Cognitive Workload Analysis in Visual and Auditory task using EEG signals

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Declaration

I, *Muhammad Ali Bilal* declare that this thesis titled "Cognitive Workload Analysis in Visual and Auditory task using EEG signals" and the work presented in it are my own and has been generated by me as a result of my own original research.

I confirm that:

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To The Loved Ones ...!

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Abstract

Cognitive workload can affect the number of errors one makes during a task. Measuring the cognitive load can be beneficial for understanding the factors effecting the performance of an individual. There is a lot of research about the measurement of cognitive workload, however a standard metric for cognitive workload estimation, applicable to multiple situations does not exist.

In this study a task is designed to induce variable mental workload. This task varies not only the intrinsic workload by changing the difficulty level of task, but also the extraneous workload by varying the input methods (i.e. visual and auditory). Brain waves of participants were recorded during the task using a commercially available single channel EEG device having dry electrode at Fp1 location. Participants were also asked to give the subjective feedback about the tasks using NASA-TLX questionnaire. Power spectral densities of brainwaves are used for the estimation of mental workload and results are verified using subjective feedback.

The results from experiments and power spectral densities of different brainwaves are analyzed while comparing the relaxed and working state of participants. It helps us conclude that single channel EEG device is able to differentiate between relaxed and working state of brain. Similarly, while using the already available metrics of mental workload, we observed that auditory task demands less mental resources as compared to visual tasks. Still, those metrics are not sensitive enough to differentiate among the different difficulty levels of a same task.

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Chapter 1

Introduction

1.1 Motivation

Measuring the cognitive load can be beneficial for understanding the factors effecting the performance of an individual, whether it's a simple learning task or a critical job, because cognitive workload is one of the most important factors in human performance during a task. It can affect the number of errors one made during a task. Also, inducing the right amount of workload in an operator can increase the productivity and safety. Moreover, persons or operators will be more satisfied during their tasks if they are subjected to adequate amount of mental workload. If we can identify the type of tasks or what representations of tasks produce what amount of mental workload, then it will be very helpful for us to design any task in a way to maximize the operator's output.

For past several years, there is a lot of research about the measurement of mental workload and many researchers proposed methods for this purpose. However, a standard metric for cognitive workload estimation applicable to a multitude of situations does not exist. Even a thorough analysis of existing metrics is not available.. Most mental workload estimation techniques are for particular scenarios and can be used for specific type of tasks. Our primary motivation for this research is to compare existing cognitive workload metrics and identify which of these metrics are best for what type of task. Secondly, our aim is to specify the equipment and process so that everyone would be able to use this system for workload estimation which will be further useful for better designing of human interfaces and better representation of task to the operators of critical jobs.

1.2 Cognitive Workload

Cognitive workload is one of the most important factors in human performance during any task, it can effect human error, safety, productivity and operator satisfaction. Psychological stress can seriously effect the mental health of an individual irrespective of age[1]. A more exact definition of cognitive workload involves the depletion of human mental resources, to accomplish a task[2]. Cognitive Workload can also be defined as the allocation of working memory resources during a task. It is a characteristic that depends on both, an individual and a task, every individual can perceive mental workload differently and it also depends on other factors like practice and personal capabilities of a person.

1.3 Measurement methods

Traditionally, cognitive workload was predominantly measured with different subjective techniques. In subjective techniques the operator was asked about his perception of workload, different questionnaire and scales were used. Operator's feedback can be influenced by many things other than mental workload. For example, they can confuse between mental and physical workload, and sometimes they can be unaware of subconscious allocation of mental resources to a task. Moreover, the subjective feedback of operators additionally depends on their short-term memory as mostly subjective evaluation is performed after the completion of a task.
Alternatively, there are performance based measures that implicitly reflect the amount of mental workload induced in a person. For example, an operator can be asked to do a secondary task in parallel with primary task so that accuracy on the secondary task can help us estimate the mental workload induced due to primary task.

Lastly, the physiological techniques used for this purpose include, measurement of breathing rate, Electrooculography (EOG), Electrocardiography (ECG), galvanic skin response, Pupil dilation, blinking rate etc. These methods are not considered very reliable for the measurement of cognitive workload because, firstly, these methods are indirect indicators of workload and secondly, these indicators can also be changed due to other stimulus, like breathing rate can also be effected by physical workload, pupil dilation can be varied by changing intensity of light in the environment etc. That is why Electroencephalography (EEG) is considered one of the more reliable method for estimation of mental workload, as it measures the brain signals which are directly influenced by changing workload conditions. In fact, there are different methods for recording brain signals some of them are invasive like Electrocorticography (ECoG) while some are non-invasive like Magnetic resonance imaging (MRI) or electroencephalography (EEG). For estimating the mental workload in routine tasks, EEG is the best suitable technique, due to being non-invasive and user friendly beacause of personalized EEG devices available now a days.

1.4 Problem Statement

A number of different metrics for the estimation of mental workload exist, but these metrics are suitable for a specific type of tasks or working environment. We analyze two mental workload metrics, while designing the tasks that are bound to induce different levels and different types of mental workload.

1.5 Objectives

- To analyze the role of prefrontal cortex in estimation of mental workload using a single channel EEG device.
- To design a task for induction of different levels and types of mental workload.
- To compare different metrics of mental workload estimation and analyze them

for Visual and Auditory tasks.

- To have subjective feedback from participants and use it to validate the results of mental workload metrics.

1.6 Thesis Organization

This chapter provides the motivation, introduces cognitive load and measurement methods, discussed the problem statement and outlines our objectives. Chapter 2 provides an overview of literature surveyed on different types of cognitive workload and various measuring techniques of mental workload. Chapter 3 discusses the adopted methodology in which different mental workload metrics are elaborated and experimental design is explained. Chapter 4 consists of results which are obtained from the experiments on processed EEG data. Chapter 5 concludes the study and provides a rationale for future work.

Chapter 2

Literature Review

2.1 Cognitive Workload

Cognitive load is fundamentally taken into consideration while designing any learning and training task or developing a user interface for critical jobs. The aim is to reduce cognitive load associated with presentation and interface of a task [3]. According to the cognitive load theory there are three types of cognitive loads (Fig. 2.1) i.e. intrinsic, extrinsic and germane workload [4].

Intrinsic load, is constant for a task, because it is related to basic elements of task. It is associated with an individual's background and nature of task or material being learned and the level of expertise an individual had about that task or topic [5]. Simply by changing the difficulty level of task we can vary the intrinsic workload of an individual.

Extraneous cognitive load is the result of instructional techniques that require learner to engage his working memory in activities that are not directly related to schema (long term memory) construction [6]. Early research revealed that many interfaces require the user to allocate mental resources that are not directly related to the task nor they help in schema construction [4]. Such mental resources are allocated for extraneous cognitive load, which can simply be defined as the cognitive workload related to how the information is presented. Unlike Intrinsic load extraneous load can be varied by change in instructional design or user interface.

Figure 2.1: Types of Cognitive Workload

Germane load is the mental resources used to memorize something, or make an information part of long term memory. Primary goal of many instructions and information is schema construction or to be stored in long term memory, so it can be useful in future for performing different tasks [4]. Germane load can also be varied but it depends on the extraneous load i.e. it varies positively with extraneous load because working memory is directly involved in the learning process.

For schema construction i.e. storing information in long term memory, an individual needs to manipulate the instructions in working memory during learning phase [7]. Most individuals face difficulties when asked to solve complex problems or asked to follow a complicated set of instructions because of extremely limited working memory [8]. Cognitive load theorists assert that overloading the working memory can effect the learning process, which is most effective when saturation of working memory (excessive workload) is avoided [4, 9]. Due to effect of limited working memory on learning, the learning environment designers not only try to reduce the extraneous load, but also engage the individual to allocate maximum mental resources for germane load [10]. An appropriate design of the learning environment or the user interface can reduce the extraneous workload [11].

2.2 Measurement of cognitive workload

Without measuring the cognitive workload, we cannot accurately decide that which learning environments or user interface demands more mental resources. Mental workload of operator can be measured by subjective rating techniques, performance based measures and physiological measures [12]. Cognitive workload can also be estimated through analytical techniques like expert opinion and using analytical data like mathematical models, task analysis etc. Commonly, cognitive load is estimated using empirical methods like, subjective measures using rating scales, performance measures using primary and secondary tasks and physiological measures. Empirical techniques of mental workload received a lot of attention from researchers [9]. Physiological techniques for cognitive load measurement received much attention in last few decades in different knowledge areas like human factors, ergonomics, automation system, military or life critical systems [13].

2.2.1 Subjective measures

Traditionally, mental workload is measured by subjective feedback from an operator. Subjective measure of mental workload mainly depends on the users perception about the task [14]. Although, physiological measures of mental workload are more precise but subjective measures are more practical and easy to conduct. Subjective measures are flexible for different persons of different capabilities, as this feedback is from operator himself, so subjective measures take into account operators state of mind, abilities and attitude [15]. This feedback is directly influenced by different aspects like, limits of operators memory, his answering style, social desirability and interpretations of the questions and answers [16]. Even though, subjective and objective methods of mental workload assessment are very different, it has been observed that subjective and objective measures correlates positively with physiological measures [17]. Some subjective feedback techniques use rating scales for standardization of answers, common of them are NASA-TLX [18], Cooper Harper [19] Scale, Likert Scale [20], etc.

One drawback of subjective measures is that, they cannot continuously measure the workload *during* the task [21]. If we try to have subjective assessment from operator during the task it can effect the primary task performance of operator. But it is recommended to perform subjective assessment just after performing the task, mainly because operator can forget about what amount of mental workload they were feeling during a particular segment of task, if the delay was excessive [22]. Another factor to keep in mind while having subjective measurement is the use of rating scales, because rating scales and rating environment can greatly effect the result of subjective measurement [18]. When using rating scales, it is recommended to provide verbal explanation of every rating index. Problems may also occur if the operator becomes familiar with the task. As operator becomes comfortable performing the task his perceived workload may decrease [23]. That's why subjective feedback can be a problem while running multiple trials of same experiment, or testing a person who is extremely familiar with environment.

Subjective measure of mental workload can be divided in two main categories, uni-dimensional and multi-dimensional ratings. Uni-dimensional rating sclaes focus on single aspect of mental workload whereas multi-dimensional rating scales includes different aspects of mental workload like temporal demand, mental demand, physical demand etc. Uni-dimensional ratings are simplest to use because they don't have any complicated analysis techniques. Generally, uni-dimensional scale is more sensitive scale than multi-dimensional scale. The multi-dimensional scale is considered to be more complex and time consuming form of mental workload assessment, but its more generally more diagnostic than uni-dimensional [24].

2.2.1.1 Uni-dimensional Measures

Modified Cooper-Harper Scale (MCH), is a 10-point uni dimensional rating that can be used for rating of workload [19]. MCH was developed to be different from the psychomotor Cooper-Harper Scale to increase the applicability to situation commonly found in modern systems, that's why MCH can be used to measure cognitive, perceptual and communication workload [25]. There is contradictory evidence about the effectiveness of MCH, generally MCH was considered to be good indicator of overall mental workload

[26, 27], but it was argued that MCH wasn't much sensitive and had poor description of workload [19].

The overall workload scale (OW) utilizes uni-dimensional scale from 0-100, where 0 represents very low workload and 100 represents very high mental workload. Ow is the 20 step rating scale in which score of 0 to 100 (assigned to nearest 5) is obtained. The OW scale is found to be excellent way to measure cognitive workload on uni-dimensional scale [28]. It has been found that even OW produce results comparable to NASA-TLX [29]. This scale doesn't take much time to complete and is easy to administer and analyze, it is also considered to be as sensitive as multidimensional scales [19, 28].

