A Novel EEG Classification for Baseline Motor Cortex using Adaboost

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Abstract: This paper contains a new method for EEG classification and specifically for baseline hand motor cortex recognition. This work is based on the determination of links between all electrodes when moving hands using covariance and correlation matrices, also the importance degree for every electrode from the best to the bad in the classification stage, and thus the application of differential evolution (DE) optimizer to increase the prediction accuracy of AdaBoost algorithm to the best state. The results obtained show that the prediction accuracy value for hand EEG motor cortex classification takes the value of 100% when using more than six electrodes without using feature extraction algorithms, knowing that the related work has a maximum average accuracy value of 99.1% using the PNN algorithm. Therefore, this work has a very important role in increasing the EEG signals prediction quality, either on the side of improving the classification algorithms or minimizing the number of acquisition channels needed.

1 INTRODUCTION

The Brain-Computer Interface (BCI) transmits brain activity acquired from the human scalp to a computer for controlling external devices and assisting the handicapped in regaining organ abilities (Abenna et al., 2021a). It's almost research for the use of electroencephalogram (EEG) in the controls intelligent in robotic arms and other external devices. Compared to other signal types, EEG signals have several different direct communications between a human brain and a computer (Jin et al., 2015; Li et al., 2016; Tang et al., 2020; Zhang et al., 2018). The collected brain signals vary depending on the structure of the human brain and the subject's mental state, and these brain activities of each subject are unique. EEG signals are not woody and non-stable, which means that the EEG signal properties change over time (Khosla et al., 2020; Tang et al., 2020; Yin and Zhang, 2017). Furthermore, the recorded EEG signals are frequently intermingled with noise, making analysis difficult. As a result, efficient steps to enhance the signal-to-noise ratio (SNR) of EEG data should be taken (Michelmann et al., 2018; Tang et al., 2020; Whitmore and Lin, 2016). EEG waves convert brain waves, which means that it is a continuous record of the brain's electrical activity by placing metal electrodes on the scalp (Jasper, 1958; Khosla et al., 2020; Patel et al., 2018). Neurons communicate spontaneously with each other by generating electrical currents and remain active at all times, even when a person is asleep or relaxed. Low cost, high time resolution, high flexibility, usability, non-invasive, portability, and safe nature make the EEG a powerful tool compared to other functional neuroimaging techniques such as magneto-encephalogram (MEG), positron emission tomography (PET), functional magnetic resonance imagery (fMRI), and transcranial magnetic stimulation (TMS). This work is interested in developing a new method more efficient for the predicting system of EEG signals, in this sense, this work uses the covariance and correlation matrices to determine the acquisition system quality used and finds electrical leaks between all electrodes, thus optimization algorithms like DE used to maximize the quality of the results found, and ultimately the AdaBoost classification algorithm used to generate the prediction models (Abenna et al., 2021a), Fig. 1 presents a basic architecture of the prediction system

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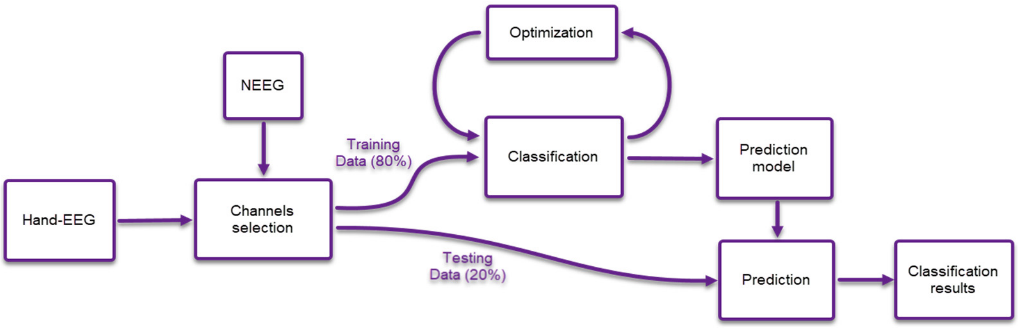
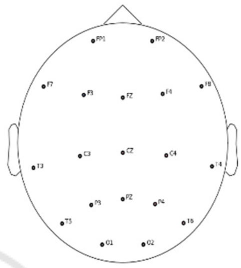


