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Survey of various techniques used for brain computer interface

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Abstract : A Brain Computer Interface (BCI) system classifies a user's brain activity into a signal to which a computer can respond. To control a BCI, the user should produce various brain activity patterns which are taken in the form of Electroencephalogram (EEG) and converted to commands by identifying the patterns by the system. A brain computer interface (BCI) is a hardware and software communications system that permits cerebral activity alone to control computers or external devices. The immediate goal of BCI research is to provide communications capabilities to severely disabled people who are totally paralyzed. Brain Computer interface is a new field of research and interests, this paper is extending the concept of BCI interface on MATLAB software. The current research work that has been done involves three parts: Preprocessing, feature extraction and classification.So, a lot of feature extraction techniques like Fourier transform, wavelet transform and other simple time domain signal statistical calculations like average, root mean square, standard deviation, variance, kurtosis, skewness and many others. This paper has conducted an exclusive study and implementation on BCI competition data set 1. The result of this database is a 64 channel information which is a simple recording of brain activities for different regions of muscles and other nervous systems. This paper reflects the effect of channel 11 and 29 which are used for tongue and fingers. Now the channels are framed in 110 frames and then each frame is Fourier transformed, later continuous wavelet transform i.e. morlet wavelet is applied and the energy of morlet wavelet is used finally for features. The accuracy is calculated by using classification algorithm like SVM, LDA and K-NN.

Keywords : Brain computer interface, electrocorticogram, electroencephalography, wavelet transform, preprocessing and feature selection, classifiers.

1. Introduction

Electroencephalography (EEG) is an instrument for recording the electrical activity of the brain by placing electrodes on the scalp. A brain computer interface (BCI) is also referred to as a brain machine interface (BMI), is a hardware and software communications system that enables humans to interact with their surroundings, without the involvement of peripheral nerves and muscles, by using control signals generated from electroencephalographic activity. A BCI is an artificial intelligence system that can recognize a certain set of patterns in brain signals following five consecutive stages: signal acquisition, preprocessing or signal enhancement, feature extraction, classification, and the control interface [1]. The signal acquisition stage takes the brain signals and may also perform noise reduction and artifact processing. The preprocessing stage prepares the signals in a suitable form for further preprocessing. The feature extraction stage identifies discriminative information in the brain signals that have been recorded. Once measured, the signal is mapped onto a vector containing effective and discriminant features from the observed signals. The extraction of this interesting information is a very challenging task. Brain signals are mixed with other signals coming from a finite set of brain activities that overlap in both time and space. Moreover, the signal is not usually stationary and may also be distorted by artifacts such as electromyography (EMG) or electrooculography (EOG). The classification stage classifies the signals taking the feature vectors into account. The choice of good discriminative features is therefore essential to achieve effective pattern recognition. Finally the control interface stage translates the classified signals into meaningful commands for any connected device, such as a wheelchair or a computer.

Brain computer interface

A Brain Computer Interface (BCI) is a direct communication pathway between brain and computer. BCI system measures the specific features of brain activity and translates them into device control signals..Electroencephalography (EEG) is an electrical signal recorded from a person's scalp, and is used to monitor the neurological state of the patient. EEG signal analysis and classification is one of the prominent researches in the field of Brain Computer Interface [23]. Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp [2]. Brain rhythm many neurological disorders can be easily identified by brain rhythms which can be easily recognized by visual inspection of the EEG signal. The clinical applications using EEG are to characterize the seizures, to monitor the depth of anesthesia and to locate areas of damage following head injury, stroke, tumor, etc. Indeed, EEG is portable, non-invasive, relatively cheap and provide signals with a high temporal resolution.

