A review on different classification techniques used in EEG based biometric system

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Abstract- Electroencephalogram (EEG) signals are recorded from brain electrical activity along the scalp, which measures voltage fluctuations resulting from ionic currents within the brain. EEG signals contains various information. EEG signals can be used in various applications, one of them is biometric authentication. Various studies show that EEG signals can act as good biometric parameter. For any biometric system first step is to process that signal, extract useful information as features from them. After that classification of the signal is done. Choice of classifier is a very important factor for determining the performance of EEG based biometric system. This paper presents review of recently published research focusing on various classification techniques used for EEG biometrics-based systems. K-nearest neighbour (k-NN), Elman neural network (ENN), Linear Discriminant Analysis (LDA), Support vector machine (SVM), Principal component analysis (PCA), Linear vector quantization (LVQ), BP Neural Network, simplify fuzzy artmap, Naïve based classifier and various other methods are discussed in this paper. A table is given at the end of paper which shows comparison between different classification techniques and the efficiency values of the system after using those classification techniques.

Keywords- Electroencephalogram (EEG), K-nearest neighbour (k-NN), Elman neural network (ENN), Linear Discriminant Analysis (LDA), Support vector machine (SVM), Principal component analysis (PCA),

1. Introduction

Now a day's human bio-electric signals such as Electroencephalogram (EEG), Electrocardiogram, Phonocardiogram (PCG), and Electrooculogram (EOG) etc. are used in various applications. Recent researches include these signals as a biometric parameter to authenticate an individual. Commercial biometric systems include fingerprint, palm print, face recognition etc. but these can't be used in high security areas, because they can be easily forged for example finger print can be forged by using gummy finger, face print can be extracted using photo. On the other hand, if we use bioelectric signals, it will be very difficult to replicate them, EEG signals can act as a good biometric parameter. EEG signals fulfil all properties of any biometric system. Main advantage of EEG is its uniqueness [1].

In this paper, we discuss about various kind of classification techniques used for EEG based biometric systems. A table (Table1) is given at the end of the paper which compares different classification techniques used by researchers, their year of publication, database used, number of subjects used in research, and efficiency values obtained.

2. Different Methods of EEG Classification

The selection of suitable classifier plays a vital factor for any biometric system. Here we discuss common classification techniques used for EEG based biometric systems.

A. K-Nearest Neighbours (K-NN)

K-NN classifier technique is commonly used for the classification of EEG patterns and is one of the simplest algorithms. It can also applied for the classification as well as for the regression. In classification, it compares the similarities between the two samples viz., template feature and the test sample. Further, the test function is used to locate the closest classified samples in the training feature templates and make a decision on the priority basis of its neighbours. This classifier is vulnerable to noise data. So to eliminate this problem, the distance (d) weight is applied to any K-NN classifier.

Palaniappan and Mandic [2] used k-NN algorithm using Manhattan distance metric to locate nearest neighbours. They also used ENN with three layers for comparison. To train ENN they used RBP algorithm. They got performance of ENN higher than that of k-NN, so they claim that ENN classifier was suitable for VEP biometrics. Using ENN they got maximum classification accuracy as 98.12 ± 1.26 (HU=200) whereas for k-NN they got 92.87 ± 1.49.

Palaniappan and Ravi [3] uses VEP signals from 20 subjects. To use 61 channel system to acquire their data. They use PCA for noise removal and use PSD features. They use 3 types of classifiers for better classification performance i.e., simplified *fuzzy* ARTMAP, LDA and K-NN. Here, to locate nearest neighbours they use two distances i.e., Euclidean and Manhattan. During their study they found that by applying PCA the classification performance was improved for LD and SFA but for k-NN performance was degraded.

Yazdani et al. [4] uses VEP signals from gamma band i.e. (GBVEP) from 20 subjects using 61 channel sensor system. For feature extraction they use AR and PSD coefficients. They employ k-NN as classifier their work and got 100% accuracy when k=5 is used.

