Non- Invasive EEG-based BCI system for Left or Right Hand Movement

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ABSTRACT:
A brain computer interface (BCI) records the activation of the brain and classifies it into different classes. BCIs can be used by both severely motor disabled as well as healthy people to control devices. The study addresses the development and application of a novel medical technology to measure a patient's brain activity, translated it with intelligent software, and uses the translated signals to drive patient-specific effectors. In this work, the EEG pattern recognition approach is used based on brain computer interfaces for moving hands right and left. Electroencephalographic (EEG) signals produced by the brain were used as input to the proposed BCI system. There are two BCI approaches used in this paper; the offline BCI approach and the online BCI approach. In the offline approach, the Dataset of motor imagery EEG recordings is used, while in the online approach we used our own BCI system to capture EEG recordings. The practical online testing demonstrates the feasibility of using the proposed system with the ability of real-time processing, automatic analysis. The Principle Component Analysis (PCA) is used for both artifact removal and feature extraction. Wavelet Transformation is also developed to extract the important information from EEG recordings. The K-Nearest-Neighbor (KNN) and Neural Networks (NNs) classifiers were used to find out what the user wants. The results show that we can effectively classify two kinds of tasks based on both BCI approaches with best predictive accuracy of 99.2% for offline approach and 98 % for online approach when wavelet transform and Neural Networks used together. This gives an ideal solution for people with severe neuromuscular disorders, such as Amyotrophic Lateral Sclerosis (ALS) or spinal cord injury, people who are totally paralyzed, or "locked-in", help them to have a communication channel with others.

KEYWORDS: EEG- Electroencephalography, BCI- Brain Computer Interface, K- Means clustering, neural networks, PCA, Wavelet transform.

1. INTRODUCTION

First signs of BCI research can be dated back to 1960's [1], but it was in 1990's when the BCI research really got started. Faster computers and better EEG devices offered new possibilities. To date there have been over 30 BCI research groups [2]. They have taken different approaches to the subject, some more successful than others. More than half of the BCI researches groups have built an online BCI, which can give feedback to the subject. None of the BCIs have yet become commercial and only a couple has been tested outside laboratory environments [3].

Despite the technological developments numerous problems still exists in building efficient BCIs. The biggest challenges are related to accuracy, speed and usability. Other interfaces are still much more efficient. If a disabled person can move eyes or even one muscle in a controlled way, the interfaces based on eye-gaze or EMG switch technology are more efficient than any of the other BCIs. However, BCI could provide a new communication tool for people suffering from so called locked-in syndrome. They are completely paralyzed physically and unable to speak, but cognitively intact and alert [4].

There has been a lot of improvement in the field of Human Computer Interaction (HCI). There is lot of invasive techniques to record activity signals from the human brain. Human BCI research has focused mainly on noninvasive methods for monitoring brain activity, such as electroencephalography (EEG), magneto encephalography, near-infrared spectroscopy, and functional magnetic resonance imaging. Attempts to control the hand movement right or left using EEG BCI directly have been too complicated, and it requires a series of complex decision makings even to complete a simple command [5]. The EEG or electroencephalogram is electrical activity recorded from the scalp and produced by neurons in the brain. The development of a Brain Computer Interface, or in our case, an EEG-based communication device, requires the raw EEG signal to be converted into a new output channel through which the brain can communicate and control its environment [6]. The aim of this work is to develop a non- invasive EEG- based BCI system that analyzes the brain-electrical activity of a subject, tries to find out the subject's intention, and generates output commands to give a decision for moving hand right and left with high prediction accuracy.

2. METHODS

BCI is a system in which the user's choices or selections are made by brain signals instead of the usual neuromuscular activity. The signals are acquired through electrodes, processed for signal extracts that reflect the intent of the user, and then translated into device commands. In this work, a non- invasive EEG-based BCI system is developed by which the user performs imaginary right and left hand movements. As the design of any BCI system depends on Time to learn, Performance Speed, Number of errors user can make, retention ability of users, subjective satisfaction and the effectiveness in extracting specific features from brain's electrical activity is directly related to efficiency of BCI, so we present our EEG- based BCI system in both offline and online approaches [7].

