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# EEG Based Cognitive Workload Assessment for Maximum Efficiency

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***ABSTRACT:*** *Modern work requires multitasking and the need for sustained vigilance, which result in work-related stress and increase the possibility of human error. So methods for estimating cognitive overload and mental fatigue of the brain during work performance are needed. Cognitive load (CL) refers to the amount of mental demand imposed by a task on a person, and has been associated with the limited capacity of working memory. It is very important to maintain the optimal cognitive load so as to achieve the maximum efficiency and productivity. So real time non invasive measurement of cognitive load is very important. Physiological measures are good for continuous monitoring of workload levels. Five most important physiological areas to measure workload are: cardiac activity, respiratory activity, eye activity, speech measures, and brain activity. Tracking the level of performance in cognitive tasks may be useful in environments, such as aircraft, where the awareness of the pilots is critical for security. EEG has the potential to identify changes in cognitive load in tasks that require continuous and intensive allocation of attention. This paper describes the usefulness of EEG brain activity in the workload prediction. The important benefit of this method is that it can be used continuously without the interference of any task but the drawback is it requires a special instrument to capture process and interpret the signal.*

***Keywords -*** *Brain Imaging, Workload, EEG, Cognitive Load, and Theta-Alpha Waveforms.*

## I. INTRODUCTION

Modern imaging methods provide the opportunity for non-invasive *in vivo* study of human organs and can provide measurements of local neuronal activity of the living human brain *(A Toga et al, 2001)*. These imaging modalities can be divided into two global categories: Functional Imaging or Structural Imaging (*Fantini et al, 2001).* Functional imaging represents a range of measurement techniques in which the aim is to extract quantitative information about physiological function from image-based data. The emphasis is on the extraction of physiological parameters rather than the visual interpretation of the images. Structural imaging represents a range of measurement techniques which can display anatomical information (*Shriram et al, 2012*). The brain is responsible for information processing, decision making and initiating actions on the external environment (*Brookings et al., 1996*). It is generally agreed that the most precise measurement of mental workload comes directly from measuring the activity of the brain (*Berka et al*).

## II. WORKLOAD CLASSIFICATION

Workload is classified into three classes as follows:
Subjective Workload: Subjective measurement of levels of workload is based on the rankings or scales to measure the amount of workload a person is feeling. It is devoted primarily to the intermittent question-answer type response at various levels of workload (*Embrey et al, 2006; Miller et al, 2001*)
Performance Based Workload: Performance measurement of workload relies on examining the capacity of an individual by means of a primary or secondary task. By measuring how well a person performs on the task with increasing workload, an estimate of mental workload can be determined (*Miller et al, 2001*).
Physiological Workload: Physiological measurement relies on evidence that increased mental demands lead to increased physical response from the body. This workload measures the continuous physical responses of the body. This measures the physical reactions of the body to the amount of mental work a person is experiencing. It is the most exact an objective measurement and therefore the best way to find workload because it does not require a direct response from the person, unlike subjective measures (*Embrey et al, 2006*). Most of the research focuses on five main physiological areas to measure workload: cardiac activity, respiratory activity, eye activity, speech measures, and brain activity (*Miller et al, 2001*). Cardiac activity is measured through heart rate, heart rate variability, and blood pressure. Respiratory activity measures the amount of air a person is breathing in and the number of breaths. Eye measures include horizontal movements, blink rate, and interval of closure. Speech

measures take pitch, rate, loudness, jitter, and shimmer into account to determine the workload. To measure brain activity the electroencephalograph (EEG) is usually used (*Hope et al, 2011*).

## III. EEG BASED NEUROIMAGING

EEG signal originates mainly in the outer layer of the brain mainly known as the cerebral cortex, a 4–5mm thick highly folded brain region responsible for activities such as movement initiation, conscious awareness of sensation, language, and higher-order cognitive functions (*Strangman et al, 2005*).

