

A Cognitive Workload Identification using EEG Power Spectrum



Anshul, Rashima Mahajan, Dipali Bansal

Abstract: Now a days, Electroencephalography (EEG) is popular to monitor human's cognitive workload. EEG signals are delicate to the variation in cognitive load in various fields including observing cognitive workload for the intricate environment of military chores. Earlier to acquire the EEG signals high-cost EEG systems were used which bounds their use but now a day's low-cost headsets are available to capture EEG which makes it a promising set-up to measure cognitive workload. EEGs are initially preprocessed to reflect the artifacts present in it. After preprocessing, signals are ready for further processing. The power spectral density corresponds to the power distribution of EEG signal in the frequency domain which is used to assess the changes in the pattern of the brain. This paper discusses the present progress of research in cognitive workload identification and identifies the techniques associated with the cognitive workload. This proposed research gives the analysis of EEG signal power spectrum density (PSD) during resting state and cognitive workload activities of a human. With power spectral analysis of the EEG signal, seven statistical parameters have been calculated (minimum, maximum, mean, median, mode, standard deviation and range) have been calculated. Analysis showed that the in cognitive workload, PSD has significantly changed if compared to the resting state.

Keywords : Electroencephalography, Cognitive workload, Power Spectral Density, Feature Extraction, Statistical Parameters.

I. INTRODUCTION

The analysis of human cognitive activity has fascinated a lot of researchers [1-4]. The process of activation of various areas of the brain during the cognitive tasks has been mostly considered by the spectral analysis (power spectral density) which is based on Fast Fourier Transform [1]. The automated analysis of the electroencephalogram to evaluate mental states of human like the cognitive workload is increasing day by day [5, 6]. For some specific task, the capacity of mental demand is indicated by cognitive workload [7, 8]. EEG signals are categorized on the basis of frequency: alpha waves (8 - 13 Hz), beta waves (≥ 13 Hz), theta waves (3.5 - 7.5 Hz), delta waves (≤ 3 Hz) [9,10,33]. The noise present in the acquired EEG signal is known as artifacts [11, 12]. The

removal of the artifacts is essential for further processing. Power spectral density (PSD) is one of the potential feature extraction techniques to differentiate the variations in electrophysiological processing of the brain [13]. Artifact-free EEG signal is segmented into epochs and power spectra are computed by the use of FFT [14, 15]. Many researchers explored EEG based cataloging along with an assessment of person working memory load [16-19]. The several mental workload evaluation methods are classified into two groups: subjective questionnaires and objective. The techniques implemented to evaluated cognitive workload in literature and the feature extraction using power spectral density are discussed in Section II. The detail materials required and method to be used for feature extraction spectral amplitude using power spectrum density of resting state and cognitive workload state is discussed in Section III followed by the results and discussion in Section IV. The paper is concluded by the conclusion in Section V.

II. RELATED WORK

The function of power over frequency is spectral analysis. EEG is used as a Physiological measurement for the cognitive workload identification. Through the Physiological measurement, EEG mental resources spent in a task can be predicted through the spectral power of the EEG signals. The delta power increases during task performance while theta band and alpha band power decreases during complex mental tasks like arithmetic tasks. The beta band power increases in occipital, temporal and fronto-central acquired by EEG channel locations. This increase in the beta band power indicates the increased in cognitive load. Therefore, the analysis of the power spectrum of EEG data has been used for the measurement of cognitive load [20]. The feature extraction of EEG signals can be done in the time domain, frequency domain and combination of both domains. The frequency domain feature extraction techniques have been used to capture EEG signal characteristics which may be relevant to evaluate cognitive workload. The Power Spectral Density (PSD) feature is generally used for feature extraction in the frequency domain [1, 13, 20]. Numerous techniques are applied by researchers to estimate cognitive workload like identifying multiple biomarkers, data mining, machine learning, and attention training, which reduces time complexity and the signal dimension representations. The concept of cognitive training involvements, human brain connectome has been introduced and the proposed EEG biomarkers for cognitive workloads. It has been explained that cognitive overwork and mental exhaustion eradicate cognitive training interventions which affect not only a particular brain area but the brain sub-networks [21].