The offline BCI approach is used as train dataset that randomly chosen to test our methods. The online BCI was developed after all offline experiments were performed. The online BCI is the actual working BCIs as the artifact removal, features extraction, classification, are done in real-time; this makes it possible to provide feedback for the user which is not possible in the offline approach. Figure 1 summarizes the overall process of the proposed system.

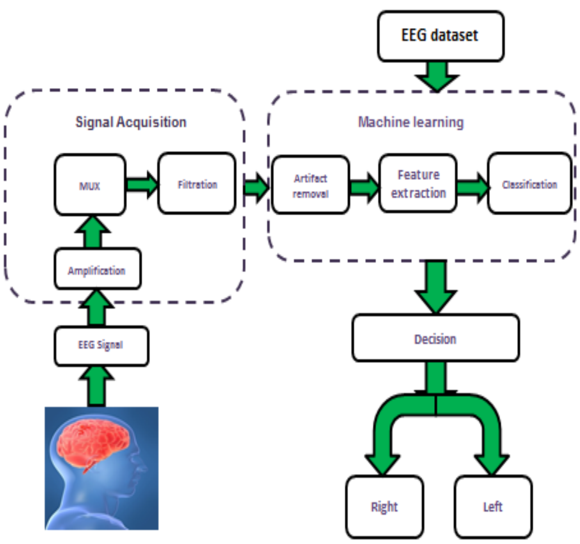

Fig. 1. General bock diagram of the proposed BCI system for hand movement right and left.

The proposed system describes the two BCI approaches; it consists of the following main stages: Artifact removal, feature extraction, and Classification. For artifact removal, the principle component analysis (PCA) was used, and then a number of features from the EEG signals were extracted by both PCA and wavelet transforms to be feed to the classifier. Lastly, the k- means clustering and artificial neural network were used in the classification step. The programming language used in this work is MATLAB 7.0 Mathwork, Inc., because it has robust tool boxes that can help in this work.

2.1 System architecture

The block diagram of the developed online EEG-based BCI system is shown in Figure 2. To get the acquired signal to the computer, there are a number of stages to pass through. The electrical brain activity will be picked up using nine EEG silver electrodes placed on the motor cortex at positions: F3, F4, C3, Cz, C4, P3, Pz and P4 according to the international 10- 20 system.

The primary motor cortex is a brain region that in humans is located in the posterior portion of the frontal lobe. It works in association with pre-motor areas to plan and execute movements. The aim is highly focused to acquire the EEG signal from the motor cortex area when the patient wants to plan and execute a movement. After signal acquisition, the amplification is necessary to filter out the artifacts, The EEG amplifying circuit consists of a preamplifier (instrumentation amplifier) designed for data acquisition applications requiring high accuracy under worst-case operating conditions with the gain of 100, an isolated amplifier to protect subject, a bandpass filter that was composed of a low-pass filter and a high-pass filter to reserve 1–100 Hz signals, a differential amplifier that had the gain of 10 or 50. The gain of the preamplifier (100) is larger than the amplifier (a gain of 10) because of the EEG signal is in microvolt level, and thus, larger amplification is needed before filtering. A 60-Hz notch filter is also included to eliminate the effect of the line noise in case we have to run the system with ac power.

2.2 Experimental setup

This work is applied at first in the offline mode on Dataset of motor imagery in ECoG recordings, session-to-session transfer BCI Competition III [8] provided by University of Tubingen, Germany used to test the efficiency of the proposed BCI system and also as a training signals.

For the offline BCI approach, which enabled us to deal with ECoG signals, to examine signals from different electrode positions, and to apply different preprocessing techniques. The Dataset consists of a labeled train dataset and an unlabeled test dataset. The train dataset consists of two parts; Part1 represents the brain activity during 278 trials. It is stored in a 3D matrix, using the following format: [trials (278) x electrode channels (64) x samples of time series (3000 ms)]. Part2 represents the label of 278 trials; it is stored as +1/-1 values.

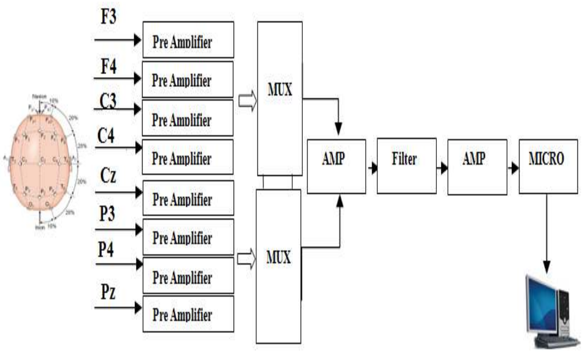

Fig. 2. The architecture of the EEG- based BCI system.