2.2.1.2 Multidimensional Measures

The multidimensional form of subjective measurement of mental workload is widely used and accepted way to assess cognitive workload. There are two main techniques/ methods used in real world or simulated environment, NASA Task Load Index (NASA-TLX) and the Subjective Workload Assessment Technique (SWAT). Apart from these two techniques there are other methods which are less common. The multi-dimensional nature of these workload assessment provides more in-depth analysis of cognitive workload which uni-dimensional methods cannot. Generally, Multidimensional form of subjective measurement takes more time to complete, so it can be difficult to use multidimensional techniques during tasks, because considerable mental resources are required to complete multidimensional subjective feedback. Similarly, gathering the results of multi-dimensional measure and analysis is also time taking process.

The NASA task load index (NASA-TLX), is a commonly used subjective assessment technique, in which operator or user rates perceived workload, to access the task. It has been widely used in Aviation and healthcare domain [30]. It was developed by NASAs research center in period of about three years and after more than 40 laboratory simulations [31]. NASA-TLX is originally divided into two parts, first one is data gathering from users and second is to analyze the gathered data. Total six types of workload are defined in NASA-TLX which are mental demand, physical demand, temporal demand, performance, effort, frustration. Brief details to these type of workload are also added which every user must read carefully before starting feedback, providing details about the every type of workload can help participants to answer accurately [32]. Answers are rated for each task within 100 points with range of 5 points step. NASA-TLX is commonly administered using paper and pencil, but official NASA-TLX app for iOS is also available [33], similarly, some third party platforms are also available for the administration of test. As there are different ways of administering the test, some may change the results of the test. A study showed that paper and pencil version of NASA-TLX led to less cognitive workload as compared to processing the information on computer screen [34].

NASA-TLX uses weighting process that requires a paired comparison task. This task requires operator to choose which aspect of workload (out of 6) is more relevant to specific task being performed. The workload scale is obtained for each task by multiplying the weight by individual dimension scale score, summing across scales, and dividing the total weight. Generally, NASA-TLX is widely accepted multidimensional subjective measure for measurement of mental workload because of its high sensitivity and in-depth diagnosis of different dimensions of mental workload.

NASA-TLX is an effective subjective measure to estimate mental workload, but it is time taking and complex measure, so NASA-TLX can also be used to estimate mental workload in simplified form, which is sometimes referred as NASA Raw Task Load Index. In this method score of all six dimensions of NASA-TLX is averaged and the result are almost equivalent to original TLX [30]. Even for driving condition it is found that RTLX is more sensitive toward mental workload and difficulty level than TLX [35].

The subjective workload assessment technique (SWAT) uses three level of difficulty – Low, Medium and High- for each of three dimension – time load, mental load and physiological stress load- for the assessment of mental workload. In this multi-dimensional test, first step is scale development which include all difficulty levels and all dimensions, second step is rating the workload, and lastly converting the cores from 1 to 100 based on the scale developed in first step. Some studies explains that SWAT scale provides useful estimation of mental workload [18, 24, 25]. It was also asserted that SWAT's three dimensions are not very distinctive and they can effect each other's results, for example increase in time load will also cause the increase in mental load [36]. When comparing SWAT with NASA-TLX , is found that TLX is generally considered as better scale for measuring mental workload [19, 35].

There are many less common subjective measures for various type of workloads, most of them are for aviation purposes and others are for specific task they were designed for. Instantaneous self-assessment technique (ISA) is a uni dimensional technique that uses five different scale for the measurement of perceived mental workload: excessive, high, comfortable, relaxed, comfortable and under-utilized. This test used visual prompt and rating was done using keypad [17]. It was also found that ISA's results are correlated with SWAT results, but one of the problem for ISA technique is that it competes for attentional resources with primary task.

Other uni-dimensional scales for mental workload estimations are The Rating Scale Mental Effort (RSME), this is a task related scale not discreetly for mental effort. The Verbal Online Subjective Opinion (VOSO), which is positively correlated with overall workload scale. Cooper Harper rating scale which is purely for mental workload estimation according to pilot's feedback. Bedford workload scale is also the modified form of Cooper Harper scale [37]. Honeywell cooper Harper scale is also the modified form of basic cooper Harper scale. The dynamic workload scale is uni-dimensional scale primarily used for the aircraft certification by airbus industry.

In subjective measures of cognitive workload, we assume that, operators are able to reflect their cognitive process and access the amount of mental effort during a task and until recently subjective techniques were supposed to be more reliable, unobtrusive, and more sensitive than physiological measures [38–40]. However, there are several drawback of subjective measurement of mental workload:

- There is always chance of confusion between mental and physical workload by operator.
- Difficulty in distinguishing between task difficulty and mental workload.
- Sub-conscious processing of information that user cannot rate subjectively.

- Disassociation of subjective rating scale and task performance.
- Operators can perceive the question differently, so questions should always be well defined, subjective rating of mental workload during a task in depending on the operator shot term memory [41].

2.2.2 Performance Measures

Performance can be defined as the effectiveness in accomplishing a particular task [42]. There are two methods for estimating mental workload using performance based measures, i.e., primary task measure and secondary task performance measure. These methods are based on the assumption that human brain has limited resources [21]. Tasks that demand same mental resources will reveal performance decrements, when operator try to do them at same time and further decrement of performance will be observed if difficulty level of one or both task is manipulated [43]. This means that workload can be estimated by observing the decrease in performance either in primary or secondary task. Primary task is more direct way to measure mental workload as compared to secondary task, but both can be useful and acceptable in different scenarios.

2.2.2.1 Primary Task Performance

Primary task performance, measures the workload based on operator's capability to perform main task [37]. Primary task measurement is direct and non-intrusive technique and it can provide an indication for operator and systems performance. Primary task performance is widely used for the estimation of mental workload in drivers, their primary task has to be determined individually for each situation [23]. Total time to complete the tour (speed), can be used as the primary task performance measure, because with increase in mental workload, speed of drivers decrease [24]. Lane keeping behavior, and deviation from center line is not much sensitive toward the mental workload of drivers, because experienced drivers can easily manage it even in increased workload conditions.

The drawback of using primary task performance as a mental workload measure is that it does not take into account the spare mental activity of operators [44]. For example, if two persons are performing same task, then there is a possibility that one person is pushing his mental capacity and other is not pushing at all [24]. Another problem while estimating mental workload using primary task performance is motivation; when people are motivated their performance seemed to increase but mental workload does not seem to increases proportionally. [29]. There might not be much change in performance of an operator unless the workload is very high. Primary task performance will be insensitive if the workload changes from low to medium, even though the workload is increasing. Also, primary task performance measure is not transferable to from one task to another task [44], for example for different tasks or operation, primary performance measure should be separately chosen.

2.2.2.2 Secondary Task Performance

The secondary task is an additional performance measure to the primary task. The main idea of secondary task is that is measures difference between mental capacity reserved by the main task and total available mental capacity [45]. Basically, secondary task performance measure, relies upon the multiple resource theory, which explains that, primary task reserves a certain amount of mental resources, so that the remaining resources theoretically, used on secondary task performance [46]. If the operator has poor performance while performing dual task, it means that there's a competition of resources between tasks. Whereas efficient dual-task performance reflects little resource competition [43]. Fundamental advantage of secondary task over primary task performance is that is exhibits how much mental resources left after allocation of resources to primary task [44]. For example, in case of driving, secondary task can be following a car, checking mirrors and/or any additional tasks, back mirror checking, etc. are embedded secondary task while driving, which means that they can be equally important as primary task [24]. The major problem using secondary task performance for mental workload estimation is that, it may disturb the primary task performance [44, 47]. Some people may not perform primary task before secondary task, which causes problem for measurement of change in secondary task performance. For validation of performance measures of mental workload, primary and secondary task performance should use same mental resources, for example, in case if primary task demands visual resources then secondary should also demand visual mental resources [24]. It is important to keep safety in mind while choosing a secondary task, because during secondary task attention can divert from primary task so, for critical tasks, the performance can be degraded to a dangerous point if work load becomes too high.

We can conclude that; most performance measures are able to estimate higher levels of mental workload. If too easy task is being performed, then performance measures will not be able to indicate mental workload, as performance will not be degraded during task. Both primary and secondary task performance can be used for mental workload estimation, depending upon type and criticality of task.

2.2.3 Physiological Measures

Physiological measures use the physical reaction of body to objectively measure the amount of mental workload a person is experiencing. It would seem that physiological measures are the most accurate way to find out mental workload because it does not require any direct response from the operator as in subjective measures. This method is not always supported because body also respond to stimulus other than mental workload, for example body also respond to physical workload or change in intensity of ambient light or other external events. Use of physiological measures to estimate mental workload mostly refers to cardiac activity, respiratory response, ocular activity and brain activity.

2.2.3.1 Cardiac

Cardiac activity can be measured through heart rate, heart rate variability and blood pressure. Cardiac measures are used because firstly, they are easy to evaluate and considered as fairly reliable indicator of mental workload and secondly, Cardiac measures can also be used in real-world environments because the measurements are unobtrusive and continuously available [48].

Heart rate measure can be most common and reliable measure of workload by cardiac means. Heart rate is an exact measurement because the ECG signals can be measured in the form of beats. Generally, it is considered that heart rate increases with the increase in mental workload [49, 50]. Although this conclusion is widely accepted, still there are critiques which argue that using heart rate to measure mental workload can be affected by various environmental, physiological and emotional factors [51–53].

Another cardiac measure for mental workload is heart rate variability (HRV). In this method inter-beat intervals of heart beat are measured overtime. This measure is not in use as extensively as heart rate, still severl recent studies focus on the use of HRV to measure mental workload because it is fairly new and promising area of research [54].

Blood pressure is a secondary measure of cognitive workload, not many studies used blood pressure as a measure of mental workload because its more obtrusive than heart rate or heart rate variability.

2.2.3.2 Respiratory

Respiration is the physiological process primarily related to exchange of oxygen and carbon-dioxide between human body and atmosphere [53]. There are different ways to estimate mental workload using respiratory response, in real world and in laboratory setup. The most common way to use respiratory response for mental workload measurement is breathing rate. Other measures include the rate of oxygen absorbed by lungs or ratio of carbon dioxide in expired air form lungs. It was generally found that increase in respiratory rate is directly proportional to mental workload [55].

2.2.3.3 Ocular activity

Several physiological changes in eye can be used as the measure of mental and visual workload. Although eye is primarily related to visual workload, but it has been observed that some measures can accurately predict the mental workload for a specific task [56]. Different physiological measures related to eye includes, Horizontal Eye Movement (HEM), Blink Rate, Interval of Closure, Eye Fixation, Pupil Diameter and Electrooculogram (EOG).

2.2.3.4 Brain Activity

All the previously mentioned physiological measures, indirectly estimate the mental workload. Cardiac, eye and respiratory response are influenced by that brain activity which is generated due to different amount of cognitive workload experienced. It is commonly agreed that most precise estimation of mental workload can be done through brain signals [55]. Another benefit of using brain signals for cognitive workload estimation is that it does not interfere with task performance and is continuously available during the task [57]. Although brain activity is direct measure of mental workload but it requires specialized equipment and training to record and interpret and data. Most commonly used methods for measuring brain activity are, Electroencephalography (EEG), Functional magnetic resonance imaging (fMRI), Magnetoencephalography (MEG), electrooculogram (EOG), etc.

