Investigating EEG Images of Cognitive Actions for Robotic Arm

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Abstract. Brain Computer Interface (BCI) systems works with brain signals. The brain activities are taken into consideration and are used to control external devices These signals are processed to extract features which are then translated to discrete command set to operate some external device like a wheel chair or an application like a speller application, a gaming system etc. In this study an activity of robotic Arm movement (Arm up, Arm down and neutral) is performed. The brain imaging signals are acquired with a low-cost EEG machine as EMOTIV EPOC whereas EEGlab software developed in MATLAB is used for processing the signals. ICA technique is used for pre-processing the acquired data. ICA works on multichannel data and the data used in this study is 14 channels. ICA Algorithm has also helped to find the active components along with the brain area where neural activity was prominently noticed. The study was carried with four participants and a dataset of 1200 events was created and used to obtain the result. During active imagination of the Arm up, Arm down and neutral (the cognitive event i.e. push, pull, and neutral of Emitiv EPOC) movement of the robotic arm the activation was observed in the electrodes F3, F4, FC3, and FC4 placed in the frontal region. Event-related spectral perturbation (ERSP), are noticed in the inter-trial coherence (ITC) which were related to baseline interval. During the imagined movement ERD (Event Related Desynchronization) are observed and ERS (Event Related Synchronization) after the occurrence of imagined movement is noticed in the mentioned electrodes. While performing the study overall 79% accuracy was obtained during arm up, down, and neutral movement. The recognition of pattern on the bases of component map activation is also done to understand the dominant part of the brain while performing a specific movements and it was found that left frontal region is more active during Arm up movement and left & right frontal part is active during an Arm down movement.

Keywords: Brain Computer Interface · Emotiv EPOC · Cognitive events · Event Related Spectral Perturbation · ICA

1 Introduction

Communication takes place when expressions, feelings, thoughts, and intentions are conveyed between people either verbally or non-verbally. Though it is a natural process, it can be proved as a big challenge to people suffering from total paralysis or individuals

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who are suffering from neuromuscular conditions like amyotrophic lateral sclerosis, brain stem stroke, and spinal cord injury. Some of the mentioned diseases are very severe, rendering the individuals motionless thus severely affecting their communication. Thus communication takes place with the help of some assistive devices that rely on nonverbal signals like finger movement and gaze between the signal acquisition and the translation part, with the use of a wireless transmission unit such as Bluetooth and Zigbee modules. By removing wire connections, portability of BCI systems is greatly improved. In recent times more efforts are there for out of lab BCI based research with the help of EEG signals from brain which has provided many applications. This technology converts specific feature of brain activity and transforms into device control actions. The pattern recognition techniques can be applied to the BCI systems for recognition and selection of the correct intentions for BCI control. The developed interface will support individuals with disabilities to become more independent and also enhance their quality of life, and nowadays wireless BCI systems have found a place in entertainment industry also. improving their quality of life, and more recently wireless BCI systems have been applied in entertainments also.

In this study we have attempted to design and develop a robotic arm and interface it with the cognitive state of mind with the help of EEG signals, through Emotiv EPOC. This Emotiv headset is used for cognitive actions of push and pull actions electrical activity which can be captured as EEG signal [2, 3]. The muscle artefacts in EEG signals can be easily decomposed with the help of linear decomposition of EEG signals into source components which is generally used. The aim is to discard the artefact components and focus on neural activity in different components so that the cleaner signals can be reconstructed from the neural components only. To achieve this ICA (Independent Component Analysis) is the most commonly used technique where the blind source separation (BSS) problem is resolved by maximizing the independence of the source components. It is seen that generally, ICA methods yield a useful separation in the maximum number of cases [4, 5]. The pattern recognition technique is also implemented for the classification of the events associated with the movements and identification of the active region of the brain. Along with the active region, dominant part of the brain is also recognised in order to know which part of brain is more dominant and active during performing a respective movement.

2 Literature Review

It is largely acknowledged and widely accepted that volume conduction and reference electrode deteriorate spatial resolution of scalp EEG, other distortions are less widely recognized in the community. As a matter of fact, the time course of brain activities is also largely distorted. For example, spontaneous EEG signals recorded by different electrodes tend to appear more phase-locked than they actually are, inducing artifactually high between site coherence. In what follows, we will show how the timing of averaged event-related potentials (ERPs) is also altered by the same factors. This degraded temporal resolution is seldom acknowledged in the literature, and it is still widely assumed that the timing of scalp potential provides an accurate timing of the underlying sources, since electrical activity propagates instantaneously to the recording electrodes. However, the mixture induced by the spatial smearing also temporally mixes the underlying activities hence making the scalp potential temporal resolution significantly lower than usually assumed. Importantly, we will show that techniques improving the spatial resolution of scalp EEG also secondarily largely improve the temporal one [6].

At present, several types of EEG signals have been classified, such as the sensorimotor rhythm (SMR), slow cortical potential (SCP), event-related potential (ERP), and steady-state visual evoked potential (SSVEP), among others [7].

Since the past few decades work on the functionality of the brain based on the images acquired during capturing the EEG signals have been going on. It is seen that the EEG signal have poor spatial resolution, but an excellent temporal resolution of less than a millisecond. In most of the cases, the process of acquisition of the signals is done using sensors that are non-invasive. The devices used are comparatively easy to use and the entire recording procedure can be done safely.

