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Biometric Authentication System Using EEG Brain Signature

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ABSTRACT

This paper proposes an algorithm to recognize EEG signals of individuals using a biometric authentication. Research on brain signals shows that each individual has unique brain wave pattern. Electroencephalography signals generated by mental tasks are acquired to extract the distinctive brain signature of an individual. Electroencephalography signals recorded during four biometric tasks, such as relax, read, spell and math activity were acquired from twenty five healthy subjects.We propose an algorithm for recognition of individuals using power spectral density using Recurrent Neural Network and Feed forward Neural Network. The performance of the Recurrent Neural Network is appreciable with an accuracy of 98% for the spell task and 95% for the read task.

Keywords: Biometric, Authentication, Signal Processing, Electroencephalography (EEG), Power Spectral Density, Recurrent Neural Network, Feed Forward Neural Network.

I. INTRODUCTION

A human identification system uses the unique features of an individual as an identifier, existing technologies, mostly use fingerprints, speech, facial features, iris and signatures. A biometric system provides two functions, namely authentication (or verification) and identification. Authentication is confirming or denying an identity claim by a particular individual, while identification is to recognize an individual from a group of people based on the identity claimed by the person [1]. Although both methods are the same, however they target distinct applications. In the verification applications the people have to cooperate with the system as they want to be accepted, while in the identification applications they are not connected with the system and generally do not prefer to be identified. Biometric characteristics can be divided into two main classes. Physiological and behavioural characteristics. Physiological is related to the human body characteristics, such as DNA, fingerprints, eye retina and irise, voice patterns, facial patterns and hand measurements for authentication purposes. Behavioral biometrics are gait, voice recognition, which relates to analyzing the behavior of a person [1].

Electroencephalography (EEG) as a biometric is relatively new compared other biometric. The main advantage of using EEG is its uniqueness and cannot be faked or duplicated. EEG is a technique that reads the scalp electrical activity generated brain structures. When brain cells or neurons are activated, local current flows are produced, EEG measures mostly the current that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. The cortex is a dominant part of the central nervous system. The highest influence of EEG comes from electric activity of cerebral cortex due to its surface positions [1]. EEG biographs are the brain activity generated during the performance of mental activities such as reading, spelling, etc. are recorded noninvasively from twenty five subjects. Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning. These oscillations represent synchronized activity over a network of neurons. The pattern of the EEG biographs varies from individual to individual for similar brain activity and this plays an important role in identifying the biometric traits of individuals.

II. RELEATED WORK

EEG based identification and authentication has been studied. Preliminary works have demonstrated that the EEG brain signatures is used for individual identification and authentication. Ravi [2] introduced an effect of noise can be generated from the body movements. The noises in the EEG signals are also called the artifacts and these artifacts are to be removed from the original signal for the appropriate analysis. Gope [3] proposed the various methods of research on EEG based biometrics have been listed in the literature. Paranjape *et.al* [4] reported that EEG biometric potential signals were able to differentiate 40 distinct subjects with autoregressive features derived from 8 channels. The maximum identification obtained was 82%. Riera *et al.*[5] collected data from 51 subjects and 36 intruders. The EEG was recorded from 2 channels while subjects were sitting with eyes closed for 1 minute. They obtained a true recognition rate of 96.6% and the false reception rate of 3.4%. Hema *et al.* [6] recorded EEG signals collected from 50 subjects (single channel) using 3 electrodes. Power Spectral Density features were used to extract the features and a Feed Forward Neural Network and Recurrent Neural Network with three layers were used to classify. Four mental tasks, namely relax, read and spell and math tasks. The maximum average classification rate is 95%. Poulos *et al* [7] proposed EEG signals from 75 subjects in one session and found a classification rate of 91%.