1.2 Electrocorticogram

ECOG is an invasive method. ECOG requires surgery to implant electrode pads directly onto the surface of the brain to receive signals from the cerebral cortex. The advantages of this are immediately clear: high spatial resolution, broad bandwidth, high amplitude, and less vulnerability to EMG[3]. ECOG is also widely used as an identifier for the localization of epilepsy focal points. An array of 64 electrodes is implanted onto a portion of the brain called the epileptic focus to identify the part of the brain that should be removed by resection surgery. During one study, patients with epilepsy were implanted with these electrodes. In the period of the one to two weeks that the electrodes are recording data to localize the seizure area, researches used the electrodes to generate a BCI. While the electrodes were removed in this instance due to the epileptic nature of the patients, the success of this study proves that these arrays are a valid method for use in BCI development and not just epileptic identification.

Electroencephalography

EEG measures electric brain activity caused by the flow of electric currents during synaptic excitations of the dendrites in the neurons and is extremely sensitive to the effects of secondary currents [4]. EEG signals are easily recorded in a noninvasive manner through electrodes placed on the scalp, for which that reason it is by far the most widespread recording modality. However, it provides very poor quality signals as the signals have to cross the scalp, skull, and many other layers. This means that EEG signals in the electrodes are weak, hard to acquire and of poor quality. This technique is moreover severely affected by background noise generated either inside the brain or externally over the scalp.EEG recording system consists of electrodes, amplifiers, A/D converter, and a recording device. The electrodes acquire the signal from the scalp, the amplifiers process the

analog signal to enlarge the amplitude of the EEG signals so that the A/D converter can digitalize the signal in a more accurate way. Finally, the recording device, which may be a personal computer or similar, stores, and displays the data. The EEG signal is measured as the potential difference over time between signal or active electrode and reference electrode. An extra third electrode, known as the ground electrode, is used to measure the differential voltage between the active and the reference points. The minimal configuration for EEG measurement therefore consists of one active, one reference, and one ground electrode. Multichannel configurations can comprise up to 128 or 256 active electrodes [5]. These electrodes are usually made of silver chloride (AgCl) [6] Electrode=scalp contact impedance should be between 1 kΩ and 10 kΩ to record an accurate signal [7]. The electrode tissue interface is not only resistive but also capacitive and it therefore behaves as a low pass filter. The impedance depends on several factors such as the interface layer, electrode surface area, and temperature [7]. EEG gel creates a conductive path between the skin and each electrode that reduces the impedance. Use of the gel is cumbersome, however, as continued maintenance is required to assure a relatively good quality signal. Electrodes that do not need to use of gels, called ‘dry’ electrodes, have been made with other materials such as titanium and stainless steel [8]. These kinds of electrodes may be ‘dry’ active electrodes, which have preamplification circuits for dealing with very high electrode/skin interfacial impedances [8,9], or ‘dry’ passive electrodes, which have no active circuits, but are linked to EEG recording systems with ultrahigh input impedance [10]. The amplitude of electrical biosignals is in the order of microvolts. Consequently, the signal is very sensitive to electronic noise. External sources such powerlines may generate background noise and thermal, shot, flicker, and burst noises are generated by internal sources [11]. Design considerations should be addressed to reduce the effects of the noise, such as electromagnetic interference shielding or reduction for common mode signal, amongst others [7].EEG comprises a set of signals which may be classified according to their frequency. Wellknown frequency ranges have been defined according to distribution over the scalp or biological significance. These frequency bands are referred to as delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) from low to high, respectively.

Wavelet transform

It is one of the method of the time-frequency transformations. It decomposes the signal into different frequency ranges and allows extraction of features relating to quality. An important point of wavelet analysis is the choice of a particular wavelet function ψ (t). Among other wavelets, we chose the Morlet wavelet function because it is well localized in the frequency domain. On the other hand, the similarity of the wavelet function and the signals to be analyzed is significant to extract useful information. Compared with other types of wavelet, the Morlet wavelet has the most similar shape to that of the signals to be analyzed. Wavelet transform is used for many BCI data analysis applications to extract features [12], [13], [14]. It has an advantage over other feature extraction methods that operate in only one domain, such as the Fourier transform, autoregressive modeling.

