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Classification of Brain Signals of Event Related Potentials using Different Methods of Feature Extraction

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Abstract— Electroencephalographic (EEG) recordings and processing open a window to have glance onto the commands running in human brain associated with task or thought. Non-invasive acquisition of EEG data has no harms or potential risks to the subject therefore it is best for the development of brain computer interface (BCI). Recorded brains waves are alternating voltage appearing on the human scalp associated with voluntary (event-related-potentials) and involuntary (artifacts) tasks of the brain. In this manner, the EEG signals existing on the surface of the scalp are in the form of mixture. Features of interest are extracted from the raw data by applying various mathematical models. In this study, non-invasive EEG data recorded from a healthy subject for up movement of right hand is processed using two feature extraction algorithms. This study also introduces a new algorithm based on independent component analysis (ICA) using co-efficient of determination. Results obtained by using proposed ICA algorithm are found to be in good agreement with those obtained using EEGLAB.

Index Terms— EEG, BCI, ICA, Signal processing, Artifacts, SNR, EEGLAB.

1 Introduction

BRAIN'S understanding is going to be very much enhanced in present-day life. It's the miracle of neuroscience that a person can have access directly to the feelings, thoughts, knowledge, intentions etc. of other person without the use of his/her ordinary communication channel [1], [2], [3]. There are numerous neuroimaging techniques that are used by neuroscientists to discover and record information of brain's functions [4]. These techniques are Steady State Topography (SST) [5]; brain tomography (BT), X-ray imaging of brain, electroencephalography (EEG), magnetic encephalography (MEG), positron emission topography (PET), functional magnetic resonance imaging (fMRI) [2], diffused tensor imaging (DTI) etc. [6]. Exciting and challenging facts about the structure and functioning of human brain are being disclosed reliably by using these technologies [7], [3].

Electroencephalography (EEG) is a superior technique [4] than others due to its better temporal resolution, portable and easy integration with other devices [6]. EEG is an imaging technology employed in the field of Biomedical through which electrical activities of brain's internal structure can be detected and recorded from scalp. These recordings are very useful to detect difference in mental activities during various actions of body parts (i.e. curling fingers, rising hand, moving leg etc.), different mental states and mental disorders as well. EEG signals clearly represent the pre-process, process and post-process patterns for an activity [4]. The electrical activities consist of alternating potentials which are recorded by placing metal electrodes on the scalp [8], [9]. Our thinking, imagination, actions, memories and feelings are representations of what happening in synapse. Synaptic shots make neurons polarized into dipoles which results voltage on cerebral cortex or scalp. Neural current consists of K+, Na+, Cl- and Ca++ [8]. A very large number of applications are associated with processing of the EEG measured signals now; these applications includes classification of mental tasks, seizure detection/prediction, classification of sleep stages, motor imagery classification, classification of emotions, lie detection [3] and drug diagnosis. There is great advancement in the EEG signal processing technique in the recent years that enable us to diagnose the disorder of the brain (brain diseases) as well as to develop communication between human brain and computer equipment's "Brain Computer Interface" (BCI) [10].

Brain Computer Interface is a system that allows to control outer devices and computers merely with encephalic activities independently from its natural pathways of peripheral nervous system [11], [12], [13]. The most important and critical step in designing the BCI application is the real-time processing and analysis of the EEG recorded signals. It is not an easy task to completely identify the mental state of subject from recorded EEG data because of very complex, non-stationary [14], noisy and highly dimensional nature of the signals. Therefore, specified signal processing techniques and programming tools (machine learning tools) are required to recognize mental state [15].

Signals of interest from complex brain activity may be distinguished by using support vector machine (SVM) [16], [2], principle component analysis (PCA), independent component analysis (ICA) [16], time-frequency distribution (TFD), Eigenvector method (EM), autoregressive method (ARM), wavelet transform packets (WT), Fourier transforms (FT) [17], standard deviation (STD) [9] and band power calculations (BPC) [18]. The comparison of five of mostly used techniques of EEG signal processing such as fast Fourier transform (FFT), wavelet (WT), autoregressive method (ARM) etc. was performed by [17] and concluded that each technique has its own specific advantages and disadvantages which make it specific for signal being analyzed. Therefore, the choice of method depends on the interests of application and information needed. As one gets more information of the mental states and the functioning of human brain can develop more powerful equipment with

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low cost per needs and the potentials of people who are suffering from disabilities.

