads. Level 3 and 4 represented the medium difficulty level. Level 3, consisting of two 2 digit figure addition showed a significant jump in the average response time. This can be interpreted with level 3 being the threshold of the start of tasks requiring higher mental workload, and the need to perform actual mental arithmetic rather than accessing memory to recall solutions to simple one and two digit summations.

The variation in the response accuracy can be correlated to the physiological measure of the mental workload. EEG analysis and investigation of alpha band behavior during different difficulty levels represented an effective physiological measure. Spectrogram of the channel Pz in subject 1 shows more pronounced alpha desynchronization across levels than subject 4 and 6. Spectrograms of subject 1 and 4 show an increase in alpha desynchronization as the difficulty level increases. This indicates a higher mental workload experienced by the subjects at each level. Higher mental workload reflects more cognitive resources being invested which correlate to the response accuracy. Subjects that experienced higher alpha desynchronization across levels achieved higher response accuracy. Subject 1 having the highest response accuracy, subject 4 having the 4th highest response accuracy and subject 6 having the lowest response accuracy validate the correlation of the performance to the mental workload in this case.

Physiological measure of mental workload on all the subjects resulted in an insignificant discrimination between ERD in level 6 and level 1 ($p<0.05$). ERD in level 6 is expected to be much lower in percentage compared to level 1, as level 6 involved higher mental workload than level 1. However, when the analysis was performed on a subgroup of 4 subjects, whose accuracy is around 90%, statistical significance was obtained between level 1 and 6. ($p=0.04$). Also, the decreasing trend in ERD was steadier and more pronounced across the levels. These findings validate that the correlation between high mental workload and ERD% is more pronounced when the performance of the subject is higher.

In the case of subjects whose accuracy was lower than 70%, no significant correlation could be made between increasing difficulty level and mental workload measured by ERD%. A factor that may explain this lack of correlation is the motivation of the subject while doing the task. If the subject is not motivated, it is less likely that they will add enough effort to properly perform the task, which can be supported by their performance quality. Other factors can be related to their emotional or physical states such as fatigue, hunger, sickness, which can affect their ability to invest cognitive resources while performing the task [11]. However, a few cases did exist where the subject had high response accuracy, yet, their mental workload, measured by alpha ERD, was low. This can be due to the fact that the performer had acquired a certain level of expertise on the task and does not require to invest as much cognitive resources as a novice. In contrast, it is possible to have the case where low response accuracy coincides with high mental workload with increasing difficulty level. This may be due to an unfamiliarity of the subject with the task being performed, or simply the subject's capacity for the task. However, since the task given, mental arithmetic, was familiar to all the subjects, this case was not observed during this study.

Localization of mental workload was achieved by determining alpha desynchronization in discrete brain lobes. Alpha desynchronization is more pronounced at the occipital and fronto-parietal lobes in association with lobe functions. The occipital lobe plays a major lobe in the processing of visual information. The fronto-parietal lobe is associated to knowledge of numbers and plays an important role in the processing of numbers, magnitude assigning and retrieval of stored arithmetic facts form memory [42].

Theta elicited a noticeable increase in synchronization across as difficulty increases, mainly in the prefrontal cortex in association with the role played by the prefrontal lobe during tasks. It has been shown that prefrontal cortex is associated with working memory, encoding and temporary storage of information. EEG oscillation in the theta band reinforce these functions and synchronization in theta band increases as attention demand and working memory load increases. Increase in theta synchronization in the prefrontal cortex across subjects at each level reflects an increase in attention experienced by subjects as the difficulty level and mental workload increases. Attention demand varies from a person to anther based on individual characteristics. However, as an average it has been proven that mental workload is associated with an increase in attention and working memory demand [43]. Classification yielded to high accuracies reflecting the efficiency of the KNN classifier and its adaptability in discriminating between mental workload levels.

6. Conclusion

This study has shown that the detection of mental workload can be performed with a high level of accuracy using a wireless, dry EEG system. In general, the assessment of mental workload can be achieved using several measures such as physiological and performance measures. Combining the output of these two measures can be informative as it reflects several characteristics of the performer. Such information can be useful when applied in the selection of candidates performing a certain task. For instance, medical residents are required to pass a training, Fundamental of Laparoscopic Procedure (FLS). This procedure consists of undergoing all the operation through a small incision instead of open surgery. While this procedure is more beneficial to the patient, it is very challenging and requires a significant amount of mental capacity to maintain high performance throughout the surgery. Most optimal candidates would be the fastest at performing the procedure, with least number of errors and amount of cognitive resources invested. Thus, such combination of workload measures will be the most optimal tool to select most competent candidates.

Discrimination of mental workload levels can be achieved using a classifier. Choosing a well-adapted classifier to the task and training it with the right extracted features is very crucial in achieving high accuracy. The ability to discriminate different level of mental workload is crucial in the case of individuals performing jobs where maintaining alertness is absolutely necessary, such as doctors and control air traffickers. A trained classifier would notify the individual when the detected mental workload is not as expected. For instance, if the surgeon is performing a basic procedure and the classifier detects a high mental workload, it might implicate the physical and emotional state of the

surgeon such as exhaustion or sleepiness. Thus, an immediate action needs to be taken in order to prevent a mistake from occurring.

Future work will include the development of a real time system capable of measuring the mental workload, where the classifier has the training set stored and is capable of providing live updates about the mental workload level. This step comes with a lot of constraints, such as sensitivity of EEG system to noise, accuracy of classification, and subject dependence.

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