Classification of Non-invasive recording of Electroencephalography Brain Signals using Hoeffding tree

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— ***Abstract***— *there* **is** *a considerable advancement in research that concern brain-computer interfaces (BCI). BCI can be defined as a communication system that is developed for allowing individuals experiencing complete paralysis sending commands or messages with no need to send them via normal output pathways of brain. EEG recording are Affected by cardiac noise, blinks, eye movement, in addition to non-biological sources (such as power-line noise).There will be an obstacle if the subject generates an artifact since will violate the specification of BCI as a non-muscular communication channel and the ability of subjects suffering degenerative diseases could be lost and This artifacts(noise) leads to incorrect classification accuracy .The presented study has the aim of being a sufficient reference in BCI system and also emphasize algorithms which are capable of separating and removing the noise that interferes with the task-related Electroencephalography (EEG) signal for the best features . The task is the motions of the index finger of right or left .The separation process based BSS technique ,This separating would be having an effective speeding impact on classifying patterns of EEG. and classified using classifier (Hoeffding Tree). The proposed algorithm is tested and trained with the use of real recorded signals of EEG . Experiments reveal that the proposed classifier with the stone algorithm leads to high classification results up to the classification accuracy 79%.*

Keywords— BCI, Electroencephalography, Stons ,FICA,JADE , Hoeffding Tree classifier.

I. INTRODUCTION

Brain Computer Interface (BCI) is defined as a software and hardware system of communication that enable the individuals to have some sort of interaction with their environments, with no participation of the muscles and peripheral nerves, novel non-muscular channel is used via the BCI for relaying the intentions of individuals to external devices like neural prostheses, speech synthesizers, computers, and assistive appliance.. BCI is considered as an AI system which have the ability of recognizing a specific sequence of patterns in the signals of the brain following 5 successive phases: signal acquisition, pre-processing or signal improvement, feature extraction, classification, and control interface [1]. The disabled patients are majorly assisted via using this system. The system of BCI require analyzing, assessment, observing and measurement regarding the electrical activity of the brain. These necessities will be obtained via electrodes which are implanted in the brain or electrodes that have been set on the scalp. One type of the signals of the brain is EEG signals. The classification regarding EGG is achieved according to the frequency which 5 major types (Delta rhythm δ that is between the frequency range 0.5-4 Hz, Theta rhythm θ that is between (4-7) Hz, Alpha rhythm α that is between (8Hz-13Hz), Beta rhythm β that is between (13Hz -30Hz), Gamma rhythm γ that is over 25 Hz[2] [3] [4]. EEG signal is one of the most widely used signals in the bioinformatics area because of its rich information about human activity. The Electroencephalogram (EEG) has been an important clinical tool to assess human brain activity [5]. Several researchers have shown their interest in BCI since the importance of the system lies in many applications, such as medical applications especially to assist people with disabilities as their assistance Dealing with computers or helping people with Syndrome In-Locked communicate with the External world , and advertising applications, educational applications and security applications, The following are some of the published works that are relevant to the current work:

In [6]: The researchers have recorded the EEG signals from 4 individuals as they were going through various mental states, they study introduced ANN-based method to classify EEG signals into various mental states . The experimental results have outperformed the other classifiers (K-NN, Naïve Bayesian, SVMs, and LDA in the data set of EEG).

In[7]:The researches have used feature extraction approach and classifier. , the extracted features be utilized for classifying right and left imagery movements via Naïve-Bayes and K-NN. The optimum accuracy for classification was recorded via K-NN for the power spectral density feature set necessitating a time of 0.0531 seconds

In [8]: ANN machine learning algorithm has been utilized as a classifier for learning EEG signals features for efficient classification of the output. They study presented performance analysis regarding the system's precision for the suggested combination of TF analysis and an NN algorithm respectively for the EEG feature extraction and classifier.

In [9]:presented efficient system for ECG signals for MI classification. Initially, the TF features will be extracted through the use of modified S-transform (MST) algorithm, after that, SVM will be used to train the classifier.

