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Measurement of Cognitive Load in HCI Systems Using EEG Power Spectrum: An Experimental Study

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Abstract

Ubiquitous computing involving complex interactive systems are leading to increase in cognitive load in day to day activities. Apart from causing stress and mental exhaustion, increase in cognitive load is likely to cause expensive human errors in case of critical tasks. Though subjective measures of cognitive load are in use in HCI, there is a need to explore non-invasive and non-intrusive physiological measures of cognitive load. This paper discusses the theory of cognitive load, identifies EEG frequency bands likely to capture the cognitive load, discusses brain locations related to the cognitive load based on literature, proposes a methodology to measure cognitive load using EEG power spectrum and verifies the framework by an experimental study.

Keywords: Human Computer Interaction; Cognitive Load; EEG; Power Spectrum Analysis

1. Introduction

With increase in complexity of user interfaces of the interactive systems, the human cognitive system is under increased pressure today[34]. Human is more susceptible to errors and suffer loss in efficiency due to increased cognitive load caused by the complex interactive information systems. As the human computer interaction (HCI) systems are becoming ubiquitous and are being used to perform critical tasks in different domains, the need to measure the cognitive load caused by an HCI system designed for a given purpose, is becoming more and more important before putting them to use[1,2]. Though HCI evaluation methods have also evolved with evolution of the HCI systems and techniques like verbal reporting, task fulfillment observations, concurrent verbalization, questionnaires etc. are being used to evaluate the interactive systems for their effectiveness and efficiency, there is still dearth of methods which can directly measure the cognitive load caused by an HCI system. This paper proposes

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use of a physiological measure, namely Electroencephalography (EEG), as an indicator of cognitive load in HCI. A method using analysis of power spectrum of EEG obtained from the scalp of the user during use of HCI system has been proposed in this paper through an experimental study, as a measure of cognitive load.

1.1. Existing evaluation methods in HCI and cognitive load measurement

The most prevalent method of evaluation of HCI systems has been Think Aloud (TA) based Usability Testing (UT)[35]. Usability testing has been traditionally used to measure the ease of use, efficiency, effectiveness, learnability, memorability and satisfaction of interactive systems[3]. For the purpose of UT using TA, the user has been modeled as an information processor in the usability testing theory[35]. Model of user as an information processor assumes that the user is using sensory memory to gather data and submits for interpretation to short term memory where the 'schemas' or 'mental models' from long term memory provide cues for interpretation of what the sensory systems have thrown to the short term memory. Schema or mental models get created due to prior experiences user has undergone. In short term memory, the users make sense of the HCI interfaces by connecting the information from the streams of data coming from sensory memory about the HCI tasks and the schema and mental models from long term memory. Usability testing uses a detailed testing protocol where real users, matching the intended persona for design, are invited to complete tasks on real applications. Verbal (TA) and behavioral data is recorded for analysis on ease of use, efficiency etc. The usability test also attempts to measure the cognitive loads caused by the interface based interactions, though in a covert way.

It has been reported that the think aloud behavior slows down when the cognitive load caused by the task increase[4]. As Think Aloud (TA) method used to elicit data from short term memory of the user itself causes a load on the cognitive resources, authors posit that TA based usability testing cannot be an efficient method to measure the cognitive load caused by the task in case of critical tasks causing heavy cognitive load. It is therefore, suggested that new methods be developed to get information on cognitive load caused by the system on user in fulfilling a given task on a given system. In this paper a method to measure cognitive load caused by HCI systems has been proposed using EEG power spectrum analysis.

1.2. Theory of cognitive load

Cognitive load theory is based on popular human cognitive architecture that consists of three processors and memory element[6]. The three processors are perceptual processor, cognitive processor and senso-motric processor. Processors interact with working memory and long term memory as per the cognitive process requirements [7].
Cognitive load or cognitive workload is name given to the load on cognitive resources of the mind generated due to cognitive demand of the task [8]. In context of HCI, cognitive load theory is concerned with the design of information systems that efficiently use users' limited processing capacity during competition of HCI tasks. In literature, cognitive load has been defined to be of three types, namely, intrinsic, extraneous and germane.