Poulos et al. [8] extended their studies by AR and bilinear model features. The maximum classification accuracy obtained from 56% to 88%. Jian-Feng [9] proposed the EEG signal identification for 10 subjects using 6 channels were recorded by Jiang Feng Hu beta waves was extracted using Welch algorithm. The maximum accuracy gained for subject authentication was in the range from 75% to 80% and 75% to 78.3% for subject identification. Marcel [10] used for imagined left and right hand movement and imagined word generation for authentication of subjects with a false acceptance rate and false rejection rate of 7% . Dan et al. [11] used the polynomial kernel SVM based on wavelet transform (WT) and AR from single channel systems are used. The average classification accuracy of 85% obtained from 13 subjects. Ferreira et al. [12] used the linear and radial basis function (RBF) SVM to classify 13 subjects on the gamma band SP. These method got an error rate of 15.67% to 38.21% and one against all method got an error rate ranging from 17.43% to 30.57%. Liang et al. [13] extracted AR from 8 channels on 7 subjects. The one against one SVM have an accuracy of 45.52%-54.96% and one against all got an accuracy of 48.41% -56.07%. Mu and Hu [14] also used back-propagation NN to identify AR and fisher distance from 6 channels. Single channel systems are used to indentify 3 individuals and have maximum accuracy of 80.7% to 86.7%. Ashby *et a*l. [15] extracted the AR, PSD, spectral power (SP), from the 14 EEG channels are used the linear support vector machine (SVM) classifier for authentication on 5 individuals and obtained the false rejection rate (FRR) of 2.4% to 5.1%, and the false acceptance rate (FAR) of 0.7% to 1.1%. Yeom et al. [16], [17] used the signal difference and least square error of time derivative features on 18 channels with the Gaussian kernel SVM on 10 subjects and got the maximum accuracy of 86%. Hema and Osman [18] used Power Spectral Density (PSD) and Feed Forward Neural Network are used to classifying individuals and got an accuracy ranges varied from 79.9% to 89.95%. Shedeed [19] used the Neural Network to identify 3 individuals based on fast Fourier transform (FFT) and wavelet packet decomposition (WPD) from 4 channels. The maximum recognization rate from 66% to 93%. Wang *et al* [20] used the naive Bayes model for authentication from 4 subjects based on AR features. The minimum half total error rate (HTER) of 6.7%. Hema *et al* [21] recorded EEG signals are recorded from 2 electrodes for 6 subjects with Power Spectral Density features using Welch algorithm to extract the features and a feed forward neural network with three layers were used. Four mental tasks, namely relax, read and spell were able to achieve an average authentication rate of 96%. In our earlier studiy single channel acquisition process system was used. In this paper two channel acquisition process is proposed. EEG biographs are collected from 25 subjects [6].

III. SYSTEM ARCHITECTURE

The proposed method involves 3 stages. The first stage involves recording the EEG signals from the subjects. In the next stage, these EEG signals are processed to remove noise. Power Spectral Density techniques are used to extract the features. The third stage involves identification of the individuals using neural networks.

A. Experimental Setup

EEG signals of the four biometric tasks were acquired using a two channel AD Instrument Bio-signal amplifier. Five non- invasive gold plated cup shaped electrodes placed on the scalp. The subjects were seated comfortably in a noise free room and were requested to perform the biometric task mentally without any overt movements. The electrodes are placed at F_3, F_4, O_1 and O_2 Fp1 as per the 10 -20 International Standards shown in Figure 1. During signal acquisition a notch filter was applied to remove 50Hz power line artifacts. The protocol for the four tasks performed by the individuals are as detailed below.

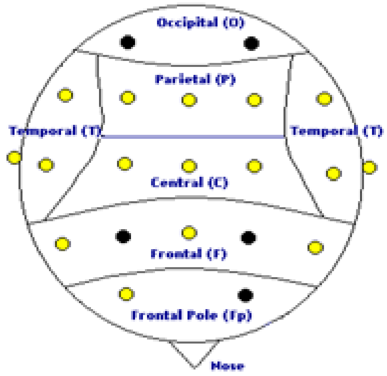

Figure 1. Electrode placement location for data acquisition

1. **Baseline activity:** The subject were asked to relax and think of nothing in particular.
2. **Read:** The subject is shown a typed card with tongue twister sentences and they were requested to read the sentence mentally without vocalizing.
3. **Spell:** The subject is shown a typed card with his name and is requested to spell his name mentally without vocalization and overt movements.
4. **Math activity:** The subject is given a nontrivial multiplication problem such as 79 times 56 and is asked to solve them without vocalizing or making any other physical movements.

B. EEG Biographs

EEG is a technique that reads electrical activity of the brain. When brain cells or neurons are activated, the local current flows are produced. The highest influence of EEG comes from electric activity of cerebral cortex due to its surface position [8]. EEG biographs or the brain activity generated during the performance of mental activities such as reading, spelling etc. are recorded noninvasively from twenty four subjects. Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning. These oscillations represent synchronized activity over a network of neurons. The pattern of the EEG biographs varies from individual to individual for similar brain activity and this plays an important role in identifying the biometric traits of individuals.