Su et al. [5] uses HXD-1 portable instrument to record data from 40 subjects. They use AR parameters and PSD as features. They used k-NN and Fisher's LDA for feature reduction and got identification accuracy as 97.5%.

B. Elman Neural Network (ENN)

Palaniappan and mandic[6] use the ENN for classification of features extracted using Davies Bouldin Index (DBI). Their ENN contains three layers, i.e. first layer is input layer, second layer is middle layer and final layer is output layer. where final layer uses sigmoid activation function while middle layer contains parabolic tangent activation function. Network weights and biases were initialise using Nguyen-window algorithm. They achieve accuracy up to 98.56$\pm$1.87%.

C. Linear Discriminant analysis (LDA)

LDA is a classification method, given by R.A Fisher. It depends on a linear combination of variables which divides into two groups. It can be used where the variance-covariance matrix is not population dependent. $S = \frac{\sigma_{inter}^2}{\sigma_{intra}^2}$, S= likelihood ratio.

This classification method assumes normal distribution of conditional probability density (CDF) function with equal class covariance. Fisher's LDA doses do not presume a normal distribution or equal class covariance and used as a dimensionality reduction technique.

Paranjape et al. [7] used discriminant function analysis in their work in which they consider 40 subjects and 8 channel device is used to capture data. AR parameters are used for feature extraction. The discriminant analysis function is then used as a classifier that minimises differences in EEG epochs created by different subjects. Results show that they achieve 100% classification when all data is used and around 80% when half of data is used.

Dan et al. [8]recorded EEG signals using Mindset headset from 13 subjects. AR parameters are used as feature extraction technique. They used 3 classifiers like BP neural network, SVM and LDA. they divide recordings into 27 groups and use 18 group for training and 9 group for testing. Results shows that SVM has highest efficiency and identification rate upto 87%.

Rocca et al. [9] employed database consisted of 36 volunteers in resting state with eyes closed. They employed BUMP modelling for feature extraction. Then for identification purpose they use LDA. For LDA model they assume that vector ξ has gaussian mixture distribution, same covariance matrix for each class and only the mean varies. Then they divide feature vectors into training dataset ξ^{train} and test dataset ξ^{test}. Results shows that the achieved identification accuracy up to 99.69%.

D. Support Vector Machine (SVM)

It is supervised learning model, which has learning model associated with it. It is used for classification purposes. SVMs are focused on decision-making planes (hyperplanes) that describe decision boundaries. The decision plane distinguishes objects from various groups. Support vectors are the data points closest to the hyperplane.

Su et al. [10] acquired their data using HXD-1 portable equipment having single FP1 electrode from pool of 40 subjects. AR parameters and PSD coefficients were used as feature vector. Then foe classification they choose 3 classifier and one of them is SVM. By using SVM as classifier they got 79.6% accuracy.

Dan et al. [8] chooses 3 classifiers for their work one of them is SVM. They record their data using MindSet headset. And they use AR parameters as feature vectors. They divide their recordings into 36 groups, and for training purpose they randomly select two third of group and rest for testing. When they use BP neural network for classification their network can't be fully trained because without adequate training set BP NN can't be fully trained and they got poor prediction performance in that case. But SVM is adequate for small sample. By using SVM with AR model order and alpha waves were 10 and 20, they got best prediction performance and correct rate as 87.1795%

E. Principal component analysis (PCA)

For dimensionality reductions, PCA is used. Karl Pearson invented PCA in 1901. The main components are orthogonal since they are covariance matrix vectors themselves. If there are n observations of p variables, min is the number of different key components (n-1, p). Koike-akino et al. [11] used PCA for dimensionality reduction which helps to achieve higher classification accuracy. They observe that for PCA, around 7% of principal components explain 90% of data variance. With several classifiers they evaluate the impact of reduced dimensionality by PCA and PLS. when LDA and QDA was used, then PLS outperforms PCA as input to both of classification algorithms. They got best performance around 72% with QDA after using PLS.