- Intrinsic cognitive load: Intrinsic cognitive load is the demand on working memory capacity generated by the innate complexity of the information being examined. All tasks have an inherent level of difficulty [9]. The intrinsic cognitive load is a measure of the complexity of the HCI task. For example, adding 2 digit number causes lower intrinsic cognitive load than solving integral calculus problem.
- Extraneous cognitive load: Extraneous cognitive load is generated by the manner in which information is presented to the learner. Extraneous cognitive load measures the load caused to users by the design of a task. This type of load is controlled by the way information is presented [9]. Complex and extra information of the design needs more working memory. For example square root of a number written in alphabetical format (sqrt) instead of the expected symbol (√) will increase the extraneous cognitive load.
- Germane cognitive load: Germane cognitive load is the load dedicated to the processing, construction and automation of schemas [9]. Schemas are the organized patterns of ideas in the neural network of the brain. Learning a new way to complete a task will increase the germane cognitive load.

In context of HCI, the different types of cognitive loads can be used to measure various aspects of interaction that may be leading to increase in difficulty. In this paper, an experiemntal study has been reported where increase in task difficulty was hypothesised to be correlated to increase in intrinsic cognitive load and a high correlation was observed between increase of EEG power spectrum at four EEG channel locations (AF3, AF4, T7 and T8) and the task difficulty.

1.3. Cognitive load measurement in HCI using EEG

Cognitive load measures are increasingly in discussion in context of interactive products and strong arguments have been made in favour of use of EEG as a tool of measurement[10, 7]. The principal reason for arguing case of EEG as a measurement tool for cognitive load is to objectively identify the mental cost of performing tasks. Such a measure would help in creating good match between the user's ability and system performance. As the EEG has temporal data, it will also help to understand the demand a given step in a task has imposed on the operator's limited mental resources. This temporal data will be useful in redesigning the HCI systems for efficiency. Physiological measurement using EEG tool for cognitive load would provide an objective measure of mental activities as the EEG gives indication of mental resources spent in a task through spectral power of the signals collected from the scalp of the user during task performance [9, 13].

For the purpose of study of brain activities in context of cognitive load, four major brain locations have been discussed in literature, i.e. frontal, temporal, parietal and occipital regions [22, 24]. EEG data captures the electrical signals of the brain by means of electrodes placed on the scalp. These electrical signals are generated in brain due to ionic movements in and around the neurons during activation and deactivation of the neurons participating in a typical cognitive process. When the active voltages develop and drop across the cell the voltages fluctuate. EEG measures these fluctuated voltages[15]. The neurological activity in the brain has been observed to cause a range of waves per second (frequencies) which are characteristically different for different levels of brain activities. For example, generally speaking, brain emanates higher frequency signals in awake condition and lower frequency in sleeping condition[16].

Several observations have been reported in literature based on EEG signals and its power spectrum analysis in context of cognitive task based study[24, 25, 26]. In 1974 Dolce and Waldeier explained delta power increases during complex mental tasks (arithmetic tasks) [18]. Also, it was reported that the increase in delta activity was found to be related to attention given by the user to the internal information processing during the performance of a task[19]. An increase in theta activity has been related with task difficulty and emotional factors[19, 20]. Theta band and alpha band power has been reported to decrease during encoding new information[21]. Higher working memory loads have been reported to cause increase in theta and low beta bands powers in frontal midline regions[22]. Frequency band and associated mental activity have been summarised in table 1 below:

Table1. Summary of literature reports on frequency bandwidth associated with mental states

Frequency bandwidth	**Associated mental state**
Delta Band (0.1 Hz to 3.9 Hz)	Deep Sleep and continuous attention tasks increase spectral power of delta band. More prominent at temporal lobe[19].
Theta Band (4.0 Hz to 7.9 Hz)	Indicative of drowsiness, resource allocation and arousal. Theta band power increases with increasing mental load. More prominent at frontal lobe[16, 22].
Alpha Band (8.0 Hz to 12.9 Hz)	Relaxed and reflecting state. Band power change occurs in thalamus-cortical circuit and the hippocampus-cortical circuit. Alpha band power is increases with increasing mental load. More prominent at temporal & occipital lobe[21, 23].Also at frontal lobe during complex tasks [25].
Beta Band (13 Hz to 29.9 Hz)	Indicative of alertness, arousal, frustration, engagement and working state. Widely used for measurement of mental workload. More prominent at temporal and occipital lobe[24].
Gamma Band (From 30 Hz up to 100Hz)	High mental activity, Hypertension. Indicative of sensory information processing. Hence associated with somatosensory cortex. More prominent at Centro- midline of the brain[16, 17].

