EEG as a tool to measure cognitive load while playing Sudoku: A preliminary study

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***Abstract*— Cognitive load or mental workload in human beings is an important parameter associated with the task being performed. The level of task and the learning curve for any task has a certain cognitive load or mental workload. Apart from causing stress and mental exhaustion, increase in cognitive load beyond a critical limit may affect the performance on the end task. There is a need to explore non-invasive and non- intrusive physiological means of measuring cognitive load to identify the subjective performance and well been. This paper discusses identification of EEG as one of the means, identification of suitable EEG frequency bands and spatial locations to assess the cognitive load based on available literature and also to demonstrate measured load based on an experimental study performed using a commonly played Sudoku game.**

Keywords— Cognitive Load Index, EEG, Sudoku, Independent Component Analysis, Workload

I. INTRODUCTION

Assessing subject engagement and mental workload during the performance of any mathematical task is one of the main challenging tasks in cognitive load estimation [1]. Electroencephalogram (EEG) based measurements that infer about the involvement of a subject in an activity has been commonly deployed as a tool to investigate this workload. [2]–[4] Changing the difficulty of cognitive tasks and mental workload, reflects noticeable changes in EEG recordings [5][6]. EEG has been a well-defined and utilized non-invasive process of acquiring electrical activity recorded from the scalp surface.[7],[8]. EEG signals are typically steady under various environmental factors and thus it is utilized in a real-world scenario [9]. Mental load, mental effort and performance are regarded as the main aspects of cognitive load[10]. When a task turns out to be a tough one, the approachability of outcome becomes slow as working memory decreases and cognitive load rises[11]. Cognitive Load Theory makes a distinction between three types of sources for the learners' cognitive load: intrinsic, extraneous, and germane cognitive load [12]–[14]. All three sources are involved in an individual's attempt to solve a problem or to accomplish a task [15],[16]. Theta increases with higher cognitive load and alpha decreases for the same [17]–[19]. This observation led to several studies that linked between theta–alpha frequency generated parameters and cognitive load estimation. [20],[21]. Cognitive Load measurement is said to be sensitive to the definite tasks offered to the participant. Therefore it is clear that cognitive load received from EEG signal is hard to relate to user studies of more multifaceted tasks that cannot be simply categorized[12]. Oscillatory activity-based BCI methods are based on changes in power in known frequency bands, in specific brain regions. Hence, there is a need to explore both the spatial and spectral statistics to determine the load variation more accurately [22].

The computer based tests creating task batteries have been designed based on pre-defined and well acknowledged literature. Computer based test has been significantly received appreciation for use in the clinical and research experiments. The American Psychological Association (APA) recognized the value of computerized psychological testing and published guidelines in 1986 [23] to support in the progress and understanding of computer based test results.

II. PROPOSED METHOD

Cognitive load measurement using EEG power spectrum analysis follows a systematic method involving understanding of the user's brain activity. The scenarios of performance are considered, to understand the level of cognitive load caused by a task. The methodology which is proposed to measure the cognitive load caused by various task using EEG system is shown in Fig. 1.

III. MATERIALS AND METHODS

A. Participants

Seven volunteers participated in the experimental study. The age of participants was between 25 to 35 years with one participant above 50 years of age. Participants met all the inclusion criteria: they did not reported suffering from any major medical illness, psychiatric conditions or addiction history. The procedure of experiment was explained and laboratory facilities were introduced to participants. A signed consent form was taken from the participants to take part in the study on voluntary basis. EEG data was collected from all the 7 participants. Among these, one was uneasy with the environmental setup and hence good quality data could not be collected. Hence, the final dataset comprised of data of six participants for further analysis.