3 Methodology

Here in our work, we have focused on the use of cognitive actions for capturing the EEG signals using the EEG headset Emotiv EPOC, research edition. The Emotiv EPOC headset is a comparatively simple, portable, cheap, and efficient acquisition device for EEG-based applications. For many EEG based research applications such as Robotic arm control, alphabet recognition using P-300, emotion detection, imagery movements, etc. Emotiv EPOC is used.

The proposed research work is user-dependent, implying that the system will work only for the users who are trained to operate the process and whose databases are already stored. The user can test the system and a comparison between the trained data which is already stored in the databases with the test data is made.

The EEG data were collected using TestBench software of the SDK research kit provided by Emotiv, from the volunteer simultaneously as the events occurred. The created database was further analysed and processed based on the experimental tasks. The pre-processing and analysis of EEG signals was carried out to classify the signals based on the intentions. The active regions of the brain were noted and checked for their relevance based on the functions of the different regions of the brain.

3.1 Participants

The number of participants participating in the proposed study was 4. The selected participants gave their consent to the experimental study. The volunteers were selected from the age group of 22–40 years. Subjects were given a briefing about the proposed study and counseled about the experiments. A log table was maintained for the events, for all the subjects. The training and testing sessions are collected from 4 subjects. Each subject has undergone five training and five testing sessions. In single session 30 events are recorded, thus total of 300 training and testing events are recorded for each subject. A total database of 1200 events is collected.

3.2 Technical Analysis

The EEG file created by using the TestBench tool is saved in the EDF (European Data Format) format. The.edf file can be analyzed in EEGLAB, an analyses GUI developed in MATLAB. BioSig toolbox was used for making our EEG file, saved as.edf compatible with EEGLAB. For processing of biomedical signals like EEG, MEG, EMG, ECG, etc. with SciLab, Matlab, Octave, C/C++, and Python, BioSig is used. More than 30 different data formats are supported by the Signal Viewer.

FIR and IIR filters are the standard pre-processing methods available in EEGLAB. Pre-processing is used for epoch extraction, baseline removal, resampling, and re-referencing for sample analysis. EEGLAB has the strength of strong integration with (ICA). EEGLAB provides ICA algorithm like extended Infomax, JADE, FastICA, and AMICA. We have made use of the default ICA algorithm available in EEGLAB, the extended Infomax. Tools and functions are available for processing and visualization. We can get channel and component data like ERP plotting, time/frequency plots, power spectra, etc.

ICA technique is used to minimize the mutual information among the data projections or maximize their joint entropy. The data projections have minimal temporal overlap. ICA can be viewed as an alternative linear decomposition to principal component analysis (PCA). PCA applied in the temporal domain would specifically make each successive component account for as much as possible of the activity uncorrelated with previously determined components whereas ICA seeks maximally independent sources [8].

In BCI, ICA is a very popular statistical technique that solves the Blind Source Separation (BSS) problem in multiple signal processing applications, like electroencephalographic (EEG) signals for artifact removal procedure. Artifacts like heartbeats, eye blink, muscle activity and noise from a set of signals extracted with some technique like the electroencephalography (EEG), magneto-encephalography(MEG), electrocorticography (ECoG), near infrared spectroscopy (NIRS), functional MRI (fMRI) can be removed with ICA.This method is used to separate a set of linearly mixed multivariate signals and transform it into another set which components are approximately the original signals and independent between them [9].

3.2.1 Independent Component Analysis (ICA)

ICA technique is implemented as follows. Let's assume that there are n linear mixtures of n independent components. Vector x (observed signals) can be written as:

$$\mathrm{x} = \mathrm{As} \tag{1}$$

where A represents a mixing matrix with the size of, and s is the vector of independent components. The aim of ICA is to find a matrix W (i.e. an inverse of the matrix A) to reverse the mixing effect. Then, after computing the matrix W, one can obtain the independent components by:

$$\mathrm{y} = \mathrm{wX} \cong \mathrm{s} \tag{2}$$

The ICA algorithms generally put some constraints on the mixed signals. First of them is a statistical independence between source signals s; second, a non-Gaussian distribution of the source signals and the third; the equality of the number of source signals and the number of mixture signals. While two first constrains are main assumptions utilized by many algorithms, the third one is introduced only to decrease the algorithm complexity (it causes that the mixing matrix is square). Furthermore, it is assumed that each source signal has the unit variance $E\{si2\} = 1$.To hold this assumption, the matrix of the source signals is whitened before the ICA calculation. One more assumption, introduced only to simplify the algorithm, is that all mixture signals are centered.

ICA does not require any prior information about the source signals. Instead, ICA algorithms utilize the concept of statistical independency of the mixed signals. According to the formal definition, the variables a and b are said to be independent if information about the value a does not give any information about the value b and vice versa. Technically, independence can be defined in terms of the probability density function (pdf):

$$f(x1, x2, \ldots xm) = f1(x1), f2(x2), \ldots fm(xm) \tag{3}$$

where x1, x2,…xm are random variables.

There are two main approaches to measuring independence: maximization of non-Gaussianity and minimization of mutual information. Most of the existing ICA algorithms are based on one of them.