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They also proposed that for a brain enhancement system, the brain connectome approach is very helpful. With a cognitive training intervention like a video game training, working memory training cognitive functions of the brain can be improved [22-24]. Biomarkers are used to envisage a person's intelligence or learner's successive learning rate. The environment of digital learning can be established by merging various methods from Cognitive Psychology, neuroscience and computer science. A solution has been proposed to an existing problem that in a real-time there is a deficiency of an unobtrusive approach to constantly evaluate the learners working memory load [25]. A road traffic safety was assessed by studying the behavior of drivers and its consequences on the cognitive workload in composite surroundings regions. Initially, the driving workload was verified on signs of traffic among altered data. The results show that the workload is extremely associated with information on signs of traffic and response time rises with the grade of information & driving performance is affected by driving workload. Results also show that experience & gender affects the speed of a driving and track deviation [26]. The concept of the ability of the human and demand gap along with its connotation among task-evoked cognitive overload and cognitive dissonance was proposed. By the use of Kolmogorov-Smirnov statistics, the extreme gap was calculated. A cyclical and the non-linear association were found among the capacity of working memory, cognitive overload and cognitive dissonance [27].

The EEG signals used to evaluate person mental workload and the task engagement level was described. There is the change in the state of the brain as EEG changes for diverse tasks and that change was enumerated and then an arithmetical test of consequence was done on the calculated EEG index. The results showed a more mental workload was observed in persons with more tension levels were more than control experiment. The consequences are helpful in observing the astronaut or the human cognitive recital for their safety and performance enhancement [28-29].

As literature findings show spectral analysis is the

frequently used technique for analysis of EEG signal. It gives frequency content of the EEG signal i.e. the distribution of power over frequency. PSD analysis is a mathematical technique which has been used for the analysis of frequencies of EEG signals using Fourier transformations [30]. EEG patterns have been examined for resting state and cognitive workload state to investigate task-related modulation of spectral power of EEG in various subjects.

III. MATERIALS & METHODS

This research proposes the setup design for feature extraction and analysis of EEG signals to differentiate resting state and cognitive workload state. Block diagram of the EEG based system to differentiate resting state and cognitive workload state is shown in Fig.1.

(i) EEG Signal Acquisition

The spectral analysis of EEG signals has been done in MATLAB (R2016a, 64bit). The EEG signals have been loaded from online database Physiobank ATM to Matlab workspace using 'edfread' command for further processing. EEG signal dataset in the desired format is introduced from the EEG during the mental arithmetic task database of Physiobank ATM. In this database, EEG signals have been recorded using the Neurocom EEG 23-channel system. The database of EEG signals has been acquired from subjects before and during the performance of mental arithmetic tasks using different channels of the 10-20 EEG signal acquisition system. An EEG signal of five subjects, before the mental arithmetic task and during the arithmetic task has been considered in the proposed work. The arithmetic task during the recording is the serial subtraction of two numbers [31-32].

(ii) EEG artifact elimination

As literature findings show eradication of different types of artifacts in encephalogram is crucial. After loading the EEG signals from online database Physiobank ATM, the artifact has been removed using a bandpass filter. A bandpass filter is used to eliminate the low and high frequency noises with a cut off frequency of 0.1- 25 Hz.

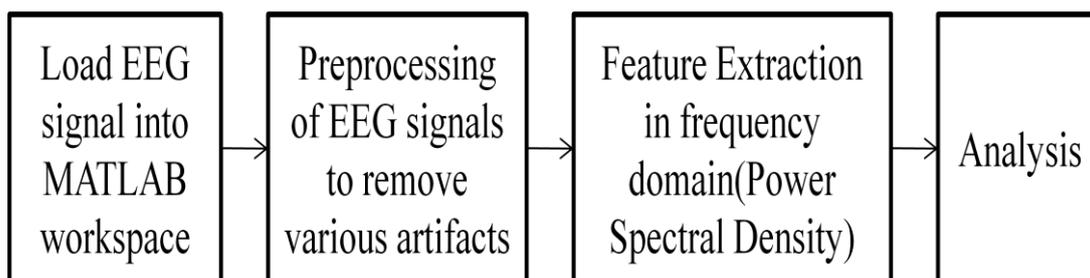


Fig.1. Block diagram of the proposed EEG system to differentiate resting state and cognitive workload state