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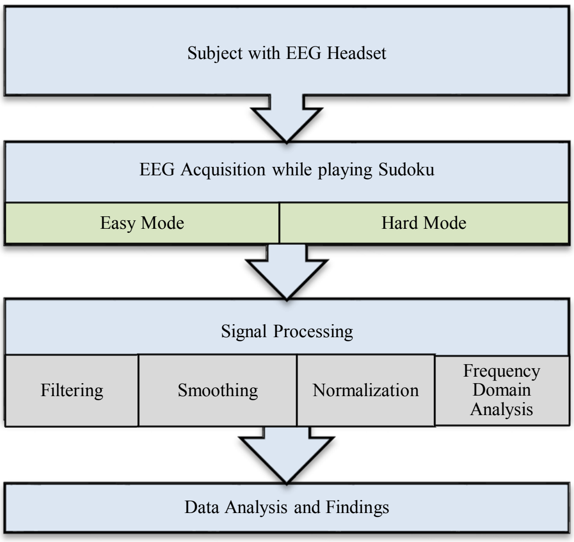

Fig. 1 Block Diagram of proposed method to access cognitive load

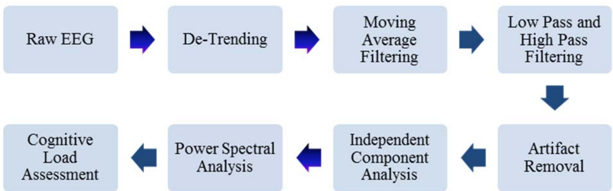

Fig. 2 Flowchart of Processing Steps for EEG Signal

B. *Task Design and Experimental Setup*

Participants performed the test in a lab environment which was well attenuated to sound and an isolated enclosed environment. Before the experiment, each and every participant was instructed on the rules of the Sudoku game, though the participants were familiar with the game. Participants had no fixed duration of time to complete each set of tasks. Two such sessions were conducted for each participant for two difficulty levels: Easy and Hard. After the first difficulty level, there was a break of 10 minutes for each participant. During the break, participants were asked to close their eyes and relax. The participants played the game on a 15.6 inch screen in a well illuminated room about 65 to 70 cm away from every participants for to avoid any discomfort during the gameplay. Participant wore the EEG headset during the period of study for duration of 35-40 minutes depending on participant.

C. *Equipment*

Active amplification electrodes are becoming more popular for ERP data collection, as they amplify the EEG at the scalp and thereby potentially decrease the influence of ambient electrical noise [24]. EEG data was collected from the participants utilizing sixty four channels. Data were digitized and amplified with identical acquisition settings. In particular, data was acquired at the sampling rate of 1000 Hz. All recordings were made in an isolated enclosed room.

D. *Data Analysis*

Out of 64 channels, initial analyses were done with eighteen channels of international 10-20 system: Frontal lobes (Fp1/Fp2, F3/F4, and F7/F8), Temporal lobes (T7/T8), Parietal lobes (P3/P4, P7/P8, C3/C4, C5/C6) and the Occipital lobes (O1/O2). The channels were selected based on available literature as these channels have been shown to provide significant information to discriminate different cognitive states [25],[26]. Since EEG measures voltages at the scalp, there are many possible sources for data corruption that must be addressed. Artifacts related to eye blinks and other muscle movements are also there due to hand movement to fill the puzzle. Data processing steps have been shown in Fig. 2.

Since these bio-signals belong to different frequency range, filters can be used to remove the artifacts i.e. Low-pass Filter, High–pass Filter, Band-pass Filter and Notch Filter etc. Smoothing and de-trending are the methods for computing fractal scaling and removing the trend from the signal. The benefits of these processes are that the external fluctuation can be removed [27],[28]. After that 8 points moving average low pass filter has been applied, which would help to remove any high frequency component which is mixed with the low frequency components of the signal. Bad blocks were removed manually, with further bad data removal done with EEGLAB software which runs with MATLAB in the background [29], [30].

Further data analysis of EEG was done in MATLAB. Short Time Fourier Transform (STFT) and Independent Component Analysis (ICA) to get hidden information from multivariable signal were used to analyze the EEG data using EEGLab [31]. In MATLAB the different components were examined and few of the components were rejected. If the scalp map of the individual component shows the major signal distribution from a specific area of brain, then it can be supposedly considered as muscle artefact. Power distribution should reflect rise in higher frequency region for the movement artifacts. Similarly for eye movement occipital region in scalp map of the component shows concentrated signal distribution. So the component has to be rejected as well.