The test dataset contains 100 trials of brain activity; it is stored in a 3D matrix. The dataset contains a huge amount of data; for example, the Train data set is [278 x 64 x 3000] and this causes long processing time. So we under sampled the data by using a smaller sampling rate, 100 HZ instead of 1000 HZ; thus reducing the data set size significantly [278 x 64 x 300] and hence decreasing processing time significantly. This procedure is valid and didn't cause any data loss, since the maximum frequency component in normal EEG is between -50 to +50 HZ, and we sampled our data by 100 HZ which is greater than twice maximum frequency.

For the online approach, the dataset was built acquiring signals from a single healthy subject in Biomedical Engineering Laboratory in MUST University [9]. The subject will be asked to imagine right and left hand movements while the time series of the electrical brain activity will be picked up during these trials using nine EEG electrodes placed on the motor cortex. Every trial consisted of either an imagined right and left hand movement and it will be recorded for 5 seconds duration. All recordings will be performed with sound card sampling rate of which is 8000Hz. By this step, all acquired signals in the online approach were stored and ready for online processing where the subject just imagines right or left hand movements.

2.3 Artifact removal.

The presence of physiological artifacts, such as eye blinks, in EEG recordings obscures the underlying processes and makes analysis difficult. Large amounts of data must often be discarded because of contamination by eye blinks, muscle activity, and pulse signals. To overcome this difficulty, signal separation techniques are used to separate artifacts from the EEG data of interest using PCA.

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension as in our data. The basic goal in PCA is to reduce the dimension of data. So it can be proven that the representation given by PCA is an optimal linear dimension reduction technique in the mean square sense [10]. Such a reduction in dimension has important benefits. First, the computation overhead of the subsequent processing stages is reduced. Second, noise may be reduced, as the data not contained in the *n* first components may be mostly due to noise. Third, a projection into a subspace of a very low dimension, for example two, is useful for visualizing the data.

2.4 Feature extraction

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features named features vector.

A. Principle Component Analysis (PCA).

More recently, multivariate statistical analysis techniques, such as Principal Component Analysis (PCA), have been used with the highest variance to separate and remove noise signals from the brain activity of interest and extract the most significant features to enable discrimination between classes [11]. This approach assumes EEG observations are generated by the linear mixing of a number of source signals, $X = SA$, where X is the matrix of p, n-dimensional, observations, S is the matrix of source signals, and A is the mixing matrix. The general assumptions of this approach are:

1. The number of sources is less than or equal to the number of observation.
2. The mixing is linear, $X = SA$
3. The mixing is instantaneous, $X(t) = S(t) A$.

For PCA to work properly, we have subtracted the mean from each of the data dimensions. The mean subtracted is the average across each dimension. Then we calculated the covariance matrix followed by Calculation of the eigenvectors and Eigen values of the covariance Matrix. Choosing components and forming a feature vector is then applied in the next step here is where the notion of data compression and reduced dimensionality comes into it. Once eigenvectors are found from the covariance matrix, the next step is to order them by eigenvalue, highest to lowest. This gives the components in order of significance. We decided to ignore the components of lesser significance. So the final data set will have lesser dimensions than the original [12] [13].

B. Wavelet Transform (WT).

A number of alternative time-frequency and time scale methods are now available for signal analysis and feature extraction. Of these the wavelet transform has emerged over recent years as the most favored tool by researchers for analyzing problematic signals across a wide variety of areas in science, engineering and medicine. It is used in this study as simple technique for feature extraction. [14][15][16][17].