As EEG signals have high temporal resolution, they can be used to understand the cognitive processes at physiological level through the interaction with interface in a step by step. It has been argued that the cognitive processes activate bunches of neurons in cortical network[25]. The degree of measurable electrical activity, from these bunches of neurons, is often related to the degree of complexity of tasks that the brain is performing [26, 27, 21, 25]. It has been reported that Delta band power increases with increased mental work load[18]. Therefore, the author posits that the cognitive load can be measured by alpha and beta band activities in the frontal region, temporal region and fronto-central region of the cerebellum cortex.

It has been reported earlier that mental workload increases with increase in alpha band power and also increase in beta band power [27, 29, 26, 30, 31]. Increase in alpha band power in frontal, temporal and parietal regions captured by channel locations AF3, AF4, F3, F4, T7, T8, P7 and P8 has been reported to be an indicator of increase in mental workload [22, 25]. Similarly, increase in beta band power in temporal, occipital and fronto-central captured by EEG channel locations Fz, T7, T8, O1, O2 and Oz [28] is also an indicator of the increased cognitive load. Further, it is argued that if delta activity is observed to be more prominent at temporal region which can be measured using channels T7 and T8 then it is a marker of visual attention during the task[19]. EEG data acquisition has been done through 14 wireless electrode using EEG headset. These locations are as follows in sequence AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2 and two reference channels (DRL & CMS) below, in fig 1, locations of 14 channel wireless EEG neuro headset as per the 10/20 international EEG system out of them four EEG channels (frontal lobe-AF3, AF4 and temporal lobe-T7, T8) were used for experimentation in this paper have been depicted and author proposed a method to measure cognitive load in HCI systems design.

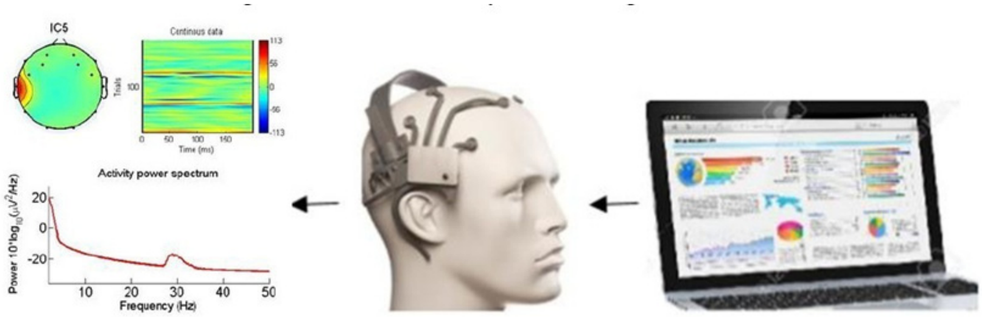

Fig 1: Experimental setup to measure cognitive load caused due to HCI design using EEG power spectrum

2. Proposed method for cognitive load measurement in HCI using EEG power spectrum analysis

To understand the level of cognitive load caused by a task, a systematic method involving understanding of the user's personas, scenarios of usage, type of HCI designs and the testing setup is suggested. The following steps are proposed to measure the cognitive load caused by an HCI system using EEG:

- User persona and scenario study: Explicit description of the user's demographic and psychographic profiles along with the description of the situation in which the HCI system will be typically used, will help in participant selection in situation creation in lab conditions.
- Task and stimuli design: Detailed description of the key tasks performed by users along with the steps involved will be required in test setup.
- Experiments and observations: While the representative users as per the persona complete the tasks as per the scenario description, EEG is used to collect mental activity data from the scalp of the user.
- Analysis of EEG signal: Analysis of power spectrum of recorded EEG data of specific frequency bands from brain locations related to cognitive load as identified for literature.

