An Experimental Study: ICA-Based Sensorimotor Rhythms Detection in ALS Patients for BCI Applications

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Abstract. Independent Component Analysis (ICA) is used in this paper to study the brain signals of patients with Amyotrophic Lateral Sclerosis (ALS) in the EEGLAB toolbox. Electroencephalography (EEG) signals are recorded in unipolar mode, wherein the Cz electrode is selected as the reference electrode. Therefore, it is expected that the independent components of brain signals can be analyzed while the patient moves his/her hands, and the event-related potential of the process can be separated as an independent component using the maximum value of its variance. The results show that by using ICA in analyzing the brain signals during hand movement, different brain activities that are related to the moving process can be separated. One of the major problems in analyzing brain activity is feature extraction. In this study, the absolute value of the amplitude, variance, θ (3–8 Hz) and α (8–13 Hz) band average power and the power of frequency components inα and θ bands are considered as the features. The results show that the features of the independent components present more accurate diagnosis compared to the brain signals characteristics. These features can be used in brain-computer interface systems to determine SMR in patients with ALS.

Keywords: Sensorimotor Rhythm · EEG · ALS patients · independent component analysis · EEGLAB · MATLAB · BCI

1 Introduction

For decades, research on Brain-Computer Interfaces (BCIs) has focused on communication and device control applications for restoring cognitive and motor functions in severely paralyzed patients [1]. Many studies on BCI have shown that people can learn to control Sensorimotor Rhythm (SMR) amplitudes in order to move cursors and other objects in one, two, or three dimensions [2]. A BCI is a communication channel between

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the human brain and computer [3]. In interdisciplinary studies, such as BCIs for cognitive diagnostic applications, the human brain can be studied. These studies may include brain imagining or use brain signals. Brain signals are collected by the electrodes placed on the scalp and then processed until special features that indicate the user's intentions are extracted. These signals contain physiological and non-physiological artifacts. Various methods have been proposed by researchers for removing these artifacts [4]. EEGLAB, running under the cross-platform of commercial software MATLAB (The Mathworks, Inc.) is employed for processing the collections of single-trial and/or averaged EEG data of any number of channels [3]. This software provides powerful tools to define analytic functions using Independent Component Analysis (ICA). In a study on a group of patients with ALS, it was proved that these patients can use the SMR to launch a BCI [5]. In a study on mu and beta frequency bands, it was found that ALS patients can learn how to create positive or negative changes in slow cortical potentials (SCPs), and by using these controls, they can select letters or objects. The connection speed is low in comparison with ordinary people, with about one or two choices per minute; however, new methods of signal analysis in BCI systems can considerably help ALS patients. In another study, the right/left hand motion detections were classified based on Artificial Neural Network (ANN) training, and the Event-Related Potential (ERP) related to the movement of each hand was obtained by a special algorithm [6]. In this method, a Support Vector Machine (SVM) algorithm was used to select the independent components, and finally, the patterns of the movement were chosen with an accuracy of 8.89%. Moreover, ICA as a developed method for.

Principal component analysis is used for blind separation of independent sources that are linearly combined [7]. ICA is an effective tool for separating all kinds of artifacts from EEG signals and can properly isolate a wide range of them, including a variety of motions, electromyography (EMG), electrocardiography (ECG), and external disturbances, from brain signals.

The present study focuses on signal processing using ICA to determine the maximum amount of variance of chosen independent components. Moreover, the purpose of this study is SMR detection related to the hand movement in ALS patients. Accordingly, an averaging method is used for pre-processing the data and ERP extraction; the ICA tool is chosen from the EEGLAB toolbox (Ver.13.5.4 b) and applied to 12 data channels so that the independent components are obtained; next, time-dependent features are extracted and evaluated. Finally, the maximum amount of variance associated with the SMR is determined.

2 Materials and Methods Data Acquisition

2.1 Description of Volunteer and Factors Affecting the Research

In this cross-sectional study, the data were gathered from a 22 years old boy, and before recording his brain signals, he was given the necessary recommendations. The parameters that must be considered to prevent any failure in the research include: (1) tasks should not belong, (2) the volunteer must be given training before recording signals, and (3) the laboratory should have ideal conditions in terms of temperature, lighting, and ventilation. The volunteer's eyes were closed during the recording to remove the eye artifacts.

