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COMPARATIVE PERFORMANCE ANALYSIS OF VARIOUS FILTERS FOR EEG BASED MOTOR IMAGERY DETECTION

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ABSTRACT

Brain-Computer Interface (BCI) is a communication technology that allows to pass on between human intellect and outer contrivance by the use of a computer with the assistance of an Electroencephalogram (EEG) signal. This communication device is primarily used for physically disabled individuals as well as it can be used to order a robot to do task-based on mental thinking. Comparative performance analysis of the different well-known bandpass filters for EEG-based motor imagery detection is provided in this paper. The purpose of the paper is to improve the accuracy of the classification of movement imagery under the unsupervised learning process. The authors have considered four traditional filters for preprocessing in this paper, namely Chebyshev filter, Butter worth filter, FIR bandpass filter, and Elliptic filter, to compare the output in terms of accuracy of classification. The filtered data is segmented and the mean, variance, and cepstrum of the segmented data have been considered as the features. The differences in features were taken as a function of the channels C3 and C4. To characterize the feature matrix, the Fisher linear discriminant analysis (FLDA), Support vector machine (SVM) algorithm was used. The Elliptic filter with variance and SVM classifier achieves 95% accuracy over the training data and 84.28% over the testing data of BCI competition II dataset III between the left and right-hand movement imagination.

KEYWORDS

Electroencephalogram (EEG), Motor imagery (MI), Fisher linear discriminant analysis (FLDA), Support vector machine (SVM).

1. INTRODUCTION

The Brain-Computer Interface is an important application of biomedical engineering. The function of the brain can be studied with the help of BCI. The BCI provides the target communication between individual intelligence and exterior machine using a computer. The originally intercontinental workshop was seized in June 1999 in Rensselaerville, New York. In this workshop, an official characterization of the BCI has anticipated "A brain-computer interface is a communication system that does not depend on the brain normal output pathway of peripheral nerves and muscles"(Wolpaw, J. R. et al. (2000); Bashashati, A. et al. (2007)).

The electrophysiological signal which is generated within the brain is used to control any machine by giving messages and commands through the BCI system (Mustafa & Mustafa (2018); Lotte, F. et al. (1999); Hema, C. R.et al. (2011)). The motivation behind ever-increasing the do research in the BCI field is to build up marginal reasoning for the conventional consultation system between a human being and a CPU device. The result and applied technique motivate to find out the best signal processing method under the unsupervised condition to get maximum accuracy for BCI. EEG is commonly used or preferable for seeking purposes for the reason of its run-down expense and its high temporal resolution of EEG data. Electroencephalogram (EEG) is the graphical demonstration of the electrical activity of the understanding faction (neuron) which is selected up by the electrodes located on the scalp. It is extensively old for the authentic-time purpose such as emotional steering wheel lead influence. The EEG signal is widely used for motor imagery prediction and for controlling assistive devices which are based on instruction generated by the person's brain. The signal processing algorithm and the quality of brain signal play an important role in the accuracy of the BCI system. Here, the quality of the signal depends on the position of the electrode, the quality of the amplifier that is used for the recording, and the storage system.

Two methods, i.e. invasive and non-invasive, perform signal acquisition. The electrodes are invasively mounted inside the brain and the electrodes are non-invasively placed on the brain's scalp. Using noninvasive recording, EEG offers a direct measure of cortical activity with millisecond temporal resolution. There are two EEG-recording methods: unipolar and bipolar. The human brain has two left and right hemispheres. Each hemisphere has been divided into tiny lobes and the individual mental tasks have their function and activation pattern. The brain's primary motor cortex region over the central lobe of each hemisphere is responsible for events related desynchronization (ERD) (Ramoser, H(2020)) and events related synchronization (Ramoser, H(2020)) (ERS). These ERD and ERS trends are reported by placing sensors at channels C3, C4, and Cz, identified by the 10-20 electrode placement method, over the primary motor cortex region.

The external devices represent the human mind's intended actions. The precise prediction of any decision depends on the different parameters,

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such as information present in brain signals and signal processing algorithm output in terms of recognition and extraction of features (Wang, H. et al. (2016)). The information found in the signal depends on the strength of the signal, the location of the electrode, the quality of the electrode, and the quality of the amplifier used for recording. In the literature of Hochberg et al. (Hsu, H. T.et al. (2015)), numerous EEG signal acquisition systems and methods have been presented. The pre-processing of the EEG signal requires noise extraction, artifact extraction, using band-pass filtering of the captured signals. The different pre-processing techniques such as regression-based and independent component-based approaches are discussed in Srinivasulu and Reddy's literature (2012). Some special filters, such as recurrent common spatial patterns (CSP), short-time Fourier transformation (STFT), singular value decomposition (SVD), are also used for pre-processing purposes (Srinivasulu & Reddy (2012)). Using a variety of feature extraction algorithms such as cepstrum, Hjorth parameter, power spectral density, relative spectral power (RSP), time-frequency is extracted from the pre-processed signals in the various articles (Wang, Y.et al. (2012); Bhattacharyya & Mukul (2016, September); Liang, W. (2018); Bhattacharyya & Mukul (2018); Mukul & Matsuno (2010); Das, B. Ether et al. (2016)). A variety of machine learning algorithms such as support vector machine (SVM), discriminant analysis (DA), probabilistic Bayesian classifier (Duda, R. O. et al. (2012) can be applied to the extracted features to get the final decision.; Stock & Balbinot (2016)).