Different ICA algorithms are used in BCI for artifact removal which generally include: INFOMAX, this algorithm is based on the maximization of entropy and presents a natural gradient form for the independent components computation. FastICA, Hyvärinen's algorithm is often used in 'real time' applications because of the possible parallel implementation. This algorithm converges quickly as it seeks for a component one by one. FastICA uses kurtosis for the independent components estimation. Whitening is usually performed on data before the execution of the algorithm. SOBI, this algorithm relies on second order statistics to explode the time-correlation structure assumption of the signals. It requires computing the following steps: Whitening, Computation of Lagged Correlation Matrices and Joint Diagonalization (JD). JADE (Joint Approximation Diagonalization of Eigenmatrices) JADE, as SOBI does, uses JD and whitening. However, the main difference between both is the set of target matrices on which JD is done [10].

In EEGLAB time analysis or frequency analysis measures like power spectrum, event-related spectral perturbation (ERSP), inter-trial coherence (ITC), and event-related cross-coherence can be done. ERSP visualizes event-related changes in the averaged power spectrum in a broad frequency range relative to a baseline interval whereas ITC measures the amount of event-related phase-locked activity as a function of time and frequency [11].

3.3 Analyzing .edf Files via EEGLAB

Figure 1 demonstrates detailed information of the .edf file selected for analyses in EEGLAB.

The selection of the number of channels and their location has to be mentioned for correct analyses of the components with EEGLAB, as mentioned in Fig. 2. It is based on the location of electrodes of the acquisition device.

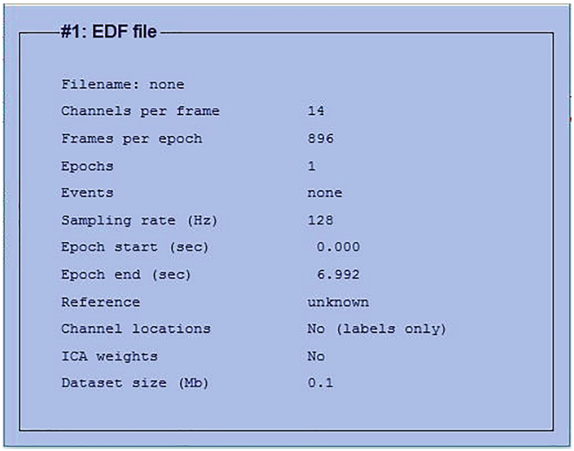


Fig. 1. File information after processing by BioSig software

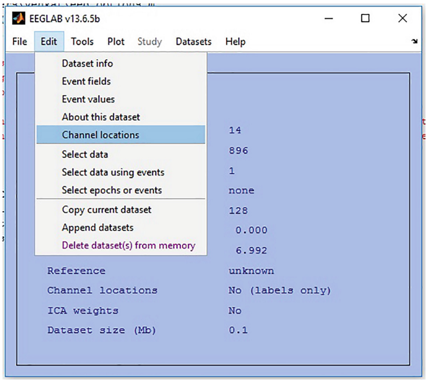


Fig. 2. Information about the channels and their location

After giving the details of the channels, the EEGLAB displays the names of the channels their location and axis details that are shown in Fig. 3. After receiving the channel details, we can execute ICA. The Runica algorithm is selected as it is an extension of the infomax ICA algorithm. Matlab functions allows faster and less memory-intensive computation.

The entire process of executing the ICA technique has been stated in Figs. 3, 4, 5, 6, 7, and 8 stepwise. The particular ICA out of the different techniques has to be selected, in our study as mentioned we have selected “runica”. Then the channels out of the available channels for our system for which the component analysis has to be made, have to be selected. The iterations as mentioned in Fig. 6 will be displayed. Then we can view the component maps as stated in Figs. 7 and 8.