3.1 EEG: Electroencephalogram

EEG signal describes electrical activity of the brain measured by unpolarized electrodes and belongs to the group of stochastic (random) signals in frequency band of about 0 – 50 Hz with rather high time resolution (units - tens of ms) *(T. Heinonen et al, 1999)*. Figure 1 shows the human brain and the various lobes. Brain is divided into 4 lobes; Frontal, Parietal, Temporal and Occipital. Musical tasks and spatial processing is carried out in right brain while mathematical skills and verbal processing is carried out in left brain.

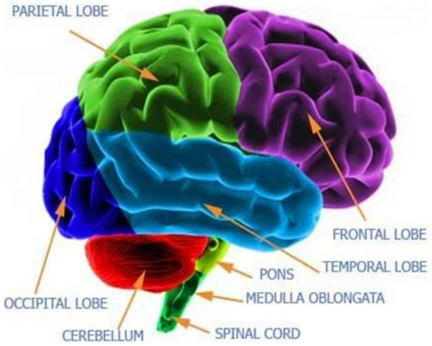
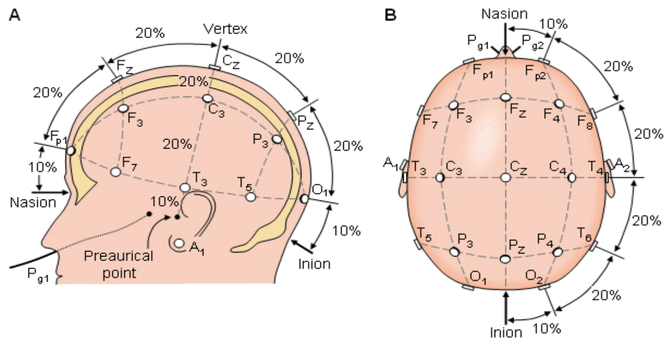



Figure 1: Human Brain and Various Lobes

Figure 2 shows the placement of EEG electrodes on the scalp according to 10-20 electrode placements. Total 21 electrodes are used to capture the EEG, among them 19 are active electrodes and 2 reference electrodes are placed on the ear (*Mehran et al, 2012*). Electroencephalography waveforms generally are classified according to their frequency, amplitude, and shape and the sites on the scalp at which they are recorded. The most familiar classification uses various frequencies in the EEG waveform (e.g., alpha, beta, and theta).




Alpha waves - 8-13 Hz
Beta waves - Greater than 13 Hz
Theta waves - 4-7.5 Hz
Delta waves - 4 Hz or less

Figure 2: EEG 10-20 Electrode Placement

## IV. EEG SIGNAL ANALYSIS SCHEMES

EEG signals are the neural activity signatures. These signals are generally represented in time domain. To study these signals various algorithms are developed based on time domain, frequency domain and spatial domain. Spectral analysis is carried out study the various brain abnormalities and the sources of various physical and mental activities.

4.1 Spectral Features:

Investigation of spectral features derived from the EEG is carried out for measuring the workload. Five spectral features are generally estimated (*Brouwer et al, 2012*) as shown below:

- Spectral entropy (SpEn)
- Subband energy (Enrg)
- Intensity weighted mean frequency (IwMf)
- Intensity weighted bandwidth (IwBw)
- Spectral edge frequency (EdFr)

Spectral entropy based on the Fourier Transform is used as a measure of regularity. Power spectral density is calculated by the following formula, where *pi* are the spectral amplitudes of frequency bin *i* and *N* is the number of frequency bins (*D Aba´solo et al, 2006*).

$$H(f) = -\frac{1}{\ln(N)} \sum_{i=1}^{N} p_i \ln(p_i),$$

90% energy of the spectral components resides in 0-4 Hz region. So the performance of all the features was examined in the delta band.

4.2 Statistical Features:

In this method, EEG signal is first divided into segment of length 1-2 seconds. Then various statistical features are used to analyze the give EEG data. Statistical features like mean, variance, and root mean square are calculated for each data segment (*Belyavin et al*).