F. Linear Vector Quantization (LVQ)

Supervised learning is used by LVQ. It is the method of classifying a pattern where a class is represented by each output unit. Training patterns with a known classification are given to the network and initial distribution of the output class is also provided. After finishing the training process, LVQ would define the input vector by assigning it to the same class as the output class. Poulos et al [12] described LVQ and used AR coefficient as features. Then these features are classified by artificial neural network classifier. Su et al. [10] used 3 classifier for their work one of them is LVQ. They collect their data using only single electrode FP1 from 40 subjects. They used AR an PSD coefficients as feature set. By using LVQ as classifier they got 81.9% classification accuracy. Poulos et al.[13] acquires data using PHY-100 Stellate software from fours subjects and subjects having rest with eyes closed. They used PSD coefficients as features of EEG signal. Then they perform neural network classification. They employed LVQ to classify features obtained in previous step. Because of their capacity to classify incoming vectors into groups that are not nearly separable in function space, they choose LVQ. They get correct classification scores between the range 80%-100%.

In their other Poulos et al. [14] extracted AR features from EEG signals and then fed these features to artificial neural network i.e. Kohonen's Linear Vector Quantizer. They choose LVQ neural network having hidden layer or competitive layer with 4 nodes, with help of which feature space was segmented into 4 subclasses, then these were grouped into 2 classes by second, linear layer. They got correct classification scores up to 72% to 84% in their work.

G. Polynomial Based Classification

Rocca et al. [15] acquired data for 45 subjects resting with eyes closed condition and auto regressive stochastic modelling was used as feature extraction. And they used polynomial based classification for their work.

H. BPNN (Backpropagation Neural Network)

It is a feed-forward multilayer network trained according to the algorithm of error backpropagation. It can be used to learn and store a great deal of I/O model mapping interactions. Dan et al. [8] recorded their signals using MindSet headset. They use AR parameters as features. For classification stage they choose 3 classifiers one of them is BP neural network. They divide the recordings into 36 groups and randomly select two-third of groups for training and rest for testing. In their work they use four-layer network. First, they serve AR model parameters of alpha wave as feature vectors and they got correct rate around 65%. Then they add whole EEG signals AR parameters and got 75% as correct rate. Hu [16] used dataset from BCI competition 2003, in which data was acquired from electrodes C3, C4, P3, P4, O1 and O2. Dataset include data from 3 subjects i.e., K3b, K6b and L1b. Then he used bandpass filter to retain information between 2 and 40 Hz. he chooses two different types of feature in his work one is based on single channel and other is two channel feature. Then to classify different subjects he trained Multilayer back-propagation neural networks. Remaining 50% testing set were classified by trained network.

I. Simplified Fuzzy ARTMAP

SFAM is incremental NN classifier, so it follows incremental supervised learning. It is faster and simpler than fuzzy ARTMAP. Its training ability is higher than other NN.

Palaniappan and ravi[17] used SFA in their in which they acquired VEP signals from 20 subjects and gamma band power (GBP) features were extracted from them. Then the SFA grouped these features into different categories that reflect the person. SFA is chosen because of its ability to train at high-speed. SFA network used in their work is consisted of Fuzzy ART module and Inter ART module. Then supervised learning is performed. Here, the stage of testing is similar to training, i.e. learning. Results shows average classification rate upto 94.18%.

J. Naïve Based Classifier

Kathikeyan and sabarigiri[18] made use of Naïve bayes classifier n their work to classify feature set which is composed of AR and PSD coefficients. As training and rest for testing, they randomly select four recordings for each subject. The model from Naïve Bayes was learned by fitting the templates. Posterior probability was used as similarity match. They got 4.16% EER using proposed method.