2.1 Proposed EEG power spectrum analysis for cognitive load measurement

It is proposed that the EEG power spectrum analysis for cognitive load measurement be done in six steps namely, data acquisition, pre-processing, re-referencing, ICA, PSA and statistical analysis. The summary of steps proposed to be followed for the EEG power spectrum analysis for cognitive load measurement is the presented below flowchart in fig 2. In this paper MATLAB scripts have been used as an example for the proposed steps [32,33].

Step1: Data Acquisition using EEG → Step2: Noise & artefact rejection → Step3:Re-referencing data at required EEG channel → Step4: Independent component analysis → Step5: Plot spectral power of alpha frequency band (8-13Hz) → Step6: Cognitive load detection by statistical analysis of power spectrum

Fig 2: Steps involve in the EEG signal analysis for cognitive load measurement in HCI design

EEG analysis part starts with the first step which was loading of raw EEG data into analysis software. The second step was pre-processing of data, which involved electrical cable noise attenuation using basic band pass filter (0.1 Hz to 40Hz) and artefact rejection. Re-referencing the EEG channel data to the average reference, which means that the average signal gets subtracted from all the channels. The purpose of re-referencing is to nullify the ambient activity present in all channels.

In the next step, power spectrum of all the channels was plotted together with a full scale of EEG frequency band i.e., 0.1 Hz to 35Hz to visualize the change in the frequency band as well as to select the specific frequency band of interest visually. In the next step independent component analysis were carried out. Independent component analysis is a technique to separate independent sources linearly mixed from various channel sensors. ICA has been taken for artefact rejection as well as identifying brain related activity region through colour topography. In this paper alpha band has been consider in four channel locations i.e., two frontal and two temporal locations (AF3, AF4, T7 and T8). Alpha band is more prominent at these locations[25]. EEG spectral power at these locations has been traced out for all six participants detailed in section 3.3.

The EEG spectrum traditionally includes range from 0.1 Hz to 100Hz [16]. The spectral power change of the EEG signals in all four channels were recorded and plotted with respect to alpha band power i.e., 8-13Hz which were analysed using EEGLAB. In the step 5 power spectrum of individual channel at alpha band has been plotted and observation has been traced which was discussed in section 3.3. The study of power signal distribution along the range of frequencies (frequency band) is known as power spectrum analysis. Each component of the EEG were traced and their power spectrum were studied in context of demand of the task or cognitive load. Power spectrum of scalp was plotted in 2D map with color shades depicting the range of power with respect to region of the brain [33]. Power spectrum analysis of the EEG signals has been discussed in next section.

3. An experimental study with EEG power spectrum analysis for cognitive load

An experimental study was conducted to verify the feasibility of using EEG power spectrum for cognitive load measurement as per the method described section 2. The sample EEG data was collected from six participants using 14 channel wireless EEG neuro-headset in a lab environment. The task for the participants was to solve mathematical problems mentally, presented to them through a computer based program. Two types of mathematical problems were given to participants to solve. One was relatively easy, namely one digit multiplication and another was three digit multiplications. Both tasks were presented auditory through a computer based program as the participants sat in front of the computer. While the participants completed the tasks, the 14 channel EEG data was acquired. After acquisition of EEG data, the power spectrum density of the frequency bands as discussed in section 1.3 and 2.1 were calculated. It was hypothesised that the power spectrum analysis will help to provide the information about the mental activity of the brain in terms of power of the each EEG channels.

3.1 Participants

Six volunteers participated in the experimental study. The age of participants was between 21 to 25 years and all were male. Participants were graduate students. They had fair knowledge of mathematics and average reasoning aptitude. Participants met all the inclusion criteria: they did not have any medical problems, psychiatric history or major head injury. EEG data sets collected from all 6 participants were used for analysis. The procedure of experiment was explained and laboratory facilities were introduced to participants. A signed consent form was taken from the participants.