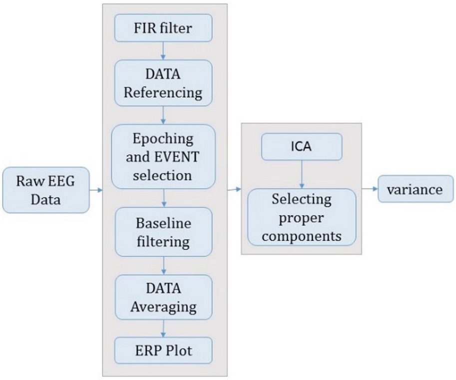

Fig. 1. The task sequence.

2.2 Description of Signal Recording Equipment and Task

The data used in the current study was recorded using a 12-channel BCI in the EDF file format based on the NCBI EEG system (PMCID: PMC3388484). A Cz electrode was selected as the reference electrode, and the entire head surface was covered by 12 electrodes according to the 10–20 standard protocol. The sampling frequency was 256 Hz and recording channels were FP1, F3, Fz, F4, C3, Cz, C4, P3, and Pz, while channel P4 was considered as the earth. The volunteer was seated on a chair, and relaxed, with a pedal in his hand. During the experimental session, he was told to do an action for certain periods (motor execution) to record the event-related signal, and then to perform only motor imagery of the movement. It took about 20 min to record all signals. The whole experimental procedure, as shown in Fig. 1, has been approved by Neurosciences research center of Tabriz University of medical sciences university, Tabriz, Iran.

3 Technical Work Preparation

The proposed method consists of three parts:

(1) Pre-processing, (2) ICA, and (3) the determination of the maximum amount of variance.

3.1 Pre-processing and Time-Frequency Analysis

Steps to perform pre-processing and ERP extraction are as follows: electrodes were first introduced in accordance with 20–10 standards [8]. Figure 2 shows the channel spectrum, areas of brain activity, and signal strength at different frequencies. According to the results, the obtained signal was examined to determine whether the signal met the criteria necessary to continue the analysis or not. In the channel related to the motion, alpha and mu band signal had a high power, which implied the obtained signal's integrity. A Finite Impulse Response (FIR) low-pass filter was then used to remove DC-offset with a low cutoff frequency of 3 Hz. To remove the eliminating, the baseline values, the DC

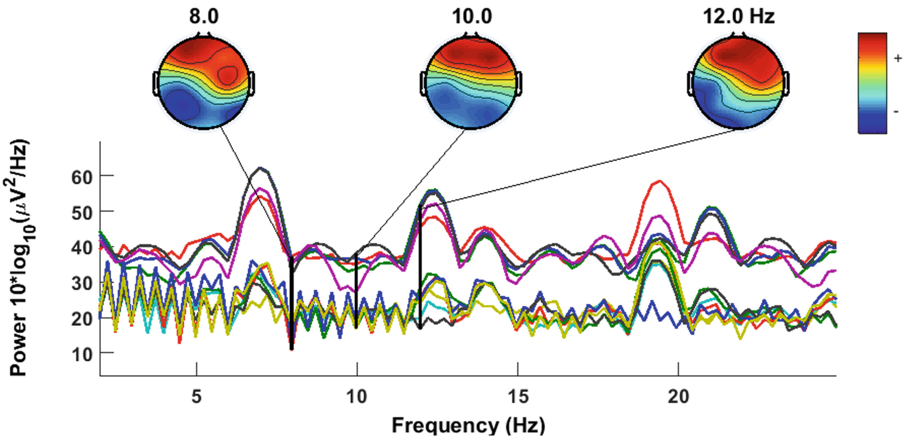

Fig. 2. Channel spectra

level of the signal was altered so that the morphology of the signal was preserved [9]. In the next step, synchronous averaging was performed and the signal was ready for feature extraction. Then, time features were extracted from the obtained signal, and then, the extracted features were evaluated by statistical methods as shown in Fig. 3. After obtaining optimum characteristics, ICA techniques were used for independent component extraction [10]. Finally, after independent component analysis, the target-independent component was selected and the maximum variance was determined.

Neurological processes that produce EEG signals are inherently dynamic [11]. Time-lapse changes in signal strength or maximum frequency of EEG can give information about the basic interests. The non-stationary nature of the EEG signal makes it inevitable to use methods that can quantify the spectral content as a function of time. Time-frequency analysis is a useful tool for the study of spontaneous change and changes resulting from a vibrational mode. To evaluate the spectral range (event-related spectral amplitude), phase, and turmoil dependence (coherence perturbation), two spectral decomposition techniques were used in this article: (1) event-related spectral perturbation (ERSP), and (2) inter-trail coherence within the test.