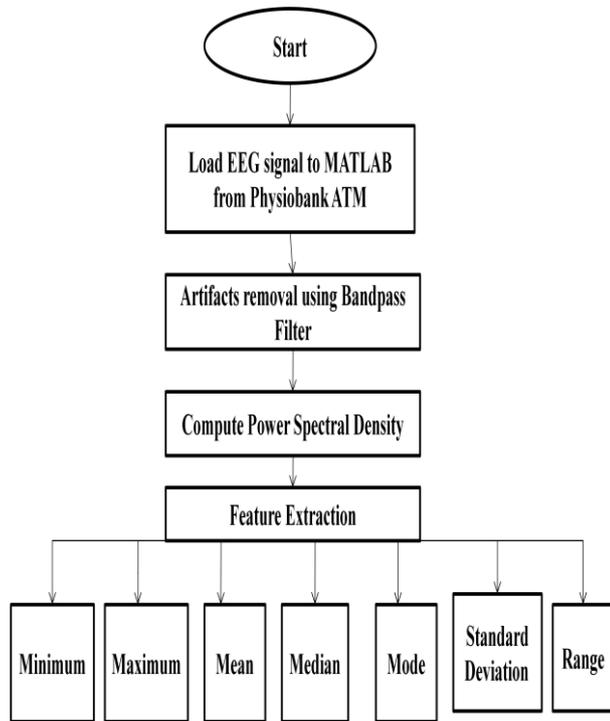


Fig.2. Detailed workflow of the proposed EEG system to differentiate resting state and cognitive workload state
(iii) EEG Signal Processing

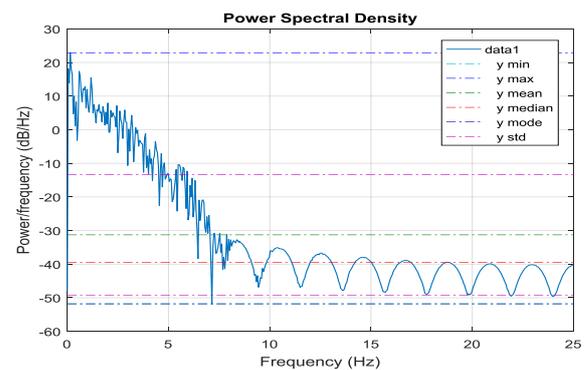
In Matlab, EEG signals have been loaded and then noise has been eliminated in loaded EEG signals. The feature extraction has been done in the frequency domain. Fig.2 shows stages of the work employed in this study. There has a variety of potential techniques which has been used in EEG signal analysis with feature extraction to be made in the frequency domain, time domain or both the domains. The spectral analysis can be done in two ways parametric and nonparametric. Here, nonparametric FFT (Fast Fourier Transform) has been employed to obtain the power spectral density of the loaded EEG signals. The FFT involves a signal length of some power of two for the transform and divide the procedure into cascading groups of 2 to develop the symmetries which considerably improves its processing speed. Therefore, before applying the FFT algorithm, the matlab function `nextpow2` has been used to pad the signal which fastens the computation of the FFT when the signal length is not an exact power of 2. A discrete Fourier transform of artifacts free EEG signal has been computed using an FFT algorithm and then using `abs` function, the absolute value of each element in the array has been calculated and power spectral density of EEG signals have been plotted. With power spectral analysis of the EEG signal, following statistical parameters have been calculated:-

1. Minimum- Smallest or minimum value of the power frequency.
2. Maximum- Largest or maximum value of the power frequency.
3. Mean – Average of all sample of power frequency of EEG signal.
4. Median- median of the power frequency of the EEG signal.
5. Mode- The frequent occurrence of the power frequency of the EEG signal.
6. Std- Standard deviation evaluates electrodes power frequency deviation from a mean value.

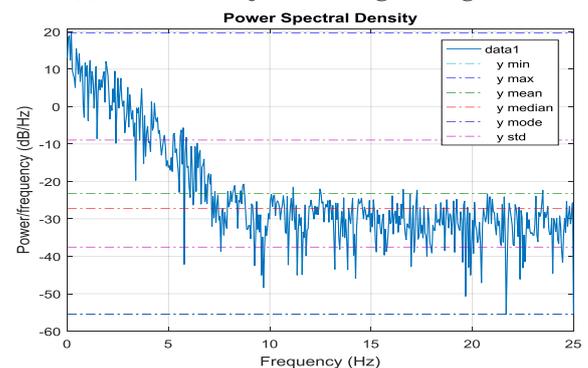
7. Range- The range is the difference obtained between the minimum and maximum values in the power frequency. The loading of EEG signals to MATLAB workspace, preprocessing of EEG signals and computational of power spectral density with feature extraction minimum, maximum, mean, median, mode, standard deviation and range can be summed up in the form of a competent MATLAB algorithm, as shown in Fig.2.

