EEG Correlates of Visual Signal Processing: Spectral Decomposition using ICA

Vamsi Krishna Vadla, Ramesh Naidu Annavarapu

***Abstract:** Studies on signal processing of biological activities is a way to ascertain the anatomical and functional behavior of complex systems. Many biomedical signals represent their significance for understanding the systems, like ECG signals of heart and EEG, MEG signals of brain's electro- and magneto-behavior reveals their importance. Availability of enormous amount of EEG data, with unwanted noise and artifacts, from complex systems, is challenging to uncover the underlying dynamics of signals sources. Functional analysis of this data requires various methods to remove the artifacts and noise present in it and further investigation of the system dynamics. In this paper, we discussed the removal of artifacts and noise from brain's EEG activity to achieve artifact rejections of continuous EEG data and to apply Independent Component Analysis (ICA) to analyze the event-related tasks. Cluster decomposed signal components allow us to visualize the independent components of any number of subjects and subject groups. Differentiating vast electrical activity of an abnormal subject in comparison with a normal subject is possible with the decomposing signal. ICA approach helps in correlating the event-related EEG signals for a subject in two or more conditions of the same experiment; hence, it suggests in creating the data sets of epochs for every condition.*

***Keywords:** Artifacts, brain rhythms, electroencephalogram, event-related potentials, independent component analysis, spectral density*.

I. INTRODUCTION

Electroencephalogram measures the electrical activity of the scalp regions of the brain [Vogel F(1970), Annavarapu R. N.et al, (2019)]. Neurons are the fundamental units of the brain and nervous system. A neuron receives and sends electrical signals over long distances within the body. EEG records these charge flow, as currents at the synaptic excitation of pre- and post-synaptic neurons in the cortex region. Neurons in the cerebral cortex are responsible for higher-order functions like information, thought processing and language. Mostly, firing patterns of EEG signals are due to well-aligned pyramidal neurons in the cortex [Silva, L. R (1991)]. One of the common issues from the measured EEG signals is the electrical potential from the non-brain origin, which might be due to instruments and source environment [Islam, M. K et al, (2013), Attarian H.P., Undevia N.S. (2012), Coburn, K. L., & Moreno, M. A. (1988)]. Biological artifacts like eye-blinks, muscle, and teeth movements are common in EEG recordings [Babušiak B., Mohylová J. (2009), Joyce, C. A., (2004)]. Presence of ocular artifacts contaminates mostly the delta band [Romero, S.,(2003), Vigário, R. N. (1997)].

A wide variety of methods is available in the literature to suppress the artifacts from measured EEG signals [Roháľová, M.,et al (2001), Miwakeichi, F., et al (2004), Park, H. J., et al (2002)]. We have decomposed the EEG signals using the independent component analysis (ICA) for signal analysis [Lee, T. W. (1998), Viola, F. C., et al (2009)]. ICA assumes that the signal recorded at each electrode of EEG is a linear combination of sources. When we analyze multivariate data at each recorded single channel, signals processed via a group of simultaneously recorded outputs [Hyvärinen, A., & Oja, E. (2000)]. ICA decomposition involves statistically maximum independence of the processed signals to produce maximum temporal independent signals [Vigário, R., et al (2000), Sun, L., (2005), Comon, P. (1994)]. Using the dimension reduction of principle component analysis (PCA) minimizes the nature of independent components of EEG [Artoni Fet al, (2018)]. Algorithms of ICA play a key role in identification and localization of neural generators [Dale, A. M., & Sereno, M. I. (1993)]. The ERP studies proved the importance of using them in the theories of attention and perception [Woodman, G. F. (2010)].

II. ELECTROENCEPHALOGRAM

Electroencephalogram (EEG) is a non-invasive neuroimaging modality used for the recording of electrical activity of firing neurons in the brain. Communication between neurons is responsible for the electrical activity in the brain. EEG records activities like visual, auditory and sensory stimuli and sends to the brain. In the cerebral cortex of the brain, the neurons process the data in response to external stimuli.

