
Investigation on EEG Features and Classification Methods for Brain Computer Interface

Huynh Tri Quang, Nguyen Thanh Chau, Huynh Nhu Ngoc Hien, Nguyen Duc Thang, and Toi Vo Van

Abstract

Currently, the number of disabled people is increasing rapidly, requiring the development of applications with the aim to establish a communication between the human brain and external assistance devices through a computer, also known as brain computer interface (BCI). Most commonly, EEG signals are used for BCI system because they have high temporal resolution and are noninvasive. In this study, we focused on classifying EEG signals acquired through two experiments, (1) using two channels C3, C4 and (2) by six channels attached on the motor cortex to distinguish the left and right hand movement imaginations. For the classification task, k-Nearest Neighbor (kNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Decision Tree were investigated. Furthermore, we combined the Principal Components Analysis (PCA) method and the Common Spatial Patterns (CSP) method to reduce redundant features in the recorded signals from 6-channel experiments in order to enhance the classification accuracies. The overall accuracy of recognizing two hand movement imaginations was 85% for KNN, 97% for ANN, 97% for SVM and 100% for Randomized Forest respectively with ratio 50% train data and 50% test data. These results show the potential of further developing applications in BCI electric wheel chair. The data is recorded by self-implement EEG system using ADS1299.

Keywords

EEG • BCI • Features extraction • kNN • ANN • Decision tree • PCA • CSP

1 Introduction

Brain Computer Interface (BCI) is a method in which the brain signals is processed to control an external device. In simple terms, this technology acts as a bridge platform between the brain and the instrument. Today, BCI is popularly known by the names such as Brain Machine Interface (BMI), Synthetic Telepathy Interface (SMI), Direct Neural

Interface (DNI), or by Mind-Machine Interface (MMI). Generally, BCI is an interactive system between computer and human, specifically computer-based systems that record the brain signals.

In this paper, we focus on the classification of EEG data to distinguish the left and right-hand movement imagination. To collect raw EEG data, we use the combination of EEG-FE ADS1299 Kit and STM32F407VG—Microcontroller. Particularly, in the preprocessing stage, after obtaining the raw data we implement a low-pass filter to remove the noise and cut them up into smaller segments. Then we proceed to the classifying step. We surveyed four methods of classification to figure out the most effective one in specific situations through some activities. Those classification techniques include Artificial Neural Network

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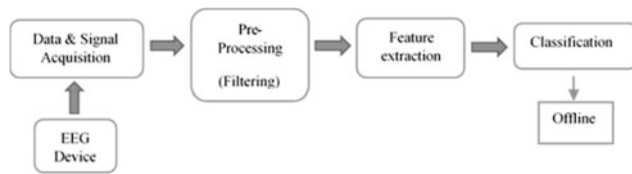


Fig. 1 The process of activity recognition

(ANN) [1], K-nearest neighbor (KNN) [2], Support Vector Machine (SVM), and Randomized Forest [3–5]. Results of the collected data will be an important precondition for the initiation of BCI models in the future (Fig. 1).

2 Methodology

2.1 Hardware

The self-implement EEG system using ADS1299 TI EEG sensor and controlled by STM32F4. ADS1299, which is a low-noise, 8-channel, simultaneous-sampling, 24-bit, delta-sigma ($\Delta\Sigma$) analog-to-digital converter (ADC) with a built-in programmable gain amplifier (PGA), internal reference, and an onboard oscillator. With its high levels of integration and exceptional performance, the ADS1299 enables the creation of scalable medical instrumentation systems at significantly reduced size, power, and overall cost (Fig. 2).