(1) ERSP measures the mean event-related changes in the power spectrum at a data channel or component. They generalize the narrow-band event-related desynchronization and synchronization [3]. Calculating an ERSP requires computing the power spectrum over a sliding latency window and then averaging across data trials. The color of each image pixel then indicates the power (in dB) at a given frequency and latency relative to the time locking event [12]. Typically, for n trials, if, Fk(f,t) is the spectral estimate of trial k at frequency f and time t, then ERSP is given by:

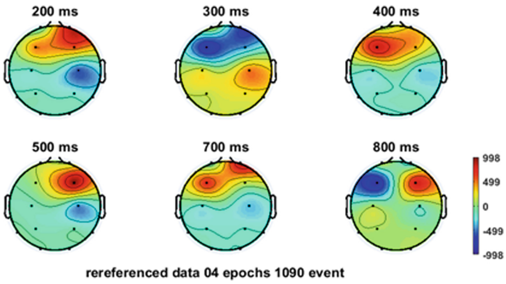

Fig. 3. ERP statistical analysis at selected times

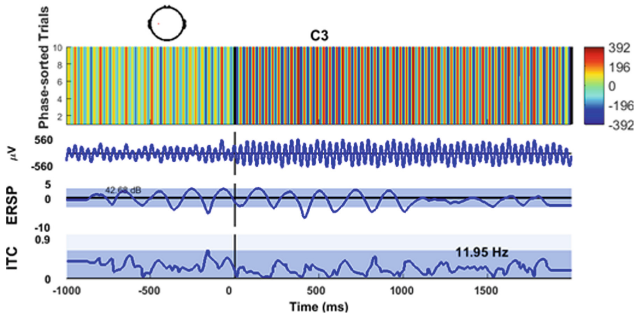

Fig. 4. ERP dynamics related to the channel C3

$$\mathrm{ERSP}(f, t) = \frac{1}{n}\sum_{k=1}^{n} |F_k(f.t)|^2 \tag{1}$$

Figure 3 shows the characteristics of channel C3. The ERSP of C3 is about 42.68 dB at a frequency of 11.95 Hz. To compute Fk(f,t), EEGLAB uses either the short-time Fourier transform (a sinusoidal wavelet (short-time DFT) transform) or a Slepianmultitaper decomposition that provides a specified time and frequency resolution [3] (Fig. 4).

(2) Inter-trial coherence (ITC of magnitude and phase) at single channel or components. ITC is a frequency domain measure of the partial or exact synchronization of activity at a particular latency and frequency to a set of experimental events to which EEG data trials are time-locked. The term ‘inter-trial coherence’ refers to the event-related phase coherence (ITPC) or event-related linear coherence (ITLC) between recorded EEG activity and an event-phase indicator function (e.g., a Dirac or cosine function centered on the time locking event) [3]. ITPC and ITLC are defined by:

$$\mathrm{ITPC}(f, t) = \frac{1}{\mathrm{n}}\sum_{\mathrm{k}=1}^{\mathrm{n}} \frac{\mathrm{f_k(f.t)}}{|\mathrm{f_k(f.t)}|} \tag{2}$$

$$\mathrm{ITLC}(f, t) = \frac{\sum_{i=1}^{n} f_k(f.t)}{\sqrt{n \sum_{i=1}^{n} |f_k(f.t)|}} \tag{3}$$

3.2 Independent Component Analysis

Analysis of data by ICA (or any linear analysis method, such as PCA or its derivatives) includes a linear change of data collected from brain signals to convert the space-based imagery data [13]. This method converts data to a set of simultaneously recorded output of spatial filters applied to multiple channels of information. These spatial filters are designed in different ways and for different purposes. In the obtained brain signals, each row of the matrix represents a period of voltage difference between a data channel and one or more reference channels. After analyzing by ICA, each row of the data matrix indicates information about the spatial filter process components.

In ICA, an independent component filter is selected to produce independent signals available to the channel data [14]. In fact, these components are the sources of the information contained in the data which have been mixed through the transfer of the recorded data values of the brain. The mixing process for the EEG signal through the transmission of information is passive and linear and does not add any additional information to data content. These sources of information may introduce synchronous or semi-synchronous activities that are related to one or more cortical activities or not related to a cortical activity (movement of eyes or a muscle, etc.).