4.3 Feature Extraction based on ICA:

Independent component analysis (ICA) is a recently developed method in which the goal is to find a linear representation of non-gaussian data so that the components are statistically independent, or as independent as possible (*Kothe et al, 2011*). Such a representation seems to capture the essential structure of the data in many applications, including feature extraction and signal separation (*Aapo et al, 2000, Trejo et al 2007*).

$$xj = a_{j1}*s_1+a_{j2}*s_2+...+a_{jn}*s_n, \quad \text{for all } j$$

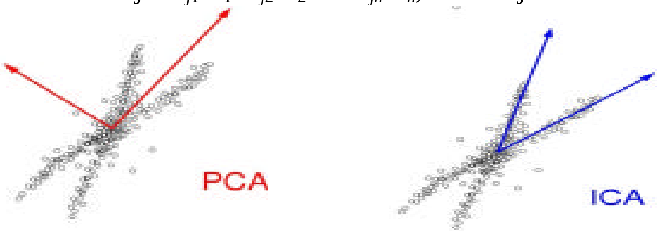



Figure 3: Representation of PCA and ICA Based Data Fit (*Hong et al, 2012*)

## V. WORKLOAD PREDICTION

Physiological measures are good for continuous monitoring of workload levels. A few physiological measures have potential use in a real-world environment.

Table 1: EEG Features and the Trend followed

| FEATURE | EEG CHANNEL | TREND |
|---|---|---|
| Spectral Entropy | $Fp_1$, $AF_3$, $F_7$, $CP_5$, $P_7$, $P_z$, $P_8$, $CP_6$, $CP_2$, $T_8$, $F_4$, $F_8$, $AF_4$ | Decreasing |
| Sub-band Energy | $Fp_1$, $AF_3$, $F_7$, $T_7$, $CP_3$, $P_7$, $P_z$, $P_8$, $CP_6$, $CP_2$, $T_8$, $F_4$, $F_8$, $AF_4$ | Decreasing |
| Intensity Weighted Mean Frequency | $F_7$, $FC_5$, $T_7$, $C_3$, $P_7$, $P_3$, $P_z$, $P_8$, $CP_2$, $FC_6$, $FC_2$, $Fp_2$, $F_z$ | Increasing |
| Intensity Weighted Bandwidth | $Fp_1$, $AF_3$, $F_7$, $T_7$, $C_3$, $CP_5$, $P_3$, $P_z$, $PO_3$, $P_4$, $CP_2$, $FC_6$, $FC_4$, $F_4$, $Fp_2$, $F_z$ | Increasing |
| Spectral Edge Frequency | $Fp_1$, $AF_3$, $F_7$, $P_3$, $P_z$, $CP_2$, $Fp_2$, $F_z$ | Increasing |

The eye blink rate measure is the best way to find out visual workload. Measuring brain activity by using an EEG machine is also beneficial (*Embrey et al, 2006*). Workload can be estimated by measuring the decrease in performance by either the primary or secondary tasks. The primary task measure is a more direct way to measure workload than the secondary task measure, but both are used and at least moderately accepted. Table 1 shows the EEG features and the trend followed by the features with increase in the load (*Fang et al, 2011*). The performance in the multi-task was significantly decreased after sleep deprivation when compared to the performance in the normal sleep protocol at the same time of day. The following figure shows the EEG waveforms for the two subjects when they were presented with a ‘single’, ‘dual’ and ‘multi’ tasks. Figure shows the increase in reactivity ratio of theta activity to alpha activity to continuous change in the task demand for the two subjects (*Holm et al, 2009*).

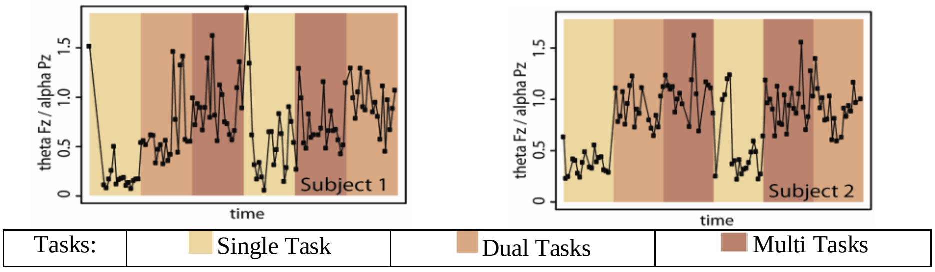


Figure 3: Change in Theta and Alpha activity w.r.t. the tasks

## VI. CONSIDERATIONS

The relative importance of these considerations may change as circumstances change. Some of the most important considerations in any circumstance are the accuracy, reliability, validity, and predictability of the measure. These are very important to consider because the measure must be useful in determining workload or else it is a waste of time. The following table shows the various considerations (*Sarah et al, 2001*).