STM32F407VG is a great microcontroller which is stronger than MMB0 with A RM Cortex-M4 32-bit MCU, 1 MB Flash/192 + 4 KB RAM, USB OTG HS/FS, Ethernet, 17 TIMs, 3 ADCs, 15 comm. interfaces and a camera. It is designed for high performance and ultrafast data transfers with ART Accelerator, 32-bit, 7-layer AHB bus matrix with 7 masters and 8 slaves, Multi DMA controllers: 2 general purpose, 1 for USB HS, 1 for Ethernet, SPI™-Compatible Serial Interface. Moreover, with its outstanding power efficiency and extensive tools and software solutions providing a wide choice within the STM32 ecosystem to develop this applications (Fig. 3).

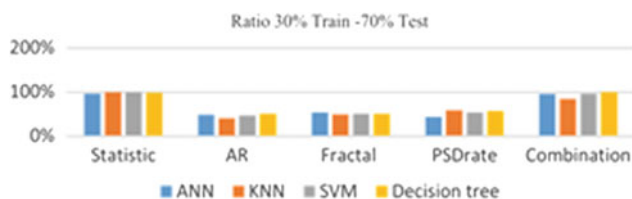


Fig. 2 Result of Classification with PCA, CSP and ratio 30% Train—70% Test for 6 channels

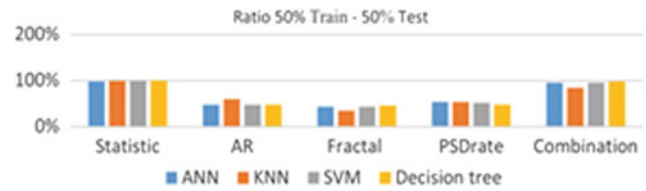


Fig. 3 Result of Classification with PCA, CSP and ratio 50% Train—50% Test for 6 channels



Fig. 4 Result of Classification with PCA, CSP and ratio 70% Train—30% Test for 6 channels

USART module FT232R (cable) and FT232RL (blue-tooth module) is the lastest device to be added to FTDI's range of USB USART interface Integrated Circuit Device. Basically, it is an USB to Serial converter which is used to transfer data from Serial interface of microcontroller to the USB Port of received devices (Fig. 4).

The Electrode Adapter is implemented with Standard (0.060) 1.5 mm DIN safety plug and Standard Gold Cup (0.060) or 1.5 mm DIN EEG Electrodes connector with a 48" leads and gold cup, then connected and built as Electrode Adapter.

2.2 Protocol and Data Collection Setup

Data for the left and right hand movement imagination and relaxing are collected six times. Duration of each experiment lasts for 120 s. The sampling frequency is 250 Hz, gain is 1 and Baudrate is 384,000.

2.3 Features Extraction

We use a diversity of features for data including the data of thinking to control your left hand and right hand and of relaxing based on these features that we recorded a number of data sets. This is an important preliminary step for the main stage, the process of data classification between two status signals of thinking to control hands and of relaxing. The features that we apply include are statistics, AR model, Fractal dimension, PSD rate and Combined features.

2.4 Classification

ANN is defined as a computational model originated from biological neural networks. There are three fundamental elements of a neural model: weight, summation and activation function. An input signal x_j connected to neuron k is multiplied with its own weight w_{kj} . The summation module adds all the input signals together and combines the result to the bias b_k . The activation potential v_k is the summation of the inputs with weights and bias. The activation function is the function that limits the amplitude of an output of a neuron. Common activation functions are a threshold, piecewise and sigmoid functions. An ANN has three layers named input, hidden and output layers. The input layer is given with signals from external environments or other networks. The hidden layer is involved with inputs and outputs in several useful manners. The more added hidden layers, the higher order statistic the network is enabled to extract. The output layer constitutes an overall response of the network to the activation pattern (Table 1).

The non-parametric KNN algorithm serves as classification. The training examples are multidimensional labeled vectors in feature space. In this research, the neighbors were drawn from two activities (Relaxing and control movement

hand imagine). Recorded data with class labels was divided into two sets: training set (classified) and testing set (unclassified). The Euclidean distance equals to the distance between points $x = (x_1, x_2, \dots, x_n)$ and $y = (y_1, y_2, \dots, y_n)$ in a feature space. The distance from each sample in the testing set to all the samples in training set is calculated and the minimum value is chosen. As a result, the classified label is defined by the nearest distance of each testing point to the corresponding class in the training set (Table 2).