EEG has an advantage of temporal resolution over spatial resolution. Due to intrinsic temporal properties of neural activation, EEG measurements are prominent for analyzing scalp signals. EEG is used to differentiate between the abnormal from normal subjects. Millisecond domain of EEG temporal resolution indicates ideal measuring linking neural activation. Moreover, changes in neuronal activation instantaneously reflected in changes in EEG, whereas with hemodynamic measures such as functional magnetic resonance imaging (fMRI) there is a lag between the neuronal response and the onset of a corresponding Hemodynamic change [Casey, B. J., et al (1996)]. Measures derived from the electrical activity of the brain are thus ideally suited for tracking the neural changes coincident with rapid phasic changes in the behavioral state [Stern, J. M. (2013)].

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All thoughts, emotions, and behavior are a representation of communication of neurons among themselves and within the brain. Brain waves represent the electrical activity through which neurons communicate with each other. Measured EEG signals are classified according to their frequency, measured in Hertz, to understand their functioning in the brain. Frequencies of EEG in different bands reflect the behavioral performance of human beings [Klimesch, W. (1999)]. Though it is complex to distinguish them, their function is different in different locations. Mostly they are divided into slow, moderate and fast waves [Stern, J. M. (2013)].

Gamma waves have high frequencies ranging between 38-42 Hz and they involve in cognitive processes like learning, memory and information processing. Beta waves range from 12-38 Hz and of high frequency but lower amplitude. Beta waves are dominant in awakened state. Logical thinking, decision-making, problem solving are several events to raise beta waves. Alpha waves found in relaxed state or visualizing of some imaginary senses of auditory, visual, taste and smell. Typically, alpha waves range between 8-12 Hz. Theta waves have frequency range 3-8 Hz. They are seen in meditation state and normally in young children. Theta waves seen in the metabolic encephalopathy or deep mid-line disorders are some instances of hydrocephalus. Delta waves range up to 1-4 Hz and are present in deep sleep state.

Removal of artifacts recorded in EEG signal data, including but not limited to electromyography (EMG) is the fundamental problem faced by EEG researchers [Urrestarazu, E., et al (2004)]. The instrumentation involved in EEG is insensitive to other non-biological sources, which influence the data. For example, if 60 Hz noise from nearby electrical devices is present and its noise source cannot be located, 60 Hz notch filters may be used either offline or during data collection to reduce the effect of the noise source on the data. High electrode impedances or a faulty ground connection can exacerbate 60 Hz noise problems. Other sources of artifacts direct from the recording electrodes, due to contact mismatches and care must be taken to see that the electrodes are carefully cleaned after every use to avoid corrosion and to avoid the build-up of electrical potentials across the electrode surface. Ocular frequencies are in the range of (0-16Hz) [Krishnaveni, V., et al (2006)].

The standard 10-20 system of EEG electrode location mappings is useful for electrode placements over the scalp. The location of these electrodes are based on the ratio of spacing between the electrode placements over the scalp area of cerebral cortex i.e., the numbers 10 and 20 refer to the inter-electrode spacing between them. Electrode locations are indicated by the first letter of the underlying lobe. Mostly C – Central lobe, F - Frontal lobe, O – Occipital lobe, P – Parietal lobe and T-Temporal lobe. Each electrode-placement indicated by a number or another letter to identify the hemisphere location. The ‘10’ and ‘20’ refers to the 10% and 20% inter-electrode distance [Homan, R. W., et al (1987)]. Generally, 8, 16, 32, 64, 128, 256 channel EEG instruments are available. The accuracy of EEG can be increased from high to low channel instruments. Figure 1 shows a 32-channel EEG employed in this recording along with the channel locations of EEG electrodes.

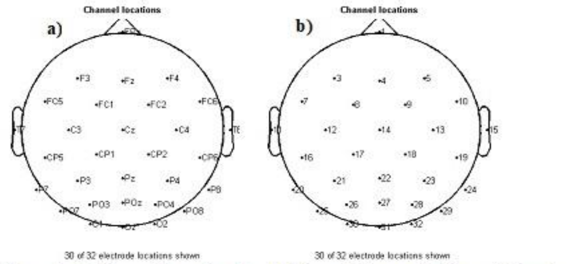

Figure.1: 32-Channel Locations by (a) Channel Name, (b) Channel Number

III. METHODS AND MATERIALS

Different parameters can characterize normal EEG. However, the most common parameters used to characterize the EEG are frequency and amplitude. A method for separation of a set of signals including noise without the knowledge of original signals involved and the process in which they are mixed up is known as Blind Source Separation. Here, we have difficulty in identifying the original signal, which is composed of artifacts. For the analysis of original signal sources, we approached methods to employ signal separation from the clustered signal measured at electrodes.

A) INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis is the method of decomposing a set of linearly mixed up data into its independent components because each measured signal is affected by underlying physical phenomenon [Stone, J. V. (2002)]. According to Hyvarinen and Oja [Hyvarinen, A., et al (2001)], the independent component analysis uses the model of statistical latent variables. In ICA, the sources for obtaining such mixed up signals are as follows:

(a) Recorded speech of a lecture in a class is mixed up with several unknown noises represents an example of the multivariate source.
(b) Signals measured from Electroencephalogram (EEG) and Magneto-encephalogram (MEG) are recorded with noise that arises from eye blinks, muscle movements, etc. [Makeig, S., et al (2002)].

To decompose the recorded signals using time-series, few assumptions are made in ICA. They are

(i) The currents measured at each scalp electrode are linear, provided signal conduction timings are similar.
(ii) Spatial arrangements are unchanged for every component across conditions and recorded timings.
(iii) All signal sources are assumed temporally independent from one another in the input signal.
(iv) The statistical distributions of components of signals are non-Gaussian [Jung, T. P., et al (2000)].

The advantages of using ICA on EEG data are that it provides a way to segregate the artefactual components originated from non-brain locations and ICA enables isolation of multi-component EEG waveforms of spatially-varying event-related potentials [Makeig, S., et al (1996)].

B) DATA DESCRIPTION

A spatial-visual attention data is used to analyze the ERP's, which directs the attention, evoked in the space over scalp region. Data is recorded using 32-Channel EEG during a visual selective process. Task intended to subjects is to press the button held at right-hand thumb in response to stimuli appearing in one of the five square blocks. The screen is designed to display five squares, where one is green in color and the rest in blue, where green square is marked as a location of stimulus, in the form of a white disc centered in green square [Makeig, S., et al (1999), Townsend, J., & Courchesne, E. (1994)]

Data is acquired through a visual task experiment, where the stimuli appear in the form of five squares which arranged in an array. In each event, the stimulus projected in a target box is differently colored from other squares. The task assigned to the subjects is to respond quickly whenever a squared element appears in the target box with right thumb (rt) press button and ignore if it falls in other geometry shapes like a circle or a sphere. The constructed data is a concatenation of three-second epochs from each subject; each squared target is represented by a square in the signal followed by the response of squared event represented using 'rt'. A 32-channel EEG is employed in recording the data of this experiment. Filtering of known frequencies is risk-free by selecting the desired frequencies manually. It is possible to filter the data within a range of frequencies. Figure 2 (a)-(d) shows the comparative filtering in low range frequencies at 2 Hz, 10 Hz and 20 Hz. The rejection of ocular artifacts is sensitive which are in the range of 0-16 Hz [Krishnaveni, V., et al (2006), Croft, R. J., & Barry, R. J (2000)].