2.3 Electroencephalography (EEG)

Electroencephalography (EEG) is the technique to record electrical activity of the brain. It is a non-invasive method of measuring brainwaves, in which electrodes are placed on scalp. There are also invasive methods of recording brain activity like Electrocorticography (ECOG). EEG records voltage fluctuation due to ionic current within the neurons of the brain [58]. Whenever EEG is recorded over a period of time, it can be used for further diagnosis either by event related potential (ERP) or by using spectral contents of EEG. ERP investigates fluctuations in brain signals potential, time locked to an event, such as external stimulus or an internal event of brain. Spectral content analyses the type of neural oscillations (popularly called "brainwaves") that can be observed in EEG signals in the frequency domain.

2.3.1 Advantages

EEG can be used to diagnose epilepsy, sleep disorders, coma and other brain related disorders, but recently techniques have been developed to estimate mental workload over a period of time based on spectral contents of EEG. EEG is emphasized area of research for mental workload estimation because of different advantages like:

- The hardware of EEG is less costly as compared to other techniques like fMRI, PET, MEG, ECoG etc [59].
- EEG does not require any huge equipment as compare to other techniques which mostly are immobile and requires bulky equipment
- EEG does not require its subject to be exposed to high amount of radiations or magnetic fields.
- EEG is non-invasive and provides very high temporal resolution i.e. between 250-2000 HZ, which is not very common in other non-invasive techniques.
- EEG is more tolerant to subject movement as compared to other neuroimaging techniques. There exist methods to minimize or even eliminate the movement artifacts [60].

2.3.2 Electrodes

EEG recording can be obtained by placing electrodes on scalp, for this purpose conductive gel can be used to increase the conductivity of EEG signals, but also there exist EEG devices which support dry electrodes without any conductive gel or paste. Conventional systems use electrodes which are connected to individual wires. While some modern systems are like caps or headsets which are wearable and electrodes are embedded in them. EEG caps become very useful when high density array of electrodes is needed.
Historically, conductive gel was used for recording of EEG through an electrode, but in 1994 for the first time, a single channel (one electrode) dry electrode was constructed.

Dry electrode was demonstrated to perform better than other sliver/silver chloride electrodes. Similarly, there are other advantages of using dry electrode EEG device as compared to conductive gel:

- No electrolyte needs to be used.
- No skin preparation required.
- Significantly reduced sensor size.
- Compatibility with EEG monitoring devices.
- Less setup time required (which encourage personal EEG devices).

2.3.3 International 10-20 system

The locations on the scalp where electrodes are placed are named and standardized by the international 10-20 system [61]. This system ensures that naming and location of electrode is same for all laboratory and clinical studies around the world. This system, shown in Fig. 2.2, is based on relationship between underlying area of brain and location of electrode. The '10' and '20' refer to the point that the actual distances between adjacent electrodes are either 10 percent or 20 percent of the total distance from front to back or right to left of skull.

The alphabet in electrode name refers to the specific lobe of the brain like pre-frontal (Fp), frontal (F), temporal (T), parietal (P), occipital (O), and central (C). Even number electrode (2,4,6) refers to electrodes placed on right side of skull whereas odd number electrodes (1,3,5) refers to the electrodes placed on left side of skull. For example, the electrode name Fp1 suggest that it is located at the left side of pre-frontal lobe.

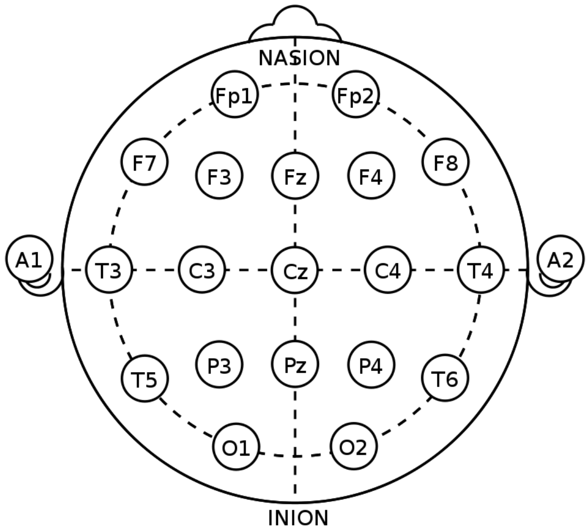

Figure 2.2: Location and names of electrodes according to international 10-20 system

2.3.4 Brainwaves

EEG is typically described in terms of rhythmic activities; that are divided into categories on the basis of their frequencies. These rhythmic brainwaves are actually produced by synchronized electrical pulses caused by neurons communicating with each other. These electrical pulses are recorded by an EEG device which have values in micro volts. The pulses recorded by a device are in time domain; to extract different brainwaves from this single pulse we need to transform this pulse into frequency domain using techniques like Fast Fourier Transform (FFT). According to their frequencies there are 5 types of brainwaves, Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz) and Gamma (30-50 Hz). Each brainwave is supposed to be dominant in brain according to different state of mind.

- Delta waves are highest in amplitude and have lowest frequency, they are generally dominant when a person is asleep. Delta waves cannot be exactly zero which means that the brain is dead, but in deep dreamless sleep it can approach very low values such as to 2 to 3 Hz.

- Theta waves, on other hand, are related to memory loads and plays an important role during memory encoding and retrieval [62]. Theta waves are also dominant when a person is daydreaming or just about to sleep and it also help improve creativity [63]. It has been shown that theta activity in frontal midline area reflects a meditative state or mental concentration [64].

- Alpha waves have frequency range of 8 to 13 Hz, they are easily observable and one of the first brainwaves to be discovered. Alpha waves are also responsible for a person to be calm and relaxed state. It is also asserted that increased alpha waves not only induce relaxed state but also enhance autonomic response to external stimuli [65]. It is also reported that alpha waves are positively correlated with enhanced cognitive functions [66].

- Beta Waves, which have range of 13 to 30 Hz, are mostly dominant when a person is in alert state, for example having an active conversation, decision making or problem solving. Although beta waves are related to attentiveness, selective attention, and tasks related to high concentration, but having too much dominant beta frequency may lead a person to have stress or anxiety. It is also reported that increase in beta power also depicts the increase in difficulty level of task [67]. Hence we can consider beta waves as a variable related to high concentration and task difficulty.

- Gamma waves, which have frequency of 30 to 50 Hz, is said to be dominant when there is simultaneous processing of information from multiple parts of brain. These waves are involved with high cognitive processing task and important for learning, memory and information processing. Induced gamma waves are correlated with high level information processing, attentional and perceptual mechanisms and visual information processing [68].

Table 2.1 compares different brainwaves. These waves can be used to estimate mental workload; some researchers use single brainwave for the estimation of cognitive workload. Alpha brainwaves are used as an indicator of attentional resources in 3D virtual learning environments [69]. A research also suggests the use of beta brainwave for the estimation of mental workload in marine pilots [20].

It was observed that a single brainwave cannot be used reliably for the estimation of workload because whenever the mental state of an individual changes it effects more

Brainwave	Frequency	Description
Delta	<4	Dreamless sleep. Normally dominant in babies.
Theta	4-8	Dominant when person is near to sleep. Normally higher in young children. Related to learning. Effect memory encoding and retrieval.
Alpha	8-13	Relaxed. Enhanced cognitive process. Normally dominant. when eyes closed.
Beta	13-30	Active thinking. Focus. High alert. Stress/anxiety. High concentration.
Gamma	30-50	High level information processing. Visual information processing. Important for learning and memory Perceptual mechanism

Table 2.1: Comparison of Brainwaves

than one brainwave. Hence, researchers started using multiple brainwaves as a metric of mental workload. It has been discovered that delta, theta, alpha and gamma frequencies are correlated to mental workload [70]. A study showed that, alpha brainwave can differentiate between different task demand levels, but alpha power is not optimal for estimating overall cognitive load because it increases when alert users perform easy tasks and sleep deprived users perform difficult tasks. So, for better estimation of cognitive workload, ratio of alpha and theta was purposed i.e. theta Fz/alpha Pz which represents a better estimation of cognitive workload [71].

2.3.5 Headsets

Initially, EEG systems were lab based and this lack of mobility caused the limitation of recording context and situations [72]. Discomfort is also reported by participants during long setup and calibration process [73]. Hence, wireless EEG devices are preferred and their results are reliable. EEG power in the range of 4-50 Hz is almost same in wired and wireless systems except the marginal reduction of delta power in wireless EEG system, similarly, EEG power of theta, alpha and beta has also been correlated in both systems [74]. Some wireless EEG devices employ wet sensors which requires application of conductive gel [75], but in parallel there is considerable use of wireless EEG headsets having dry electrodes [76, 77].

A Number of wireless EEG devices exist which not only provide usability and portability but also maintains the data quality which is comparable to conventional EEG recording system with correlation > 0.85 [78]. Even single channel wireless EEG devices with dry electrodes are now available as a personal EEG headset. It is also found that data from single channel wireless device having dry electrode is comparable with conventional EEG recording systems [73].

To verify the reliability of single channel wireless EEG device Rogers et al. performed experiments, n-back test and auditory oddball test, over a period of time under same conditions repeatedly and concluded that using a single channel device has minor trade-offs associated with it in term of quality and major trade-offs in term of location of EEG data, and the EEG data was very reliable in some cases and in some cases it was reasonably reliable [79]. Accuracy of 97-98 percent is achieved using single channel EEG device for authentication purpose [80].

Table 2.2 shows the comparison of different commercially available wireless EEG headsets.

Headset	**Number of channel**	**Electrode type**	**Sampling rate**	**Connectivity**
Open BCI Mark IV	16	Dry 5 mm EEG comb electrodes	200Hz	Wired connectivity
Emotive Epoc	14 + 2 ref	Saline solution Soaked felt	128 Hz	Wi-Fi 2,4GHz Bluetooth 4.0
Emotive Insight	5 + 2 ref	Semi-dry polymer	128 Hz	Wi-Fi 2,4GHz Bluetooth 4.0
Muse 2	4 + 2 ref	Metal	256 Hz	Bluetooth 5.0
Senzeband	4 + 2 ref	Metal	250 Hz	Bluetooth 4.0
Brainlink Pro	1 + 2 ref	Metal	512 Hz	Bluetooth 4.0
Mindwave Mobile 2	1 + 1 ref	Metal	512 Hz	Bluetooth 4.0

Table 2.2: Comparison of wireless EEG headsets

2.4 Research Gap

There exist several methods for the estimation of cognitive workload like subjective methods, performance measures and physiological measures. Much research has been carried out about EEG, types of brainwaves and what each brainwave is responsible for. Different metrics have been proposed for mental workload measurement, however a comparative analysis is needed to establish that which brainwave and which metric is best for what type of task. It also needs to be validated that single channel EEG device can be able to estimate the cognitive workload.

Humans sense stimuli using different sensory inputs like visual, auditory, touch, taste and smell. In this study, we focus on the difference between mental workload induced while performing task with visual and auditory information. We also intend to analyze whether a single channel EEG device is able to identify with reasonable accuracy the change in mental workload due to different types of tasks. Basic difference between visual and auditory sense is that, user perceives the data serially while listening an audio input and perceives it in the form of chunks while having visual input. This study compares the mental workload of subjects while they were performing visual and auditory task of solving arithmetic questions having different difficulty levels.

Chapter 3

Methodology

In this chapter we discuss the adopted methodology for the estimation of mental workload and elaborate different mental workload metrics. Moreover, the design of workload task and experimental setup is explained.

