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Automatic channel selection in EEG signals for classification of left or right hand movement in Brain Computer Interfaces using improved binary gravitation search algorithm

Alireza Ghaemi [a], Esmat Rashedi [a,*], Ali Mohammad Pourrahimi [b], Mehdi Kamandar [a], Farhad Rahdari [c]

[a] Department of Electrical Engineering, Graduate University of advanced technology, Kerman, Iran
[b] Neuroscience Research Center, Institute of Neuropharmacology, Kerman University of Medical Sciences, Kerman, Iran
[c] Department of Computer and IT, Institute of Science and High Technology and Environmental Sciences, Graduate University of advanced technology, Kerman, Iran

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ABSTRACT

This paper presents an automatic method for finding optimal channels in Brain Computer Interfaces (BCIs). Detecting the effective channels in BCI systems is an important problem in reducing the complexity of these systems. In this research, Improved Binary Gravitation Search Algorithm (IBGSA) is used to automatically detect the effective electroencephalography (EEG) channels in left or right hand classification. To do this, at first, data is filtered with a bandpass filter in order to reduce the amount of different types of merged noise. Then, the electrooculography (EOG) and electromyography (EMG) artifacts are corrected based on Blind Source Separation (BSS) algorithm. Data is epoched according to the left or right hand motor imageries and central beta frequency band is isolated for Event Related Synchronization (ERS) analysis. Feature extraction process is carried out by analyzing EEG signals in time and wavelet domains. The logarithmic power of each channel is computed in time domain and the features of mean, mode, median, variance, and standard deviation are calculated in wavelet domain. IBGSA is employed to detect the optimal channels to achieve better classification results. Support Vector Machine (SVM) is used as the classifier. The maximum accuracy of 80% and average accuracy of 76.24% were obtained for eight subjects in BCI competition IV dataset. The results of this research confirm that automatically detecting effective channels can enhance the practical implementation of BCI based systems and reduce the complexity.

1. Introduction

A network of more than 100 billion individual neurons forms the human nervous system. These cells are interconnected in systems and they create neural circuits, so the way we see this world, think, learn, remember and control the machinery of our actions are being originated from these neural circuits [1].

It is considered that electrical signals of human brain caused by its neural activity, include valuable information. According to this assumption, lots of experiments have been carried out on human EEG signals by researchers in previous decades. These experiments were performed by covering various techniques of classification and digital signal processing methods. One of the main goals in EEG signal processing is to develop a system for constructing a non-physical communication between human and an external device. Such a device can be a robotic arm, an speller, or a wheel chair [2,3]. A brain computer interface (BCI) is a system that enables a person to control an external device by using brain's neural activity. The main goal of creating such a system is the handicapped people helping and enabling them to do their daily routines [4]. Fig. 1 shows the block diagram of a BCI system. According to this figure, after signal acquisition, preprocessing methods such as filtering or blind source separation algorithms are employed to reduce the merged artifacts and different types of EEG noises. In the preprocessing step, the SNR of the EEG signals are increased. In the next step, the related features can be extracted to train the classifier. The more the SNR of the EEG signals are enhanced, the more the extracted features are reliable and as a consequence, better classification results

* Correspondence to: P.O. Box 76315-117, Iran
E-mail addresses: alirezaghaemi83@gmail.com (A. Ghaemi), e.rashedi@kgut.ac.ir (E. Rashedi), am.pourrahimi@kmu.ac.ir (A.M. Pourrahimi).

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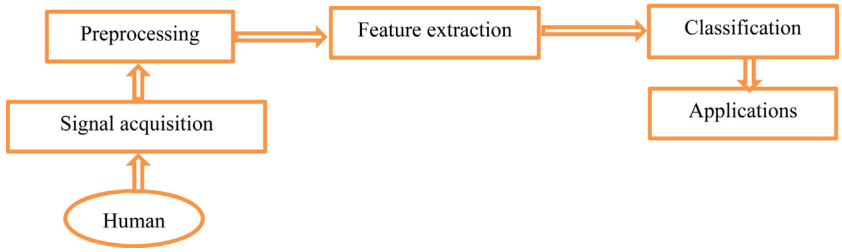

Fig. 1. BCI systems block diagram.

will be achieved. When the classification process is completed, the related commands are produced to control a device or complete a task.Event Related Synchronization (ERS) and Event Related Desynchronization (ERD) are two common neurological phenomena which are being used frequently in BCI systems for translating EEG signals. Both phenomena are known as temporary change of power in EEG signals. If this change is the enhancement of power, it is known as ERS and if that's power decrement, it refers to ERD [5,6]. ERS and ERD are detectable in beta and mu rhythms respectively and they are not phase-locked but they are time-locked [5,6]. Both phenomena occur when a person imagine or perform a motor activity. ERS and ERD are computable using Eq. (1) [3].

$$\text{ERS\&ERD} = \frac{P(f, n) - P_{ref}(f)}{P_{ref}(f)} \tag{1}$$

Here, P (f, n) is the signal power in a specific time and frequency of an average power map, and $P_{ref}(f)$ is an average power during some reference time and frequency f.