Individual's brain wave patterns are unique. This is probable to differentiate subjects merely according to their distinctive brain activity. This study focuses on the analysis of the theta (3 - 8 Hz) alpha (8.5 – 12 Hz) and beta (12.5 – 25 Hz) frequency bands, which have been identified as reflecting cognitive load assessment in two different levels of activities. Analyzing the power spectrum, heat map and color map of all eighteen channels, the most contributing channels have been narrowed down. The ICA of one subject indicating five components has been depicted in Fig. 3.

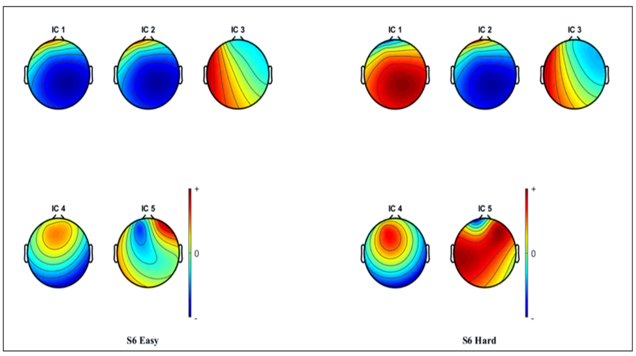

Fig. 3 ICA of S6 for Both Level of Task

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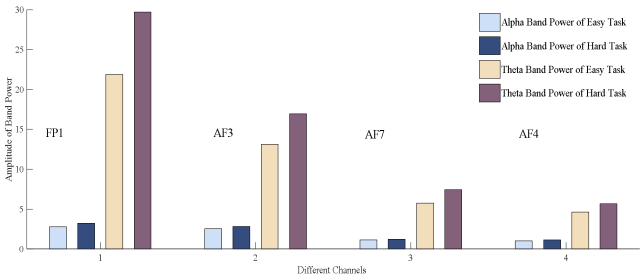
Five major components could be found from the study which was showing major changes from easy to hard level task. Out of them some components are related to brain activity and others are artifacts. ICA attempts to reverse the superposition by extraction the EEG into mutually independent components from selected channels [29], [32].

IV. RESULTS AND DISCUSSION

The main objective of this study was to estimate the difference between the two activities of low and high mental workload respectively. Though, EEG signal handling is a tough task, due to the external noise, power line interference, non-stationarity, complexity of the signals. In particular, it is required to pre-process the EEG data for further analysis.

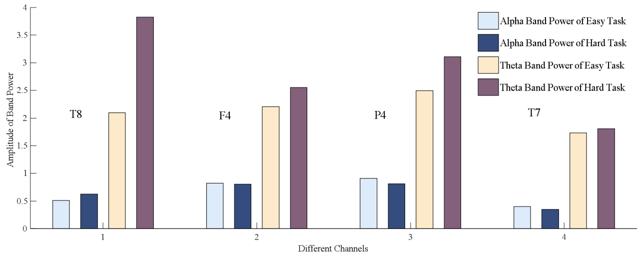
Cognitive load comparison of S6 can be done in terms of STFT variation of easy and hard mode of Sudoku for different bands for channel FP1. Thus, cognitive tasks seem to be more challenging for the subject in hard level as compared to low level of Sudoku. These results show that relating neural measures to a mathematical puzzle solving task provided significant confirmation about mechanisms and based on mental fatigue in low and high mode of Sudoku. The main results were highly comparable to literature [33-34] and therefore, validity and reliability of data seems to be satisfactory.