2 Methods

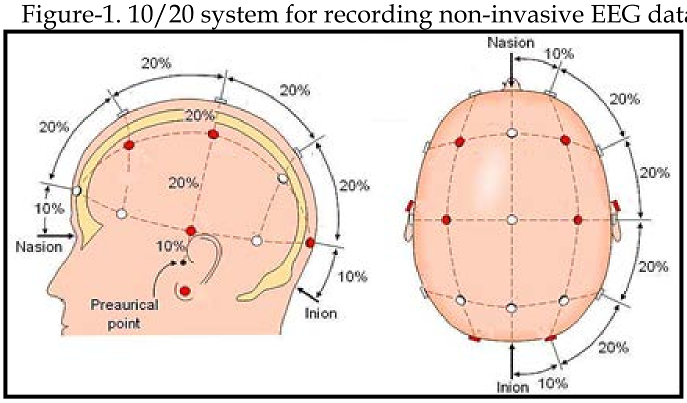
2.1 Experimental Paradigm

The volunteer or patient whose brain's signals are being recorded is known as the subject. In this research, the subject was a healthy woman, seated on a comfortable chair with open eyes observing on a screen present in front of her. The subject was taught about up movement of right hand when arrow appear on screen. The indicator shown on screen served as a stimulus in the response of which subject rise right hand gradually. EEG data was recorded by using 10/20 system with fourteen (14) electrode portable device. 10/20 system is recommended protocol of the "International Federation of Societies for Electroencephalography and Clinical Neurophysiology" [19]. During the data acquisition subject was also taught to avoid eye-blinking, producing motion in any other part of body or concentrating on any other thought/activity. Datasets were recorded for duration of about a minute long (63 seconds) and consist of more than eight thousand data points. The EEG data acquisition device has ability to record 128 data points per second (f = 128 Hz).

2.2 10/20 System & Electrode Placement

To measure the brain's generated signal by non-invasive technique an "international 10/20 system" is used for the placement of electrodes. Actually, this system refers to a relationship between positions of electrode and area of the cerebral cortex under it. The "10" and "20" are representing the "10%" and "20%" of the total length from front-to-back and left-to-right of the skull which are utilized as separation between two adjacent electrodes as shown in figure-1.

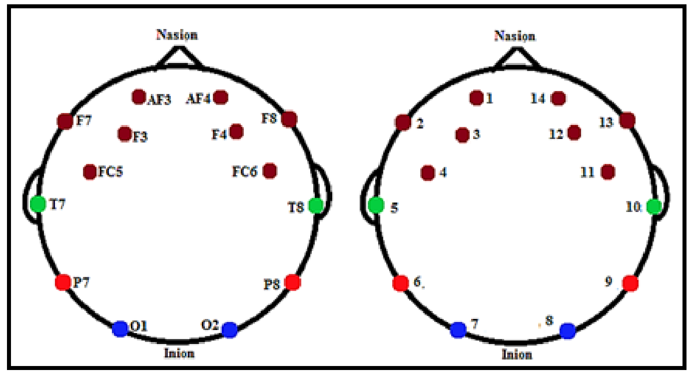
Figure-1. 10/20 system for recording non-invasive EEG data.



There are four landmarks which are crucial for electrode positioning. The nasion: It is the junction point between nose and the forehead. The inion: Onion is skull's low laying point in the backside. Left and right preauricular points: These points are anterior (in front) of the ears.

The electrodes are tagged by some letters F, O, P, T, and C which are referring to lobe location as frontal, occipital, parietal, temporal and central (not a lobe but central point of skull) respectively. A line that joining nasion and inion divides scalp into two hemispheres (i.e. left and right). Electrodes positioned at this line are labeled as zero (z). The electrodes on left side are numbered as odd (1, 3, 5, 7) while on right side are labelled as even (2, 4, 6, 8). The positioning of the 14 electrode EEG system along with labels is depicted in figure-2.

Figure-2. Electrode placement by names and by numbers



2.3 Independent Component Analysis

Independent component analysis (ICA) is one of most demanded EEG signal processing techniques due to its better resolving ability. There are manifold applications of ICA such as signal-to-noise-ratio (SNR) enhancement, artifacts removal and electrode selection. In the case of SNR enhancement, ICA is designed as a spatial filter so to decrease the magnitude of noise without affecting signal. SNR of event-related-potentials (ERPs) can be greatly enhanced by applying ICA. In artifact removal ICA decompose the EEG recorded data from scalp into neural and non-neural independent components (ICs) which then need expert's observation. The non-neural independent components are contributed by eye-blinking, blood flow, internal movements, muscles contraction etc. The prime aim of electrode selection application is to minimize the number of electrodes used in fabrication of BCI [20]. To understand the state-of-the-art in better a literature survey is performed on research articles associated with application of ICA. 11 articles are enlisted in table-1 which are relevant with the above said applications. These articles are chosen from research journals and conference proceeding using google scholar and "whereisdoc.com".