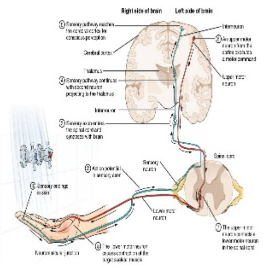
Figure 1: Illustrate of EEG acquisition and processing.

for an EEG signal. This method has been applied for hand EEG motor cortex, in such a way the prediction accuracy values are usually 100% using more than 6 acquisition electrodes, compared to related work that has accuracy values less than 99.1% using PNN.

The rest of the article is organized as follows: Section 2 presents all algorithms of classification and optimization proposed for the system. Results and discussion are presented in section 3, while section 4 provides conclusions and an overview of the future work.



(a) Location of all electrodes



(b) Nerve system between the left hand and the central lobe

Figure 2: Positioning of all electrodes used to acquire the EEG signals for the motor cortex of hands.

2 METHODS

2.1 Dataset

'Projectbci-1D' dataset: The motive is a 21-year-old right arm with no known health condition. An EEG consists of a random movement of the actual left and right hands, such as the recorded is with closed eyes. The electrodes used in this work (FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, FZ, CZ, and PZ) are distributed as following the international system 10-20 as illustrated in Fig. 2.a. The recording sampling at 500 Hz with NeuroFax EEG device using 19 electrodes for acquisition. The data were exported with a common reference 'eemagine-EEG', where the AC line operates at 50 Hz. Fig. 3 illustrates some of the EEG signals acquired by the NeuroFax device using 19 electrodes when eyes are closed and the left-hands move. We notice that the EEG signals are very noisy and misunderstood.

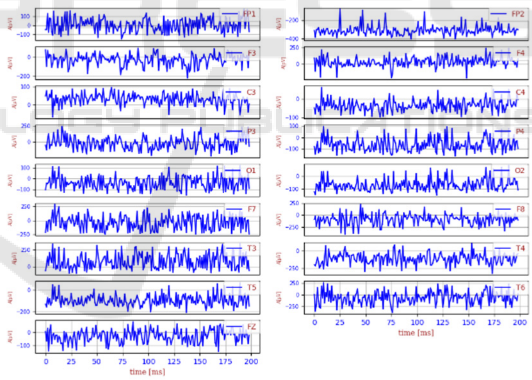


Figure 3: A part of EEG signals acquired using NeuroFax device.

2.2 Adaptive Boost

Freund and Chapyle invented AdaBoost in 1996 as an iterative boost procedure. The primary goal of this recovery effort is to focus on situations that are difficult to categorize. First, each instance is assigned the same weight. Iteration increases all weights of lower-ranked instances and reduces correctly ranked instances, more details are in (Chatterjee et al., 2019). The AdaBoost is supported by the Algo. 1. Such as the x_i and y_i represent the feature set and the corresponding decision class label for the ith instance. It represents the variance vector with n size because there is a T iteration, and each instance starts with a distribution of *1/n*. A_t is calculated in the n training instance (Chatterjee et al., 2019). The weak learner is applied at each step, and AdaBoost employs the exponential loss function $exp(-a_t y_t \phi_t(x_i))$ to calculate a weighted error epsilon of A_t. a_t, y_i, and

Algorithm 1: Adaptive boosting.

- Inputs: Given $(x_1, y_1), \ldots, (x_n, y_n)$, where n is the total number of training data instances, x_i is the feature data and y_i is the associated decision class, x_{test} is the testing data;
- Initialize: $A_i = 1/n$, where $i = 1, \ldots, n$;

for each iteration t **in** T **do**
  Use distribution to train weak learners A_t;
  Choose: $a_t = 12 * log(1 - \epsilon_t/\epsilon_t)$;
  Loss: $exp(-a_t y_i \phi_t(x_i))$;
  Update: $A_t + 1(i) = (A_t(i) * loss)/g_t$, where g_t is a new normalization factor;
  $g_t = \sum_{i=1}^{n} A_t(i) * exp(-a_t y_t \phi_t(x_i))$;
End.