C. Database

Data was collected from volunteers subjects in two sessions for different days. All subjects who participated in the experiments are university students and staff aged between 18 to 48 years. During signal acquisition it was ensured that the subjects are free from illness and medication. The sampling frequency is set at 200 Hz. Each trial lasts for 10 seconds with breaks of 10 minutes between trials. Signals from five trials are recorded per session. Ten signals per task are collected from four such sessions. Sessions are conducted on different days. 40 data samples are collected from each subject for four tasks.

D. Feature Extraction

EEG signals are very noisy and they can be easily affected by electrical activity of the eyes or muscles. During acquisition a notch filter is applied to remove the 50Hz noise due to electrical power source. To improve the quality of the signal, preprocessing of the raw data is performed. The raw EEG signals are acquired and segmented into four frequency bands, namely delta (0.5-3 Hz), theta (3-7 Hz), alpha (7 – 12 Hz) and beta (12- 40 Hz). Among the four, alpha and beta are seen in the conscious state of a human. Hence, these are consider the frequency bands alpha and beta from the original frequency bands. The EEG signals are band pass filtered using twelve frequency bands from the alpha and beta rhythms of 7 Hz to 42 Hz with a bandwidth of 3 Hz. Chebychev filter is used to segment the signals in 3Hz band frequency in the range of 7Hz to 42Hz . The 12 band pass signals are ((7-10) Hz, (10-13) Hz,(13-16) Hz,(16-19) Hz, (19-21) Hz, (21-24) Hz, (24-27) Hz, (27-30) Hz, (30-33) Hz,(33-36) Hz, (36-39) Hz, (39-42) Hz. This segmentation is used to remove the lower range noise frequencies from 0.1 Hz to 6 Hz arising due to EOG signals and EMG signals above 43 Hz. 12 signal segments are obtained from the pre-processed EEG signals. In this study, feature patterns are extracted from the EEG signals using following six PSD algorithms. Power spectral density of the segmented signals is estimated and used as features. Power spectral density describes how the energy of a signal or a time series is distributed with frequency. The power spectral density of six algorithms are compared in this study.The power spectral density of six different algorithms are covariance, modified covariance, music, burg, Welch and yule-walker.

a) Power Spectral Density

In this study Power Spectral Density(PSD) algorithm is used for feature extraction process. Power spectral density, which describes how the energy of a signal or a time series is distributed with frequency. The Power spectral density analysis provides the basic information about how the power is distributed as a function of frequency. Spectral estimation techniques can be defined as the methods of non parametric, parametric and high-resolution methods Non parametric methods include a technique called Welch method. Parametric methods consists of Yule-Walker, Burg, covariance and Modified Covariance. Multiple Signal classification method is a type of High resolution methods.

a) Parametric methods

The parametric spectrum estimation is based on the assumption and a model of the data with prior knowledge. The frequency response of the model gives the estimate of power spectral density. Covariance, modified covariance, burg, Yule-Walker methods are based on parametric methods. The power spectral density using the covariance method gives the distribution of the power per unit frequency and the pre order of AR model . The covariance method for the AR spectral estimation is based on minimizing the forward prediction error in the least squares sense and no windowing is performed on the data for the formation of autocorrelation estimates .

Burg technique performs the minimization of the forward and backward prediction errors and estimates the reflection coefficient. The primary advantages of the Burg method is resolving closely spaced sinusoids in signals with low noise levels, and estimating short data records, in which the AR power spectral density estimates are very close to the true values. The accuracy of the Burg method is lower for high-order models, long data records, high signal-to-noise ratios and its high frequency resolution.AR model are always stable and computationally very efficient .The major advantages of the Burg Method is high frequency resolution, AR model is always stable and computationally very efficient.

The modified covariance method is based on minimizing the forward and backward prediction errors. This method is based on AR model to the signal by minimizing the forward and backward in the least square sense. The difference between the modified covariance and covariance technique are the definition of the autocorrelation estimator. Based on the estimates of the AR parameters.[21]

$$P(f) = \frac{\sigma^2}{\left|1 + \sum_{k=1}^{p} \hat{a}(k) e^{-j2\pi fk}\right|^2}, k = 1,2, \ldots \ldots, n \quad (1)$$

Yule–Walker method, or the autocorrelation method as it is sometimes referred to the AR parameters are estimated by minimizing an estimate of prediction error power [12].

b) Non-parametric methods

Non-parametric methods do not assume a fixed structure of a model. It can be expanded to accommodate the complexity of the data. The applicability of non parametric methods is much wider than parametric methods since it is based on the wide sense stationar. Welch method is based on the nonparametric method.