3.1 Mental Workload Metrics

As discussed in the preceding chapter, different metrics have been proposed for estimation of mental workload, but the metrics we've chosen for comparative analysis are Cognitive Load Index (CLI) and EEG Workload Index (EWI), as they don't rely solely on a single brainwave and use more than one brainwaves to estimate mental workload. CLI is the ratio of only two brainwaves that are alpha and theta, it was first proposed in 2009 by Holm et al [71]. Later, this metric showed positive correlation with changing mental demand in a learning task [81]. For calculation of CLI we need to calculate the Power Spectral Density (PSD) of a brainwave, which in our case was calculated using Matlab. After the calculation of PSDs we calculate the relative PSDs and which are used for the calculation of CLI as given in Eq. 3.1:

$$CLI = \frac{\Theta_{PSD}}{\alpha_{PSD}} \tag{3.1}$$

Unlike CLI, EWI, given in Eq. 3.2, uses four brainwaves to estimate the mental workload, i.e. theta, alpha, beta and gamma. EWI was recently proposed for the estimation of mental workload in a nuclear power plant simulator [82]. EWI was claimed to have better estimation of mental workload because relative PSDs are used for calculation of EWI as compared to absolute PSD and secondly EWI shows positive correlation with other mental workload estimation techniques.

$$EWI = \frac{\beta_{PSD} + \gamma_{PSD}}{\Theta_{PSD} + \alpha_{PSD}} \tag{3.2}$$

The authors asserted that the numerator of this metric contains brainwaves related to concentration and stress, whereas denominator of EWI consists brainwaves that are related to relaxation and mediation.

3.2 Experiment design

3.2.1 Participants

A total of thirty-eight subjects with no physical or mental impairments were the part of this study. Twenty-one males and seventeen females between the ages of 20 and 39, with mean age of 24.94 and standard deviation of 3.64, were asked to avoid any unnecessary jaw and neck movement to avoid muscle artifacts as much as possible. All the participants had more than sixteen years of education. All participants were engaged in task for approximately 45 minutes (including relaxed state and working state) continuously.

3.2.2 Tasks designing for induction of mental workload

We not only compared mental workload between visual and auditory task but also each type of task further has three difficulty levels. The experiment used for the induction of mental workload consists of basic arithmetic questions. There were 2 types of tasks i.e.

visual and auditory, and for each type of task there were 3 difficulty levels. Difficulty level of task is varied by varying the range of numbers which are generated randomly for arithmetic question, i.e for easy, medium and difficult tasks participants were required to perform arithmetic calculations in ranges of 0-10, 0-50 and 0-100 respectively.

- For visual task, every participant had to sit in front of a computer, while a randomly generated arithmetic question showed on screen and participant had to type the right answer, next question would be displayed after entering the right answer.
- For auditory task, participants listened to arithmetic questions and after every question they were given 10 seconds to solve the question and to write answer on a paper. They were instructed that if they felt confused about any question or unable to answer in 10 seconds then they may leave space for that question and continue to next question.

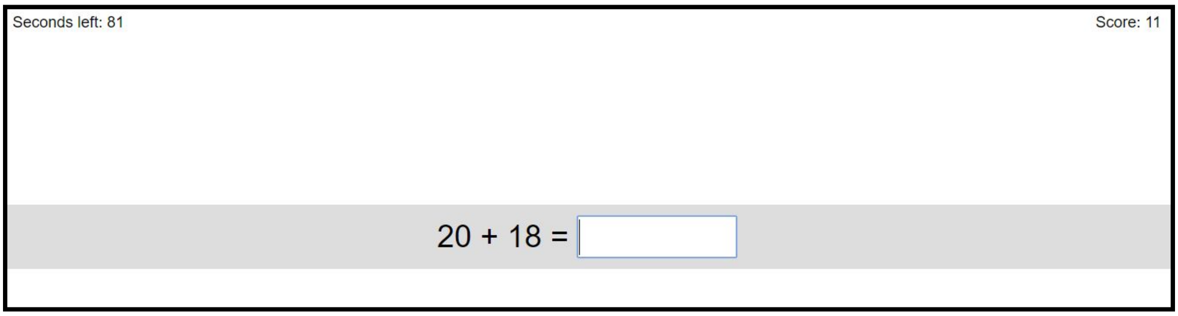

Figure 3.1: Visual task for induction of mental workload

3.2.3 EEG Recording

EEG data was recorded using a single channel wireless device, Neurosky Mindwave Mobile 2. It is a wireless EEG device with single electrode at fp1 location, according to 10-20 EEG placement system, with reference electrode placed at left ear. It was connected to an android app via Bluetooth, and it transmits the data on sampling rate of 512Hz.

Figure 3.2: Neurosky Mindwave Mobile 2

3.2.4 Task Timelines

First, the headset was placed on participant's head and made sure that electrode is in its placed as should be and reference electrode is clipped with left ear. After that, headset is connected to its android application, which provides feedback about whether the headset is connected and electrode is in its place. After this initial setup which takes about 2-3 minutes, participant was asked to be in calm state, close his/her eyes and try to think as less as possible. Therefore, first the data for a participant was recorded for 5 minutes in relaxed state.

There were totally 6 tests that each participant had to perform, each test had the duration of 5 minutes. So participants were subjected to different levels of workload for about 30 minutes. After each test they were provided a subjective feedback form i.e. NASA-TLX in which they were asked about mental workload, physical workload, stress, perceived performance and frustration about the last test they performed (Appendix A). So in total participants had to fill six NASA-TLX questionnaires, one after each test.

While filling NASA-TLX, the difficulty levels of the task were shuffled as shown in Fig. 3.3.

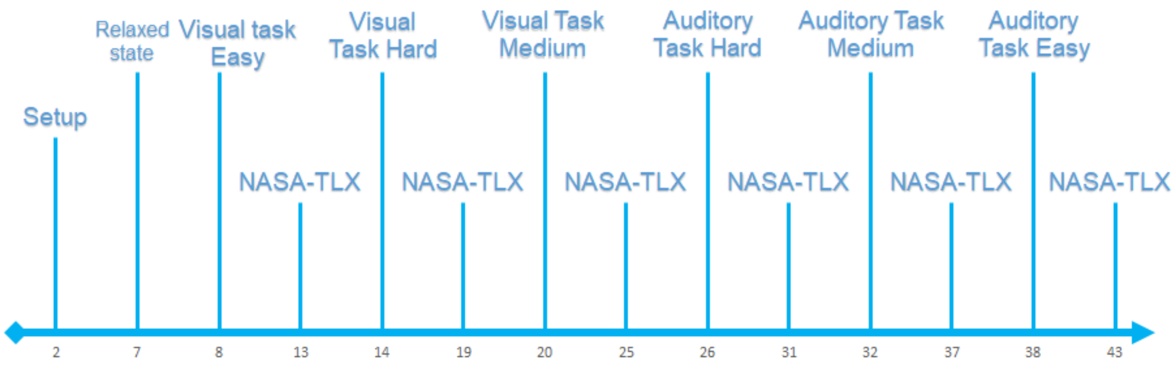

Figure 3.3: Timeline of tasks performed

Before starting the test, they were briefed about the different tests they were about to perform and what they have to do, but they were not informed about the difficulty level of task in order to avoid their bias while filling out NASA-TLX questionnaire after the test. Also, before starting test participant were asked to sit relaxed with their eyes closed for five minutes.

3.3 Data recording and processing

As the Neurosky Mindwave headset only have Bluetooth connectivity, so this device transmits its recorded data via Bluetooth to a third party android application called "EEGid". This application saves the recorded data in a CSV file, which not only contains the raw EEG data but also other information about quality of signals and EEG power, which we are not using in our case. These CSV files, are then imported in Matlab and the raw EEG signal is extracted as a .mat file suitable for EEGLab.

EEG data was processed using MATLAB toolbox EEGLab. First of all, EEG data was band pass filtered from 0.5 Hz to 50 Hz (Fig. 3.4), because any wave below 0.5 Hz will be in delta band, which can be easily effected by neck movement, similarly NeuroSky headset had capability to measure brain waves of up to 50 Hz so it means that any wave beyond 50 Hz will be recorded as noise.

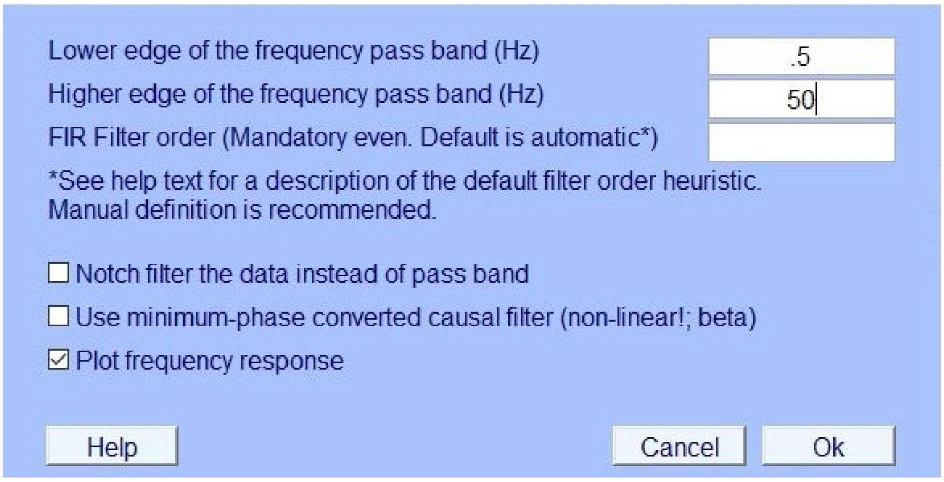

Figure 3.4: EEGLab Band pass Filter

The data was then inspected for any muscle and eye movement artifact which was removed manually using EEGLab (Fig. 3.5). As EEG lab doesn't have any algorithm to automatically detect artifacts for single channel data that's why we have to manually inspect every second of data and remove any abnormal wave.

After that, power spectral densities of brainwaves were calculated using MATLAB (Appendix B), EEG signal was divided into 2 second Hamming window with 10 percent overlap. PSDs of that EEG were calculated according to frequency range of different brain waves like delta (0.5-4Hz), theta(4-8Hz), alpha(8-12Hz), beta(13-30Hz) and gamma (30-50 Hz). After calculating PSDs, relative PSDs were calculated by dividing each PSD with the sum of all PSDs.

Using the relative PSDs of EEG data, mental workload is estimated using two existing metrics of mental workload i.e. CLI and EWI. The results of this estimation will be used to analyze the mental workload under relaxed and working state. This process will not only provide the estimation of mental workload but also it will validate the CLI and EWI metrics. Also, the obtained results will be verified by comparing them with subjective feedback from subjects.