Suppose we observe n linear combination of n independent components:

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \cdots + a_{jn}s_n, \text{ for all j} \tag{4}$$

In this equation, the time dependence is not included. Instead, it is assumed that the mixtures, xj, and the independent components, si, are random variables, so x (t) and s (t) are the samples of these random variables. It is also assumed that both the mixture variables and the independent components have zero mean [15]. If the zero average hypotheses do not hold, then the variables observed by subtracting the sample average can be placed at the center. Equation 5 shows the sum in Eq. 4 with matrix-vector notation:

$$\mathrm{X} = \mathrm{A.S} \tag{5}$$

where X denotes the observed vector image and its components, and S is the observed vector (EEG signal) and its components. A is a fixed matrix with one component. The model can also be defined as follows:

$$X = \sum_{i=1}^{n} a_i s_i \tag{6}$$

Matrix A is also referred to as the weight matrix. The problem is the determination of the weight matrix as a linear transformation of observed variables involving a suitable property. The suitable property means that components are non-Gaussian and independent from each other (not symmetrical). To determine the values of weight matrix, many

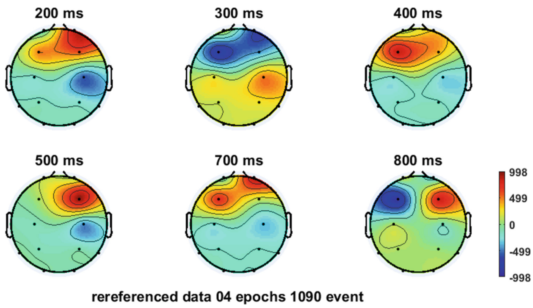

Fig. 5. Independent components

methods have been proposed, such as principal component analysis, factor analysis, independent component analysis, and projection pursuit.

$$\mathrm{S} = \mathrm{W.X} \rightarrow \mathrm{W} = \mathrm{A}^{-1} \tag{7}$$

The non-Gaussianity can be calculated in several ways. Here the classic method of fourth-degree kurtosis or cumulantis used as follows:

$$\mathrm{Kurt}(s(i)) = E\left\{s(i)^4\right\} - 3\left[E\left\{s(i)^2\right\}\right]^2 \tag{8}$$

The values of kurtosis for a signal with Gaussian, sub-Gaussian and super-Gaussian distributions are zero, negative and positive, respectively. Figure 5 shows the result of the ICA that is applied to the obtained signal. Considering the signal strength in the motor cortex of the brain, the fourth independent component is selected and the remaining components are removed. The independent component activity is shown in Fig. 6. According to this figure, the maximum signal power occurs at 12 Hz. The obtained ERP signal from the independent component is shown in Fig. 7. It can be seen that from 12 independent components obtained from this analysis, 9 components have been omitted in the first place and 3 components have been selected by applying ICA. The selected components have more signal strength than the other ones. From the 3 remaining independent components, the fourth one (IC4) that refers to channel C3 has the maximum signal strength at 12 Hz. As Fig. 7 illustrates, IC4 that has an amplitude of ±377 microvolts and a frequency of 11.95 Hz is selected as the ERP signal. The time delay of this signal is about 500ms, which shows that the potential distribution in the imagery part of the brain occurs in this time range. According to this figure, by using ICA for ALS patients, SMRs can be detected and used for BCI applications.

3.3 Variance of ERP

An ERP signal obtained from ICA has a normal or Gaussian distribution. Since the maximum power occurs around 12Hz, the variance and deflection are calculated at this frequency. In Fig. 8, the maximum values of independent components at 12 Hz are shown. As can be seen, the maximum power at 12 Hz corresponds to the fourth independent