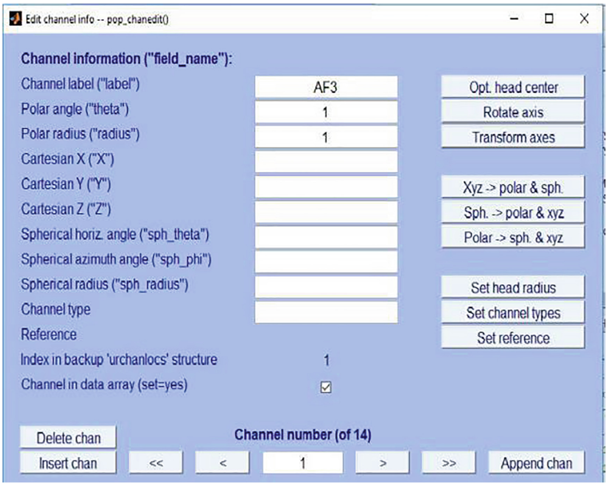


Fig. 3. Channels details

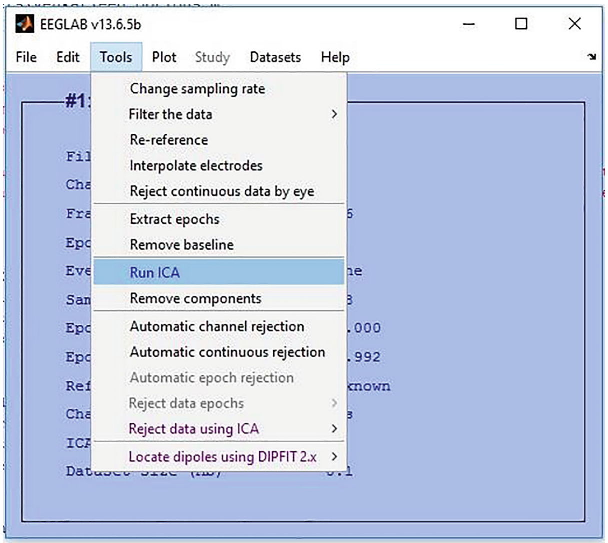


Fig. 4. Execution of ICA through tools

3.4 Robotic Arm Overview

The Technology Uncorked OctaMotion Robotic (TUOM) arm with the degree of freedom as three is considered for this study. The TUOM Robotic Arm DIY Kit was produced from eBay [12]. It contains 84 parts along with Gripper which has the following movements open, close, up, and down movements. Modifications were made in the procured arm, for this experiment. The movements of this arm that are considered are grip open and grip close, up and down movements.

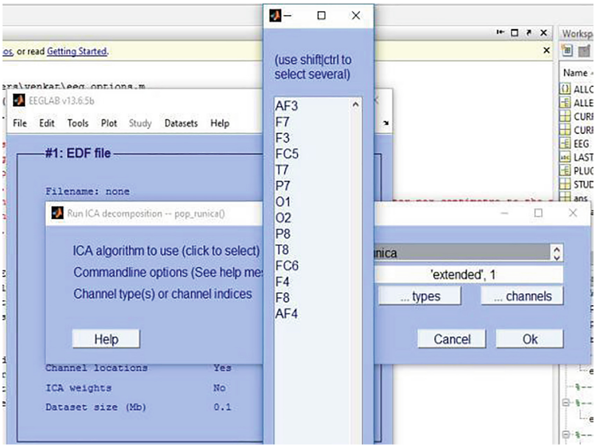


Fig. 5. Select one of the ICA technique

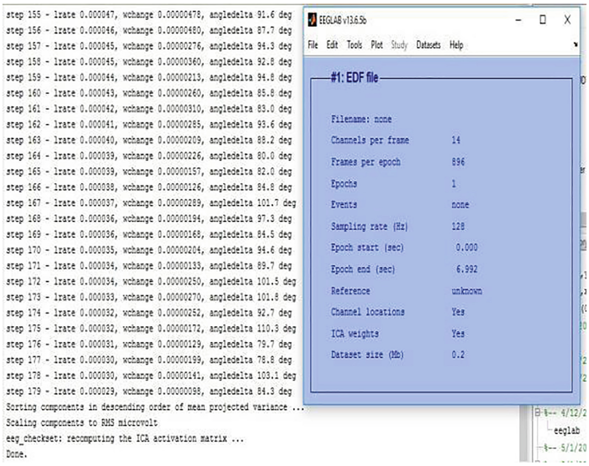


Fig. 6. Iterations observed during ICA

3.5 Active Region Identification

For this study, the region covered by the following electrodes namely F3, F4, FC5, and FC6 is considered. The actual electrodes over the motor cortex are C1, C2, C3, and C4, but these electrodes are not available for Emotiv EPOC, therefore the said electrodes are selected.

As mentioned in Fig. 9, the area of the brain which is involved in motor activity is the frontal lobe, therefore the above-mentioned electrodes are selected. The marked region in Fig. 10 covers these electrodes and the placement location of these electrodes.

The component maps observed during the events of Arm Up, Arm Down, and Neutral of the robotic arm are analyzed. The selected electrode activation has been noted for

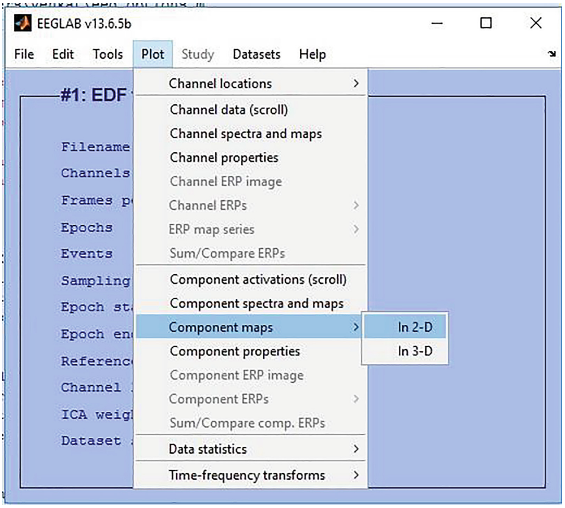


Fig. 7. Component map selection result

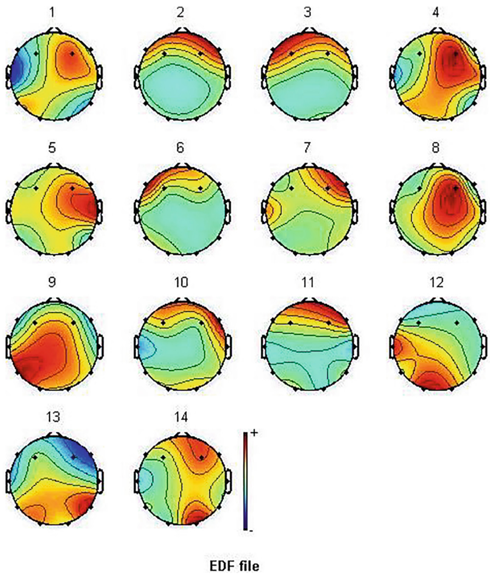


Fig. 8. Component map activation result

different events and a relation between the occurrence of the events and the region of activation is established.