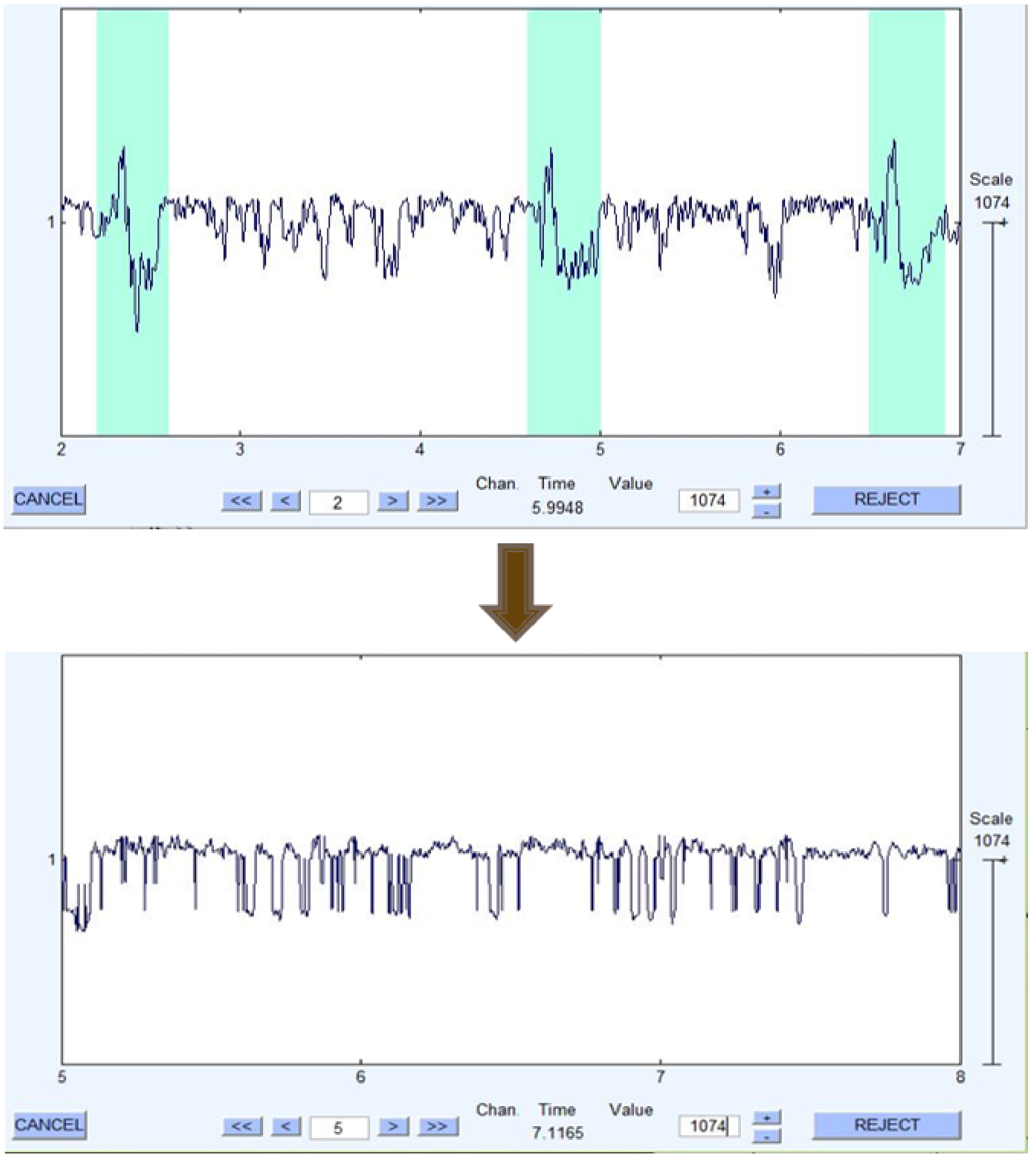

Figure 3.5: After manually removing muscle artifacts

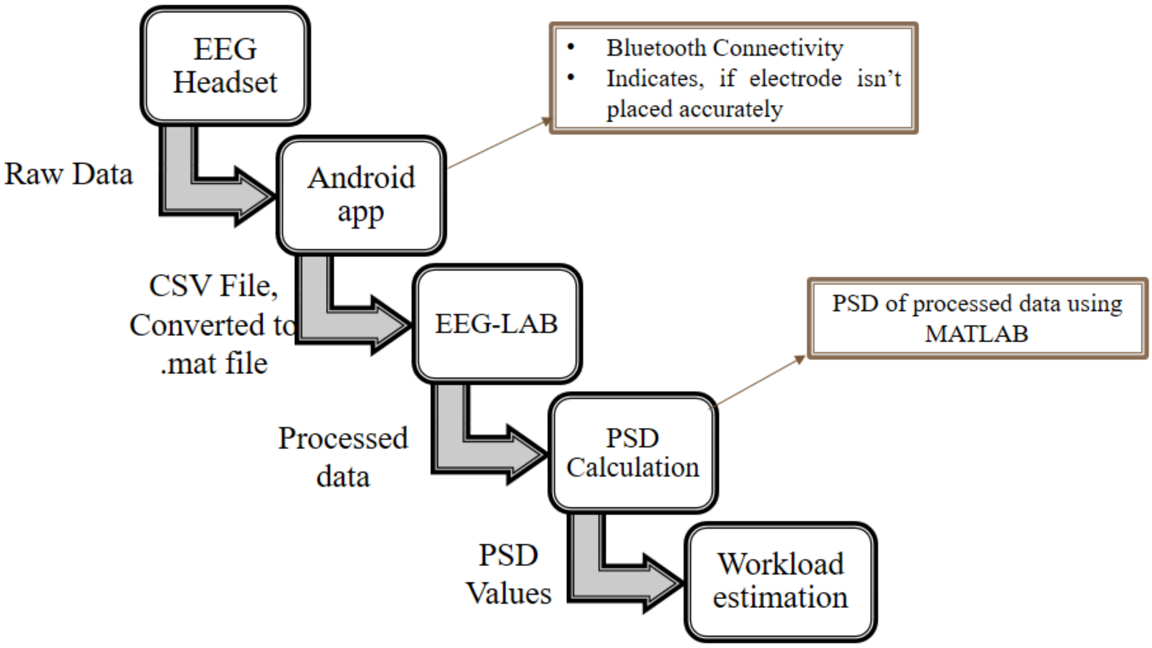

Figure 3.6: Process for estimation of mental workload using EEG

Chapter 4

Results and Discussions

Firstly, the results from experiments and power spectral densities of different brainwaves are analyzed while comparing the relaxed state of participants and working state (in which participants were asked to perform the task). It will help us to determine whether single electrode on prefrontal location is able to significantly identify the intrinsic cognitive load or not.

Secondly, results of different input modes of task i.e. visual and auditory will be analyzed, which will ultimately help us to analyze if used device and task have the capability to estimate extraneous cognitive load and which type of input cause lesser amount of extraneous load to participant.

Lastly, we will also analyze if given task to participant significantly vary in difficulty levels and if yes, are pre-defined metrics of cognitive workload, using single electrode on prefrontal location, be able to differ among the three difficulty levels for visual and auditory task.

4.1 Relaxed state vs working state

While comparing the relaxed condition of participants with working condition, values of all difficulty levels are averaged over time for the comparison. For analysis of results, t-test is applied on each parameter in different conditions.

4.1.1 Visual task

After calculating the PSDs of brainwaves of all 38 subjects, we observe that there is a difference in theta wave PSD while comparing relaxed and working state, but it is observed that difference in PSDs isn't as significant as in alpha waves. PSD of theta wave increased when participants are subjected to mental workload conditions Average relative theta wave PSD in relaxed state was 0.20 which increased to 0.23 when subject are in working conditions (Fig. 4.1) . According to results of t-test $t = -3.4$ and $p = 0.005$, which confirms the significance of difference in theta wave PSD.
Similarly, we observe that power spectral density of the alpha wave is greater while the

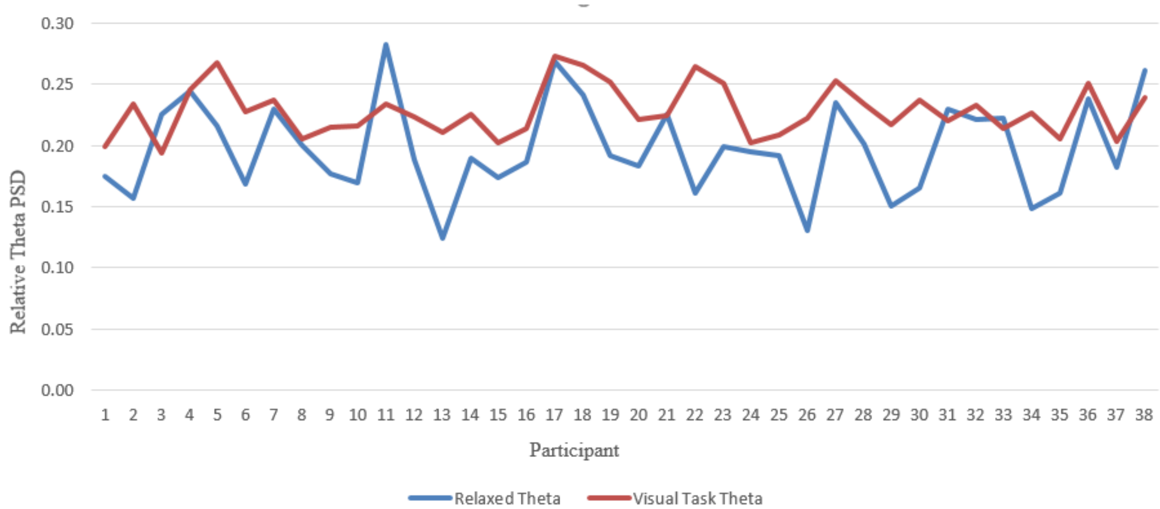

Figure 4.1: Theta waves comparison: relaxed vs working state

subjects are in relaxed state as compared to the working state. Average relative PSD of alpha wave for relaxed state is 0.19 whereas average relative PSD of alpha wave in working state is 0.11 (Fig. 4.2). According to the t-test difference of alpha brainwave PSD is significant as $t = 5.72$ and $p < 0.001$.
That is why we can observe that Cognitive Load Index (CLI) is significantly varying from relaxed to working state because CLI is the ratio of theta and alpha. Average value of CLI in participants during relaxed state is 1.24 which increases to 2.11 while performing the given task (Fig. 4.3). According to t-test effect size of CLI is huge i.e. $t = -8.5$ and $p < 0.001$.

Relative PSD of beta wave in relaxed condition of all participants is on average 0.22,

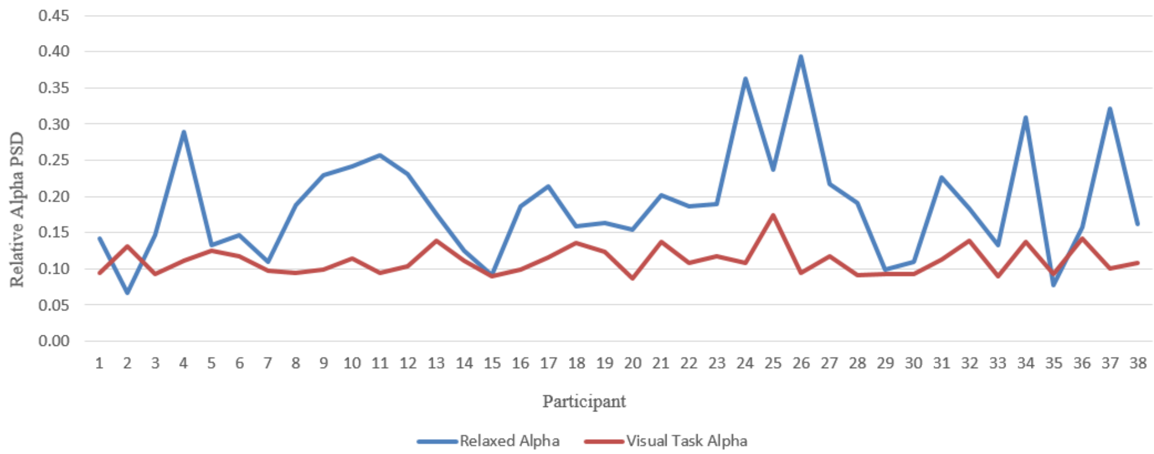

Figure 4.2: Alpha waves comparison: relaxed vs working state

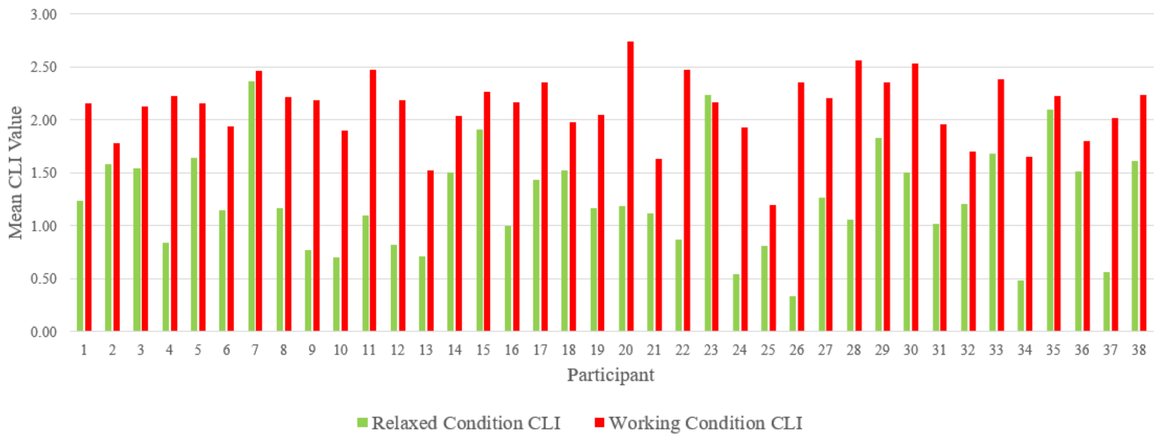

Figure 4.3: CLI comparison: relaxed vs working state

but during the working condition their beta wave PSDs dropped to 0.17 which is statistically significant ($t = 2.5$ and $p = 0.04$). Also, the relative PSD of gamma wave in relaxed state is averagely 0.036, which also decreases to 0.030 while participants are in working condition ($t = 1.78$ and $p = 0.094$). EWI estimates the cognitive workload on the basis of four brainwaves, but the results of EWI are not much significant while comparing between relaxed and working conditions. EWI in relaxed state is on average 0.64 and during working its 0.61 ($t = 0.79$ and $p = 0.51$).

