BIOMETRIC AUTHENTICATION USING BRAIN SIGNATURES

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Abstract

This paper proposes an algorithm to recognize EEG brain signatures of individuals for biometric authentication. Research on brain signals show that each individual has unique brain wave patterns. Electroencephalography signals of biometric 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. The proposed algorithm for recognition of individuals uses power spectral density and neural networks. The performance of the existing algorithm was found to be 95% for spell task using single channel data. The performances of the proposed algorithm are appreciable with an accuracy of 98% for the spell task and 95% for the read task. Comparisons are also made using single channel and two channel data. Experimental results show that two channel acquisition process yields better recognition rates.

Keywords : Index Terms —Biometric, Authentication, Signal Processing, Electroencephalography, Power Spectral Density, Recurrent Neural Network, Feed Forward Neural Network.

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I. Introduction

Biometric systems use the unique features of an individual as an identifier, existing technologies, use fingerprints, speech, facial features, iris and signatures as a biometric modalitees. A biometric system provides two functions, namely authentication 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 biometric authentication 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 iris, voice patterns, facial patterns and hand measurements. Behavioral biometrics are gait and voice recognition, which relate to analyzing the behavior of a person [1].

Electroencephalography (EEG) as a biometric is relatively new compared to other biometric modalities. 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 by 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]. 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. The pattern of the EEG signals 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

Earlier studies on EEG have shown that EEG signals are unique for individuals for similar activity, some of the studies are listed. Paranjape *et.al* [2] reported that EEG signals were able to differentiate 40 distinct subjects with autoregressive features derived from 8 channel data. The maximum identification accuracy obtained was 82%. Riera *et al.*[3] collected data from 51 subjects and 36 intruders, 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%. Poulos *et al* [4] use EEG signals from 75 subjects and obtained a classification rate of 91%. Poulos et al. [5] extended their studies using AutoReggrasive and bilinear model features. The maximum classification accuracy obtained was 88%. Jian-Feng [6] proposed EEG signal identification for 10 subjects using 6 channels, beta waves are extracted using Welch algorithm. The maximum accuracy gained for subject authentication was in the range from 75% to 80%. Marcel [7] used four tasks, namely imagined left and right hand movement and imagined word generation was able to achieve an average authentication rate of 93%. Dan et al. [8] used the polynomial kernel SVM wavelet transform and AR features from single channel systems, the average classification accuracy of 85% was obtained from 13 subjects. Ferreira et al. [9] used the linear and radial basis function SVM to classify 13 subjects on the gamma band and an error rate of 15.67% to 38.21% was obtained. Liang et al. [10] extracted AR from 8 channels for 7 subjects. The one against one SVM has an accuracy of 45.52%-54.96% and one against all got an accuracy of 48.41% -56.07%. Mu and Hu [11] used back-propagation neural network to identify AR and fisher distance features from 6 channels. Single channel systems were used to indentify 3 individuals and have maximum accuracy of 80.7% to 86.7%. Ashby *et al.* [12] extracted the AR, PSD, spectral power, from the 14 EEG channels and used linear support vector machine classifier for authentication of 5 individuals and obtained the false rejection rate of 2.4% to 5.1%, and the false acceptance rate of 0.7% to 1.1%. Yeom et al. [13] 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 [14] used Power Spectral Density and Feed Forward Neural Network to classify individuals and got an accuracy ranges varying from 79.9% to 89.95%. Shedeed [15] used Neural Network to identify 3 individuals based on Fast Fourier transform and wavelet packet decomposition from 4 channels. The maximum recognition rate obtained 66% to 93%. Wang *et al* [16] 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* [17] 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. Four mental tasks, namely relax, read and spell were able to achieve an average authentication rate of 96%. In our earlier study single channel acquisition process system was used [18]. In this paper two channel acquisition process is proposed and compared using biometric data collected from 25 subjects.

III. Methods

The proposed method involves three stages. The first stage involves recording the EEG signals from the subjects. In the second stage, these EEG signals are processed to remove noise. Power Spectral Density(PSD) techniques are used to extract the features. The third stage involves identification of the individuals using neural networks.EEG signals of the four biometric tasks are acquired using a two channel and single channel acquisition process. The electrodes are gold plated cup shaped electrodes. 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, O_2, F_{p1} and F_4, O_2, F_{p1} for two and single channel systems respectively as per the 10 - 20 International Standards shown in Fig.1. During signal acquisition a notch filter was applied to remove 50Hz power line artifacts. The sampling frequency is fixed at 200Hz. The protocol for the four tasks performed by the individuals are as detailed below.