2. Preprocessing and feature selection

Many different features have been thought up to be extracted from EEG signals. The most frequent transformation used is Fourier analysis to be able to look at specific frequency bands [15]. Firstly, we applied the Common Spatial Patterns (CSP) method (Müller-Gerking, Pfurtscheller and Flyvbjerg (1999) to the raw EEG data. The standard CSP is applicable to two class problems; it transforms the original signal into a new space where the variance of one of the classes is maximised while the variance of the other is minimized. Good feature selection is the key to the success of a classification algorithm. It is needed to reduce the number of features by selecting the most informative and discarding the irrelevant and redundant features. As EEG data is known to be highly correlated, a feature selection method which exploits this property seems appropriate. We applied a simple, fast and efficient method, called Correlation-Based Feature Section (CFS) (Hall 2000). It searches for the "best" sub-set of features where "best" is defined by a heuristic which takes into consideration 2 criteria: 1) how good the individual features are at predicting the class and 2) how much they correlate with the other features. Good subsets of features contain features that are highly correlated with theclass and uncorrelated with each other. The search space is very big for employing a brute-force search algorithm. We used the best first (greedy) search option starting with an empty set of features and adding new features. It is important also to note that the feature selection was done using the training data only[16]. The features properties are as follows:

2.1 Band power

Band power at each electrode position is estimated by first digitally bandpass filtering the data, squaring each sample and then averaging over several consecutive samples. Before the band power method is used for classification, first the reactive frequency bands must be selected for each subject. This means that data from an initial experiment without feedback are required. Based on these training data, the most relevant frequency components can be determined by using the distinction sensitive learning vector quantization (DSLVQ) algorithm [17], [18]. This method uses a weighted distance function and adjusts the influence of different input features (e.g., frequency components).

2.2 AutoRegressive (AR) modeling

AR modeling is preferred for real-time control of an EEG based brain–computer interface. Autoregressive (AR) modeling is a commonly used technique for spectral estimation of biosignals because it exhibits several advantages over other spectral estimation techniques in this domain. The AR filter is an all-pole model making it very good at resolving sharp changes in the spectra [20]. Conversely, the fast Fourier transformation (FFT) is a widely used nonparametric approach that is very accurate and efficient but lacks spectral resolution for short data segments. AR modeling has been used successfully for EEG but has not been evaluated extensively for use with ECoG. Because of its superior resolution for short data segments, AR modeling is preferred for real-time control of an EEGbased brain–computer interface (BCI) [19].

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2.3 Common Spatial Patterns (CSP)

Common spatial pattern (CSP) is very successful in constructing spatial filters for detecting event-related synchronization and event-related desynchronization. In statistics, a CSP filter can optimally separate the motor imagery- related components. However, for a single trail, the EEG features extracted after a CSP filter still include features not related to motor imagery. In this study, we introduce a linear dynamical system (LDS) approach to motor-imagery-based brain-computer interface (MI-BCI) to reduce the influence of these unrelated EEG features.

3. Classifiers

3.1 Linear Discriminant Analysis (LDA)

In order to classify the extracted features, Linear Discriminant Analysis (LDA) is one of the most popular and efficient classifier for EEG-based BCI. Linear Discriminant Analysis, have a low complexity. They are said stable as small variations in the training set does not affect considerably their performance. The aim of LDA (also known as Fisher's LDA) is to use hyper-planes to separate the data representing the different classes. This technique has a very low computational requirement which makes it suitable for online BCI system. Moreover this classifier is simple to
use and generally provides good results.

3.2 Quadratic Discriminant Analysis (QDA)

Quadratic classification aims at assigning to a feature vector the class it belongs to with the highest probability. The Bayes rule is used to compute the so called a posteriori probability that a feature vector has of belonging to a given class [21]. Using the MAP (Maximum A Posteriori) rule and these probabilities, the class of this feature vector can be estimated. Bayes quadratic consists in assuming a different normal distribution of data. This leads to quadratic decision boundaries, which explains the name of the classifier.