Table1: Existing research on different classification techniques used by authors

Reference	Year	Database	Subjects	Classification technique	efficiency
[14]	1999	Poulos DB	4	LVQ	72%-84%
[13]	1999	Poulos DB	4	LVQ	82%-100%
[7]	2001	Paranjape DB	40	Discriminant function analysis	83%
[10]	2010	Their own DB recorded by HXD-1 dataset	40	LVQ, SVM, FDA with k-NN	k-NN (70.7%) kNN+FDA (97.5%) SVM (79.6%)

					LVQ (81.9%)
[15]	2012	Rocca DB	45	Polynomial classifiction	98.73%
[18]	2012	Own DB using ENOBIO device	40	Naïve Bayes	EER- 4.16%
[9]	2013	Rocca DB	36	LDA	89%
[8]	2013	Their own dataset recorded by MindSet Headset	13	BP-NN, SVM, LDA	87% (SVM)
[19]	2014	PhysioNet BCI	108	Mahalanobis distance based classifer	97.5% (EC) 96.26% (EO)
[20]	2015	Physionet DB	109	EC (eigen vector centrality)	99.5% (REO), 98.1% (REC)
[21]	2016	Own DB using NeuroskyMindwave Headset	31	LDA	
[17]	2003	Palaniappan DB	20	SFA	95.75%
[2]	2007	Palaniappan DB	10	ENN, k-NN	98.12±1.26
[6]	2007	Palaniappan DB	40	ENN	98.56±1.87%
[22]	2010	Santos DB	13	SVM	
[23]	2010	UCI KDD	70	K-NN, SVDD	95.1%(k-NN) 98.5% (SVDD)
[24]	2015	Own DB using EASY CAP device	32	ANN (feed-forward, multi-layer perception, BP NN)	94.04%
[11]	2016	Their own DB recorded by Emotiv EPOC	25	SVM, LDA, QDA, NB, DT, k-NN, LR, DNN	96.7%
[25]	2004	Own DB recorded with Biosemi system	9	GMM (gaussaian mixture model)/ MAP	FRR- 96%
[26]	2008	Keirn and Aunon DB	5	PCA, two stage authentcation method with modified four fold cross validation procedure	FRE and FAE = 0
[27]	2008	NIPS 2001 BCI workshop DB	9	MTL NN	95.6%
[16]	2010	BCI compitition 2003	3	Multilayer BP-NN	TAR- 100% (when threshold is 25%)
[28]	2012	BCI competition IIIa, BCI competition 2008 (Graz a, Graz B), australian EEG DB, Alcoholism (large), Alcoholism (full)	3, 9, 9, 40, 20, 122	SVM	99%, 80.8% (GrazB), 46.24% (GrazB), 92.8% (Alcoholism(large)), 61.7% (Alcoholism(full)).
[29]	2015	Own DB using NeuroskyMindwave headset	25	LDA	97.3%
[30]	2013	EMM/I dataset	50	LDC (linear discriminant classifier)	95.5%
[31]	2012	Own DB	50+20 intruders	DA, TREE, COP, LDA, QDA, D-LDA, D-QDA	93.8%
[12]	2002	Polous DB	4 + 75 intruders	LVQ	76% to 88%
[32]	2008	FORENAP DB	51 + 36 intruders	DA	98.1%
[33]	2010	Ralph DB	5	BP NN, FFNN	94%
[34]	2010	Own DB using gMobilab+ console	10	NN	81%
[3]	2006	Palaniappan DB	20	SFA, LDA, k-NN	96.5%
[5]	2010	Own DB usng HXD-1	40	k-NN+ FDA	95.4%
[35]	2018	Own DB using g.USBamp	40	CNN and BPNN	97.6%
[36]	2019	Physionet DB	109	1D LSTM	99.58%
[37]	2020	Own DB	20	Rule-KNN	92.46%

3. Conclusion and Future Scope

This article provides a brief summary on different classification techniques used in EEG based biometric systems. We surveyed most recent research published in same filed. In this research most commonly used classification methods used in biometric systems based on EEG signals such as K-NN, ENN, LDA, SVM, PCA, LVQ, BPNN, SFA, Naïve based classifier etc. We found that Discriminant analysis, BP Neural Network higher efficiency values. This paper includes a table which consists of year of publication, number of subjects used in research, database used and compare different classification methods used and their efficiency values.

For future work, these techniques can be implemented on EEG data and different optimization techniques can be applied to that for getting better efficiency values.

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