$$\hat{p}welch(f)" = \frac{1}{L}\sum_{t=0}^{L-1} \hat{s}\,xx(f) \quad (2)$$

L is the length of the time series. Examination of the short data registries with conjoint and non rectangular window reduces the predictive solution. The Welch method is segmented into eight sections of equal length with 50% of overlapping with a hamming window in each segment [21].

c) High-resolution method

High-resolution method includes techniques such as Multiple Signal Classification and Eigenvector. These methods define a Pseudo-spectrum function with large peaks that are subspace frequency estimates, and they are commonly used in the communication area. A multiple signal classification method is based on the high-resolution method.

$$P_{MU}(e^{jw}) = \frac{1}{\sum_{i=p+1}^{m} |e^{H} vi|^2} \quad (3)$$

The MUSIC is a noise subspace frequency estimator. It is used to distinguish the desired zeros from the spurious ones using the mean spectra of entire eigenvectors matching to the noise subspace. From the orthogonality condition of both subspaces, the MUSIC can be obtained using the following frequency estimator [21]. 24 features were extracted for each trial per subject per task. Each task is repeated ten times. 250 data samples from 25 subjects were obtained. The features are extractedto train ten trials and test the neural network.

E. identification using neural network

Two neural network models such as FFNN and RNN are used to identifying individuals. FFNN is a multilayered network with one layer of hidden units. Each unit is connected in the forward direction to every unit in the next layer. The input layer is connected to hidden layer and output layer is connected by means of interconnection weights. The bias is provided for both hidden and the output layer to act upon the net input. The network activation flow is in one direction only, from the input layer to output layer passing through the hidden layer. Back propagation algorithm resembles a multilayer feed forward network. The errors propagate backwards from output nodes to the input nodes [20][25-30]. The RNN with feedback unit from the hidden layer is used in this study. The architecture of RNN is similar to that of a multilayer perceptron except that it has an additional set of context units with connections from the hidden layer. At each step, the input is propagated in a standard feed-forward fashion. The fixed back connections result in the context units to maintain a copy of the previous values of the hidden units. These networks have an adjustable weight that depends not only on the current input signal, but also on the previous state of the neurons. In this experiment features are used to train and test the classifiers to identifying individuals. The data is divided into 4 datasets. The four data sets were used as training and testing sets (similar to the cross validation procedure). Each dataset contained 250 patterns. The network is modelled using 24 inputs and 9,10 hidden neurons chosen experimentally and 5 output neurons. Out of the 250 samples 75% of the data is used in the training of the neural network and 100% data were used in the testing the network. RNN is trained with gradient descent back propagation algorithm. Forty eight patterns from the training set were given as initial class to the FFNN and RNN network because of 25 subjects in the dataset. The learning rate is chosen as 0.0001. Training is conducted until the average error falls below 0.001 or reaches maximum iteration limit of 1000 and testing error tolerance is fixed at 0.04.

IV. RESULTS AND DISCUSSION

Fourty eight neural network models and their performance are listed in Figure 3 and 4 for Convolution features and PSD features using FFNN and RNN respectively.

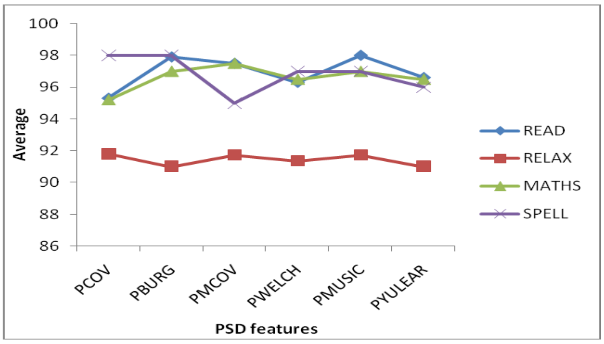

Figure 3. Mean Recognition performance of Feed Forward Neural Network

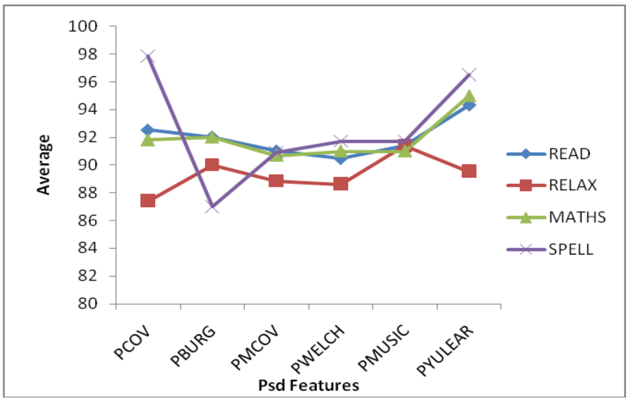

Figure 4. Mean Recognition performance of Recurrent Neural Network

In the FFNN model highest recognization accuracy of 97% was obtained, for the relax task using covariance algorithm and lowest accuracy of 87% was obtained for relax task using covarience and burg algorithm. The remaining features sets can be achieved better results. The lowest standard deviation was obtained for read task. The standard deviation varied from 4.19 to 0.5 for read task using covariance algorithm using FFNN model.