3.3 Gaussian Mixture Model (GMM)

Gaussian classifier separate the signal into the different classes of mental task. Each class is represented by a number of Gaussian prototypes, typically fewer than four. Training of the classifier starts from an initial model that can be either a previously trained classifier or a new classifier created by estimating the prototype centers with a clustering algorithm. This initial estimate is then improved by stochastic gradient descent to minimize the mean square error.

3.4 Support vector machine (SVM)

The SVM aims at finding a hyper-plane in the feature space, which simultaneously minimizes empirical classification errors and maximizes the distance between this hyper-plane and the nearest data point of each class. The architecture of the SVM depends on the regularization parameter C and the type of the kernel function. There are various kernel functions including: linear, polynomial, radial basis function (RBF), and sigmoid.

3.5 K-nearest neighbor (k-NN)

K-nearest neighbor classifiers (k-NNC) are based on the principle that the features corresponding to the different classes will usually form separate clusters in the feature space, while the close neighbors belong to the same class. This classifier takes k metric distances into account between the test samples features and those of the nearest classes, in order to classify a test feature vector. The metric distances are a measure of the similarities between the features of the test vector and the features of each class. The advantage of taking k neighbors into account in the classification is that error probability in the decision is decreased. Some training samples may be affected by noise and artifacts, which may seriously influence the classification results. If a decision involving several neighbors is made, then it is less likely that an error will occur, because the probability of several simultaneous erroneous datum is much lower [22]. Rather than only the closest sample, if several k closest classes are considered, then a voting scheme is required to decide between competing choices. Since there are no reasons to assume that the distributions of those neighbors are homogenous, it is clear to see that the k-NNC has to assign different ranks to the nearest neighbors, according to

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their distances from the test example. Therefore, k-NNC needs to define a weighting function, which varies with the distance in such a way that the output value decreases as the distance between the test feature vector and the neighbor increases.

4. Conclusion

A wide variety of signal features and classification algorithms have been tested in the BCI design. The main moto of analysis of EEG Signal based brain–computer interface (BCI) is to allow an individual with severe motor disabilities to have effective control over devices such as computers, speech synthesizers, assistive appliances and neural prostheses. Such an interface would increase an individual's independence, leading to an improved quality of life and reduced social costs. In this paper we proposed a wavelet based method for improving the speed and classification accuracy of BCI signal. The experiments proved that a normalization procedure is necessary in order to alleviate the impact of the magnitude change in between the training set and test set of motor imagery ECOG signals, recorded in different sessions. On the other hand it is shown that signal analysis based on WTCs can be reliably used as feature to accurately classify two types of imagined movements. Higher classification accuracy is obtained by K-NN algorithm .

For low dimensional feature vectors the LDA algorithm is the fastest technique compared to the K-NN and SVM in terms of training and testing speeds. However, it could obviously mentioned that the K-NN algorithm has reasonable speed and also achieved much better classification accuracy performance than the LDA and SVM algorithm.

S.NO	Author	Feature Extraction Techniques Used	Classification technique
1	Zhou et al.,(2008)	Bispectrum based feature extraction	LDA classifier, SVM classifier, and NN classifier were adopted to classify a Graz BCI data set.
2	Hubert Cecotti and Axel Graser (2009)	feature selection strategy based on salient connections in the first hidden layer of a neural network trained with all the electrodes as input	MLP NN trained with all electrodes as input

3	Coyl et al.,(2004)	Four SOFNNs are used for Feature Extraction. Features are derived from the MSE in prediction or the MSY	LDA is used for Classification
4	Hazrati et al., (2010)	Adaptive and static classification schemes and III data set got by Graz group	Bayes' classifier using probabalistic neural network
5	F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi (2007)	Band power features	SVM, LDA,, K-NN is used for classification
6	Enzeng Dong, Liting Li, Chao Chen (2015)	ICA, CSP	SVM, LDA
7	T. Gandhi , A. Jena, A.B. Pal (2010)	Energy, standard deviation, Entropy	SVM

Table: Survey paper

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