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Table-1.
DIFFERENT APPLICATION OF ICA FROM THE LITERATURE SURVEY

Application	Study related with Application	Studied by
EEG artifact removal	Removal of the artifacts generated by the movement of electrodes due to blood flow or cardiac cycle.	Srivastava et al., [21]
	Artifacts rejection which arises due to rotation of eyeball and the eye-blinking of blind people	Flexer et al., [22]
	Reduction of the extra-physiological artifacts appears due to constant current in tDCS	Coffmana et al. [23]
	Computer based rejection of physiological artifacts	Ghanbari et al., [24]
	An automated artifact rejection method	Radüntz et al., [25]
SNR enhancement	Noise reduction in the EEG signals by using spatial filters or SNR enhancement by using spatial filters	Maki et al., [26]
	SNR enhancement of P300 for increasing lie detection accuracy	Gao at al., [27]
	SNR enhancement for P300 based on multi-resolution using ICA	Vahabi et al., [28]
Electrode Selection	Reduction in dimensionality and selection of optimal electrode	Naeem et al., [29]
	Estimation of most prominent electrode from high density EEG recordings (64 electrodes)	Rasmussen et al., [30]
	Determination of minimum number of electrodes necessary for the application	Troy et al., [31]

2.3.1 Proposed ICA Algorithm

The EEG data was recorded with 14 channels portable device which recorded 8064 data points for each of the 14 channels for about 63 seconds long. Therefore, for 14-channel EEG data signals x= [x_1, x_2 ……x_{14}] are assumed to be generated by s= [s_1, s_2 ……s_{14}] sources (It is not necessary that number of recorded signals and source signals is same).

$$\mathbf{x} = \mathbf{As}$$

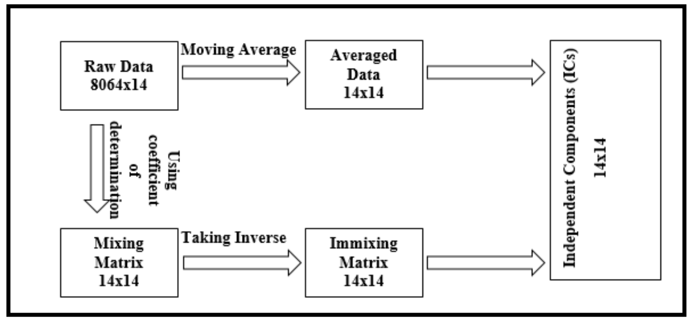
where **A** is a mixing matrix of 14×14 in the given model. The source signal can be recovered if one applies immixing matrix to the recorded EEG signals as;

$$\mathbf{s} = \mathbf{A}^{-1}\mathbf{x}$$

$$\mathbf{s} = \mathbf{Wx}$$

where s is the source signal or the independent component (IC), W is immixing matrix of 14x14 elements in the model. It may also be considered as the spatial filter for the recorded EEG data. For the determination of mixing matrix an rithm is proposed that is based on the coefficient of determination r^2 "square of Karl Pearson's coefficient of correlation (r)". The immixing matrix **W** is the inverse of the **A**.

Figure-3. ICA algorithm



2.4 EEGLAB

MATLAB is an attractive computational language through which brain signal may also be processed to extract features. Numerous familiar signal processing tools are available in MATLAB as built-in functions including wavelets, Fourier transform etc. To enhance the performance of EEG signal processing via MATLAB another program which provides many other choices to elaborate the information contained in EEG signals is EEGLAB. In this research EEGLABv11.0.3.1b was used in MATLAB R2009b.

Sampling rate of dataset, electrodes positioning, epoch timing etc. are pivotal parameters of signal processing and provided to program at the time of selecting dataset. The dataset was then filtered by using finite impulse response (FIR) filter that is a basic & built-in filter in EEGLAB. In order to filter data low-pass frequency was adjusted 5Hz and hi-pass frequency was maintained at 40Hz.

Independent components, channel selection through maximum activity is measured, the most prominent IC, location of IC generation, frequencies in ICs, frequency-power spectrum, most probable location as well as channel which measure selective frequency are recorded by using EEGLAB.