IV. RESULTS AND DISCUSSION

The algorithm to compute power spectral of EEG signal has been implemented in MATLAB release (R2016a). The description of the results obtained and its analysis is discussed. The power spectral density of 5 different subjects during resting and cognitive workload state has been shown in Fig.2. It shows that there is the variation in the power intensity and slight frequency shift was observed in different participants. The artifact-free EEG signals have been extracted for spectral analysis using Fast Fourier Transformation algorithm in MATLAB and power density spectrum in frequency band 0.1 Hz to 25Hz of every subject during resting and cognitive workload state has been plotted for all five subjects.



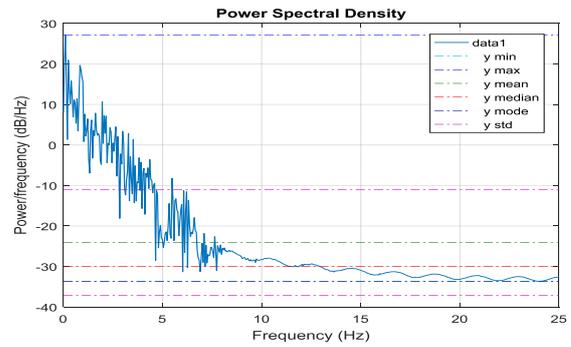
(a) PSD of Subject1 during resting state



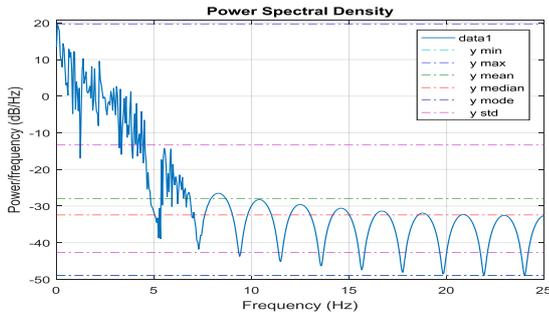
(b) PSD of Subject1 during cognitive workload state



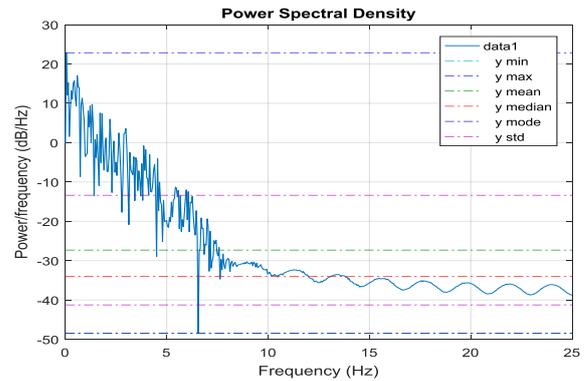
(c) PSD of Subject2 during resting state



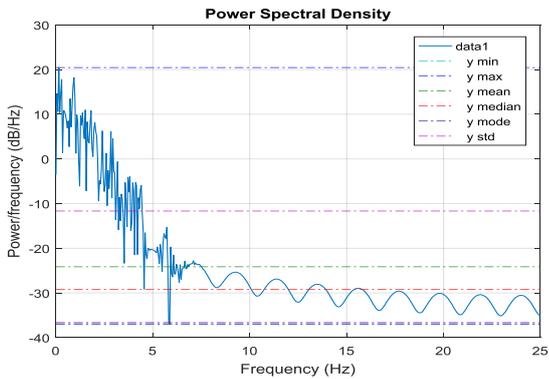
(g) PSD of Subject4 during resting state



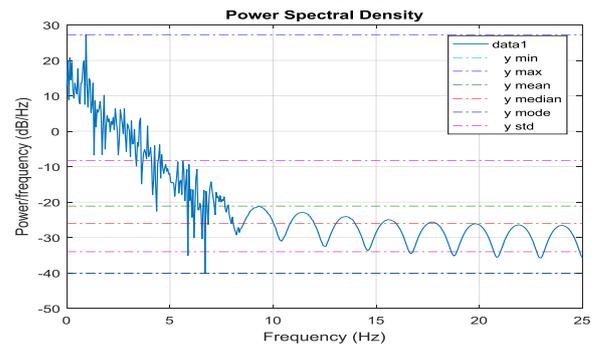
(d) PSD of Subject2 during cognitive workload state