The remnants of the paper are organized as follows: We touch the proposed system in the next section. Part (3) presents the Experimental results. Finally, the paper conclusion is in part (4).

II. PROPOSED SYSTEM

In this part the implementation of the proposed system is presented in details to show the main steps to implement BCI system able to analysis and classify the brain signals that exported from the brain to predict of the people actions In our system this ,the behavior of people (the left or right index finger movement) with high accuracy .The proposed system is shown in Fig 1.

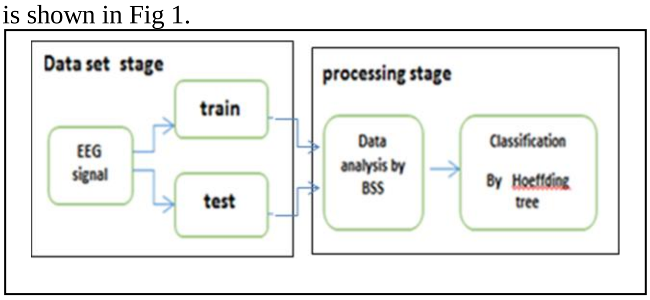

Fig. 1. Block diagram of the proposed system

A. *Data set collection*:

this step include gathering the information collected from EEG device and form it as an excel sheet for further processing. A 24 year age healthy male participate in data set collected sitting on a comfortable chair without moving with 1 meter distance from the computer monitor. The data recording in two sessions one for left index finger and the other for right movements every session consist of many trails each trail is 10 sec period. Nineteen channels signals each signal consist of 256 samples in Hz. Table 1. shows the main specification for this data.

TABLE I. DATA SET SPECIFICATION.

Gender	*age*	*position*	*motion*	*Medical condition*	*situation*
male	24	1meter from computer monitor	static	healthy	Sit on chair

B. *Cross validation:*

The critical data of the brain signals can be very useful for human and the results of such system need to be accurate as possible and the system is training and testing for kind of data that is not processed before since each movement is different signal than the other for that reason a validation method is used to mix the data and provide each data in the system with a chance to be a train data and test data to ensure that the numerical relationship between data is kept.

Algorithm 1 shows the main steps of the used cross validation algorithm

Input: data set
Output: train data , test data
start
step1: set the k to 13 (try and test shows 13 is better than 5,7,9,10)
step2: for i=1 to k
Split the data to k folds where one fold is test and the remains fold is train.
Step3: fitting the model using k-1
Step4: loop
end

According to algorithm 3.2 the k value is choose k=13 which mean 13 times the data will split to train and test and the data spilt to train and test and the process is repeated until all the data is being train data and test data in the system.

C. *Data analysis:*

The analysis phase is aimed to recover this original source signal from the mix signals, the analysis is done using blind sources separation BSS(STONE ,FICA,JADE) algorithms
Stone: statistical algorithm (second order) used a batch algorithm with very low complexity which leads to produce

better separation to the signals utilize the temporal predictability feature of the mixed signals. The step of stone algorithm is mainly consisting of:

- Finding the value of X (k) which is the Mixture observation signals as follow:
  X(k) = A S(k)
  Where $x(k)=[x_1, x_2 \ldots X_n]^t$ and superscript , t refers transpose operator. Which is represent mixing system without noise
- Finding the recovered signals are calculated by the separating model which is value of XL (k) = Filter Response (L) ,As follow Y(K)= W X(K) Where $y(k)=[y_1, y_2 \ldots y_n]t$
- Stone's measurement of the temporal predictability of a signal y(k) has been characterized as:

$$F(K) = LOG\frac{VY}{UY} \quad (1)$$

Which is simplified to

$$F(K) = LOG\frac{\sum_{k=1}^{n}(\text{ylong}(k) - y(k)) * (\text{ylong}(k) - y(k))}{\sum_{k=1}^{n}(\text{yshort}(k) - y(k)) * (\text{yshort}(k) - y(k))} \quad (2)$$