Figure 4.4 compares the average values of Theta, Alpha, CLI and EWI for visual task in relaxed and working conditions of participants.

Relative PSDs of beta wave and gamma waves are not varying accordingly, when

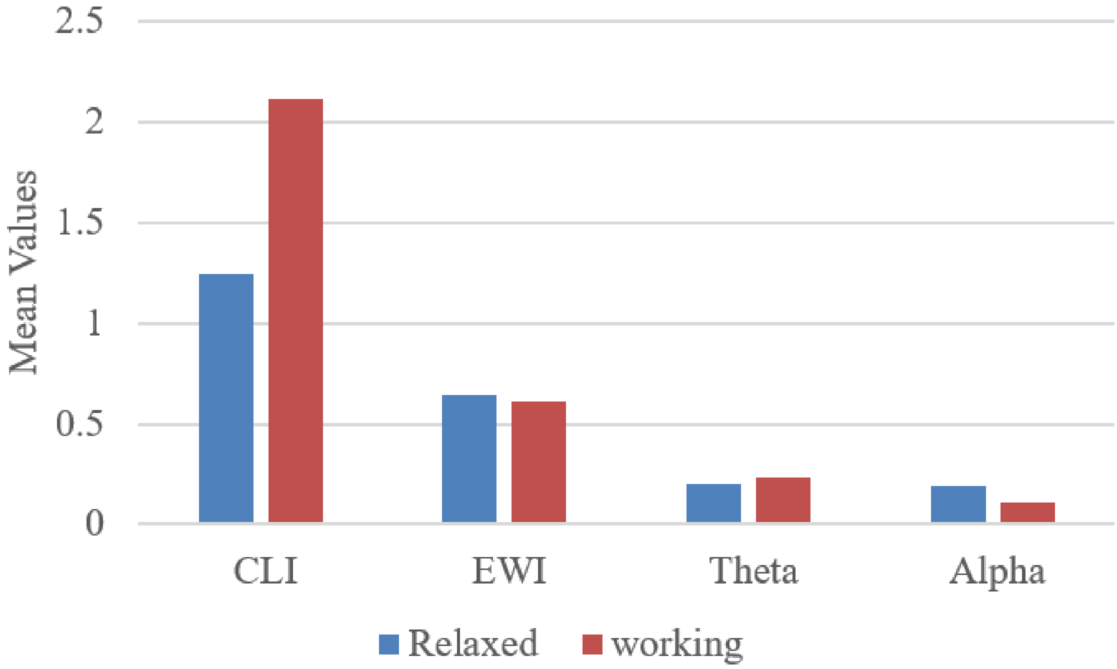

Figure 4.4: Visual task comparison: relaxed vs working state

participants are in working and relaxed state. This insignificance could be either due to limitation of EWI or single channel EEG device at prefrontal location.

Comparison of t-test results of visual task is shown in table 4.1

Visual Task	t-test results	
Relaxed Theta Vs Working Theta	t=-3.4	p=0.005
Relaxed Alpha Vs Working Alpha	t=5.72	p<0.001
Relaxed Beta Vs Working Beta	t=2.5	p=0.04
Relaxed Gamma Vs Working Gamma	t=1.78	p=0.094
Relaxed CLI vs Working CLI	t=-8.5	p<0.001
Relaxed EWI vs Working EWI	t=0.79	p=0.51

Table 4.1: Visual Task t-test comparison

4.1.2 Auditory task

While comparing the PSD of theta brain wave between working and relaxed state, just like in visual tasks, theta PSD increases from relaxed state to working state. The average PSD of theta in relaxed state is 0.20 and while performing task its average value increases to 0.24 (Fig. 4.5). According to the *t*-test the effect size of this variation is large i.e. $t = -3.9$ and $p = 0.003$

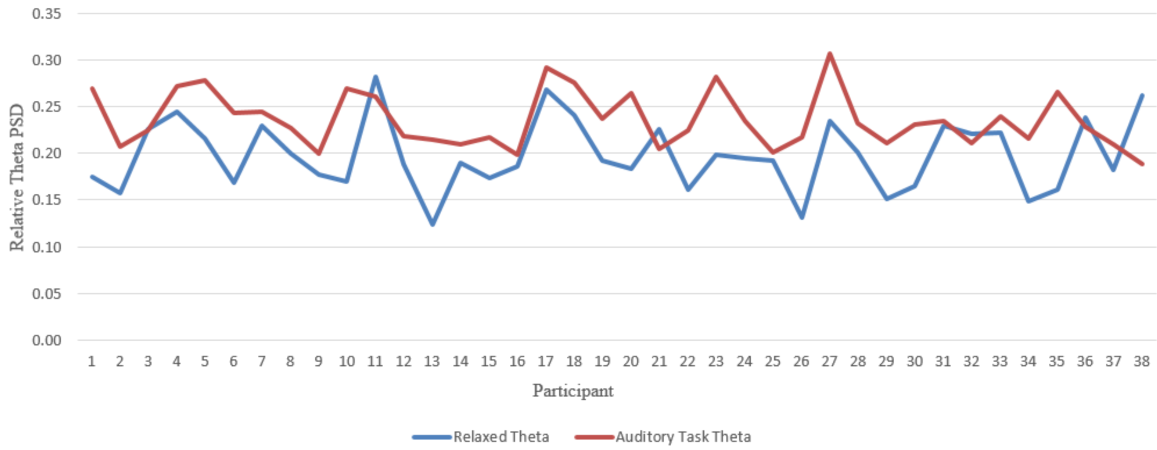

Figure 4.5: Theta comparison: relaxed vs working state

It is observed that in auditory task alpha wave also follows its trend as in visual task, it decreases with increase in mental workload, average PSD of alpha wave in relaxed condition is 0.19 which decreases to 0.12 while performing the tasks (Fig. 4.6). It also has huge effect size according to t-test results i.e. $t = 4.6$ and $p < 0.001$.

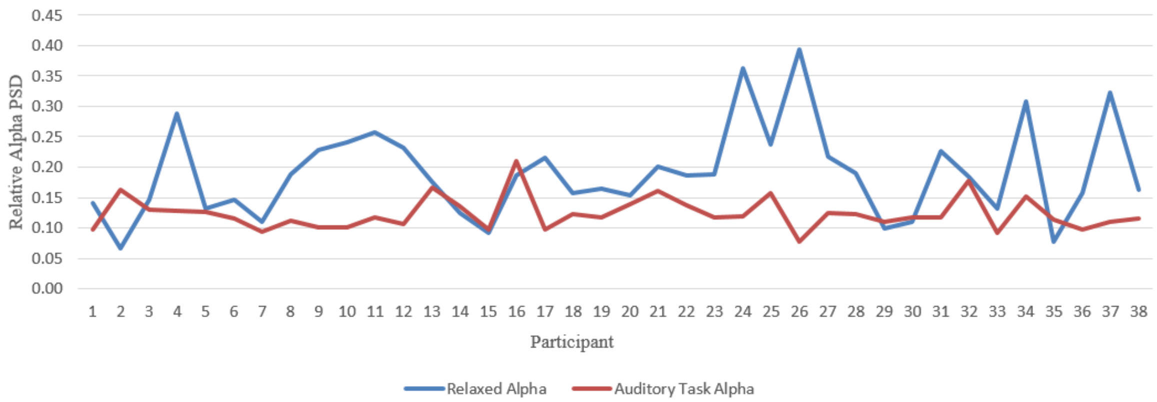

Figure 4.6: Alpha comparison: relaxed vs working state

We also observe that Cognitive Load Index (CLI) is significantly varying from relaxed to working conditions just as in visual task. Following the pattern of theta and alpha waves, CLI can also differentiate between intrinsic workload during relaxed and working state. Average value of CLI for relaxed state is 1.24 which increases during the task performance up to 2.04 (Fig. 4.7). Results of t-test also proves the large effect size of CLI i.e. t=-6.01 and $p < 0.001$.

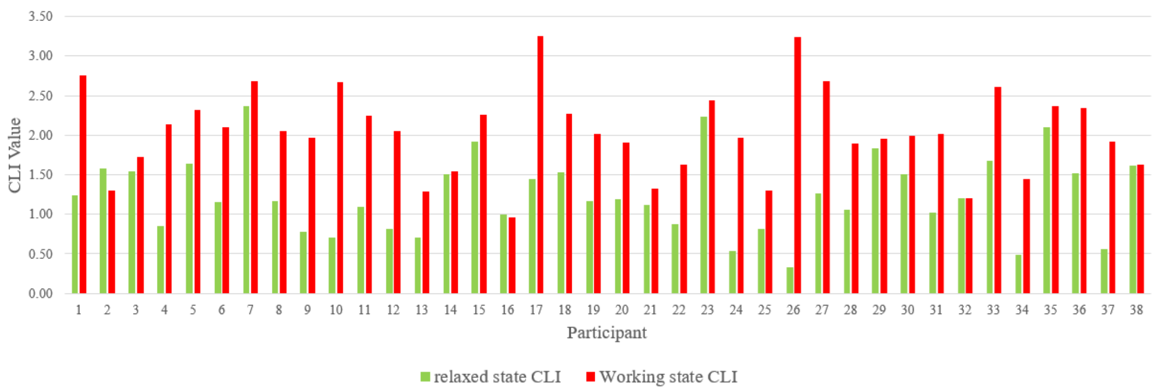

Figure 4.7: CLI comparison: relaxed vs working state

Figure 4.8 compares the average values of Theta, Alpha, CLI and EWI for audio task in relaxed and working conditions of participants.