According to literature, it can be inferred that during the work, which demands higher cognitive load, an increase in theta band activity can be observed and it varies according to different level of difficulties of the task. Alpha band power and upper beta band powers also show a rise in higher cognitive load activity. The study involved a good player to realise how much the change in power is reflected in some selected regions of brain for change in task difficulty. A comparative study shows here how much change in power in both alpha and theta band took place when the difficulty level went higher (Fig. 4(a)). The four channels shown here, FP1, AF3, AF7 and AF4 have been found most dominating channels being active during high load tasks. The result justifies the established findings and proposed results of previous works. Few other channels have been also mentioned by previous studies. Hence,



(a)

Similar comparative results among four less dominating channels have been also shown (see Fig. 4(b)). The channels selected here, T7, P4, F4 and T8 are also showing the same patterns as earlier. But, the amplitude of band power indicates these four channels have lesser effect than shown by primary four channels. Though the study of P4 supports the fact that alpha band power in the parietal region of the brain shows fall while increase in load. And among the secondary four channels, T8 was found to be most prominent. Hence, five channels could be taken into consideration for further studies, which includes FP1, AF3, AF7, AF4 and T8.



(b)

Fig. 4 Alpha and Theta Band Power Comparison for Two Different Types of Task at Four Major Effective Channels (a) Primary Dominant Channels (b) Secondary Dominant Channels

As the task result indicates and it has been described earlier that three subjects S4, S5, S6 were good at playing Sudoku and S1 and S2 were inadequate players. Out of efficient subjects S6 and from inefficient subjects S1 has been chosen to observe the effect of load due to different ability factor between two subjects. Here the objective is to identify the difference in load between a person who is familiar to some task and another person who is not aware at all. To compare between these two subjects, signal power of every frequency band has been calculated from the selected channels. For the most dominating channel FP1 it can be clearly seen that every band shows a change in band power for different levels and different subjects (see Fig. 5).

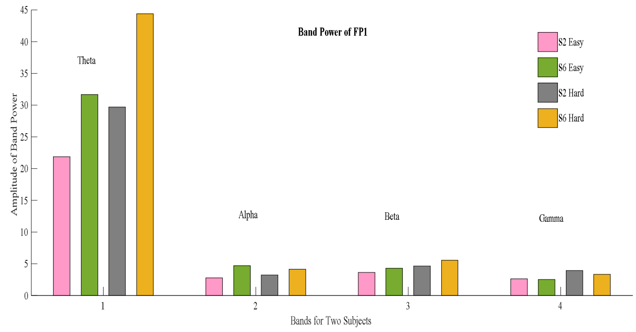


Fig. 5 Band Power Comparison of Two Subjects for Two Different Level of Task for FP1

Another interesting finding, which was observed for the channels: AF7, AF4 and T8, where the poor performance with the high cognitive load showed a fall in alpha band power. This could not be observed in case of good performer. Alpha band power of subject S6 showed a rise from easy task to hard task. Few studies have shown that alpha power decreases with increase in load where unfamiliar and new informative tasks are involved. As it can be clearly seen form the graphical result that the poor subject with high cognitive load and unfamiliarity with the game shows a decrease in alpha band power in hard task compared to the easier task (Fig. 6). So this can be labelled as higher cognitive load, which is taking place in higher amount for the poor performer as he just learned the game

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and was not really comfortable with the game, especially the hard one. But as usual increase in theta band power can be observed in every case. This is also larger for the poor performer; hence, it was in agreement with literature.

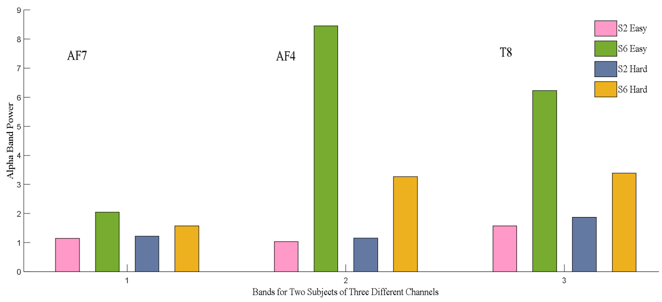

Fig. 6 Comparison of Band Power for Two Level of Task in Alpha Band for two different subjects

After that, the whole data set of each subject for both level of tasks have been divided into epochs of 1 second each. From both level, power of each and every epoch has been calculated for theta and alpha band separately. Hence, each level and each frequency band there are 180 power components. Then the difference set has been plotted along with their mean to easily understand the dominating band power. It could be seen that theta band power shows more prominent change with change in task difficulty (Fig. 7).