The paper is structured as follows: Section 2 addresses the explanations of the experimental paradigm used in this work; Section 3 explains the specifics of the signal processing algorithm neuro-feedback system; Section 4 outlines the outcome and discussions, and finally, Section 5 reports the conclusion and future.

2. EXPERIMENTAL PARADIGM

The data set used in this experiment was supplied by the Institute for Biomedical Engineering, Graz University of Technology, Department of Medical Informatics. Correspondence (Gert Pfurtscheller) to Alois Schlögl & lt alois.schloegl@tugraz.at & gt.

During a feedback session, this dataset was recorded from a normal subject (female, 25y). In a relaxing chair with armrests, the subject was seated. The role was to use left or right-hand gestures to manipulate a feedback bar using imagery. The order of the right and left signs was random. The experiment is made up of 7 runs, each with 40 trials. Both runs were performed with several minutes of break in between on the same day. There are 280 trials of the duration of 9s in total. The first 2s was quite an auditory signal indicates the beginning of the trial at t= 2s, the trigger channel (# 4) went from low to high, and for 1s a cross "+" was shown; then an arrow (left or right) was shown as a cue at t= 3s mentioned in Fig.1. The EEG was sampled at 128Hz and filtered from 0.5 to 30Hz. The training and research trials were chosen randomly. Because of the reviews, this should avoid any institutional effect.

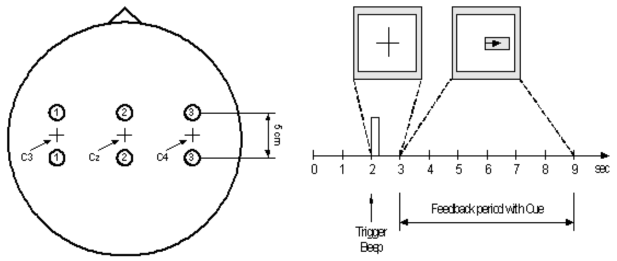

Figure 1: Electrode positions (left) and timing scheme (right).

3. METHODOLOGY

In this paper, the authors focus on the batch processing for mental classification using unsupervised learning reflection. The block diagram of the proposed method is shown in Fig.2. In the paper, the raw EEG signals were filtered by 15 bands from the alpha region and 36 bands from the beta region mainly two types of filters are used with 6 coefficients such as finite impulse response (FIR) and infinite impulse response (IIR). In the IIR filter, the Chebyshev and elliptic filter have been considered for the filtration.

The recorded EEG signals based on the channel name and type of imagination (i.e., left and right-hand movement imagination) represented as $X_C^k(n)$, where C ∈ [C3, C4] and k ∈ [left, right].

The filtered EEG signal $E_C^k(n)$ represented as

$$E_C^k(n) = h(n) * X_C^k(n) \quad , \tag{1}$$

where $h(n)$ signifies the impulse response and $X_C^k(n)$ signifies EEG signal

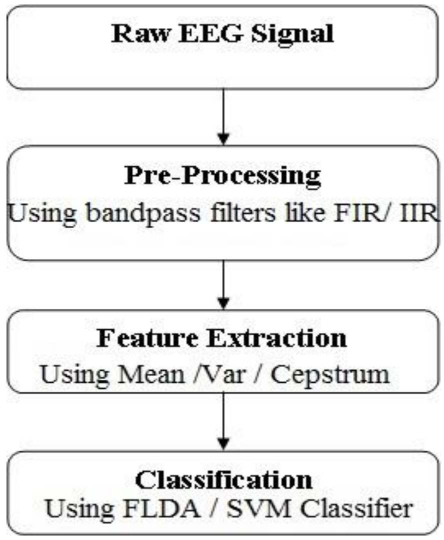

Figure 2: Proposed methodology

This filtered EEG signal is further processed for the feature extraction like mean, variance, or cepstrum estimation.

$$V_C^k(n) = \mathrm{var}(E_C^k(n)) \tag{2}$$

$$M_C^k(n) = \mathrm{mean}(E_C^k(n)) \tag{3}$$

$$C_C^k(n) = \mathrm{Ceps}(E_C^k(n)) \tag{4}$$

This extracted feature is further processed for the classification using linear classifiers like FLDA and SVM separately.

4. RESULTS AND DISCUSSIONS

The processing of the EEG signal was considered to achieve maximum classification accuracy. The raw EEG signal was filtered by the FIR and IIR (Butterworth, Chebyshev, and Elliptical) filters to extract the rhythmic band information corresponding to the 0-30 Hz frequency band. The extracted rhythmic band signal was further applied to the feature extraction step, where we estimated the mean, variance, and Cestrum of both channels. After working with the different brands, we came to know that the MI is hidden in the alpha and beta band having frequency range 8-13 Hz and 18-26 Hz. so we have a total of 48 tables for alpha and beta band, 24 for each where we used different filters, feature extraction method, and classifier.