Return $f(x_{test}) \leftarrow sgin(\sum_{t=1}^{T} a_t \phi_t(x_{test}))$;

$\phi_t(x_i)$ denote an n-dimensional weight vector, a vector containing the actual decision class of *n* cases, and a vector containing the anticipated outcome for the ith instance, respectively. The weight combination sign of the lower classifier is calculated by the final classifier *f* (Chatterjee et al., 2019).

2.3 Optimization

The optimization advantage is to select a valid classifier and to reduce the functionality used in restricted classifications to increase the prediction accuracy. This process is further optimized by the DE algorithm to determine optimal synthesis conditions (Estimators number (NE), learning rate (LR), and random-state (RS)) to maximize reaction yield, more details are in (Abenna et al., 2021a; Rodrigues et al., 2018).

3 RESULTS AND DISCUSSION

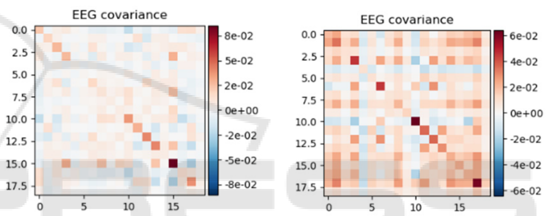
The experiments were conducted on the 2.4 GHz desktop and 6 GB of RAM with four Intel®Core (TM) i5 CPUs and 64 bit/Windows 10 operating system, and python.3.6 for programming.

3.1 Analysis Results

Fig. 4 illustrates the matrix of covariance between the 19 acquisition electrodes in the state of the left hand (Fig. 4.a) and of the right-hand movement (Fig. 4.b). In this figure, we can observe easily the existence of more connection between all electrodes when the right-hand moves compared to the left hand, indicating a large change in the distribution of electrical signals in the brain between the two hands state, which also shows that has facilitated the classification of these signals.

Table 1: Symbol and description.

Symbol	Description
NE	n-estimators
LR	learning-rate
RS	random-state
NEEG	The number of electrodes
AC	Accuracy
ZOL	Zero One Loss
Tc	Classification time
Tp	Prediction time
To	Optimization time

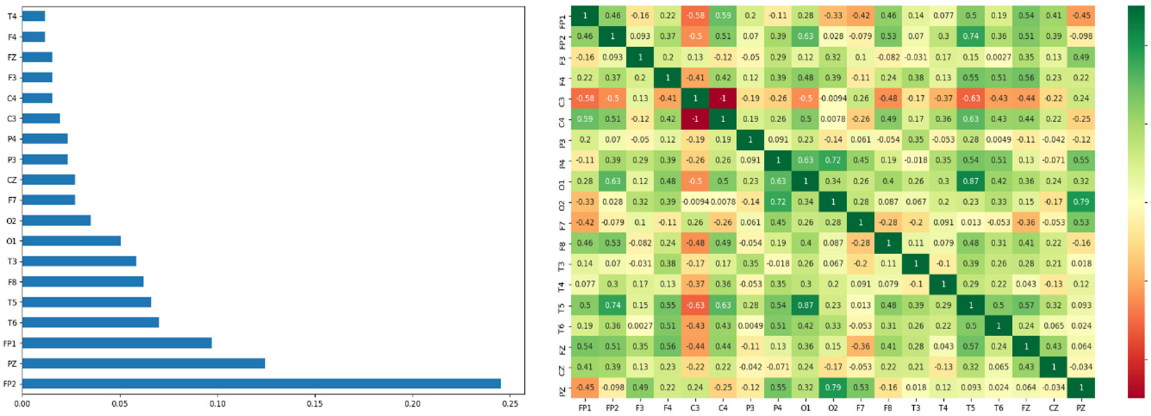


(a) Left hand (b) Right hand

Figure 4: The covariance matrix for each moved hand.