3 Results

For the sake of better understanding the phenomenon graphical representation of results is a most important factor. Figures 4 to 7 are representing the results obtained from ICA algorithm while figure-8 onward representing the results deduced from the EEGLAB.

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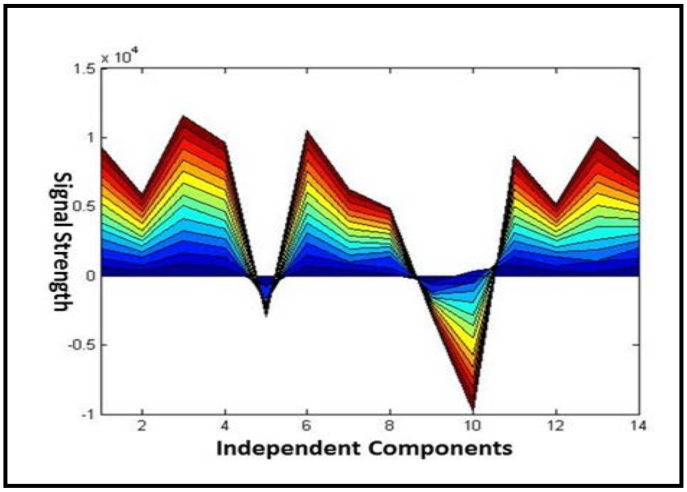
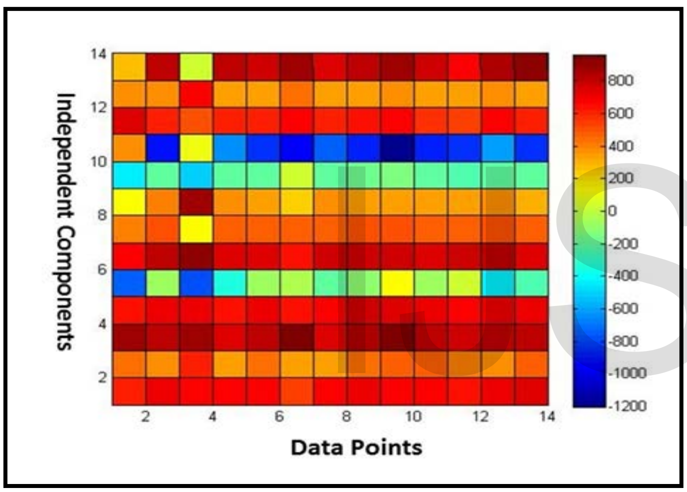
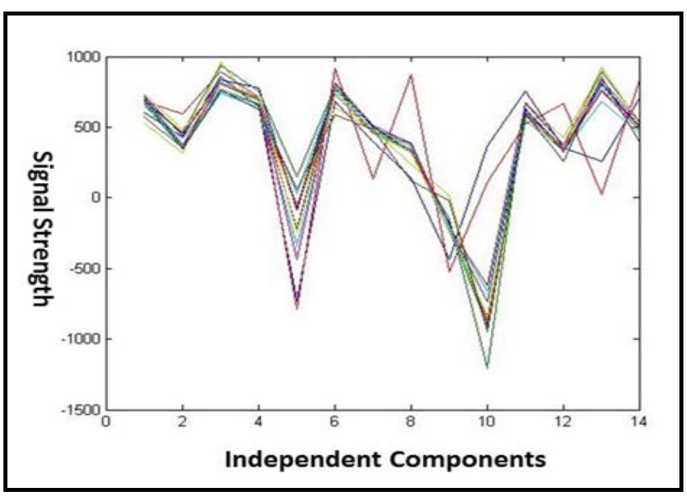


Figure-4. Area plot representing strength of signal with respect to IC number, the maximum strength of the signal is



observed at the IC-3.

Figure-5. Imagesc plot representing strength of signal with



respect to IC number, maximum strength of the signal is represented by dark brown that is observed on large scale at IC-3.