Where $Y_{short}(k)=\beta s\, y_{short}(k-1)+(1-\beta s)\, y\,(k-1)$ with $0<=\beta s<=1$
And $Y_{long}(k)=\beta S\, y_{long}(k-1)+(1-\beta s)\, y\,(k-1)$ with $0<=\beta s<=1$

- Compute the short-term covariance matrix which is calculated as follow

$$ci,j\ (short) = \sum t\ (xit - xit\ (short))(xjt - xjt\ (short)) \quad (3)$$

- Compute the Long-term covariance matrix which is calculated as follow

$$ci,j\ (long) = \sum t\ (xit - xit\ (long))(xjt - xjt\ (long)) \quad (4)$$

- Finding the eigenvectors ($W_1,W_2,W_3,\ldots,W_M$) of matrix as follow

$$W_i\, c^{short}\, w_j\ \ (short) = \sum t\ (yit - yit\ (short))(yjt - yjt\ (short)) \quad (5)$$

$$W_i\, c^{long}\, w_j\ \ (long) = \sum t\ (yit - yit\ (long))(yjt - yjt\ (long)) \quad (6)$$

- De mixing the matrixes

D. Classification:

the output from analysis phase as input to Classifier to classify the EEG signal. classification of the analyzed data is done using algorithm(Hoeffding tree).Decision tree which have the learning ability for the data streams enter the system (in our cases the input is the signals (data sources without noise)), this classification algorithm assume while working that distribution is not changing overtime, the strength of this algorithm that is it can work with small amount of data and it will be enough to choose the main split attribute.

Algorithm 2 shows the main steps in Hoeffding tree

HOEFFDING TREE(Stream , *δ)*

In put *:a stream of labeled examples ,confidence parameter δ)*

1- Let HT be a tree with a single leaf (root)
2- Init counts n_{ijk} at root
3- **For** each example (x,y) in stream
4- **do HTGROW**((x,y),HT,*δ*)

HTGROW((x,y),HT,*δ*)

1- **Sort**(x,y) to leaf L using HT
2- Update counts n_{ijk} at leaf L
3- **If** examples seen so far at L are not all of the same class
4- **Then**
 Compute G for each attribute
5- **If** G(best attribute) – G(second best)> $\sqrt{\frac{R^2 \ln L/\delta}{2n}}$
6- **Then**
7- **Split** leaf on best attribute
8- **For** each branch
9- **do** start new leaf and initialize counts

III. EXPERIMENTAL RESULTS

discusses this section the results obtained from the proposed methodology as shown below. Data is processed by blind source separation . and classification by Hoeffding Tree classifier. and Comparison The results obtained from both .

A. Input brain signal processing:

The brain signals are entered to the system and the mixture is done using the cross-validation algorithm to ensure that all data will be in the system as a training and test data. The input signal for 19 channel one trial of right index finger movement and input signal for 19 channel one trial of left index finger movement is shown in Fig.2, Fig.3.