SVM is a supervisor learning method that maps inputs to their corresponding outputs. It can be used for classification (categorize the inputs) or a regression (estimate the desired output). For classification, the inputs are transformed to high dimensional feature spaces in which they become more separable in comparison to the original input spaces. Firstly, a hyper plane is assembled to optimally divide the training data into two classes. Then, two parallel hyper planes (or support vectors) are built on each side of the hyper plane. By maximizing the distance between the two parallel hyper planes, the data is assigned into two classes. SVMs have competitive performance in many fields, such as medical diagnosis, bioinformatics, face recognition, image processing and text mining, which has used SVMs as one of the most popular, state-of-the-art tools for discovery and mining data (Table 3).

Table 1 Result of Classification with PCA, CSP and ratio 30% Train—70% Test for 6 channels

30% Train 70% Test	Statistic (%)	AR model (%)	Fractal (%)	PSD rate (%)	Combination (%)
ANN	97	49	54	44	96
KNN	100	41	50	59	85
SVM	100	47	51	54	97
Decision tree	99	51	51	57	100

Table 2 Result of Classification with PCA, CSP and ratio 50% Train—50% Test for 6 channels

50% Train 50% Test	Statistic (%)	AR model (%)	Fractal (%)	PSD rate (%)	Combination (%)
ANN	98	48	44	54	96
KNN	100	60	35	54	85
SVM	100	48	44	52	96
Decision tree	100	48	46	48	98

Table 3 Result of Classification with PCA, CSP and ratio 70% Train—30% Test for 6 channels

70% Train 30% Test	Statistic	AR model	Fractal	PSD rate	Combination
ANN	97	63	50	50	97
KNN	100	60	40	50	83
SVM	100	47	50	50	97
Decision tree	97	57	53	53	100

Random Forests are an ensemble learning method (also thought of as a form of nearest neighbor predictor) for classification and regression that construct a number of decision trees at training time and outputting the class that is the mode

of the classes output by individual trees. Random Forests are a mixture of tree predictors where each tree depends on the values of a random vector sampled independently with the same distribution for all trees in the forest (Tables 4 and 5).

Table 4 10-fold validation for Combination feature with PCA, CSP and and ratio 50% Train—50% Test for 6 channels

Combination				
	KNN (%)	SVM (%)	ANN (%)	Decisition tree (%)
1st	85	96	94	100
2nd	85	98	96	92
3rd	81	96	94	98
4th	88	98	98	100
5th	81	98	96	94
6th	83	96	96	100
7th	88	98	96	100
8th	85	98	98	100
9th	81	98	100	100
10th	88	98	98	100
Average	85	97	97	98

Table 5 Confusion Matrix for KNN method of Combination feature with PCA, CSP and and ratio 50% Train—50% Test for 6 channel

KNN						
	Confusion matrix		SPC (%)	TPR (%)	FPR (%)	FNR (%)
1st	20	4	84	87	16	13
	3	21				
2nd	19	5	81	90	19	10
	2	22				
3rd	20	4	83	80	17	20
	5	19				
4th	21	3	88	88	12	12
	3	21				
5th	21	3	86	78	14	22
	6	18				
6th	22	2	90	79	10	21
	6	18				
7th	22	2	91	85	9	15
	4	20				
8th	20	4	84	87	16	13
	3	21				
9th	19	5	80	83	20	17
	4	20				
10th	19	5	82	95	18	5
	1	23				

3 Results

We surveyed five characteristic features is statistic, AR model, Fractal Dimension, PSD rate and Combination features through different filters. They are Artificial Neural Network (ANN), K-nearest neighbor (KNN), Support Vector Machine (SVM), Decision tree with 3 different configurations of Train and Test dataset. Besides the data are divided into 2 major categories including classification with PCA and without PCA. To improve accuracy while classifying signals between the left and right hand movement imagination. We adopt the Common Spatial Patterns method (CSP) for the received signal to select the 2-channel randomly from 6 original channels. Besides retain characteristics have made with the classification of C3 and C4 2 channels. The dimensional signal will be reduced by PCA method and spent 4 kinds of classification to collect the results (Table 6).