3.2 Task design and Experimental Setup

Participants performed the test in a lab environment which was sound attenuated and in isolated enclosed environment. In the experiment, a computer program gave auditory instructions for mathematical tasks. Each participant had a fixed duration to complete each set of tasks. Each participant had to complete as many tasks in a set as one could in 3 minutes. Two such sessions were conducted for each participant. The purpose of fixing the time duration was to build time pressure so as to observe the cognitive load due to tasks. A total of 40 quick mental multiplication tasks were present in repository. The tasks were of two levels of difficulty. After the first difficulty level of tasks, there was a break of 5 minutes for participants. During the break, participants were asked to close their eyes and relax. The purpose of break was to bring the mental activities to a normal level and remove any prior stress effect of the prior set of tasks. The participants sat in front of stimuli screen of 14 inches, about 70 to 80cms away. Participant wore EEG headset and facilitator adjusted the electrode positions on the participant's scalp.

3.3 Results & Discussion

The acquired EEG data from the all 6 participants from all 14 locations were collected. Pre-processing of raw EEG data was done by filtering of electrical cable noise and artefacts rejection, the power spectrum of frequency bands was plotted as shown in below figure 3(a). Initially activity power spectrum and independent component analysis were conducted on all the 14 channel data to identify the brain locations which were more effective during tasks. After individual channel analysis using independent component analysis techniques, 4 channel locations were identified for further analysis. These four channel locations were on frontal and temporal location of the brain (AF3, AF4, T7 and T8).

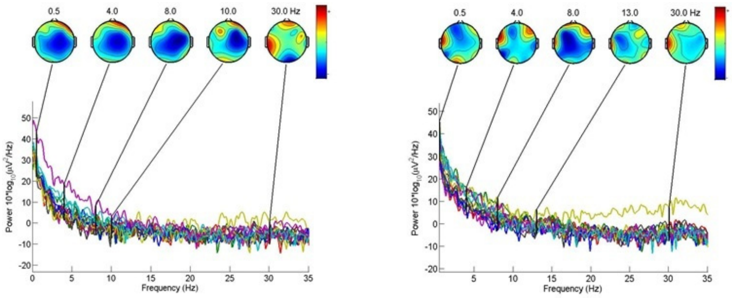

Fig 3 (a): power spectrum (0.1 to 35 Hz) of 2 participants before ICA (X-axis: Frequency in Hz; Y-axis Power in dB)

As observed in fig 3(a), the frequencies of all the channels appear overlapping. So visually it is difficult to analyse the power of different frequency bands associated in cognitive load related activity in the brain during tasks. Therefore, independent Component Analysis (ICA) was performed by eliminating artefacts from scalp component data and identifying spectral peaks at typical EEG frequency from the component data.

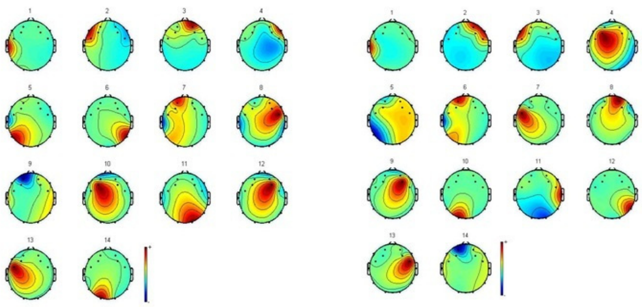

Fig 3(b) Power spectrum after Independent component analysis (ICA) - left side first participant and right side second participant

The independent component analysis of 2 participants has been shown in figure 3(b) indicates 14 components for each participant out of which some are brain related components and some are artefacts (eye and muscle). Artefacts were rejected and brain related activity component were consider for further study. The change in spectrum of the individual components of EEG channel data for brain related components were recognised by some criteria that are they have dipole like scalp maps, smoothly decreasing EEG spectrum and spectral peaks at typical EEG frequency and for components recognised as artefacts that they have scalp map shows a strong frontal projection typical of eye artefacts shown in red colour in frontal lobe. For example in above components in second participant – component 2, 3, 6 and 8 shows a strong far frontal projection typical of eye artefacts and 1 and 11 shows muscle artefacts while component 7, 9, 10, 12, 13 and 14 show minimum eye and other artefact with faithful event related potential. So likewise, components have been recognised both as rejecting components and brain related components. Similarly, ICA was done for all the participants' data and it was observed that the ICA plot shows similar patterns. Though ICA has brought out the channel independent data, we further need to identify the power in each of the alpha, beta and delta bands in each of the brain locations of interest from cognitive load perspective.