3.2 Feature Selection Results

Fig. 5 shows a classification of electrodes according to their importance for the classification stage using the AdaBoost algorithm (Abenna et al., 2021b), knowing that each electrode has been represented by its degree of importance from 0 to 1, in this figure we notice that the best electrodes used are FP1, PZ, and FP2, knowing that the number of electrodes can be decreased up to 3 or 1 single electrode without a great degradation of the system accuracy. Fig. 5.b illustrates the correlation matrix between the electrodes signal to detect all links between them and avoid electrical leaks that degrade the quality of the acquired signals, such that we notice that all degrees are low except between some electrodes such as T5, O1, O2, CZ, and FP2, which implies the best quality of the acquisition system, and we are not needed to use any spatial filter to decrease the correlation between the channels (Whitmore and Lin, 2016).



(a) Channels selection using AB (b) Correlation matrix

Figure 5: Channels selection and correlation matrix for EEG signals classification of hands moved.

3.3 Evaluation Metrics

Accuracy and Zero-One-Loss are typically metrics used to measure the performance of biomedical and complex data during classification.

$$AC = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$ZOL = \text{FP} + \text{FN} \quad (2)$$

Where True Positive (TP) refers to a circumstance in which an alarm is generated although the left hand has moved during testing. The term TN (True Negative) describes a circumstance in which the right-hand moves but no alarm is generated. When the left hand is employed, the alert is not raised, which is referred to as FP (False Positive). The term FN (False Negative) describes a circumstance in which the right-hand moves but no alarm is triggered (Abenna et al., 2021b).

3.4 Classification Results

Table 2 shows a main parameter optimization of AdaBoost to well improve the quality of prediction, as it can find during testing large combinations of AdaBoost parameters for that gives precision values of 100%, knowing that we can choose only those corresponding to a low value of NE, to guarantee a high speed of classification and prediction, thus a good quality of prediction. Table 3 shows a size improvement of the acquisition system without degradation of prediction performance, such that we do the recognition of EEG signals during testing using these AdaBoost parameters (NE = 257, LR = 0.9969, and RS = 911), so we choose only the best NEEG-channel have been selected in Figure 5.a, and we notice that the accuracy value remains at the level of 100% when NEEG ≥ 6, we notice that the use of just two electrodes FP2 and PZ gives an accuracy of 97%, indicating the possibility of developing new devices for the baseline hand EEG motor cortex prediction with a small size, as well as Tc and Tp, decreases when we decrease the NEEG. In table 4, the work of Hossain et al. (Hossain et al., 2015) who uses the BP and PNN algorithms for the EEG classification finds that the precision value cannot exceed 99.1% but at the work of this paper the accuracy value take 100% when using more than six acquisition electrodes.

Table 2: AdaBoost parameters optimization using DE.

AdaBoost parameters			Optimization results		
NE	*LR*	*RS*	AC (%)	ZOL	To (s)
257	0.9969	911	100.0	0	97.73
319	1.5301	559	100.0	0	124.94

Table 3: Improving the number of channels used for hands EEG classification.

	Classification results			
NEEG	AC (%)	ZOL	Tc(s)	Tp(s)
10	100.0	1	48.47	1.43
6	100.0	0	33.39	1.17
3	99.58	108	22.91	1.62
2	97.00	771	18.40	1.00
1	90.10	2547	15.03	1.00

Table 4: Comparative results with related work.

Work	Accuracy	Methods
Hossain et al. (2015)	88.9%	BP
	99.1%	PNN
This work	100%	AdaBoost

4 CONCLUSIONS

In conclusion, the method used in this work shows its efficiency in predicting the hand moved from the EEG signals without any mistake, such that this work uses the covariance matrices to show all changes in the distribution of the brain activities when moving every single hand (left or right), so the correlation matrix used to determine the electrical leaks between all electrodes, also the use of AdaBoost algorithm to classifying the EEG signals and the minimization of the number of channels (NEEG). Also, the use of the DE optimizer improves the classification performances, knowing that the accuracy value in this work takes the value of 100% when using more than six electrodes. We hope that this work will help other researchers to develop a good EEG signals prediction system. In future work, our team focuses on developing new and more efficient methods and instigating this work for real-time applications of the BCI systems.

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