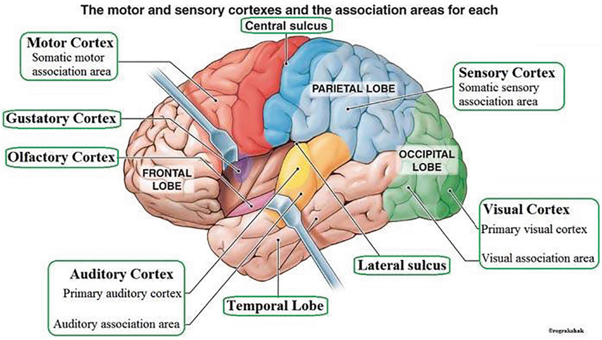
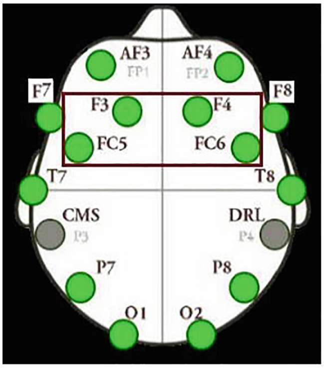


Fig. 9. The Sections and lobes of Brain [13]



1	AF3
2	F7
3	F3
4	FC5
5	T7
6	P7
7	O1
8	O2
9	P8
10	T8
11	FC6
12	F4
13	F8
14	AF4

Fig. 10. 10–20 system and electrodes of Emotiv EPOC

3.5.1 ARM UP Component Activation

Figure 11 Observations: In Fig. 11 there are four instances of the occurrences of Pull event, of four subjects namely A, B, C, D which results in arm up action in the robotic arm.

11A: Result of Pull event of subject A.
11B: Result of Pull event of subject B.
11C: Result of Pull event of subject C.
11D: Result of Pull event of subject D.

During the occurrence of the pull event of the Cognitive suite, the Arm up action takes place in the proposed robotic arm. Figure 11A, B, C and D display the result of ICA, 2-dimensional components activation. From the figure, it can be observed that the frontal region of the brain is active in most of the components. The 2-dimensional component maps were further classified with reference to the 4 electrodes which were located in the frontal region.