To check the accuracy of classification results, we set up two tables are k-fold Validation and Confusion Matrix for Combination features with PCA, CSP and ratio 50% Train—50% Test (Table 7).

4 Conclusions

Thanks to the results from the classification of signals obtained from the two experiments, we can conclude that the combination of CSP, PCA on conventional classification including ANN, KNN, SVM, especially Random Forest achieve positive classification results (Table 8).

We are planning to develop additional filters and conduct measurements on more participants to increase the sample size, thus raising the reliability of the project. Finally, we attempt to enhance the algorithm for a BCI application to help disable people to control the electric wheelchair using the brain signals (Table 9).

Table 6 Confusion Matrix for SVM method of Combination feature with PCA, CSP and and ratio 50% Train—50% Test for 6 channels

SVM						
	Confusion matrix		SPC (%)	TPR (%)	FPR (%)	FNR (%)
1st	24	0	100	92	0	8
	2	22				
2nd	23	1	96	100	4	0
	0	24				
3rd	22	2	92	100	8	0
	0	24				
4th	23	1	96	100	4	0
	0	24				
5th	23	1	96	100	4	0
	0	24				
6th	24	0	100	92	0	8
	2	22				
7th	23	1	96	100	4	0
	0	24				
8th	23	1	96	100	4	0
	0	24				
9th	23	1	96	100	4	0
	0	24				
10th	23	1	96	100	4	0
	0	24				

Table 7 Confusion Matrix for ANN method of Combination feature with PCA, CSP and and ratio 50% Train—50% Test for 6 channels

ANN						
	Confusion matrix		SPC (%)	TPR (%)	FPR (%)	FNR (%)
1st	24	0	100	89	0	11
	3	21				
2nd	23	1	96	96	4	4
	1	23				
3rd	23	1	96	92	4	8
	2	22				
4th	23	1	96	100	4	0
	0	24				
5th	21	3	96	96	4	4
	3	21				
6th	24	0	100	92	0	8
	2	22				
7th	23	1	96	96	4	4
	1	23				
8th	24	0	100	96	0	4
	1	23				
9th	24	0	100	100	0	0
	0	24				
10th	21	1	96	100	4	0
	0	24				

Table 8 Confusion Matrix for Decision Tree method of Combination feature with PCA, CSP and ratio 50% Train—50% Test for 6 channels

Decision Tree						
	Confusion matrix		SPC (%)	TPR (%)	FPR (%)	FNR (%)
1st	24	0	100	100	0	0
	0	24				
2nd	20	4	86	100	14	0
	0	24				
3rd	24	0	100	96	0	4
	1	23				
4th	24	0	100	100	0	0
	0	24				
5th	22	2	92	96	8	4
	1	23				
6th	24	0	100	100	0	0
	0	24				
7th	24	0	100	100	0	0
	0	24				
8th	22	2	92	96	8	4
	1	23				
9th	24	0	100	100	0	0
	0	24				
10th	24	0	100	100	0	0
	0	24				

Table 9 Average of Confusion Matrix of Combination feature with PCA, CSP and and ratio 50% Train—50% Test for 6 channels

	Confusion matrix		SPC (%)	TPR (%)	FPR (%)	FNR (%)
KNN	12	12	85	85	15	15
SVM	12	12	96	98	4	2
ANN	12	12	98	96	4	0
Decision tree	12	12	97	99	3	1

Acknowledgements We would like to thank Dr. Le Quoc Trung and Mr. Vu Ngoc Thanh Sang for their supports.

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