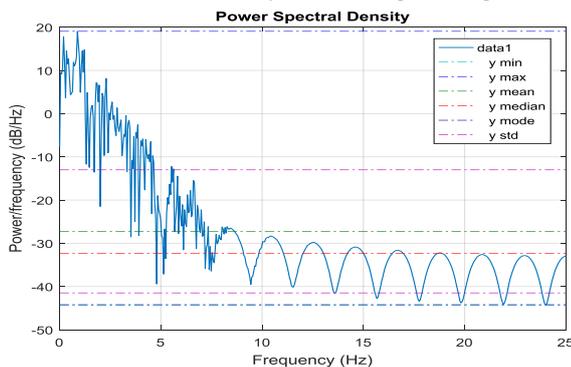
(h) PSD of Subject4 during cognitive workload state



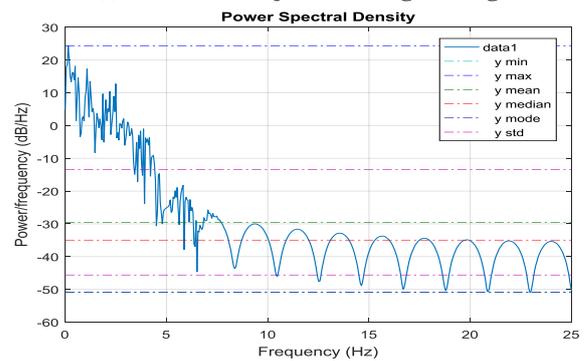
(e) PSD of Subject3 during resting state



(i) PSD of Subject5 during resting state



(f) PSD of Subject3 during cognitive workload state



(j) PSD of Subject5 during cognitive workload state

Fig.3. Power Spectral Densities of various subjects using FFT algorithm in resting and cognitive workload state.

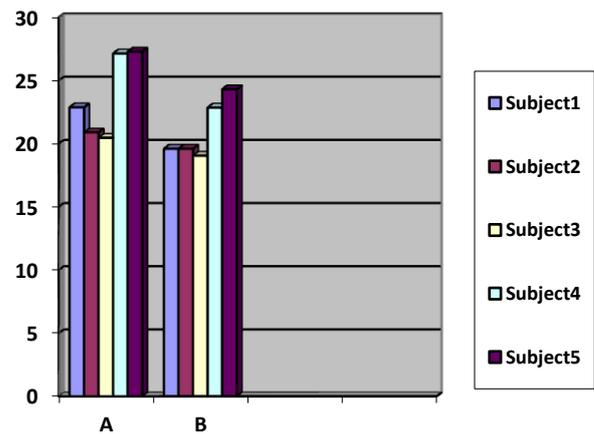
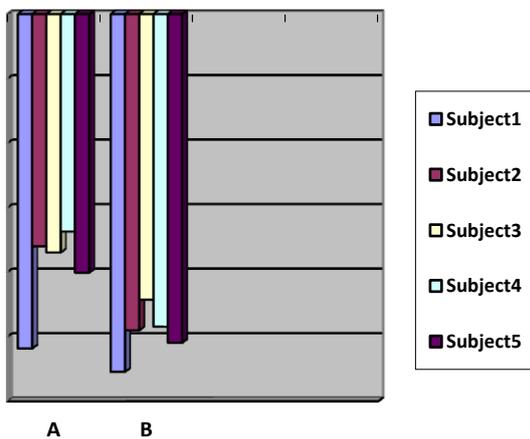
Fig.3 shows power spectral density plots of EEG signals of five subjects during resting state and cognitive workload state. As there have been significant differences in power spectral density of resting and cognitive workload states, it is considered as an excellent option for a feature extraction technique. It could also be used as an indicator of cognitive workload. These power peaks were common, both in resting and cognitive state though slight variation such as power intensity and slight frequency shift (between 7Hz and 25Hz)

has been observed in different participants. The maximum signal power is up to 27.28 dB during resting state while in the cognitive state it is 24.3 dB having a frequency range of 0-5 Hz. Table.1 shows that statistical parameters: minimum, maximum, mean, median, mode, standard deviation and range of the power frequency of the EEG signal have been calculated.