Wavelets are localized in both time and frequency and often give a better signal representation using Multi-resolution analysis [18]. The wavelet transform is often compared with the Fourier transform, in which signals are represented as a sum of sinusoids. The main difference is that wavelets are localized in both time and frequency whereas the standard Fourier transform is only localized in frequency. The Short-time Fourier transform (STFT) is also time and frequency localized but there are issues with the frequency time resolution and wavelets often give a better signal representation using Multi resolution analysis. There are two types of wavelet analysis; Continuous Wavelet Transforms (CWT) and Discrete Wavelet Transforms (DWT). In CWT, the signal to be analyzed is matched and convolved with the wavelet basis function at continuous time and frequency increments. In DWT, the inner product of the original signal with the basis wavelet function is taken at discrete points and the result is a weighted sum of a series of bases functions, the basis for wavelet transform is wavelet function. [19][20].

In this study, the discrete wavelet transform (DWT) is used because it has a less computationally complex, taking O (N) time as compared to O ($N \log N$) for the fast Fourier transform (N is the data size). The wavelet coefficients are calculated using the Matlab wavelet tool box as follows: starting from the EEG signal S, two sets of coefficients are computed: approximation coefficients CA_1, and detail coefficients CD_1. These vectors are obtained by convolving S with the low-pass filter Lo_D for approximation and with the high-pass filter Hi_D for detail, followed by dyadic decimation. The length of each filter is equal to $2N$. If n = length(s), the signals F and G are of length $n + 2N - 1$, and then the coefficients CA_1 and CD_1 are of length equals floor (n-1/2) +N. There are many wavelet families; here we used haar family at level one. We selected only the coefficients of the resolution level which has maximum energy to be the input data to the classifier. [21], [22], figure 3, describes the calculation steps of wavelet coefficients and figure 4, shows the Wavelet energy of the resolution level which has maximum energy.

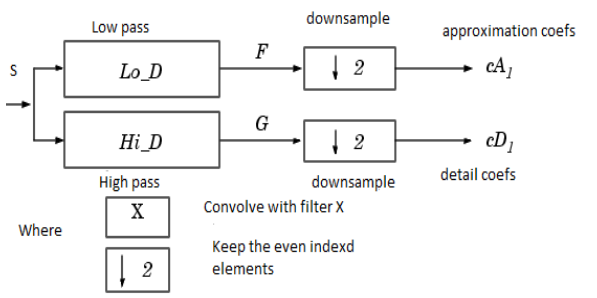

Fig. 3. The calculation steps of wavelet coefficients.

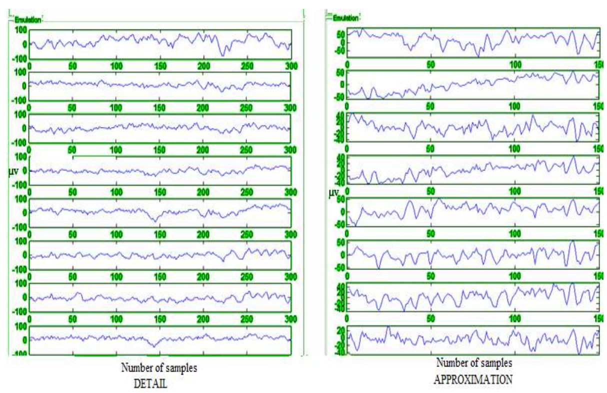

Fig.4. Wavelet energy of the resolution level which has maximum energy.

2.5 Classification

In order to find out the user's decision, a BCI system has to classify the preprocessed data. This means that the system does not attempt to understand the user's intentions, but it "compares" the data symbolizing a segment to representatives of a limited number of classes, and selects the class matched best. We used k-means clustering [23] and Artificial Neural Networks [24] in the classification step.

1. K- means clustering.

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate *k* new centroids as barycenters of the clusters resulting from the previous step. After we have these *k* new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the *k* centroids change their location step by step until no more changes are done [25][26][27].

In this work, k-means clustering is used as a simple algorithm that has been adapted to many problem domains as follows: suppose that we have n sample feature vectors $x_1, x_2, ..., x_n$ all from the same class, and we know that they fall into k compact clusters, $k < n$. Let m_i be the mean of the vectors in cluster i. If the clusters are well separated, we can use a minimum-distance classifier to separate them. That is, we can say that x is in cluster i if $|| x - m_i ||$ is the minimum of all the k distances. This suggests the following procedure for finding the k means:

- Make initial guesses for the means $m_1, m_2, ..., m_k$
- Until there are no changes in any mean
    - Use the estimated means to classify the samples into clusters.
    - For i from 1 to k
        - Replace m_i with the mean of all of the samples for cluster i.
    - end_for
- end_until

2**. Neural networks (NNs)**

Neural networks (NNs) were originally developed with the goal of modeling information processing and learning in the brain. Neural networks are composed of simple elements, neurons operating in parallel. Probabilistic neural networks are used here in the classification step. The network is formed of three layers: one input layer, two hidden layers and one output layer. When an input is presented, the first layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input.