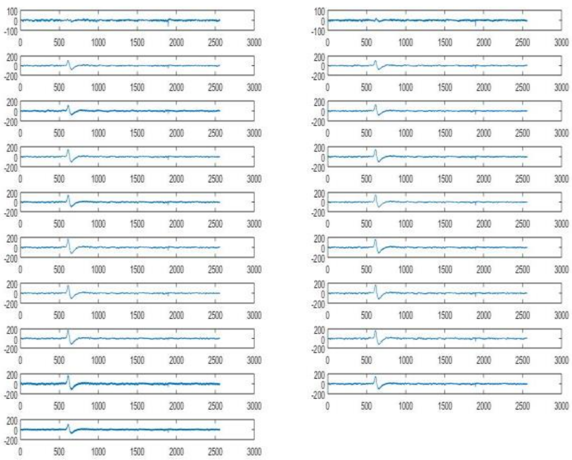

Fig. 2. the input signal of left index finger movement

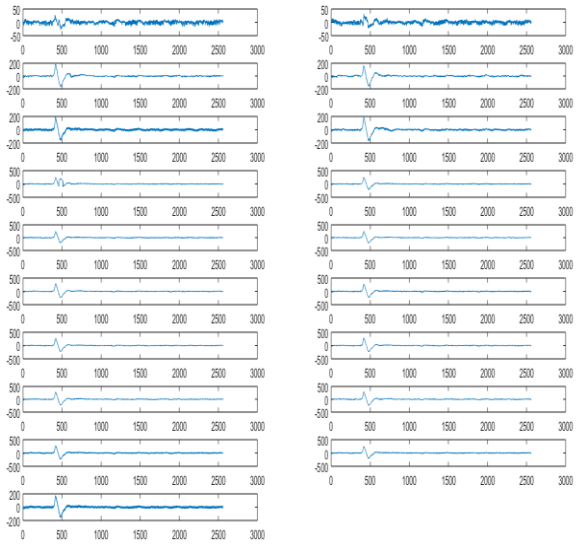

Fig. 3. the input signal of right index finger movement

B. *Results Left and right data without preprocessing or signal analysis by Hoeffding Tree classifier Affiliations*

The EEG signals which is entered to the system and split up to train and test using cross-validation and classified using the Hoeffding Tree classifier . table 2. and Fig. 4 shows the results obtained after classifying it.

TABLE II. .CLASSIFICATION USING HOEFFDING CLASSIFIER WITHOUT PREPROCESSING

TP Rate	*FP Rate*	*Precision*	*Recall*	*F- Measure*	*Class*
0.669	0.602	0.526	0.669	0.589	1
0.398	0.331	0.546	0.398	0.46	2

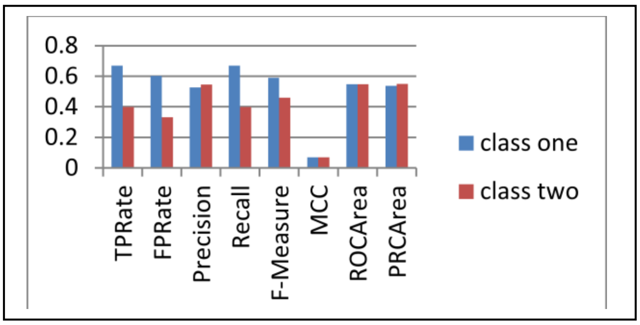

Fig.4. results obtained for execute the system using Hoeffding Tree classifier

C. *Results Left and right data with signal analysis by (BSS) And Hoeffding Tree classifier*

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data is analyzed using BSS method to return to the source object classified using the Hoeffding Tree classifier. table 3. table 4. table 5 .

TABLE III. . CLASSIFICATION USING STONE

TP Rate	*FP Rate*	*Precision*	*Recall*	*F- Measure*	*Class*
0.947	0.474	0.667	0.947	0.783	1
0.526	0.053	0.909	0.526	0.667	2

TABLE IV. CLASSIFICATION USING FICA

TP Rate	*FP Rate*	*Precision*	*Recall*	*F- Measure*	*Class*
0.947	0.813	0.581	0.947	0.72	1
0.188	0.053	0.75	0.188	0.30	2

TABLE V. CLASSIFICATION USING JADE

TP Rate	*FP Rate*	*Precision*	*Recall*	*F- Measure*	*Class*
0.316	0.632	0.333	0.316	0.324	1
0.368	0.684	0.350	0.368	0.359	2

table 6. and Fig. 5. shows the results obtained after Analysis of brain signals by blind source separation algorithms For the brain computer interface system (BCI) and then classifying it by Hoeffding Tree classifier.