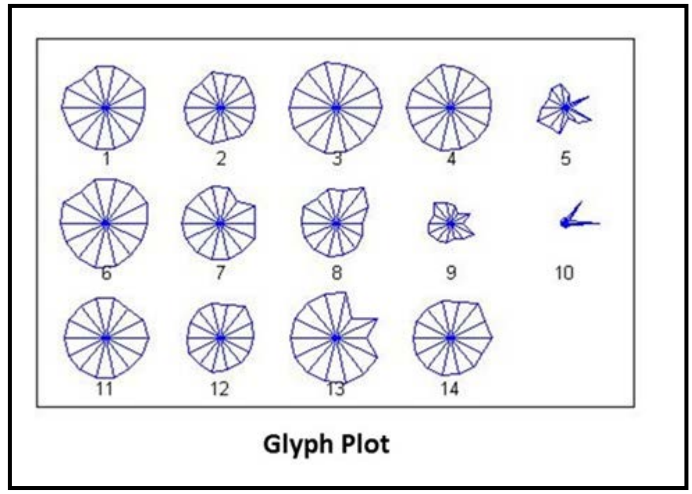
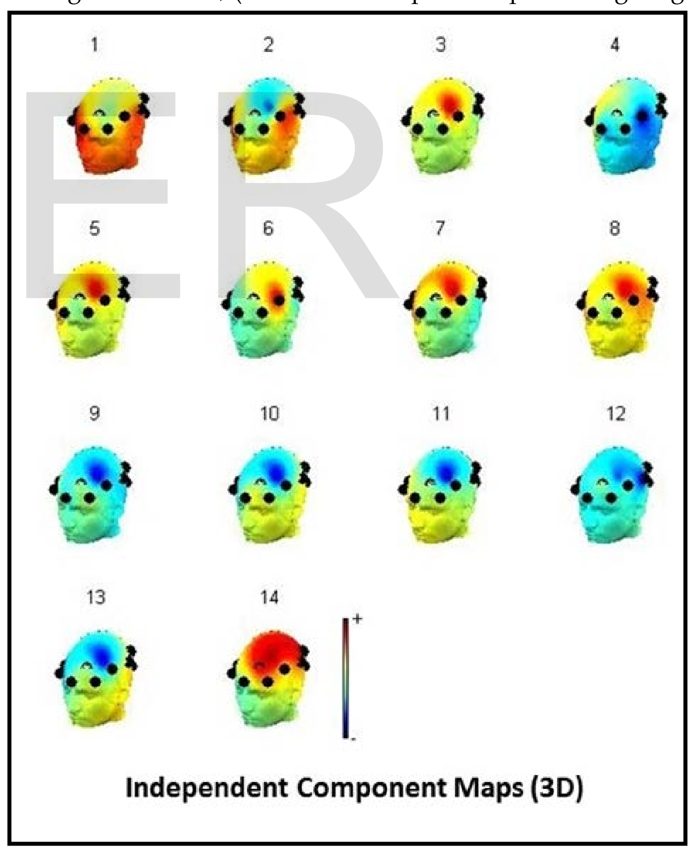


Figure-6. The Line Plot representing the consistency & signal strength of the ICs, the most consistent and strong signal is present at IC-3.

Figure-7. Glyph Plot is representing the consistency & signal strength of the ICs, (radii of the shape are representing magni-



tude of signal voltage for data point, the IC with maximum area has maximum strength while IC with smallest variation in radii is most consistent. Both properties are present in IC-3.

Figure-8. Three dimensional plots of Independent Components representing the strength of signal and generation of the signal from the part of scalp. Independent Component 3 is most clear and has maximum strength.

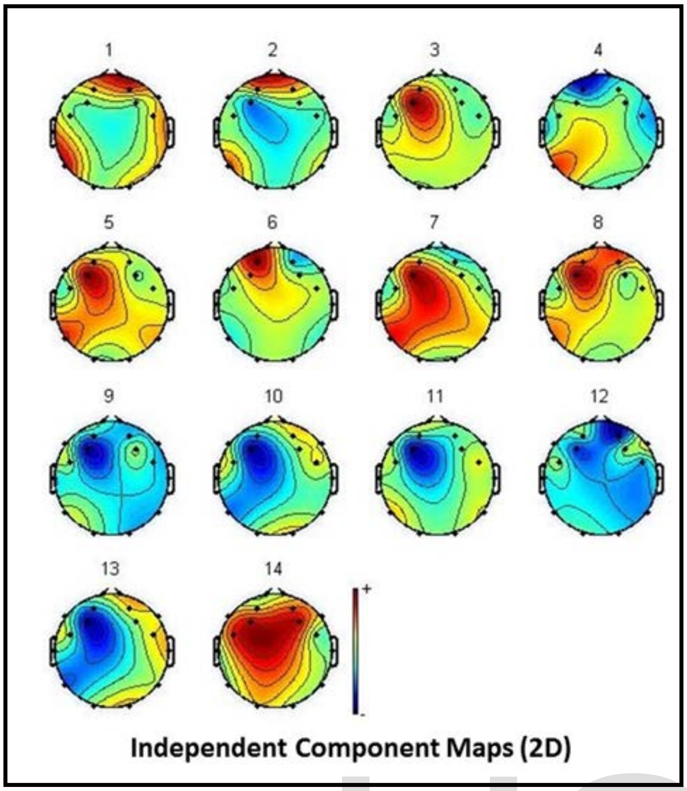


Figure-9. Independent Components are represented in two-dimensional graph (top view of the head) with their maximum and minimum strengths. Location of the maximum neural activity is shown in each component. The IC-3 has the best contrast which represent the reliable signal and its generating location.