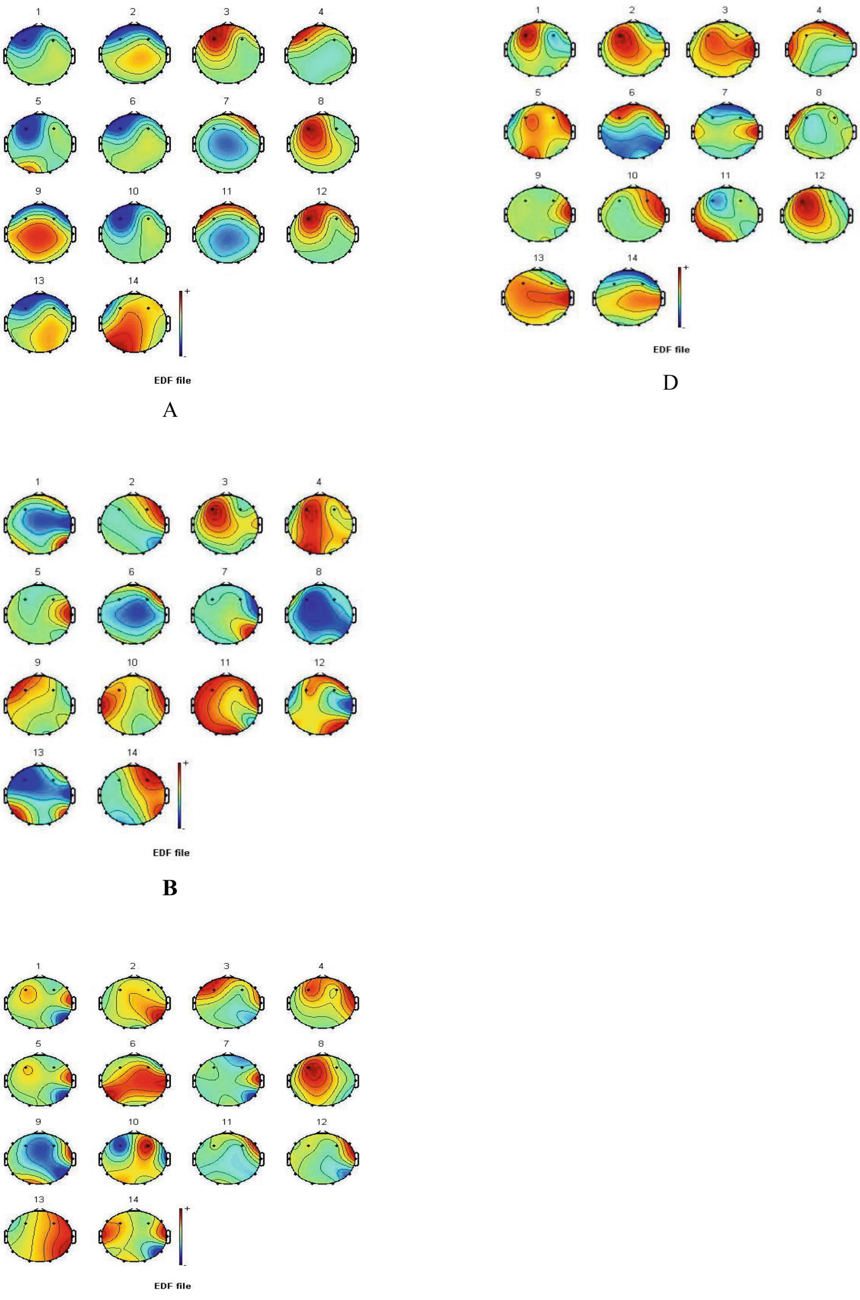


Fig. 11. Component activation during Arm up action

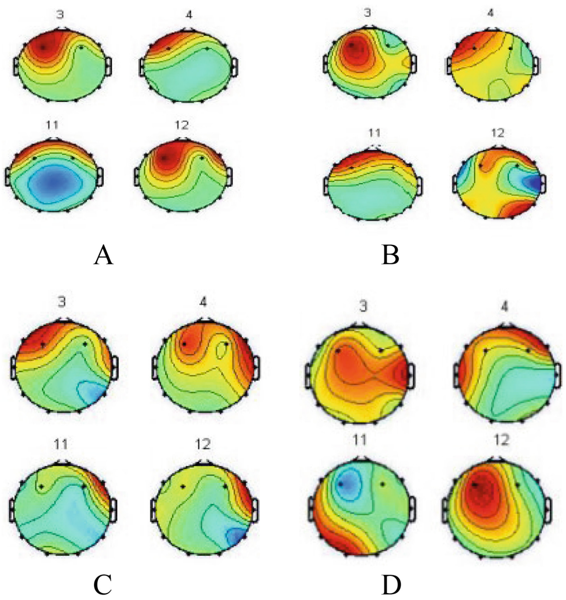


Fig. 12. Frontal region activation during Arm up action

Figure 12 Observations: In Fig. 12 there are four instances of the occurrences of Pull event, of four subjects namely A, B, C, D which results in arm up action in the robotic arm.

12A: Result showing activation in the frontal region of subject A.
12B: Result showing activation in the frontal region of subject B.
12C: Result showing activation in the frontal region of subject C.
12D: Result showing activation in the frontal region of subject D.

From Figs. 12A, B, C, D it can be observed that during imagination of movement that frontal region where the motor cortex is located, becomes active which can be noticed in the results of 2d activation components placed in that region, which we have acquired after running ICA algorithm.

Figure 12 represents the 2D component map that was classified as 4 electrodes located in the frontal region which represents the motor activity while performing the Arm up movement. Form these images it is observed that the red part represents the activity and blue represents no activity. Therefore based on these color patterns it can be observed that more activity is found in the left frontal region.

3.5.2 ARM Down Component Activation

Figure 13 Observations: In Fig. 13 there are four instances of the occurrences of Push event, of four subjects namely A, B, C, D which results in arm down action in the robotic arm.

13A: Result of Push event of subject A.

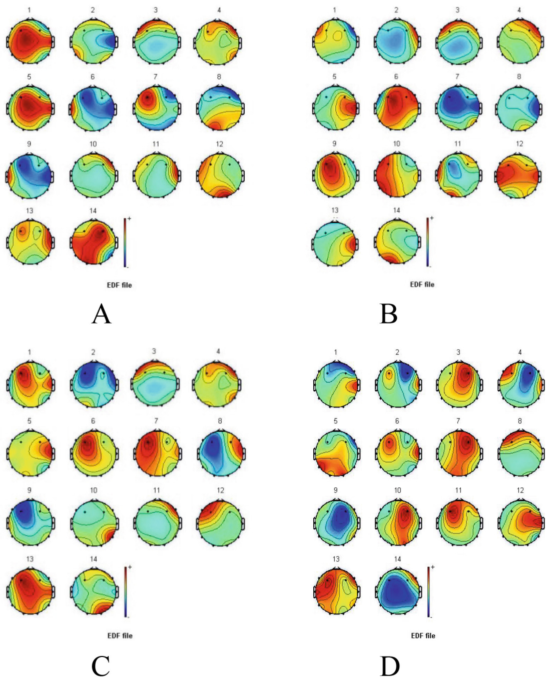


Fig. 13. Component activation during Arm down action

13B: Result of Push event of subject B.
13C: Result of Push event of subject C.
13D: Result of Push event of subject D.

During the occurrence of the push event of the Cognitive suite, the Arm down action takes place in the proposed robotic arm. Figure 13 displays the result of ICA, 2-dimensional components activation. From the figure, it can be observed that the frontal region of the brain is active in most of the components. The 2-dimensional component maps were further classified with reference to the 4 electrodes which were located in the frontal region.

Figure 14 Observations: In Fig. 14 there are four instances of the occurrences of Push event, of four subjects namely A, B, C, D which results in arm down action in the robotic arm.

14A: Result showing activation in the frontal region of subject A.
14B: Result showing activation in the frontal region of subject B.
14C: Result showing activation in the frontal region of subject C.
14D: Result showing activation in the frontal region of subject D.

From Figs. 14A, B, C, D it can be observed that during imagination of movement that frontal region where the motor cortex is located, becomes active which can be noticed in the results of 2-dimensional activation components placed in that region, which we have acquired by implementing ICA algorithm.