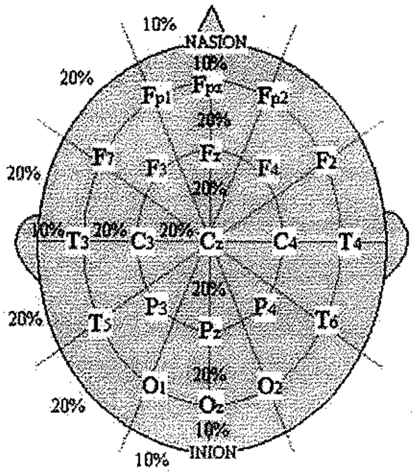

Figure 1: Electrode location for data acquisition

Baseline activity: The subject is asked to relax and think of nothing in particular.

Read: The subject is shown a typed card with tongue twister sentences and they were requested to read the sentence mentally without vocalizing.

Spell: The subject is requested to spell his name from a card with his name mentally without vocalization and overt movements.

Math activity: Nontrivial multiplication problem such as 79 times 56 are given to the subject to solve them without vocalizing or making any other physical movements..

Data was collected from volunteer subjects in two sessions for different days. All subjects who participated in the experiments are university students and staff aged between 18 and 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 two such sessions. Sessions are conducted on different days. 40 data samples are collected from each subject for four tasks. Fig2 and 3 show the plot of signals generated for the four biometric tasks for subject 2.

FEATURE EXTRACTION

EEG is generally divided into four frequency bands, namely, the 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

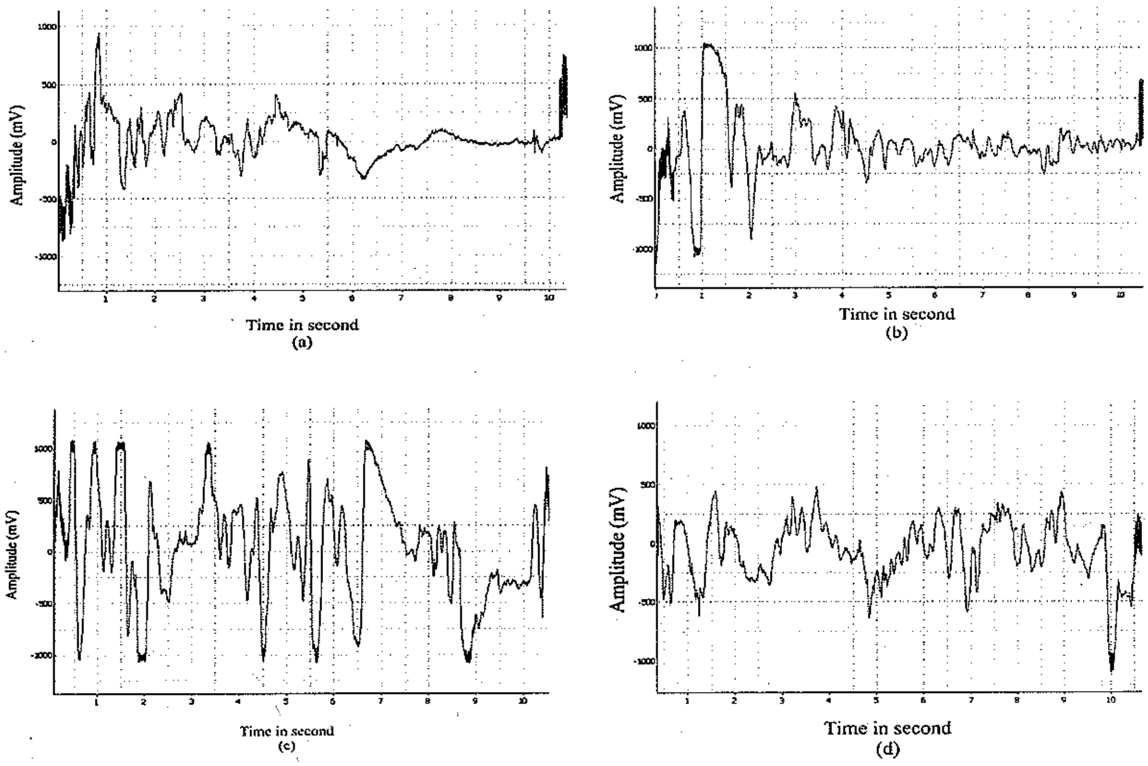

Figure 2: EEG signal using single channel acquisition process for a) Read b) Relax c) Maths d) Spell