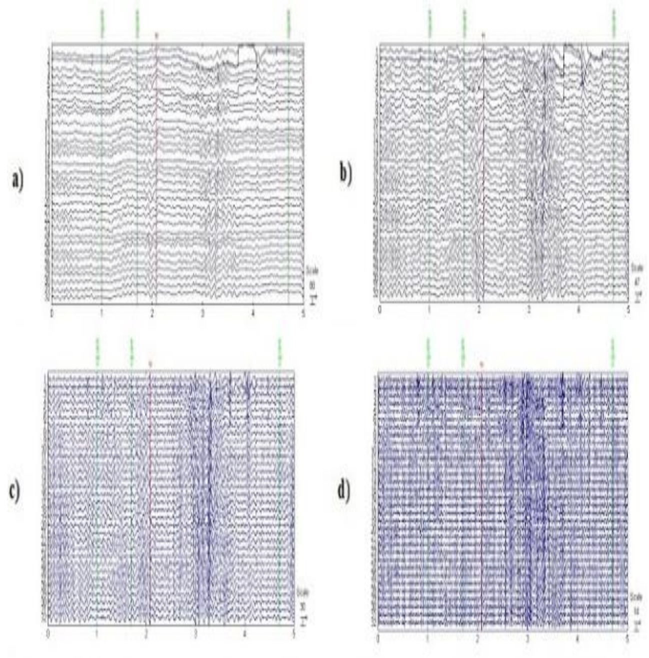

Figure.2: (a) unfiltered signal and (b), (c) and (d) are signals after applying filtering at 2 Hz, 10 Hz, 20 Hz

Using ICA, the channel properties of each electrode activity are drawn individually to examine their channel locations, data patterns and active power spectrum. Figure 3 (a)-(d) shows the spatially fixed neural generators involving in neural activations decomposed for channels 1-4 and their independent components.

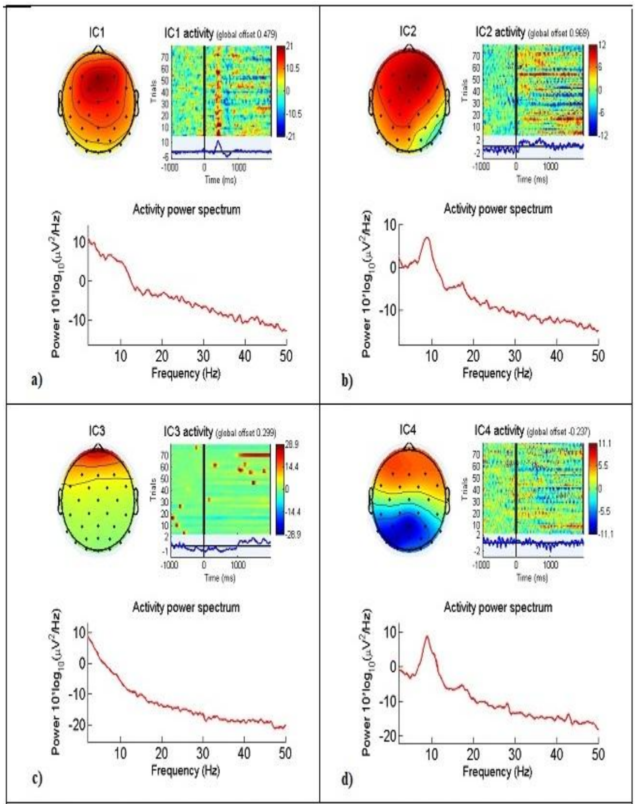

Fig.3: (a)-(d) ICA of channels-1, 2, 3, 4 along with scalp map, activity power spectrum and trail map

IV. RESULTS AND DISCUSSION

Decomposition of an EEG signal helps to uncover the underlying brain activity of a particular electrode, for a given stimulus. In this experiment, subjects are allowed to respond to a given task. Each EEG signal possesses information of the task along with artifacts. To avoid the noise and to ascertain event-related potentials (ERPs), we have carried out the independent component analysis on the obtained EEG data. We have constructed the data epochs from the continuously recorded EEG data to study the time-locked responses generated by the events of interest. Data epochs from continuous signal classify the onset of responses of a different class of stimulus that supports in extracting the potentials during the course of stimuli appeared. By data epoched time-locked events, one can analyze a signal over a range of time, where internal or external changes affect the neural responses. Hence, it suggests that while extracting the data epochs for small variations it is possible to correlate the event-related EEG signals for a subject in two or more conditions of the same experiment; hence, it recommends creating data sets of epochs for each condition. In this experiment, each event segregated as two halves, which corresponds to the first position and a second position, further to compute the grand mean of ERPs from two or more conditions. Consequently, it is possible to study the channel activity of a particular channel and it shows each channel activity in independent trails, as shown in ERP-image plot in figure 4 (a) and (b).