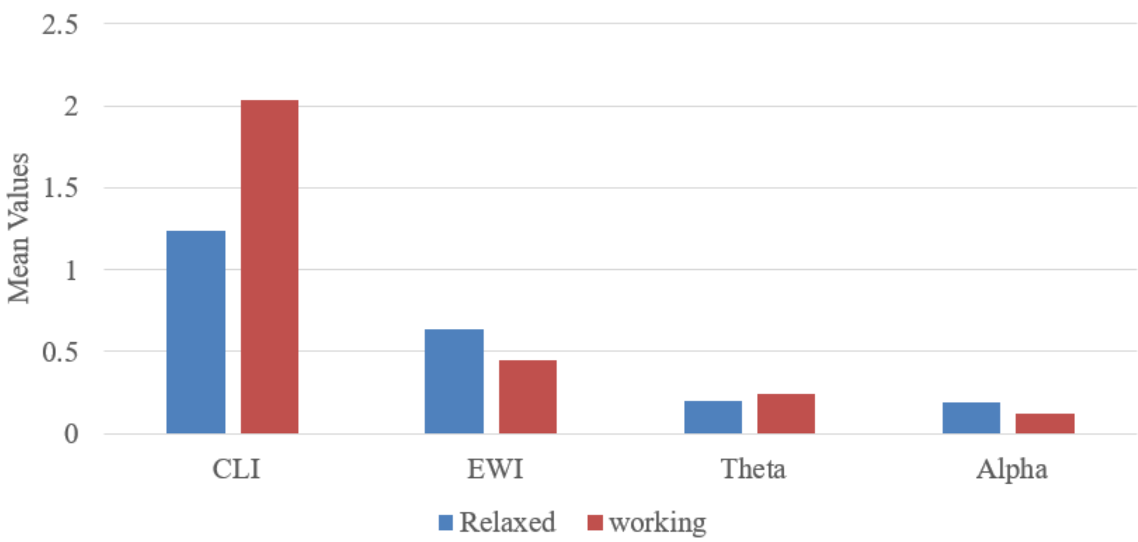

Figure 4.8: Audio task comparison: relaxed vs working state

The results of beta and gamma waves are not very significant in case of auditory tasks. Beta wave's averages PSD for relaxed condition is 0.22 and during working condition it decreases to 0.19 (t = 1.6 and p = 0.15). Similarly, gamma wave average PSD at relaxed state is 0.04 which decreases to 0.03 during tasks ($t = 1.5$ and $p = 0.16$). Just as in case of visual task, EWI didn't show any significance in audio task during relaxed state average EWI of participants is 0.64 which decreases to 0.59 during tasks ($t = 1.03$ and $p = 0.43$).

Comparison of t-test results of visual task is shown in table 4.2

Auditory Task	**t-test results**	
Relaxed Theta Vs Working Theta	t=-3.9	p=0.003
Relaxed Alpha Vs Working Alpha	t=4.6	p<0.001
Relaxed Beta Vs Working Beta	t=1.6	p=0.15
Relaxed Gamma Vs Working Gamma	t=1.5	p=0.16
Relaxed CLI vs Working CLI	t=-6.01	p<0.001
Relaxed EWI vs Working EWI	t=1.03	p=0.43

Table 4.2: Visual Task t-test comparison

4.2 Auditory vs Visual Task

As already discussed that extraneous cognitive load is due to the ways of presenting information to someone, that's why we perform same task with two different types of input modalities. While performing visual task the subjects had to complete the question as early as possible to get to the next question, but in case of auditory task test had to proceed at a fixed pace as the subjects had a specified time to solve and write the answer. It is also stated by researchers that time taken to process audio signal by brain is much less than the visual signal. That can be one of the reasons that results from single electrode EEG setup on prefrontal location shows that less mental resources are required for auditory task as compared to visual task.

CLI and EWI both are higher, when participants were performing the visual task. While performing the tasks visually participants had CLI of 2.11 and performing the same difficulty task while listening to the questions they had CLI of 2.04. Also their EWI drops from 0.61 to 0.59 if they perform task by listening to questions.

	Relaxed	Visual Task	Auditory Task
CLI	1.24	2.11	2.04
EWI	0.64	0.61	0.59

Table 4.3: Comparison of Visual and Auditory task

4.3 Different difficulty levels

As there were three difficulty levels in audio and visual task and after each task participants rated the difficulty level in terms of mental effort, frustration, temporal demand etc. Subjective ratings of users are compared for the validation of designed test, that is there actually difference in difficulty levels of task?

Comparison of NASA-TLX score of visual test shows that participants felt, clear rise in difficulty level while performing easy, medium and hard visual tasks (Fig. 4.9) . While comparing rated mental effort for easy task and medium task, $t = -2.33$ and $p = 0.10$. Between medium and hard visual task $t = -3.74$ and $p = 0.001$. Similarly, effect size between perceived effort of easy and medi um task is considerable ($t = -1.60$ and $p = 0.11$), and between medium and hard task effect size is large ($t = -2.64$ and $p = 0.012$).

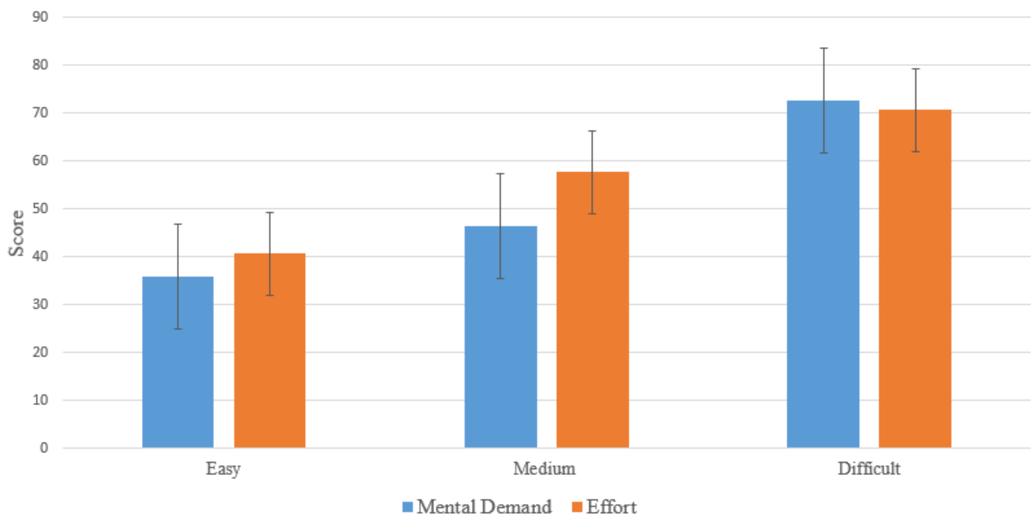

Figure 4.9: NASA-TLX score: Visual Task

Figure 4.10 depicts the insignificance of change in theta PSD, alpha PSD, CLI and EWI while comparing the three difficulty levels of visual task.

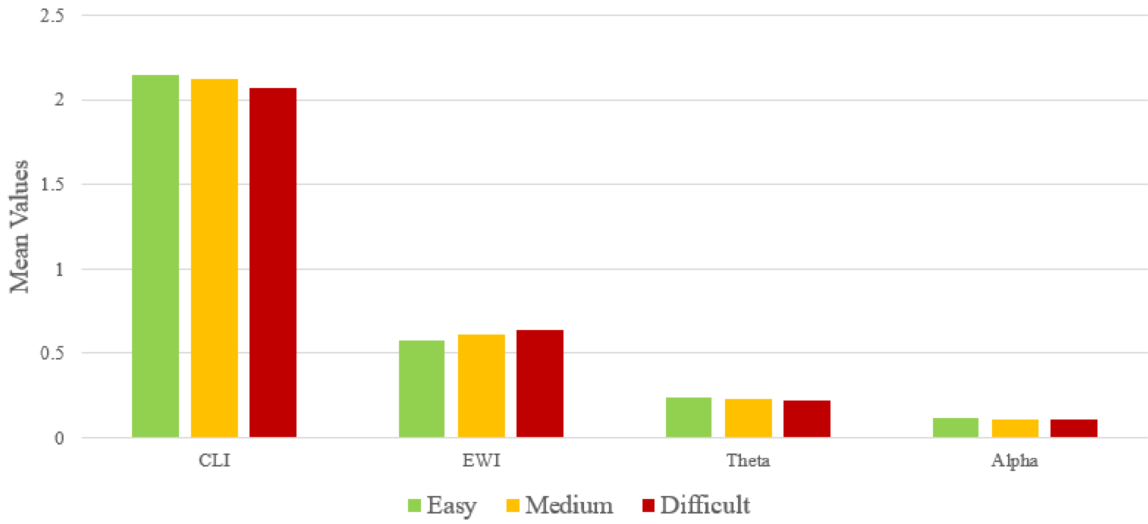

Figure 4.10: Visual task: comparison among three task difficulty levels

The NASA-TLX rating by participants for auditory task also have similar results, while comparing the perceived mental workload ratings for easy and medium auditory task (Fig. 4.11) the effect size is large ($t = -2.17$ and $p = 0.036$) and the effect size between medium and hard task in very large ($t = -5.15$ and $p < 0.001$). the effect size for perceived effort in auditory task for easy-medium and medium hard is large and very large respectively.

Same as visual task figure 4.12 depicts the insignificance of change in theta PSD, alpha PSD, CLI and EWI while comparing the three difficulty levels of auditory task.

If we compare the scores of tasks, either auditory or visual figure 4.13, we observe that in any case the effect size is either huge or in some cases its very large.
Above described subjective feedback scores of participants confirms that both visual and auditory tasks had clear difference among their difficulty levels, but the effect on CLI or EWI is insignificant.
This could be because either CLI and EWI aren't sensitive enough to measure changes

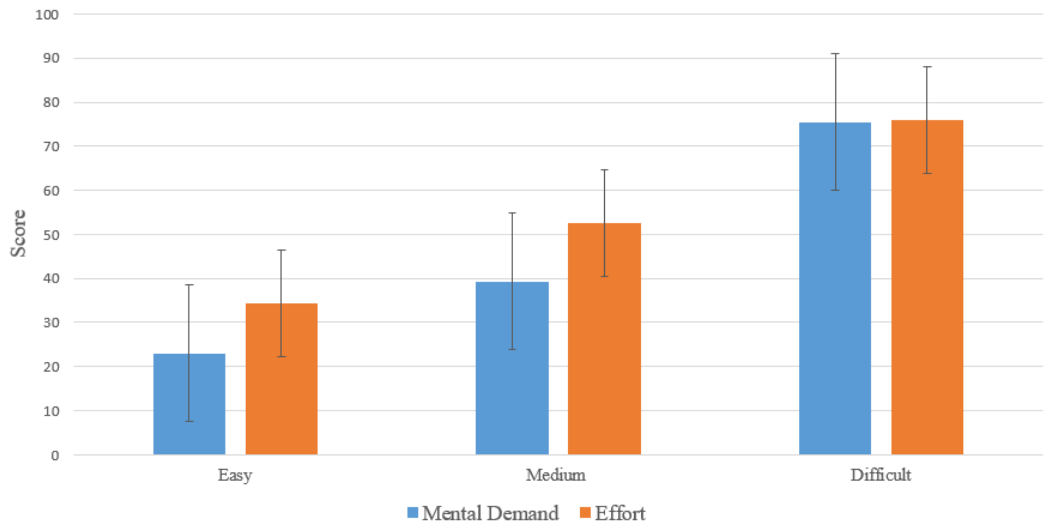

Figure 4.11: NASA-TLX score: Audio Task

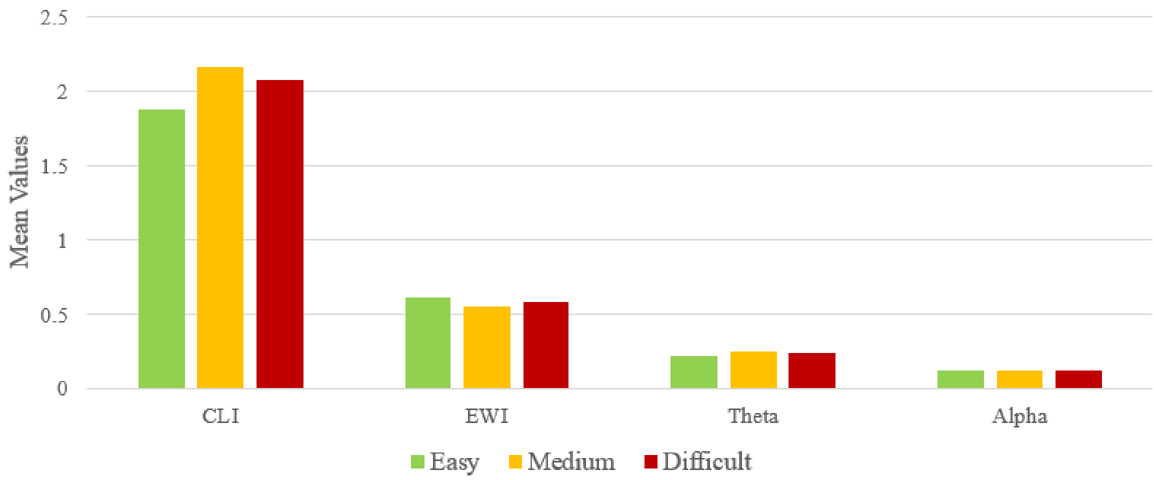

Figure 4.12: Audio task: comparison among three task difficulty levels

in mental workload or single electrode on prefrontal location is only capable of differentiating between relaxed and working state but not sensitive enough to estimate the change in intrinsic mental workload.