TABLE VI. RESULTS BY HOEFFDING TREE CLASSIFIER OF BCI SYSTEM

	Signal analyses	*Classification signal*	*Precision*
EEG DATA	Whit out filtering	Hoeffding tree	53%
	JADE		34%
	FICA		66%
	STON (SBSS)		79%

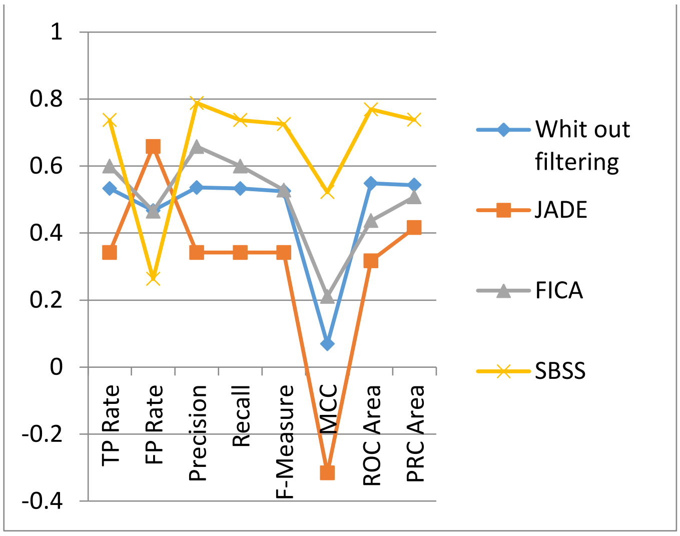

Fig .5. results obtained Detailed Accuracy by Hoeffding Tree

IV. CONCLUSION

In this study we introduce a new classification model that use Hoeffding Tree algorithm. The proposed system is based on removing artifacts using blind sources separation ; finally we use Hoeffding Tree classifier to the data obtained from grouping these features to classify the EEG signals to the movement of finger the right or finger the left. Experiments reveal that the proposed classifier with the stone algorithm leads to high classification results up to the classification accuracy 79%, compared to other blind separation algorithms.

REFERENCES

[1] L. F. GomeNicolas-Alonso and J. Z-Gil, “Brain computer interfaces, a review,” *sensors*, vol. 12, no. 2, pp. 1211–1279, 2012.

[2] F. A, R. A. El-KhoriMousabi, and M. E. Shoman, “An integrated classification method for brain computer interface system,” in *2015 Fifth International Conference on Digital Information Processing and Communications (ICDIPC)*, 2015, pp. 141–146.

[3] S. Kalagi, J. Machado, V. Carvalho, F. Soares, and D. Matos, “Brain computer interface systems using non-invasive electroencephalogram signal: A literature review,” in *2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, 2017, pp. 1578–1583.

[4] E. Gallego Jutglà, “New signal processing and machine learning methods for EEG data analysis of patients with Alzheimer’s disease.” Universitat de Vic-Universitat Central de Catalunya, 2015.

[5] S. Garg and R. Narvey, “Denoising & feature extraction of EEG signal using wavelet transform,” *Int. J. Eng. Sci. Technol.*, vol. 5, no. 6, p. 1249, 2013.

[6] N. T. H. Anh, T. H. Hoang, V. T. Thang, and T. T. Q. Bui, “An artificial neural network approach for electroencephalographic signal classification towards brain-computer interface implementation,” in *2016 IEEE RIVF International Conference on Computing & Communication Technologies, Research, Innovation, and Vision for the Future (RIVF)*, 2016, pp. 205–210.

[7] S. Bhaduri, A. Khasnobish, R. Bose, and D. N. Tibarewala, “Classification of lower limb motor imagery using K Nearest Neighbor and Naïve-Bayesian classifier,” in *2016 3rd International Conference on Recent Advances in Information Technology (RAIT)*, 2016, pp. 499–504.

[8] D. Buvaneash and M. R. S. John, “Brain robot interface using artificial neural network,” in *IOP Conference Series: Materials Science and Engineering*, 2018, vol. 402, no. 1, p. 12017.

[9] W. Zheng *et al.*, “Classification of Motor Imagery Electrocorticogram Signals for Brain-Computer Interface,” in *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, 2019, pp. 530–533.