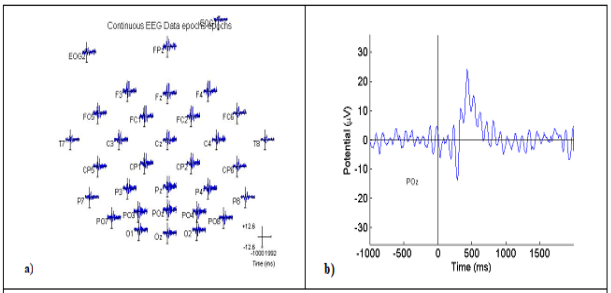

Figure.4: (a) Data epoch time-locked of ERP and (b) extraction of Poz ERP

Decomposing of data sets of EEG using ICA involves in maximizing the statistical independence of recorded data measured at each electrode i.e. each signal at a channel into independent components with the involvement of activation of spatially fixed neural generators. The measured process over the scalp by volume conduction is linear and passive which means it is a mixing process of several independent sources due to distinct functional behavior. Independent sources are due to the synchronous and partially synchronous contributions of both cortical and non-cortical activity. After ICA decomposition of data sets, one can unravel the contribution of electrodes at a particular frequency. Such analysis is used to find out the involvement of other parts of the brain for an ERP. It is possible to study the involvement of other brain areas when we measure a signal at a particular channel source. It helps to bridge the areas of the brain for event-related tasks. We have analyzed the ERP signal at a source channel along with the involvement of other sources with line artifacts, which projected along with the measured signal. At the frequencies of 5 Hz and 10 Hz, we have plotted the first three electrode contributions for the ERP analysis by other scalp areas which is shown in figure 5 (a)-(b).

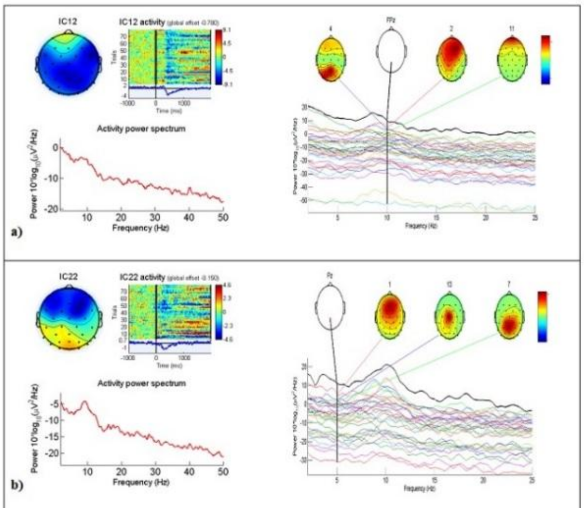

Fig.5: ICA analysis at frequencies (a) 10 Hz, (b) 5 Hz and maximum evoked potential channel contribution up to three channels

On arrival of stimuli to the subjects, non-stationarities of EEG wave-forms are identifications of changes in neural activations provide the information about its frequency and involvement of brain regions according to the task. In this way, the independent component analysis has the advantage to decompose a summed-EEG signal into actual individual signal components, without the information about source identification on scalp regions.

V. CONCLUSION

In this paper, we have discussed about how the independent component analysis is used to understand and ascertain the real-time behavior of signaling of the human brain. Estimation of independent components of signals provides the information about identification and localization of sources. Prediction of ERPs independent components helps in finding the brain regions in response to given event-related task. The extension of this work is to apply this procedure to a group of subjects, to determine the functional brain regions in response to the same task provided in the group. It helps to differentiate the functional brain regions of subjects based on the independent components, related to the event. Further studies using ICA involves the deeper understanding of computing ERPs, spectral densities and to measure the onto single-trail channel data. Such analysis allows to perform statistical comparison of multiple trails. Clustered decomposed signal components allow us to visualize the independent components of any number of subjects and subject groups. Differentiating vast electrical activity of an abnormal subject in comparison with a normal subject is possible with the decomposing signal.

VI. COMPLIANCE WITH ETHICAL GUIDELINES

This article does not contain any studies with human participants or animals performed by any of the authors. The data used in the analysis is open source, which is taken from the reference [33-34].

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CONFLICT OF INTEREST

The authors report no conflicts of interest.

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