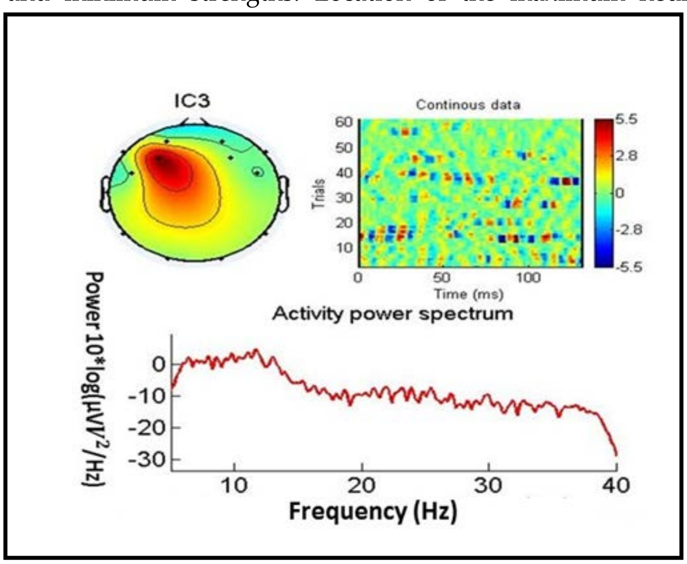


Figure-10. Independent Component properties (frequency band, power, origin, electrode positioning, time instant) of most prominent component IC-3.

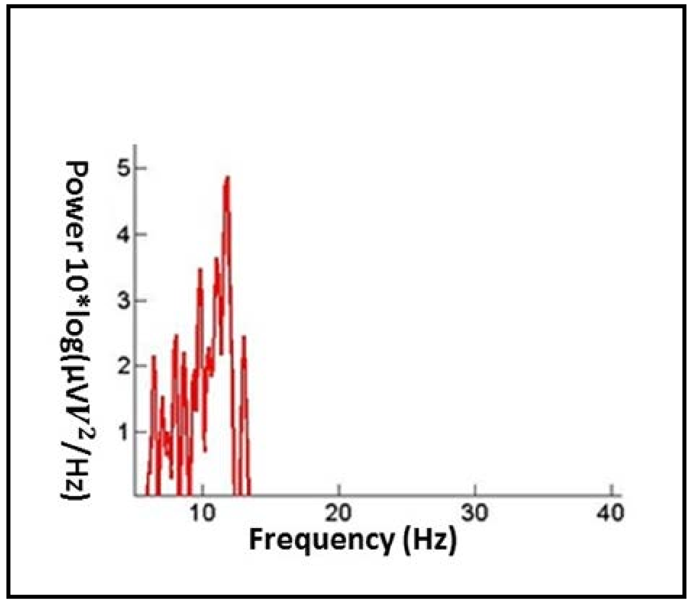


Figure-11. Fourier Transform of IC3 with maximum power at 12 Hz.

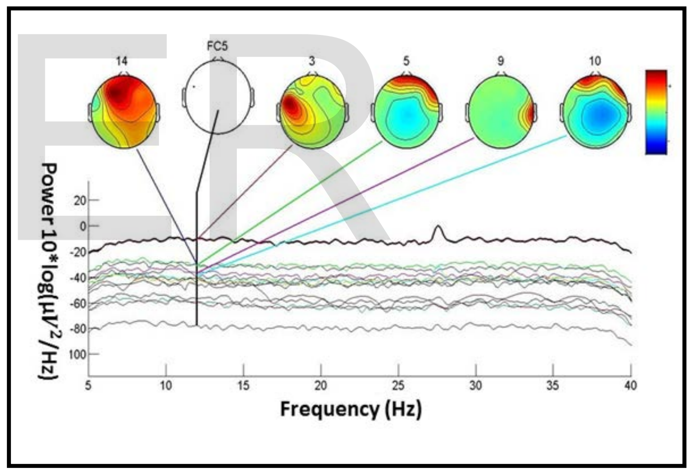


Figure-12. Determination of electrode, most prominent IC and other contributing ICs in Maximum power frequency (ranges from 7Hz to 12Hz)