Knowing about different EEG frequency bands could smooth the path to study, analyze, and detect different neurological phenomena like ERS and ERD. EEG frequency bands according to their frequencies from low to high are mainly categorized in the following order: a) delta (0.5–4 Hz), b) theta (4–8 Hz), c) alpha (8–13 Hz), d) beta (13–30 Hz), e) gamma (refers to the waves which are more than 30 Hz) [3].

1.1. BCI applications and literature review

BCI has various applications from controlling video games to artificial limbs and robotic arms. Many applications of BCI can be found in [7]. These applications can be categorized in the following fields: a) environmental control, b) locomotion, c) entertainment, and d) multimedia [8].

The authors in [8–10] compare different classifiers and statistical analysis in a BCI system for motor imagery tasks. Spatial smearing caused by volume conduction of different brain layers is an important issue in EEG signals. Yet, various methods have been considered for reducing negative effects of this problem. Most of these methods are based on spatial filtering of the data. For example, authors in [10] represent spatial filtering and independent component analysis (ICA) to separate four classes of motor imagery tasks. These imagery tasks include tongue, foot, and left or right hand movements. They compared different ICA and common spatial filtering algorithms. The best results were reported for infomax algorithm in ICA analysis and laplacian derivations pattern in Common Spatial Pattern (CSP) preprocessing. Since, detection, separation, and localization of EEG source is very difficult. In [11], 'Bell and Sejnowski' ICA algorithm were employed to completely detect source localization and identification of generated EEG.

Automatic detection of left or right hand movement can be very useful in a BCI system. The authors in [4] represented an automatic method to classify left or right hand movements. Relevant EEG channels were separated. Then, these channels filtered with a bandpass filter at the range of 0.5–90 Hz. Filtering raw EEG data is an important step to achieve a clean signal and to get rid of different noise types merged with EEG signals. To remove the line noise, a notch filter of 50 Hz was applied. Then, Automatic artifact removal toolbox of EEGLAB [12] was added and used in two steps of EOG and EMG to correct eye and different muscles artifacts of the EEG signals. Artifact removal steps were carried out by using Blind Source Separation (BSS) algorithm. Extracted features were classified with support vector machine (SVM) and Artificial Neural Network (ANN) classifiers [4].

Although different classifiers like Bayesian Linear Discriminant Analysis (BLDA), Fisher Linear Discriminant Analysis (FLDA), SVM, Generalized Anderson's Task linear classifier (GAT) and etc. can be employed in classification problems. In BCI classifications, SVM has yielded a high accuracy and is being widely used in this area of research. In [13], the performance of different classifiers were compared and the SVM and the BLDA classifiers were considered as the best classifiers for EEG signal classifications.

It is very useful to classify different types of movements in one limb. For example, different types of hand movements like grasping, opening, or reaching can be classified in a BCI system by using ERD or ERS phenomena [9,14,15]. An online method based on adaptive probabilistic neural network was used in [15] to classify hand grasping, this experiment was carried out based on a single trial EEG signal in a time varying environment and the average classification accuracies of 75% to 84.0% were obtained for three different sections and 10 naive subjects.

Surface electromyogram (sEMG) is a non-invasive method to acquire neuromuscular activities from the skin surface by using at least 2 bio-potential sensors. Combination of sEMG sensors and muscle activation strategy can be considered as a powerful tool for identifying different finger movements in BCI based systems [16,17]. The authors in [18] improve the classification of independent finger movements in handicapped people based on source separation and icasso clustering method. In the mentioned research, a new procedure is introduced for detecting different kinds of gestures based on a myometric control. This technique employs independent component analysis and icasso to consider the minimum number of the surface electromyography sensors. By utilizing fewer number of the mentioned sensors, more flexibility and less complexity of the prosthetic devices can be achieved.

Understanding different sleep stages is another important application of EEG signals. Applying basic principles of signal processing on human EEG can be useful in studying and detecting sleep problems like insomnia. It can also be useful in reducing driving accidents caused by drowsy driving [19–22].

In [22], for automatic detection of drowsiness, EEG signals were analyzed in three domains of time, frequency, and wavelet. In feature extraction, three features were calculated in time domain. These features were maximum, minimum and standard deviation values of EEG signal. In spectral analysis, 10 features were computed and these features were central frequency, peak frequency, ratio H/L, (RH/L), first and third quartile frequency (Q1F and Q3F), spectral standard deviation, integrated range, maximum frequency, asymmetry coefficient, and kurtosis coefficient. In wavelet domain,