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Detection of Auditory Response in Human Brain using EEG

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***Abstract*—EEG alpha-band activity generally represents inhibitory state related to decreased attention and plays a role in suppression of task-relevant information. Here we use EEG for a whole-brain analysis to study the effects of pre-stimulus alpha activity on event based BOLD give an auditory response and filter out the alpha region from EEG. Many methods have already been used but we change the filters and try to incorporate accuracy, precision. The detection of alpha can analyze the active region of the brain.**

***Index Terms*— EEG, alpha signals, auditory oddball task, signal extraction, filters and active region.**

I. INTRODUCTION

Analysis of brain signals in human can help patients who suffer from ill health, communication between the brain and a body. Electroencephalography (EEG) is a medical imaging technique that reads scalp electrical activity generated by brain structures. The electroencephalogram (EEG) is defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media.It consists of different brain waves reflecting brain electrical activity according to electrode placements and functioning in the adjacent brain regions. Brain patterns form wave shapes that are commonly sinusoidal. By means Fourier transform power spectrum from the raw EEG signal is derived. It is categorized in to four basic groups. The best known and most extensively studied rhythm of human brain is the normal alpha rhythm. Alpha can be usually observed in the posterior and occipital regions with typical amplitude about 50 µV (peak-peak). Most of the people are sensitive to eyes closing. In relaxation or drowsiness alpha activity rises [1].

Feature extraction of EEG signals is very important and core issues on EEG base brain mapping analysis [1]. EEG signals can be classified using set of features like auto regression, Energy spectrum density and linear complexity [2]. To isolate alpha waves, signals can be filtered using band pass filter (Butterworth second order filter, 8-14 Hz. Studies shows that some frontal site responded to both auditory and visual stimuli while other sites responded on to auditory stimuli. This leads to take auditory response in human brain instead of considering visual oddball tasks [3]. Extraction of alpha signal is essential to learn about active regions present in brain during a particular auditory oddball task. Auditory evoked potential used as a significant tool in determining the threshold levels of a person. AEP can be used to detect and estimate the hearing levels from severe to profound hearing impairment. Trends of certain linear and non-linear measures indicates that

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Audio Visual Stimulation training may serve useful tool for evoking long term changes in resting EEG The distribution of alpha activity resembles the distribution of haemodynamic response as measured with functional magnetic resonance imaging techniques (BOLD effect); both are high in functionally active cortical region.

To improve EEG signals, Neural Network based techniques based on average method and Max. Min method are used. But accuracy of Max,Min method and average method is 80% and 40%.[21]Visual Stimulus-dependent Changes in Interhemispheric EEG Coherence in Humans in this paper, they observed a decreased power in the alpha band during visual stimulation with gratings, compared with the uniformly illuminaed screen. In humans ,interhemispheric synchronization in the alpha band was shown to be dependent on the integrity of the corpus callosum(CC) in the resting state. [18] Responses to a Meaningful Auditory Stimulus in the Frontal Lobes: an Intracerebral Study in Humans, in this paper the analyzed data can only give the information on brain areas which were selected without regard to the function studied. EEG Feature Extraction for Classifying Emotions using FCM and FKM.[18] In this paper the clustering is a form of unsupervised learning that helps to find the inherent structure in data.

A large amount of data received from even one single EEG recording presents a difficulty for interpretation. Main difficulty that faces in analyzing EEG signal is noise sources. It is necessary to design specific filter to remove noise from EEG signals. In this paper we analyze the previously used methods and found out the parameters of the EEG signals and thus find out a better method of extraction of data.