Table 2: Various Considerations

| PARAMETERS | EXPLANATION |
|---|---|
| Time | Depends on when the measure is taken |
| Reliability | Must predict workload each time measure is used |
| Validity | Must be dependent on workload, not due to independent factors |
| Accuracy | Must mirror changes in workload |
| Sensitivity | Must detect changes in workload |
| Intrusiveness | May be distracting or uncomfortable for user |
| Interval of Collection | Measure during, after, or continuously throughout experiment |
| Form of Gathering Data | Different types of data may be gathered at different points (Auditory Written Machine) |

For maximum accuracy, it is necessary to use multiple measures in combination. This provides more than one estimate of workload, thus cutting down on mistakes in measurement or incomplete data. It is recommended that one measure be continuous, one measure be taken at intervals during the experiment, and one measure be taken after the experiment. To do this, a physiological measure and a subjective measure must be used (*Kamzanova et al, 2011*).

## VII. DISCUSSION

There are several brain activity measures that are not studied as extensively. These measures may hold some promise in the area of mental workload measurement. Table 3 shows the various measures used for the workload assessment, its advantages and disadvantages.

Table 3: Effect of Workload on various Physiological Parameters

| MEASURE | WORKLOAD | ADVANTAGES | DISADVANTAGES |
|---|---|---|---|
| Heart Rate | Increases | Easy to measure & widely accepted | May not be completely reliable. Doesn't measure absolute levels of work |
| Heart Rate Variability | Decreases | Better accuracy than HR | Not widely studied or accepted, Influenced by respiration, equipment req. |
| Blood Pressure | Increases | Used to calculate modulus | Not widely studied or accepted, no more information than HR or HRV |
| Respiratory Rate | Increases | Easy, unobtrusive, sensitive, reliable | Influenced by emotion, stress, speech |
| Volume/Breath | Decreases | | Hard to calculate, obtrusive, not studied |
| EEG | Alpha waves replaced by Beta waves | Extremely accurate, reliable, catches changes | Obtrusive, requires special equipment and training, may not be cost effective |
| Eye Blink | Rate decrease & pupil diameter increase | Most accurate for visual workload | Not as accurate for other work measures |
| Speech | Pitch, loudness & rate increases | Can be used to determine influence on HRV | Not studied, speech not important for all applications |

The use of the Electromyogram (EMG) is a new promising measure. The EMG measures task irrelevant facial muscles that are not required in the motor performance of a task (*De Waard, 1996*). Different facial muscles are found to be differentially sensitive to changes in mental workload. (*De Waard (1996*) identifies the frontalis and the corrugators as muscles that have been studied. Subjective measurement of workload is good for determining how much workload a person feels.

## VIII. CONCLUSION

Multitasking requires contributions from prefrontal cortical regions that control attention functions. These prefrontal regions are also susceptible to sleep restriction. The lack of sleep results in a non-optimal physiological state for performing challenging tasks. In many cases, these components of load, increased external task demands, and decreased internal physiological resources are present at the same time (*Galan et al, 2012*). Subjects suffering from even modest sleep loss have shown decreased performance in tasks that require neural control by prefrontal areas (*Holm et al, 2009*). Generally, as mental workload increases, theta increases in the frontal lobe and alpha decreases in the parietal lobe (*Hankins et al, 1998; Holm et al, 2009*). Beta waves were associated with changes in complexity. Delta and Alpha waves are affected differently by complexity and volume changes (*Brookings et al, 1996*). The power of frontal theta activity increases with the increase in awake time. The power of parietal alpha activity decreases slightly with increase in awake time (*Holm et al, 2009*). Thus EEG measures are useful in finding and evaluating the relative contributions of workload that are not detected by other indexes.

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