4 Discussions

In figures-4 area plot shows several peaks such as IC3, IC4, IC6 and IC13 but it is evidently clear that the studied ERP signal strength is decomposed on IC3. Furthermore, figure-5 also verify the signal strength on IC3 that can be visualized from the imagesc plot in figure-5 for independent components as function of data points. In line plot, the decomposition of signals is represented between signal strength and independent components shown in figure-6 that record the maximum signal strength on IC3 with most consistent voltage. In glyph plots the radius of the shape represents the intensity of signal that is decomposed to IC3, IC4, IC6, IC11 and IC13 but the consistency of signals is measured on IC3. Consequently, it can be concluded from the above discussion that ERP signals decomposes on IC3.

The contour plots of figure-8 and figure-9 representing the Independent Component maps in which IC3 has the best contrast among all other IC maps. Red color represents maximum strength while blue color represents minimum strength of the neural activity in contours. In image-3 of both figures activity is purely originated from a single point for channel FC5 which using ICA decomposes as IC3, while the whole scalp has almost zero activity.

Then figure-10 and figure-11 are representing the properties and Fourier transform of the IC3. Plots reveal that this component is generated time-to-time from motor cortex on the left side of brain (left hemi-sphere). The maximum power contained in it is based on the frequency range 7Hz to 12Hz called alpha rhythm shown in Fourier transform graph. 12Hz frequency has maximum peak (power). 12Hz frequency is analyzed and found to be generated from various parts (as shown in figure-12) in fractions but major quantity is received from the FC5 that is present over the motor cortex.

4.1 Comparison of Proposed Ica and EEGLAB

The proposed ICA algorithm is found to be much efficient to decompose the recorded EEG data into independent components and for channel selection. Results based on EEGLAB and ICA algorithm discussed in previous sections are compared and found to be equivalent for decomposing the independent components in EEG data associated with event-related-potentials. Furthermore, this is evident from the graphical representation of the analysis carried out on the recorded EEG data.

5 Conclusion

The brain signals associated with artifacts and event-related-potentials present at the surface of the scalp are recorded as EEG data using scalp electrodes. The EEG data is to be pre-processed for artifact removal and unwanted signals. The feature extraction through ICA algorithm is a straight forward method and leads to reliable decomposition of event-related-potentials into independent components. Decomposition of studied ERP using EEGLAB shows that electrical activity for the right hand up movement is recorded by channel FC5 and contains frequencies associated with alpha rhythm (7Hz to 12Hz). Therefore, data acquisition electrode for a BCI corresponding to right hand should be placed at location of FC5 and device should be taught with similar frequencies. The proposed ICA algorithm is an efficient approach to feature extraction as well as to select an optimal electrode to collect that feature. The study reveals that the results obtained using ICA algorithm written in this report and EEGLAB are in good agreement.

References

[1] Berns, G. S., Cohen, J. D., & Mintun, M. A. (1997). Brain regions responsive to novelty in the absence of awareness. Science, 276(5316), 1272-1275.

[2] Lin, C. J., & Hsieh, M. H. (2009). Classification of mental task from EEG data using neural networks based on particle swarm optimization. Neurocomputing, 72(4), 1121-1130.

[3] Wolpe, P. R., Foster, K. R., & Langleben, D. D. (2010). Emerging neurotechnologies for lie-detection: promises and perils. The American Journal of Bioethics, 10(10), 40-48.

[4] Sanei, S., Ferdowsi, S., Nazarpour, K., & Cichocki, A. (2013). Advances in electroencephalography signal processing [Life Sciences]. Signal Processing Magazine, IEEE, 30(1), 170-176.

[5] Murugappan, M., Murugappan, S., & Gerard, C. (2014, March). Wireless EEG signals based neuromarketing system using Fast Fourier Transform (FFT). In Signal Processing & its Applications (CSPA), 2014 IEEE 10th International Colloquium on (pp. 25-30). IEEE.

[6] Khosrowabadi, R., Quek, C., Ang, K. K., Wahab, A., & Chen, S. H. A. (2015). Dynamic screening of autistic children in various mental states using pattern of connectivity between brain regions. Applied Soft Computing, 32, 335-346.

[7] Canli, T., & Amin, Z. (2002). Neuroimaging of emotion and personality: Scientific evidence and ethical considerations. Brain and cognition, 50(3), 414-431.

[8] Teplan, M. (2002). Fundamentals of EEG measurement. Measurement science review, 2(2), 1-11.