The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes.

After the output presentation a learning rule was applied. We used a supervised learning method called back propagation. The back propagation calculates the mean-squared error between actual and expected output [28].

Our goal was successfully met on training 103 signals using 25 input neurons and 500 training epochs. When training the same data set with a 300 epochs the system doesn't reach the specified goal error. On using a small number of input neurons on training a large data set the system converge before reaching the goal error.

2.6 Data Visualization

A noninvasive EEG based - BCI system is proposed to acquire and analyze electroencephalogram (EEG) signals in real-time and fed them to the computer using parallel port. A good visualization and analysis of these signal is essential using a successful software package. Our work is written in the MATLAB language and has been tested on the WINDOWS platform with MATLAB version 7.0. Leveraging the rich graphics functionality of MATLAB, our GUI provides a number of functions that can be used to create graphic output. A simple graphical user interface (GUI) has been developed by using MATLAB. It aids the usage of the most frequently required functions so that users do not have to run any scripts or functions from the MATLAB command line in most cases, it has the following specifications:

- **Usability Requirements:**

- Easy to use the simple graphic user interface design.

- Easy to handle data.

- Clear and understandable presentation of the results (outputs).

- **Readability Requirements:**

- Robust implementation.

- Low frequency of failure.

- **Performance Requirements:**

- Relatively low response time.

- High throughput.

- Optimal and accurate algorithms implementation**.**

The proposed GUI enables users to work in both offline and online BCI approaches and shown in figure 5.

Fig. 5. The GUI of the proposed EEG- based non-invasive BCI system.

RESULTS

This paper proposes a scheme to develop a non-invasive EEG based- BCI system by which the user performs imaginary right and left hand movements through a simple graphical user interface that displays the EEG signals and classifies them online with high accuracy. First, we apply artifact removal PCA technique to remove unwanted noise from EEG signal to get a clean brain signal that is ready for further processing. Second, we extract only features of interest, corresponding to imaginary right and left hand movements by both PCA and DWT; so as finally our classifier can assign a test signal to either one of both classes (right or left; where each corresponds to a different device action).

The accuracy results of using wavelet transforms and PCA for feature extraction and k- means clustering and neural network classifiers in both offline and online approaches are shown in table 1 and table 2 respectively.

Table1. Prediction accuracy of the proposed offline EEG-based BCI system.

	Wavelet	**PCA**
K- means	75%	65%
Neural network	99.2%	58%

Table2. Prediction accuracy of the proposed online EEG-based BCI system.

	Wavelet	**PCA**
K- means	55%	55%
Neural network	98%	47%

CONCLUSIONS:

A Brain-Computer Interface (BCI) is a communication system in which messages or commands that a user wishes to convey pass not through the brain's normal output pathways to the muscles but are instead extracted directly from brain signals. In this work, we tried to build an accurate BCI system that discriminate between right and left hand movements. Thus the system is implemented in such a way that it is simple and cost effective so that it can aid the physically challenged people with slow cortical potentials SCP and ALS. Our system divided into two approaches; the offline BCI approach and online BCI approach. For the offline approach, we used a dataset of motor imaginary in ECoG recordings, session-to-session transfer BCI Competition III. For the online approach, we used EEG electrodes to detect microvolt brain signals, those signals are amplified and filtered to select band of signals in which we are interesting. We located the most representative electrodes within ECoG implanted grid using only 9 electrodes from 64 electrodes which decrease significantly the processing time without decreasing classification accuracy. Filtered signals entered through parallel port to the computer for artifact removal and then we extracted specific features from those signals using principle component analysis (PCA) and discrete wavelet transform (DWT), those features enabled us to discriminate between two different signals by both k-means clustering and neural network in order to classify between imagining right and left hand movement. We have found that the best accuracy of our EEG based BCI non- invasive system is obtained when we used wavelets in the feature extraction step with neural network in the classification step.

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