Therefore, as per the results of ICA shown in fig3 (b), alpha band (8-13Hz) on frontal and temporal regions of the brain has been studied further in context of cognitive load. Alpha and beta band power increases with increasing working memory load [22, 24, 25] has been discussed in the section 1.3. Spectral power change across frontal and temporal channel locations under alpha frequency band is directly proportional to the cognitive load [22]. Spectral power at alpha band (8-13 Hz) were traced out from the location of frontal and temporal regions i.e., AF3, AF4, T7 and T8 which was found more prominent at these brain locations and the cumulative average of spectral power for EEG channel locations (AF3, AF4, T7 and T8) were calculated to express the level of mental load which was tabulated in below figure 4(a) &4(b), for all the 6 participants in low and high level tasks.

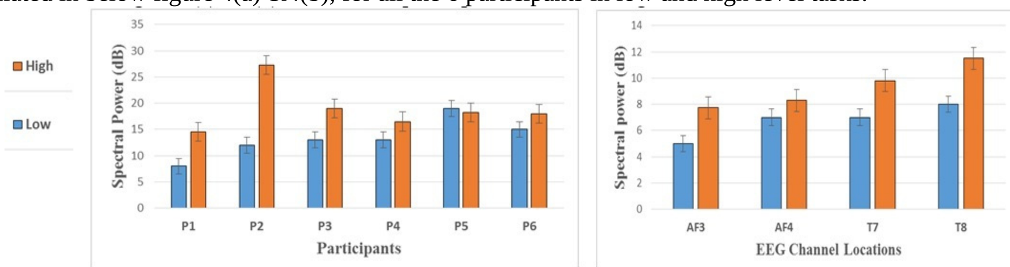

Fig 4: Spectral power change for low and high levels of complexity for tasks (a) for six participants (b) at four EEG channels

Low and high difficulty level tasks were plotted with respect to spectral power (dB). Fig 4 (a) shows the difference between the levels of task difficulties. The determined values of spectral power at frontal and temporal locations of the brain for all participants were analyzed using ANOVA (analysis of variance). The P-value is between $0.01<P<0.05$ i.e. $P=0.04$, which explain the moderate evidence against the null hypothesis. Since we reject the null hypothesis, 95% confident ($1-\alpha$). The difference between mean of spectral power of low and high auditory task was significant. Though this was a small sample study to validate the framework, the difference between mental workloads as depicted by the power spectrum was significant between the low and high difficulty level multiplication tasks. The one digit multiplication has shown low intrinsic cognitive load than the three digit multiplication problem as expected. Limitations of this study was that when calculating the power of the alpha band in the prefrontal cortex the independent components from the non-brain sources were not rejected. The hypothesis was that the power spectrum contribution by those sources would be minimal and would cancel out when comparing the signals from two tasks.

4. Conclusion

This paper has suggested use of EEG power spectrum as an objective measure of cognitive load in HCI. This method is proposed to be useful for analyzing cognitive load caused due to complexity of the tasks in HCI systems. This measurement of cognitive load in HCI systems can be particularly useful for analyzing human efficiency in critical tasks where an increase in cognitive load may cause an increased chance of costly errors. The ambient cognitive load due to the environment, the user's cognitive load due to the skill level and the additional load due to the task can be factored in while designing efficient HCI systems using the objective measures of cognitive load. The method proposed in this paper for measurement of cognitive load using EEG power spectrum has benefits of being objective, accurate and evaluator independent, while it has drawbacks of using expensive equipment, high analysis time and need for expertise in interpretation.

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