The value of the various parameters for five subjects during resting state and cognitive workload state. The average values of the statistical parameters in table shows that in cognitive workload state there is significant variation in the parameters as compared to the resting state.

Table-I: Data Statistics obtained for Power Spectral Density of five Subjects during resting and cognitive workload state

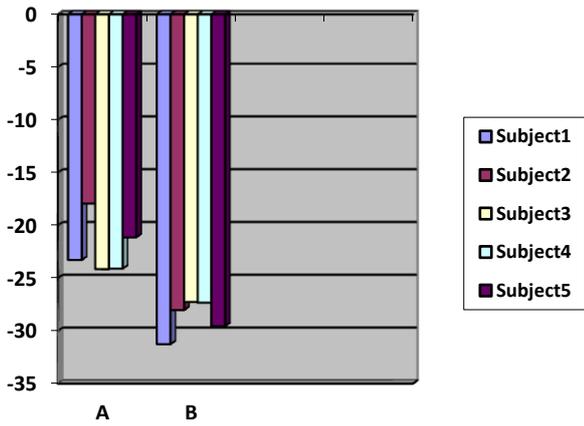
	Subject1		Subject2		Subject3		Subject4		Subject5		Average of 5 subjects	
	Resting State	Cognitive Workload State	Resting State	Cognitive Workload State								
Min	-51.8	-55.43	-35.98	-48.99	-36.92	-44.24	-33.68	-48.43	-40.06	-50.93	-39.69	-49.60
Max	22.87	19.6	20.89	19.6	20.46	19.05	27.13	22.85	27.28	24.3	23.73	21.08
Mean	-23.27	-31.25	-17.93	-28.02	-24.14	-27.25	-24.09	-27.32	-21.12	-29.54	-22.11	-28.68
Median	-27.46	-39.28	-22.38	-32.43	-29.19	-32.37	-30.03	-33.97	-26.09	-34.96	-27.03	-34.60
Mode	-51.8	-55.43	-35.98	-48.98	-36.92	-44.24	-33.68	-48.43	-40.06	-50.93	-39.69	-49.60
Std	14.91	17.29	10.7	14.67	12.48	14.23	13.02	13.94	12.9	16.07	12.80	15.24
Range	74.66	75.03	56.87	68.58	57.38	63.29	60.81	71.28	67.33	75.23	63.41	70.68



- A- Resting State
- B- Cognitive Workload State
- (a) Analysis of Minimum of Power frequency of various subjects for Resting & Cognitive State

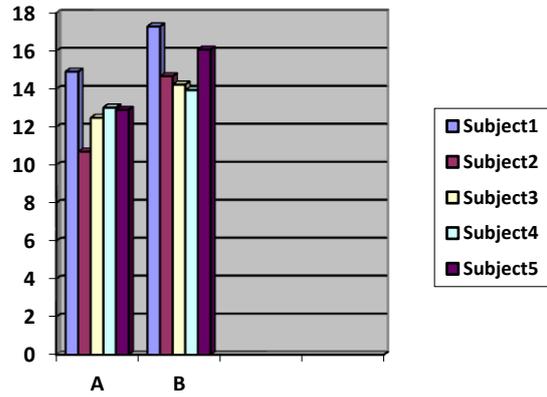
- A- Resting State
- B- Cognitive Workload State
- (b) Analysis of Maximum of Power frequency of various subjects for Resting & Cognitive State

A cognitive workload identification using EEG Power Spectrum



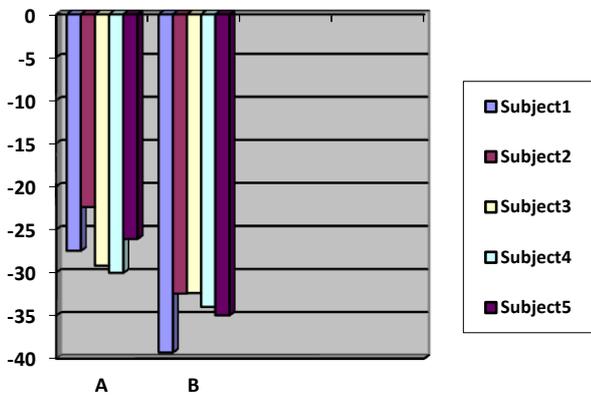
A- Resting State
B- Cognitive Workload State

(c) Analysis of Mean of Power frequency of various subjects for Resting & Cognitive State



