Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 85 (2016) 490 – 495

Procedia Computer Science

International Conference on Computational Modelling and Security, CMS 2016

Classification of EEG Motor imagery multi class signals based on Cross Correlation

D.Hari Krishna[a]*, I.A.Pasha[a], T.Satya Savithri[b]

[a]*B V Raju Institute of Technology, ECE Dept, Narsapur, Medak Dt 502313, India*
[b]*JNTU College of Engg, ECE Dept , Hyderabad 500085, India*

Abstract

Many techniques are developed for improving the classification performance of motor imagery (MI) signals used in Brain computer interfacing (BCI). Still there is scope for improvement of performance using various techniques. In this paper, cross correlation (CC) technique has been used for features extraction from EEG signal and the final classification was done based on voting method which selects the best classifier among the five classifiers used for classification. Our approach was tested on public data set 2a from BCI competition IV. The results proved that our approach outperformed already existing approaches with 29.82% improvement in kappa values.

Keywords: Brain Computer Interface (BCI); Motor Imagery; EEG multi class Classification;cross correlation

1. Introduction

The term Brain-Computer Interface (BCI) depicts a system which decodes the brain signals and allows one to communicate or control a device. BCI was originally envisioned as a means through which the individuals with physical disabilities or the ones with neurological disorders such as ALS can communicate and control the specific devices [1, 2, 3]. Current BCI approaches also include applications in recreational domain as in gaming and virtual reality devices [4]. One of the studies implements a non-invasive BCI system to control an autonomous robot [5]. Electroencephalogram (EEG) is one of the popular approaches in BCI. Even though EEG provides low spatial resolution, its low cost and high temporal resolution makes it a very favoured among researchers. In EEG based BCI, there are two main approaches which are usually applied. The two approaches are called as "Reactive BCI" and "Active BCI" [6]. The 'Reactive BCI' approach relies upon the involuntary neural reactions of the subjects to the presented stimuli. Steady-state visually evoked potential (SSVEP) is one of the example of these kind of BCI system. The SSVEP based BCI systems detects the changes in brain signal patterns related to flickering of the visual stimuli on which the subject is fixated [7]. The Second approach, "Active BCI", relies upon the voluntary cognitive

* Corresponding author. Tel.: +91-8458-222040; fax: +91-8458-222002.
E-mail address: harikrishan.dodde@bvrit.ac.in

Peer-review under responsibility of the Organizing Committee of CMS 2016
doi:10.1016/j.procs.2016.05.198

activity. This approach usually differentiates between two or more mental states. The imagination of a motor activity is considered as a mental rehearsal of motor act. This approach comes under the 'Active BCI' paradigm. The imagination of motor activity involves similar brain regions as the physical motor activity [8]. Earlier studies suggest that the motor imagery activity can produce replicable signals over primary sensory and motor areas [9] and it is possible to distinguish between different kinds of motor imagery activities [10]. In the present paper, we examined the EEG patterns related to four types of motor imagery activities. The main purpose of this process was to develop a method based on cross-correlation approach to classify amid four types of motor imagery activities with reasonable accuracy.

2. Proposed method

The proposed method is designated as 'cumulative segmentation' method. The method contains four stages of data processing (Fig 1). These stages are: First, extraction of EEG signals from native gdf files, Second, Feature Extraction, which includes separating signals epoch wise, calculating statistical features using cross-correlation technique, third, training the classifiers and lastly, validating classification using the K-Fold cross validation.

2.1. Dataset

To verify our approach, we have used the publicly available dataset 2a from BCI competition IV [11]. The dataset was recorded from nine subjects who performed four motor imagery tasks (Left Hand, Right Hand, Both Feet and Tongue). The data collection is divided into short runs where each run contains 48 trials of each of the motor imagery activities. The data was collected in two sessions in two days where session comprises of six runs with a short break between them. So, the data contains total of 288 trials of each motor imagery activity. The EEG data was recorded with 22 Ag/AgCl electrodes arranged in standard 10-20 system around the scalp. The data was sampled at 250 Hz and band pass-filtered between 0.5 Hz to 100 Hz. The amplifier sensitivity was set to 100 µV. An additional 50 Hz notch filter was enabled to suppress line noise. In addition, 3 monopolar Electrooculography (EOG) channels were recorded and also sampled with 250 Hz. They were band pass filtered between 0.5 Hz and 100 Hz (with the 50 Hz notch filter enabled), and the amplifier sensitivity was set to 1 mV. The main reason why EOG channels are provided is for the subsequent application of artifact processing methods [12].

2.2. Basic Noise removal and artifact rejection

The dataset was provided with the list of trials which contains artifacts. These trials were discarded and were not included in the analysis. For basic noise removal, we employed a moving average filter and a band pass filter with a range of 8-40 Hz. This frequency band contains alpha (α) and beta (β) bands which are used for classification in motor imagery data.

2.3. Data analysis

In the study performed by [13], they reported that the multichannel EEG signals are interrelated with each other and different signals from different scalp sites do not provide the same amount of discerning information. Based on this, we used cross-correlation technique for the feature extraction. However, as cross-correlation techniques work well in binary mode only (as it depicts the between two signals), we used one verses rest approach for multiclass classification of motor imagery activity. Fig.2 shows the Imagination activity brain maps corresponding to four activities of subject 1 & 2. The reason for variation in maps might be that different might think differently about same activity.

The cross-correlation between two signals is calculated by

$$R_{xy}[m] = \sum_{i=0}^{N-|m|-1} x[i]y[i-m]$$