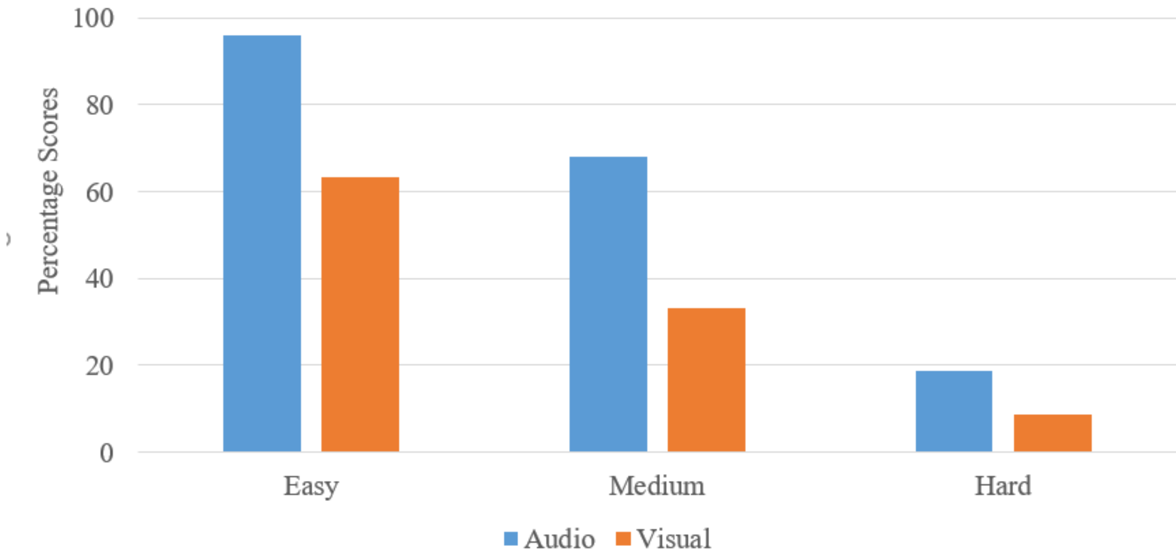

Figure 4.13: Auditory and Visual Task Scores

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In this research, we analyzed the effectiveness of prefrontal cortex in the estimation of mental workload, based on a commercially available single channel EEG device i.e. Neurosky Mindwave Mobile 2 device. We designed a task for induction of mental workload that requires the subjects to utilize their working memory. The task is efficiently able to induce intrinsic and extraneous workload. Then during this task, we recorded EEG signals of participants so that we can use different existing metrics of mental workload estimation. We also verify the results of EEG based mental workload estimation with conventionally used subjective techniques of workload estimation.

Thirty eight participants were part of our study, they were asked to sit in a relaxed state for five minutes and their EEG was recorded, after that participants performed three visual and three audio tasks of different difficulty levels while the EEG device was recording for the entire duration of the experiment. Ultimately, we had seven datasets of each participant i.e. one in relaxed state, three for visual tasks and three for auditory tasks. Then using these data sets, we calculated the Power Spectral Density (PSD) for different brain waves.

We investigated the cognitive workload associated with auditory and visual task. After experimenting on participants we compared 2 metrics of CLI and EWI. Results of CLI are correlating positively with mental workload while EWI, is not much suitable for

these type of tasks as beta and gamma PSDs were not affected by inducing or varying the mental workload. CLI increases while participants are in working state as compared to the relaxed state but it was unable to differentiate between the different difficulty levels of task. We also observe that CLI is less while participants are solving questions while hearing them and average CLI is increased when they are solving the questions after seeing the question visually.
As the subjective feedback of participants depicts the clear difference of difficulty level in auditory and visual task so we can conclude that, differentiating between mental workload related to different difficulty levels is either out of scope for a single channel EEG device or we need to use a better and more sensitive metric for the estimation. This study also validates the conclusion that less mental resources are required to perform an auditory task which emphasizes the use of auditory cues and inputs while designing a human machine interface.

5.2 Future Work

The results shown in previous chapter are proof that single channel wireless EEG device can be used to detect the mental workload from prefrontal location. This location can also be used for measuring different amount of mental workload. Similarly, reliability and quality of multiple channel EEG device is more that single channel device. In future, role of prefrontal area can be studied, so it may be used for elaborating the difference in multiple levels of mental workload.
In this study we analyze the mental workload manually with considerable sample size, in future machine learning techniques can be used for estimation of mental workload with single channel electrode on prefrontal location. For this a larger sample size of participants can be used. Similarly, using a larger sample size new metrics of mental workload can be proposed based on different processing techniques and brainwaves.

5.3 Limitations

Following are the limitations observed in the current study:

- In this study, mental workload was estimated only from the pre-frontal area of brain, other parts of brain can also indicate the change in mental workload, Other areas of brain can be studied by using multiple channel EEG devices.
- Sample size, in this study, is limited to 38 participants which can be further increased for better estimation of mental workload.
- EEG data from single channel device was subjected to manual inspection for artifacts removal. By using multiple channel EEG device "EEGLab" can be much helpful in efficiently removing artifacts using Independent Component Analysis (ICA).

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Appendix A

NASA-TLX Questionnaire

Name: ____

Age: ____

Gender: ____

Last Educational Degree: ______________________________

NASA-TLX Mental Workload Rating Scale

Please place an "X" along each scale at the point that best indicates your experience with the display configuration.

How preoccupied was your mind before starting this test?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very high

Mental Demand How mentally demanding was the task?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very high

Physical Demand How physically demanding was the task?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very High

Performance How successful were you in accomplishing what you were asked to do?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very High

Effort How hard did you have to work to accomplish your level of performance?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low |_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_|_| Very High

Visual task

NASA-TLX Mental Workload Rating Scale

Please place an "X" along each scale at the point that best indicates your experience with the display configuration.

How preoccupied was your mind before starting this test?

Very Low Very high

Mental Demand How mentally demanding was the task?

Very Low Very high

Physical Demand How physically demanding was the task?

Very Low Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low Very High

Performance How successful were you in accomplishing what you were asked to do?

Very Low Very High

Effort How hard did you have to work to accomplish your level of performance?

Very Low Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low Very High

Visual task

NASA-TLX Mental Workload Rating Scale

Please place an “X” along each scale at the point that best indicates your experience with the display configuration.

How preoccupied was your mind before starting this test?

Very Low Very high

Mental Demand How mentally demanding was the task?

Very Low Very high

Physical Demand How physically demanding was the task?

Very Low Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low Very High

Performance How successful were you in accomplishing what you were asked to do?

Very Low Very High

Effort How hard did you have to work to accomplish your level of performance?

Very Low Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low Very High

Visual task

NASA-TLX Mental Workload Rating Scale

Please place an “X” along each scale at the point that best indicates your experience with the display configuration.

How preoccupied was your mind before starting this test?

Very Low Very high

Mental Demand How mentally demanding was the task?

Very Low Very high

Physical Demand How physically demanding was the task?

Very Low Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low Very High

Performance How successful were you in accomplishing what you were asked to do?

Very Low Very High

Effort How hard did you have to work to accomplish your level of performance?

Very Low Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low Very High

Audio task

1

NASA-TLX Mental Workload Rating Scale

Please place an "X" along each scale at the point that best indicates your experience with the display configuration.

How preoccupied was your mind before starting this test?

Very Low — Very high

Mental Demand How mentally demanding was the task?

Very Low — Very high

Physical Demand How physically demanding was the task?

Very Low — Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low — Very High

Performance How successful were you in accomplishing what you were asked to do?

Very Low — Very High

Effort How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low — Very High

Audio task

NASA-TLX Mental Workload Rating Scale

Please place an “X” along each scale at the point that best indicates your experience with the display configuration.

How preoccupied was your mind before starting this test?

Very Low | Very high

Mental Demand How mentally demanding was the task?

Very Low | Very high

Physical Demand How physically demanding was the task?

Very Low | Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low | Very High

Performance How successful were you in accomplishing what you were asked to do?

Very Low | Very High

Effort How hard did you have to work to accomplish your level of performance?

Very Low | Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low | Very High

Audio task

Appendix B

MATLAB Script for Power Spectral Density Calculation

```
%clear all
clc

fr_alpha=8:.5:12;
fr_delta=.5:.5:3;
fr_theta=4:.5:8;
fr_beta1=12.5:0.5:16;
fr_beta2=16.5:0.5:20;
fr_beta3=20.5:.5:28;
fr_gamma=29:1:50;
fr_total=0.5:1:50;

%VarName1 is variable from eegid .CSV file

[pxx_delta,f_delta] = pwelch(VarName1,1024,102,fr_delta,512);
[pxx_theta,f_theta] = pwelch(VarName1,1024,102,fr_theta,512);
[pxx_alpha,f_alpha] = pwelch(VarName1,1024,102,fr_alpha,512);
[pxx_beta1,f_beta1]   = pwelch(VarName1,1024,102,fr_beta1,512);
[pxx_beta2,f_beta2]   = pwelch(VarName1,1024,102,fr_beta2,512);
[pxx_beta3,f_beta3]   = pwelch(VarName1,1024,102,fr_beta3,512);
[pxx_gamma,f_gamma] = pwelch(VarName1,1024,102,fr_gamma,512);

[pxx_total,f_total] = pwelch(VarName1,1024,102,fr_total,512);


avg_delta=mean(pxx_delta);
avg_theta=mean(pxx_theta);
avg_alpha= mean(pxx_alpha);
```

```
avg_beta1=mean(pxx_beta1);
avg_beta2=mean(pxx_beta2);
avg_beta3=mean(pxx_beta3);
avg_gamma=mean(pxx_gamma);

avg_total=avg_beta1+avg_beta2+avg_beta3+avg_theta+avg_alpha+avg_delta+avg_gamma;

r_gamma=avg_gamma/avg_total;
r_beta3=avg_beta3/avg_total;
r_beta2=avg_beta2/avg_total;
r_beta1=avg_beta1/avg_total;
r_alpha=avg_alpha/avg_total;
r_theta=avg_theta/avg_total;
r_delta=avg_delta/avg_total;

EWI=(r_beta1+r_beta2+r_beta3+r_gamma)/(r_theta+r_alpha);

CLI=avg_theta/avg_alpha;

data=[CLI EWI r_delta r_theta r_alpha r_beta1 r_beta2 r_beta3 r_gamma];
```