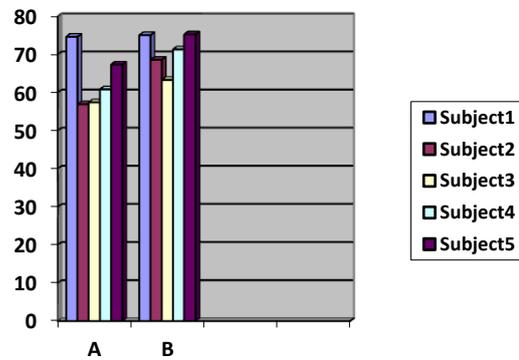
A- Resting State
B- Cognitive Workload State

(f) Analysis of Standard deviation of Power frequency of various subjects for Resting & Cognitive State



A- Resting State
B- Cognitive Workload State

(c) Analysis of Median of Power frequency of various subjects for Resting & Cognitive State

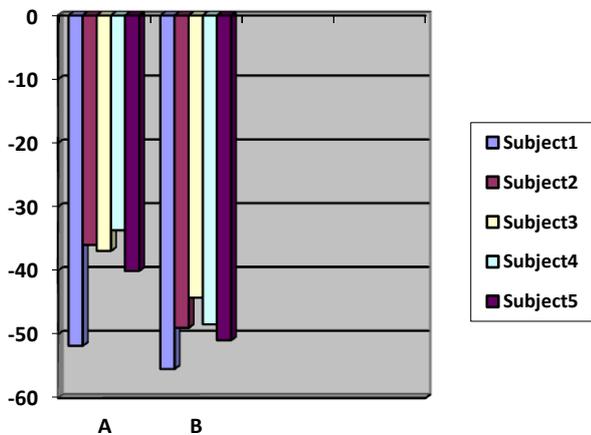


A- Resting State
B- Cognitive Workload State

(g) Analysis of Range of Power frequency of various subjects for Resting & Cognitive State

Fig.4. Analysis of Statistical Parameters of Power frequency of various subjects for Resting & Cognitive State

The statistical parameters of various subjects during resting state and cognitive workload state for EEG signal preprocessing has been depicted in Fig.4. The analysis of a minimum of power frequency(Fig.4(a)) shows that with the cognitive workload the minimum power decreases and Fig.4(b) represents that with the cognitive workload maximum power decreases as average values during resting state comes out is 23.73 and during cognitive workload, it's 21.08. Mean during resting state is more than mean during cognitive workload state as shown in Fig.4(c). The average values of median during resting state comes out to be -27.03 and during cognitive workload state, it is -34.60 as shown in the analysis Fig.4 (d) shows that median decreases with the cognitive workload. The same trend comes out for mode as shown in Fig.4 (e). The standard deviation increases with the cognitive workload. The average value of the standard deviation is 12.80 during resting state and 15.24 during cognitive workload state shows that during cognitive workload state fluctuation from the mean increases as compared to the resting state (Fig.4 (f)).



A- Resting State
B- Cognitive Workload State

(e) Analysis of Mode of Power frequency of various subjects for Resting & Cognitive State

The analysis of range shown in Fig.4 (g) shows that range increases during cognitive workload as compared to the resting state. It has been concluded that oscillations decrease in the cognitive workload state as compared to resting state. These decreases have been mainly located in parietal and temporal brain regions.

IV. CONCLUSION

At the outset, human brain behavior is a potential thrust in building the robust machine learning devices of the future technological devices. The study of brain signal is fundamentally classified into two approaches: primarily it can be carried out by employing EEG signals and the second approach involves the use of Electromagnetic waves. In this paper, the EEG signal approach for the analysis of the brain cognitive functions is studied. The limitations of the previously done work in this domain have been highlighted which will act as a strong launch pad for further research. Primarily the EEG should be captured using the low-cost headset which makes EEG as a propitious tool for continuous measurement of the cognitive workload. Enhanced EEG acquisition systems, robust signal processing algorithms, and classification rules are required to be developed to observe delicate changes in brain waves when subjected to cognitive tasks. EEG signals have been preprocessed before computing power spectral density of the EEG signal during resting and cognitive workload state. The analysis of statistical parameters (minimum, maximum, mean, median, mode, standard deviation, range) shows that in cognitive workload state, capable changes have been seen in power frequencies if compared to resting state. The power spectral density using FFT as a feature extraction technique is continued to use in the future.

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