II. METHODOLOGY

In order to study about the EEG data first of all we collected the raw datasets as mentioned in the first paper. There were 14 sets of data that had different extensions. These data sets are obtained from a standard research paper. These databases are obtained from BOLD responses after performing auditory oddball task.The auditory oddball task refers to the response of the brain to a single auditory task by concentrating the other senses in other activities.Suppose, these patients were asked to concentyrate on a switch and auditory signals with sudden peaks were sent to them,thus the EEG corresponding to it is recorded.Both EEG and MRI were stored under different extensions. This was then decoded using different softwares in order to make the data compatible with MATLAB version 2016.Since we are about to analyse the performance of the human brain using a particular portion of the EEG ,the use of filters is inevitable. At first the entire EEG was plotted using EEGlab a software supported by MATLAB. Then the alpha was extracted primarily using Butterworth filter. Butterworth filter has a fairly straight response and has a sharp cut off frequency. After that Fast Fourier transform was performed in order to analyse the data in frequency spectrum.The alpha waves range is rhythmic of 8-13Hz, mostly on occipital lobe voltage of 20-200 μ V,it will be normal, relaxed awake rhythm with eyes closed. The Beta waves range is irregular, 14-30 Hz, mostly on temporal and frontal lobe it monitor the mental activity and excitement. The theta waves range is rhythmic, 4-7 Hz,it monitor the Drowsy, sleep. The delta waves range is slow < 3.5 Hz. it will monitor in adults of normal sleep rhythm. Based on this waves from EEG signals we can determine the diseases by using EEG. These methods were proposed in the paper prestimulus EEG alpha oscillations modulate task related fMRI BOLD responses to auditory stimuli.In order to give our own contribution we altered the filters used and also changed the frequency domain analysis function. The wavelet transform was used and periodogram function was used for frequency domain analysis but that also couldn’t help us gain exact numerical values. Then we tried a very common filter known as Kalman filter.Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe. The filter is named after Rudolf E. Kálmán, one of the primary developers of its theory. This filter is a future predictive one. By calculating the values that are available the filter will remove artifacts and other undesirable components. The mean and variance of a database after the application of this filter are: From this we can understand that the accuracy and precision are improved. In order to display the BOLD responses, another software known as brainstorm was used. It displayed the MRI images with the position and the value of brain activity. Thus we can analyse from the 3D brain image and the brainstorm image the exact position of a particular signal.