For the RNN model using pcov and burg algorithm the highest recognization accuracy of 98% was achieved for the spell task and lowest recognization accuracy of 87.3% was achieved for RNN model using a covariance algorithm for the read tasks. The lowest standard deviation was obtained for spell task. The standard deviation varied from 5.63 to 0.61 for reading task using a covariance algorithm for RNN. From the figure 5 it is observed that RNN model using covariance algorithm had highest recognization accuracy compared to the static network model.

A. Performance Evaluation

Considering True Positive (TP) values we can find the true detection of signals. True Negative (TN) is detected as a non event signal. Consider P as the total number of positive cases and N be the negative case [14].

$$\text{Accuracy} = (TP+TN) / (P+N) \qquad (4)$$

Authentication system makes two types of errors: False Rejection (FR) belongs to the signals, which remain undetected. False Acceptance (FA) is a false detected signal. The performance is generally called as False Acceptance Rate (FAR) and False Rejection Rate (FRR) expressed in percentages. To aid the interpretation of performance, two error measures are often combined using the Half Total Error Rate (HTER), defined as:

$$\text{HTER} = (FAR+FRR) /2 \qquad (5)$$

Table 1 and 2 show the result of the experimental study.Table 1 shows the results using all the 256 features, To identifying 25 individuals, it reached an average accuracy of 95%-97%. All the subject gave perfect accuracy in rejecting imposter for any PSD features. The best person identification was either PSD using covariance and PSD using burg since both FAR and FRR for all the subjects gave the highest classification accuracy of 97% for the spell task. Table2 shows the FAR/FRR/HTER results obtained according to the experimental protocol Read, Spell, Maths on the evaluation set. From the results we can conclude that the performance can be improved by using training and testing performance. Three tasks and 25 subjects based on PSD features using covariance algorithm got a half total error rate (HTER) ranging from 22% - 25% . This suggests that even much better results can be achieved by using training data over all day and that there might be a potential for incremental learning.

V. CONCLUSION

In this study, we investigate brain activity for person identification. This paper proposed to statistical framework based on RNN and FFNN model. EEG Biograph of twenty five individual identification systems were used in this experiment. Experimental results validate the proposed biometric tasks and algorithms. Best performance is achieved for the spell task with a maximum classification accuracy of 98% compared to the feed forward neural network. The spell protocol proposed in this study for signal acquisition has better the recognition performance in comparison with our previous paper [11]. Future work will focus different feature extraction algorithm and more dynamic network model which will be used to improve the authentication level.

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Table1. Far/ Frr/ Hter Performance (In %) For All Tasks

Tasks	**Spell**			**Read**			**Maths**		
Features	**TP**	**TN**	**ACC**	**TP**	**TN**	**ACC**	**TP**	**TN**	**ACC**
Pcov	98	95	**97**	96	93	**94**	96	94	**93**
Pmusic	98	96	95	95	93	92	96	90	**93**
Pwelch	97	95	94	96	94	93	95	93	92
Pburg	98	96	95	97	95	**94**	96	94	**93**
Pyulear	95	94	92	96	90	93	93	92	91
Pmcov	97	95	94	96	94	93	95	92	92

Table2. Far/ Frr/ Hter Performance (In %) For All Tasks

Tasks	Spell			Read			Maths		
Features	**FAR**	**FRR**	**HTER**	**FAR**	**FRR**	**HTER**	**FAR**	**FRR**	**HTER**
Pcov	25	23	22	36	25	27.9	35	30	25
Pmusic	31	25	28.5	36	26	27.6	37	27	27.9
Pwelch	32	26	28.2	34	26	27.9	35	27	27.6
Pburg	31	25	28.5	32	26	28.2	34	26	27.91
Pyulear	37	27	27.91	37	27	27.91	34	26	27.9
Pmcov	32	26	24.1	34	26	27.9	33	30	27.6