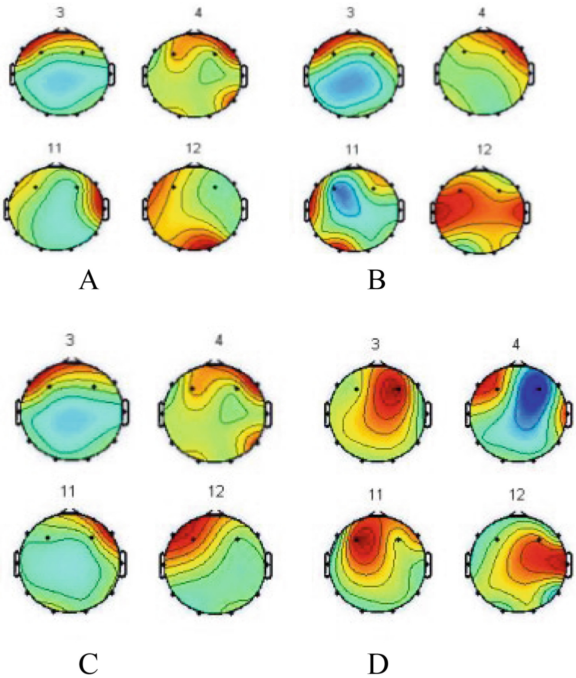


Fig. 14. Frontal region activation during Arm down action

The Fig. 14 it can be observed that while performing the Arm down movement most of the activity is found in the frontal region where both the left and right sides are equally found to be active.

3.5.3 Reduced Frontal Region Activation for Neutral Action

Figure 15 Observations: In Fig. 15 there are four instances of the occurrences of Neutral event, of four subjects namely A, B, C, D which results in no action in the robotic arm.

15A: Result of Neutral event of subject A.
15B: Result of Neutral event of subject B.
15C: Result of Neutral event of subject C.
15D: Result of Neutral event of subject D.

Similarly, during the occurrence of the neutral event of the Cognitive suite, the Arm stops moving and no action takes place in the proposed robotic arm. The Figs. 15A, B, C, and D display the result of ICA 2 dimensional components deactivation as a result of subdued action. From the figures, it can be observed that there is less activity in the frontal region of the brain when the subject is not thinking of any movement as noticed in most of the components. The 2-dimensional component maps were further classified with reference to the 4 electrodes which were located in the frontal region.

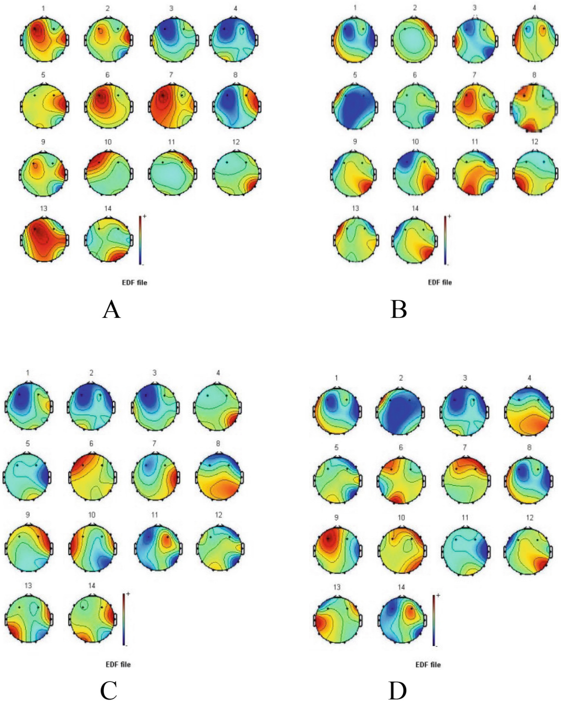


Fig. 15. Component activation during Neutral action

Figure 16 Observations: In Figs. 16 there are four instances of the occurrences of Neutral event, of four subjects namely A, B, C, D which results in no action in the robotic arm.

- 16A: Result showing no significant activation in the frontal region of subject A.
- 16B: Result showing no significant activation in the frontal region of subject B.
- 16C: Result showing no significant activation in the frontal region of subject C.
- 16D: Result showing no significant activation in the frontal region of subject D.

From Figs. 16A, B, C, D it can be observed that when the subject is not involved in the imagination of movement that frontal region where the motor cortex is located, is less active which can be noticed in the results of 2-dimensional activation components placed in that region, which we have acquired by implementing ICA algorithm.

3.6 ERD and ERS for the Components in Frontal Region

As per the literature for the physical movement, ERD and ERS were observed in the electrodes over the motor cortex which is associated with the hand movement. ERD was seen during the actual movement and ERS after the occurrence of movement. ERD were also noticed on the ipsilateral hemisphere. The reason being would have been that during the imagination of the movement of a cube, though there was no physical movement, the natural urge of the movement generated ERD activity, on the contralateral motor cortex,