III. RESULTS AND DISCUSSIONS

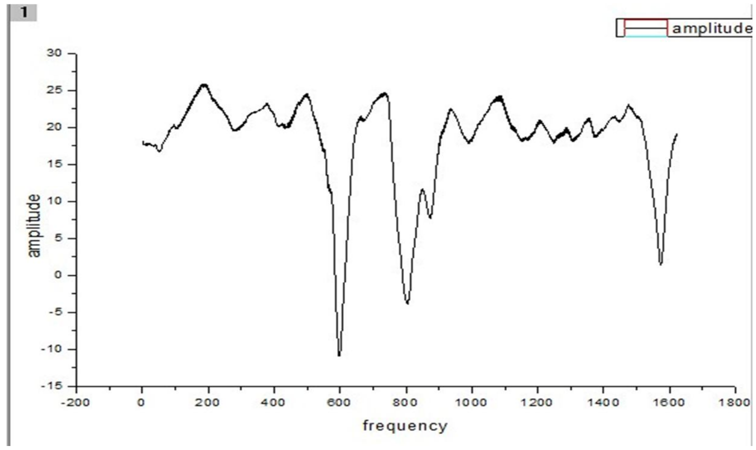

Figure.1.Graph of amplitude v/s frequency showing EEG alpha response

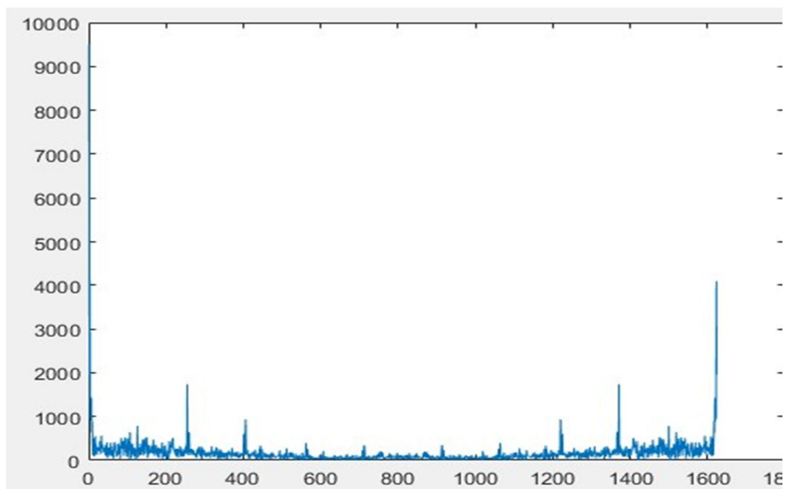

Figure.2.Frequency spectrum and related color code to depict different colours

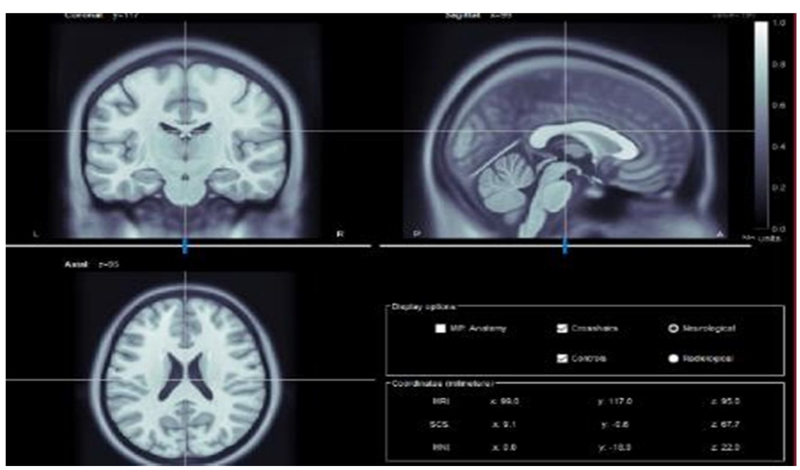

Figure.3.FMRI response to identify different prestimulus activity affecting bold response on the auditory oddball mechanism

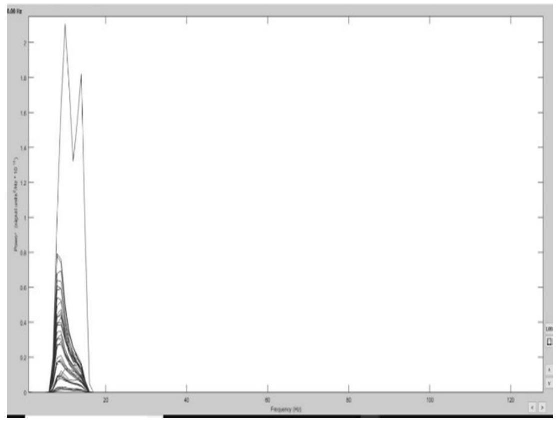

Figure.4.Positions of the brain and respective eeg signals from those position

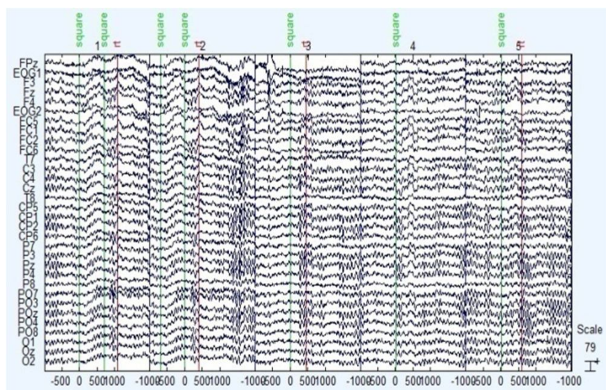

Figure.5. Frequency spectrum with distribution of alpha waves from brain

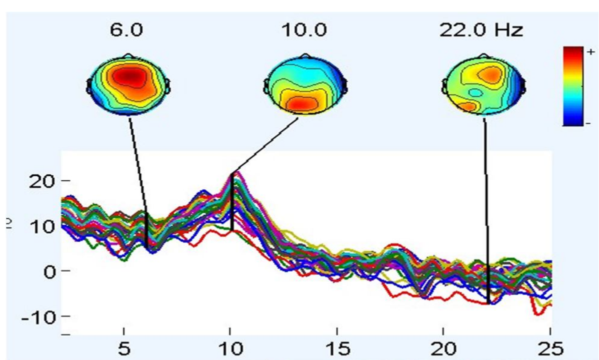

Figure.6.Response of various regions of brain measured with the colour distributions