In Table. 1, by keeping the feature extraction method and classifier constant, we varied the filters and try to find out which filter satisfy the null hypothesis (the hypothesis that there is no significant difference between specified cases due to sampling or experimental error).

Similarly, we draw different tables by keeping constant some variables while changing the other one and we got finally six tables. Among the FLDA classifier, the FIR filters gave a more satisfactory result and satisfy the null hypothesis. But in the case of SVM, all the FIR and IIR filters both are equally good and satisfy the null hypothesis. The mean, variance, and Cestrum of the estimated PSD over the training data were subjected to estimate the accuracy of the different filters for the different bandwidth. Further, the estimated accuracy was subjected to evaluate the performance over the testing data.

In Table 2, we have the training and testing accuracy for the different classifiers, feature extraction methods, and filters. The algorithm which gave maximum accuracy in the case of training and testing data is mentioned here. So we concluded that the ellipse filter (IIR) in pre-processing, variance in feature extraction method, and SVM among classifier gave maximum accuracy with 95% in training data and 84.28% in testing data.

Table 1: List of various filters with FLDA and SVM classifiers.

Sl. No.	Algorithm	Null Hypothesis		Sl. No.	Algorithm	Null Hypothesis
1	FIR_Mean_FLDA	Satisfied		13	FIR_Mean_SVM	Satisfied
2	Butt_Mean_FLDA	Not		14	Butt_Mean_ SVM	Satisfied
3	Cheby_Mean_FLDA	Not		15	Cheby_Mean_ SVM	Satisfied
4	Ellipse_Mean_FLDA	Not		16	Ellipse_Mean_ SVM	Satisfied
5	FIR_Var_FLDA	Satisfied		17	FIR_Var _ SVM	Satisfied
6	Butt_ Var _FLDA	Not		18	Butt_Var _ SVM	Satisfied
7	Cheby_ Var _FLDA	Not		19	Cheby_Var _ SVM	Satisfied
8	Ellipse_ Var _FLDA	Not		20	Ellipse_ Var _ SVM	Satisfied
9	FIR_Ceps_FLDA	Satisfied		21	FIR_ Ceps _ SVM	Satisfied
10	Butt_ Ceps _FLDA	Satisfied (Beta)		22	Butt_ Ceps _ SVM	Satisfied
11	Cheby_Ceps_FLDA	Satisfied (Beta)		23	Cheby_Ceps _ SVM	Satisfied
12	Ellipse_Ceps_FLDA	Satisfied		24	Ellipse_Ceps _ SVM	Satisfied

Table 2: Testing and training accuracy for different classifiers and filters.

Sl. No.	Algorithm	Traning(Acc.)	Testing (Acc.)
1	FIR(Beta)_Mean_FLDA	52.85	41.42
2	FIR(Beta)_Var_FLDA	80	79.28
3	FIR(Beta)_Ceps_FLDA	46.42	55.71
4	Butt(Beta)_Ceps_FLDA	60	57.14
5	Cheby(Beta)_Ceps_FLDA	61.42	60
6	Ellipse(Alpha)_Ceps_FLDA	59.28	57.85
7	FIR(Beta)_Mean_SVM	78.57	46.42
8	Butt(Beta)_Mean_SVM	97.85	52.85
9	Cheby(Beta)_Mean_SVM	97.14	56.42
10	Ellipse(Alpha)_Mean_SVM	98.57	62.14
11	FIR(Beta)_Var_SVM	89.28	79.28
12	Butt(Beta)_Var_SVM	94.28	77.14
13	Cheby(Beta)_Var_SVM	95	75.71
14	Ellipse(Alpha)_Var_SVM	95	84.28
15	FIR(Beta)_Ceps_SVM	99.28	55.71
16	Butt(Beta)_Ceps_SVM	97.85	57.85
17	Cheby(Beta)_Ceps_SVM	99.28	60
18	Ellipse(Alpha)_Ceps_SVM	97.85	59.28

5. Conclusion

The human brain is complex in nature. It is an open challenge for a researcher to find the universal feature in all subjects so one can achieve maximum information from incoming brain signals. The numerous research papers reported the maximum value of average classification accuracy greater than 80–90% and slightly above.

The performance of the BCI system depends on the advanced methods of signal processing, feature extractions, and machine learning techniques. The main objective of this project is to provide a simple algorithm for motor imagery classification. To achieve the desired goal, we segregated the proposed methodology into two parts, such as a reactive frequency band identification methodology from training data and a movement imagery classification methodology of testing data based on this reactive frequency band. Usually, a finite impulse response (FIR) filter is used to select a certain band of frequency because it reduces the burst or peaks of the biomedical signals due to their averaging operation. But we observed that the IIR filter (Ellipse filter) came up with a more accurate result with variance as feature extraction method and SVM as classifier.

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