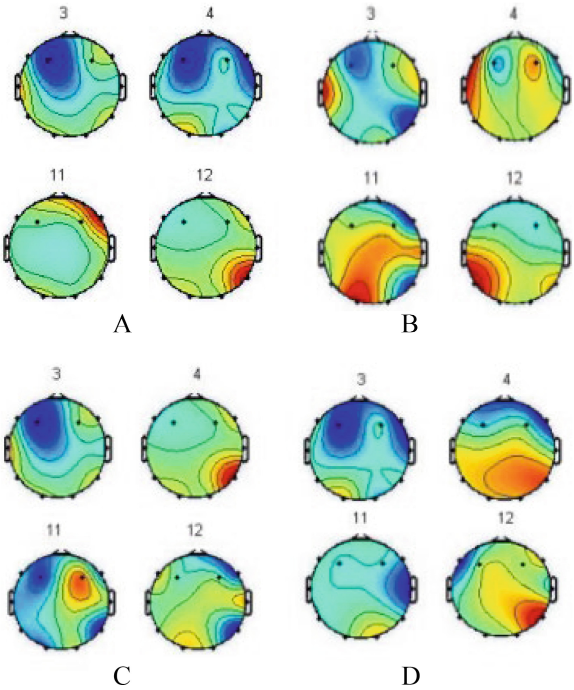


Fig. 16. Reduced Frontal region activation during Neutral action

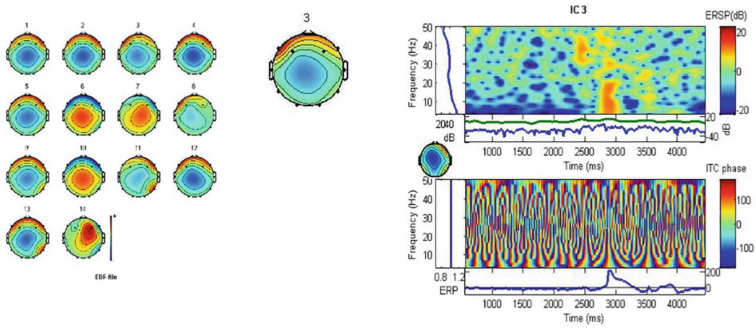


Fig. 17. Activation observed during Arm up event of the robotic arm in electrode F3

which was the ipsilateral side of the moving hand. ERS was prominently noticed after the action had taken place as seen in Figs. 16–18.

As pointed out in Fig. 9, the area or region of the brain that is involved in motor activity is the frontal lobe or frontal region. The activity used in this study is the motor activity/movement for which the frontal lobe is responsible and it is observed that the activation of activity was found in the frontal region.

Figures 16 and 17 show the time-frequency decomposition of the activations of components. Independent components are capable of directly indicating the activity of

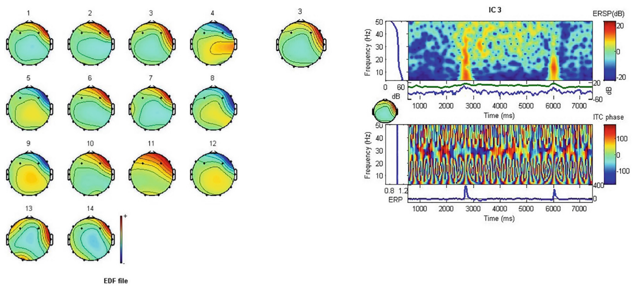


Fig. 18. Activation observed during Arm down event of the robotic arm in the electrode F3

one brain EEG sources. The image represents two images as the ERSP (dB) image and the ITC image. A correlation between the component activity and occurrence of stimulus is also seen. The ERSP (dB) (dB shows the level of waveform in decibels that are relative to digital full scale [14]) image seen in the upper panel represents the phase-lock events [15].

4 Performance evaluation of the Robotic Arm

For doing data analysis the results of all three events were required in the form of TP, FN, TN, and FP as specified in Table 1. The recording of each session five training and five testing is done. The calculations of the parameters important for performance evaluation are sensitivity, specificity, and accuracy as in Table 2.

Table 1. Outcomes Definition

Outcome	Definition
True Positive (TP)	Correct input, Correct Output
False Negative (FN)	Correct input, incorrect Output
True Negative (TN)	Incorrect input, Incorrect Output
False Positive (FP)	Incorrect input, Correct Output

Table 2. Parameter along with the formula

Parameter	Formula
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
Accuracy	$\frac{TP+TN}{TP+FN+TN+FP}$

5 Result

In this study, by implementing the ICA technique we were able to classify the region of brain responsible for cognitive control and decision making and pointed out the active region of the brain signals. We were able to get overall accuracy of 76% for Arm Down movement, 76% for Arm Up movement, and 80% for the Neutral movement of the robotic arm during testing sessions. In the same way, overall accuracy obtained during the training session is 76% for Arm Down movement, 77% for Arm Up movement, and 88% for Neutral movement. The overall accuracy rate of this study is 79%.

6 Conclusion

The EMOTIV EPOC provides 3 suites namely Expressive, Affective, and Cognitive. Expressive, reads facial expressions. Affective, reads the user's emotional state. And Cognitive, reads conscious intent for movements. In this study the Cognitive suite and the Expressive suite were considered for controlling the movement of the arm. The Pull, Push, and Neutral events of cognitive and raise eyebrow and clench of expressive events have been taken for experimental work. Looking at the patterns obtained it was found that the left frontal region of the brain is more active while performing arm up movement whereas both the left and right frontal parts of the brain are active during arm down event. The performance evaluation of the proposed robotic arm was done by calculating the sensitivity, specificity, and accuracy values. The analysis was performed with regards to find the activation regions of the brain when the movements were imagined.

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