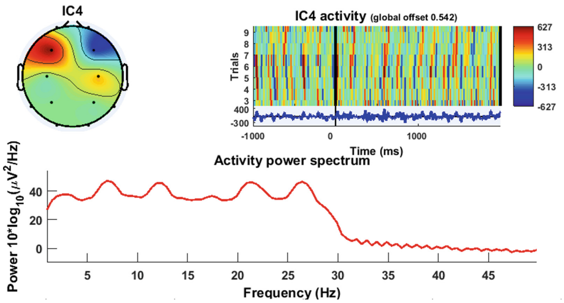

Fig. 6. The fourth independent component

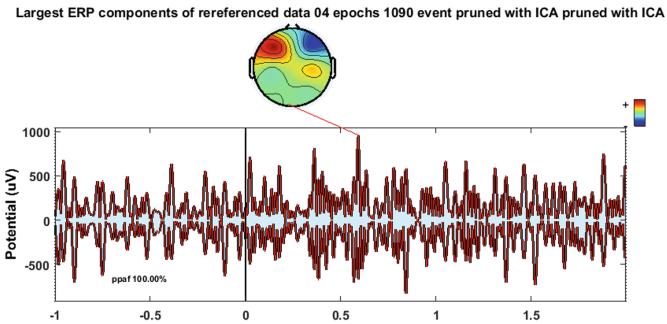

Fig. 7. ERP signal of the fourth independent component

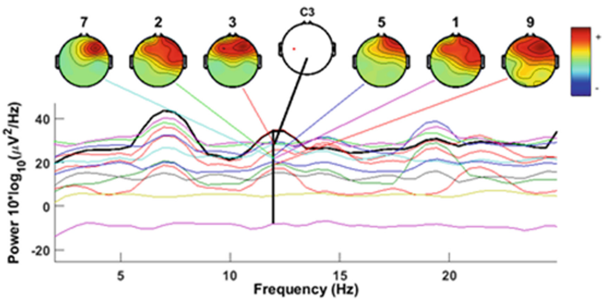

Fig. 8. Maximum amount of variance of the independent component at 12 Hz

component or channel C3. These results confirm the accuracy of the previous results and show that the selected independent component is related to channel C3 or the motor part of the brain Fig. 4.

The maximum variances associated with independent components are listed in Table 1. It can be seen that the third independent component has the maximum value. However, this is not an acceptable value and can be attributed to the brain activity area. By observing brain activity areas in the third independent component, we find that this signal is not related to the motorized part under analysis. Therefore, it can be said that according to

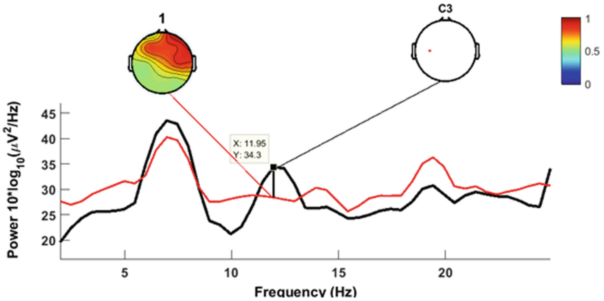

Fig. 9. Acceptable maximum amount of variance at 12Hz for the intended ERP

Table 1. Maximum variance for independent components

Independent components number	Relative variance (percent)
1	25.44
2	26.98
3	113.59
4	34.30
5	1.91
6	2.93
7	24.87
8	3.95
9	13.44
10	1.22
11	0.11
12	0.01

Table 1, the maximum variance is 34.30%, which is related to the fourth independent component of the considered ERP signal. Figure 9 shows the maximum acceptable variance at 12 Hz. This figure illustrates that the maximum power at 12Hz is related to channel 3 and the fourth independent component (IC4).

4 Discussion and Conclusion

The results of the study were observed for an ALS patient. According to the results of ERP analysis of the patient's sensory-motor brain, the SMR-related features associated with the hand movement were given in Table 2.

Moreover, the results of the study showed that the ALS patients SMR profile can be obtained using an ICA with an acceptable deviation. The omission criterion of the obtained data was based on the signals strength; by applying the ICA, 3 components

Table 2. SMR specification

SMR	Value
Latency (ms)	847
ERSP (db)	42.68
ITC (HZ)	11.95
Relative Variance (%)	34.30

were selected. The fourth independent component (IC4), which referred to channel C3, had the maximum signal strength at a frequency of 12 Hz. This value refers to the brain activity in the motor region due to the patient's hand movement. This feature can be used to communicate with a variety of BCIs. Connecting to BCIs improves the quality of life for ALS patients. For those BCIs that have the role of rehabilitation, identifying patients SMRs and studying the rhythms will determine the impact of the rehabilitation. Future studies are necessary for the refining of results of this work and evaluation of other dimensions of.

ICA application in BCI interfaces.

It is suggested that for parallel studies in this field, other separation techniques to be also used to evaluate the accuracy of this method.

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