Fig.1 shows a frequency vs amplitude graph and. Ideally these graphs should be as straight horizontally as possible. (It is not really that simple, but it's a useful simplification.) An input of the same amplitude should give the same output no matter what frequency, but real life isn't like that. As you see from the graph, the lower one comes closer to the ideal if you want truthful reproduction of eeg. That might not be what you want, but you can see on the graph at the top that the frequency response is quite uneven, with quite steep dips. But , aside from the presence peaks, you want to see consistency. Between 600 to 800 Hz the response reaches negative values showing it will have better low end response. Highest peak is observed at 100-200 Hz which would mean they have a more pronounced very low end of the midrange. Analysis of Fig.2 shows the alpha estimation using kalman filter. It estimates the value of state variable and corrected signal by removing artifacts. For this it uses covariance noise models for states and observation. Using these a time dependent estimate of state covariance is updated and from this kalman gain matrix term is calculated. The filter also minimizes the mean square. Fig.3 describes about the idea that Group level average fMRI BOLD response to auditory target stimuli Statistical maps are displayed on an MNI template brain using radiological coordinates, and z- coordinate is displayed to the lower left of each axial slice. scalp EEG with simultaneously acquired fMRI, and treat the blood oxygen level dependent (BOLD) response as a measure of task-related neural processing. Statistical maps are displayed on an MNI template brain using radiological coordinates. An inverse correlation between prestimulus alpha power and the BOLD response was seen throughout many posterior regions, suggesting a possible confound with underlying alpha–BOLD coupling. From Fig.4, it is given that the PSD for alpha in EEG signal shows strength of energy as a function of frequency. Alpha generated in drowsiness and normal relaxed stages. Hence dominate rhythm is in subjects with closed eyes in frontal, central and parietal lobes. Here shows maximum power range of 20 in frequency range between 8-14 Hz.Some limes of artifacts are seen in this graph. From the Fig.5 we can analyze the output from each lead of the electrodes that are placed on the scalp. The electrodes are placed at a 10-20 spacing which means comparing the total space, the spacing between electrodes is 10-20%.The name and the positioning of the electrodes can be alternated by the display. The output from the required leads are cumulatively analyzed.

The leads are viable to artefact due to EMG signals or magnetic fields and so on. Effect of preistimulus alpha phase on BOLD response to auditory targets is shown in Fig 6. Decision-related BOLD activity in bilateral thalamic regions was stronger when the stimulus was presented during the trough vs. the peak of the alpha wave. in the auditory domain, explored task-relevant stimulus processing (as opposed to distracter stimuli that were unrelated to the task), and we investigated decision-related processing by contrasting the target vs. standard BOLD responses. Particularly those in frontal regions traditionally associated with executive processing suggest that alpha power modulates decision-related activity significantly downstream from sensory processing. The hypothesized active processing role of alpha suggests such an effect for task-relevant stimulus processing in higher regions.

IV. Conclusion

In the past 5 years, considerable progress has been made on several fronts in combined EEG and f MRI studies of human brain function; we have again reviewed the current state of the knowledge of auditory evoked potential used as a significant tool in determining the threshold levels of a person. An area that clearly needs further research is the development, and validation, of procedures and algorithms for biophysical modeling of EEG and fMRI signals. Such models will help researchers to better integrate spatial and temporal information in fMRI and EEG.Finally, we note that although clinical applications have thus far been limited to epilepsy, in the future combined EEG and fMRI studies will also provide new insights into the dynamical bases of psychiatric, neurological.The task relevant stimulus processing investigates the decision related processing by contrasting the target vs standard bold responses .Implementation of Kalman's filter make a better response, We similarly found that decision-related BOLD activity in bilateral thalamic regions was stronger when the stimulus was presented during the trough vs. the peak of the alpha wave. We show that prestimulus power and phase of the posterior alpha oscillation differently influence task- relevant auditory stimulus processing. Our results show that prestimulus alpha power has a modulatory role (gain effect) that boosts higher-level processing related to task performance (e.g. performance monitoring) but does not show this gain effect in primary sensory areas, at least not for our easy auditory perceptual decision-making task. With this study, we move toward a deeper understanding of the role of the posterior cortical alpha rhythm in auditory task- related processing occurring across the entire brain.

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