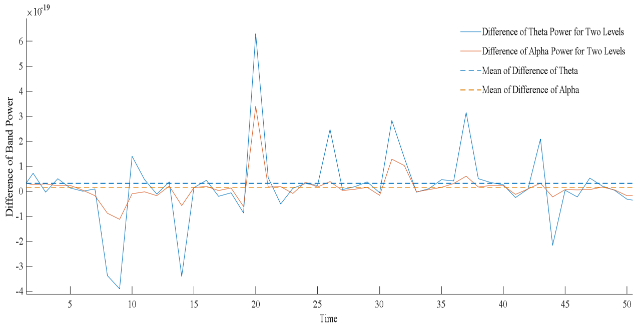

Fig. 7 Band Power Comparison of Two Subjects for Two Different Level of Task for FP1

With increase in workload ratio beta/ (alpha + theta), alpha + theta/beta or theta/alpha should reflect changes in frequency power domain [34]. As mid frontal theta power increases and parietal alpha power supresses due to load, theta power of FP1 and alpha power of P8 has been calculated to evaluate the index result. For six subjects these results have been compared between easy and hard task as shown in Fig. 8.

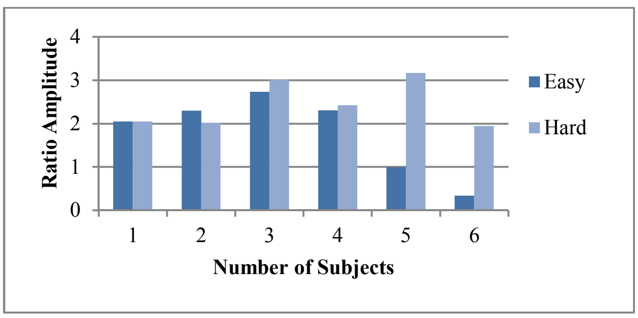

Fig. 8 Beta/ (Theta + Alpha) index for all six subjects of two different mode of Task

It can be observed that five out of six peoples showed increase in index from easy to hard level.

In addition, it is vital, that there were some individual steadiness between members in the data, particularly in verbally processing. Albeit, all members got a similar guidance, there were contrasts between the manners in which they processed. A few members were calm and must be reminded to continue thinking a few times, while others continued conversing with next to no delays. Likewise, a few members were exceptionally unequivocal in their expressions, while others continued concentrating on the undertaking. These distinctions may impact the data, hence, further research on these parameters needed members ought to be chosen or prepared more precisely. Considering all subjects, the common channels have been picked up which are showing changes for almost everyone for two different mode of task. The channels are FP1, AF7, AF3, AF4, P4 and T8 which clearly shows the difference. These findings agree with currently available literature stating channels, which could be utilized for said differentiation of difficulty levels.

V. CONCLUSION

This paper provides an idea about the changes of cognitive load for the two modes of task with different subjects from beginner to expert in the task and identifies the related contributions of subjects to perform the task. Task that is used to gather information about cognitive load has a full range of assessment process which provides a sensitive assessment of cognitive load. This paper suggested the power spectral analysis of EEG to access cognitive load. Results obtained from STFT of two modes of experimental protocols indicate that increasing the level of difficulty of the cognitive task increases the power spectral density of theta while decreases for the alpha band for definite regions. Separate band powers also showed and reinforced the findings while doing assessment of cognitive load.

A set of channels, shows significant contribution in cognitive load distribution and these have been chosen from ICA analysis and different signal power studies. The findings from previous literatures have been followed in this process. Few channels apart from the studied ones which were found to be contributory towards cognitive load and spatial distribution will be taken into studies in future. Also, the effect of other band powers in cognitive load will be studied and analyzed further.

VI. LIMITATIONS

The number of participants for experiment were not appropriate to conclude statistically significant results, though agreement with available literature was observed. This study is based on a mathematical and spatial perception task, excluding time response; hence findings are based on mental and mathematical abilities of the subject. Future studies should aim at evaluating different aspects of mental or cognitive workload- mathematical, verbal, memory short and long term, response time etc.

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