[9] Parvez, M. Z., & Paul, M. (2014). Epileptic seizure detection by analyzing EEG signals using different transformation techniques. Neurocomputing,145, 190-200.

[10] Curran, E. A., & Stokes, M. J. (2003). Learning to control brain activity: a review of the production and control of EEG components for driving brain–computer interface (BCI) systems. Brain and cognition, 51(3), 326-336.

[11] Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. Clinical neurophysiology, 113(6), 767-791.

[12] JESSY, P. (2009). Analysis of EEG Signals for EEG-based Brain-Computer Interface.

[13] Larsen, E. A. (2011). Classification of eeg signals in a brain-computer interface system.

[14] Subasi, A., & Ercelebi, E. (2005). Classification of EEG signals using neural network and logistic regression. Computer methods and programs in biomedicine, 78(2), 87-99.

[15] Lotte, F. (2014). A tutorial on EEG signal-processing techniques for mental-state recognition in brain–computer interfaces. In Guide to Brain-Computer Music Interfacing (pp. 133-161). Springer London.

[16] Cao, L. J., Chua, K. S., Chong, W. K., Lee, H. P., & Gu, Q. M. (2003). A comparison of PCA, KPCA and ICA for dimensionality reduction in support vector machine. Neurocomputing, 55(1), 321-336.

[17] Al-Fahoum, A. S., & Al-Fraihat, A. A. (2014). Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains. ISRN neuroscience, 2014.

[18] Zhendong Mu, Dan Xiao, and Jianfeng Hu. (2009). Classification of Motor Imagery EEG Signals Based on Time-Frequency Analysis. JDCTA 3.4, 116-119.

[19] Sanei, S., & Chambers, J. A. (2013). EEG signal processing. John Wiley & Sons.

[20] Wang, Y., & Jung, T. P. (2012). Improving brain–computer interfaces using independent component analysis. In Towards Practical Brain-Computer Interfaces (pp. 67-83). Springer Berlin Heidelberg.

[21] Srivastava, G., Crottaz-Herbette, S., Lau, K. M., Glover, G. H., & Menon, V. (2005). ICA-based procedures for removing ballistocardiogram artifacts from EEG data acquired in the MRI scanner. Neuroi-

mage, 24(1), 50-60.

[22] Flexer, A., Bauer, H., Pripfl, J., & Dorffner, G. (2005). Using ICA for removal of ocular artifacts in EEG recorded from blind subjects. Neural Networks, 18(7), 998-1005.

[23] Coffmana, B. A., Huntera, M. A., Jonesa, A. P., Saxona, H. A., Kolodjeskia, K., Lockmillera, B., ... & Clarka, V. P. Using ICA to Remove Artifacts Associated with tDCS From EEG data: Comparison of ICA Algorithms.

[24] Ghanbari, A. A., Kousarrizi, M. N., Teshnehlab, M., & Aliyari, M. (2009). An evolutionary artifact rejection method for brain computer interface using ICA.

[25] Radüntz, T., Scouten, J., Hochmuth, O., & Meffert, B. (2015). EEG artifact elimination by extraction of ICA-component features using image processing algorithms. Journal of neuroscience methods, 243, 84-93.

[26] Maki, H., Toda, T., Sakti, S., Neubig, G., & Nakamura, S. (2015, April). EEG signal enhancement using multi-channel Wiener filter with a spatial correlation prior. In 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 2639-2643). IEEE.

[27] Gao, J., Tian, H., Yang, Y., Yu, X., Li, C., & Rao, N. (2014). A novel algorithm to enhance P300 in single trials: Application to lie detection using F-Score and SVM. PloS one, 9(11), e109700.

[28] Vahabi, Z., Amirfattahi, R., & Mirzaei, A. R. (2011). Enhancing P300 wave of BCI systems via negentropy in adaptive wavelet denoising. Journal of medical signals and sensors, 1(3), 165.

[29] Naeem, M., Brunner, C., & Pfurtscheller, G. (2009). Dimensionality reduction and channel selection of motor imagery electroencephalographic data. Computational intelligence and neuroscience, 2009.

[30] Rasmussen, P. M., Mørup, M., Hansen, L. K., & Arnfred, S. M. (2008, January). Model Order Estimation for Independent Component Analysis of Epoched EEG Signals. In BIOSIGNALS (2) (pp. 3-10).

[31] Troy M, L., Joseph T, G., & Daniel P, F. (2012). How many electrodes are really needed for EEG-based mobile brain imaging?. Journal of Behavioral and Brain Science, 2012.