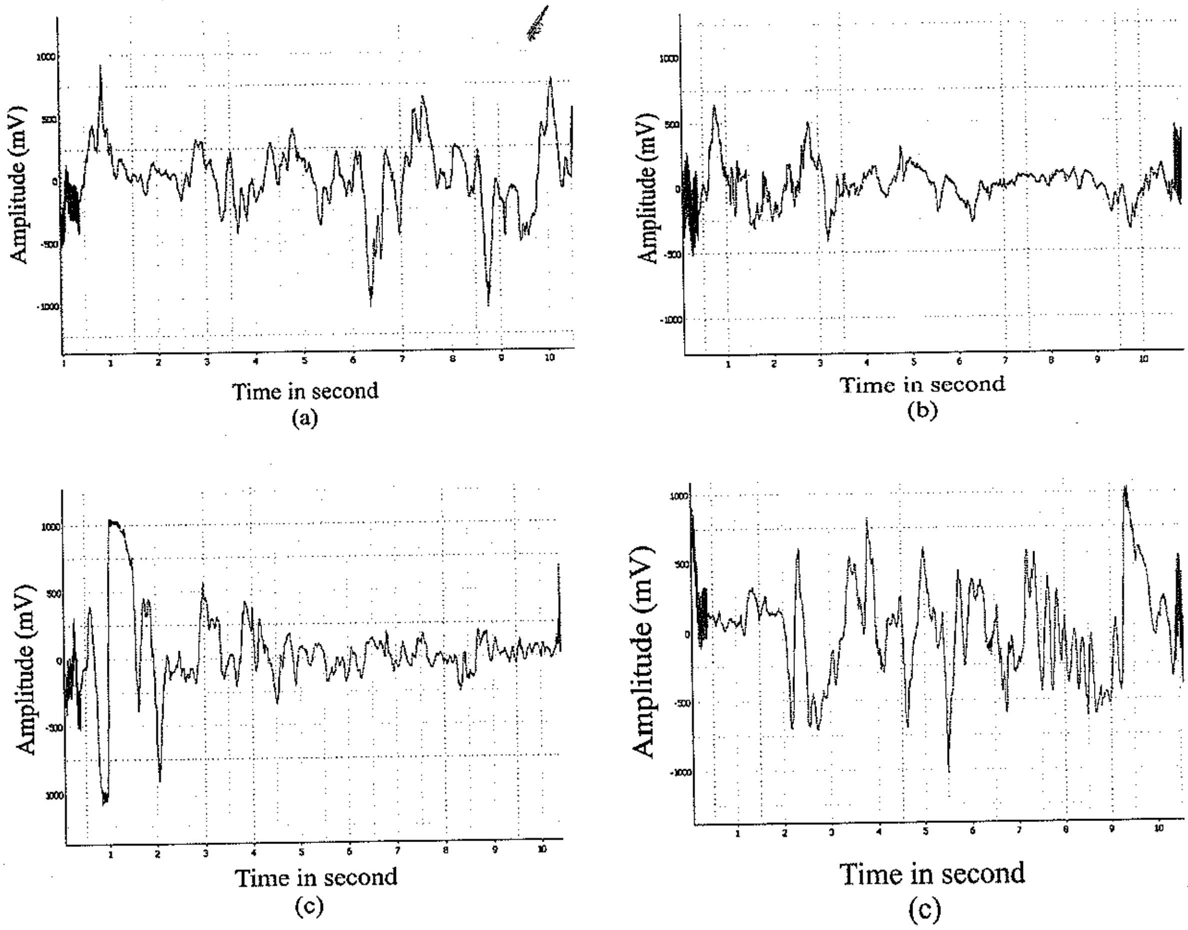

Figure 3: EEG signal using two channel acquisition process for a) Read b) Relax c) Maths d) Spell

conscious state of a human. Hence, we consider the frequency alpha and beta bands in this study. The EEG signals are band pass filtered using twelve frequency bands for the alpha and beta rhythms of 7 Hz to 42 Hz with a bandwidth of 3 Hz. This frequency range is chosen as most of the conscious activity is seen in this range. 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. The bandpass filtered signals are further processed to extract unique feature using six power spectral density algorithms.

PSD analysis provides the basic information about how the power is distributed as a function of frequency. Spectral estimation techniques can be defined as non parametric, parametric and high-resolution 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.

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

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 [17].

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 non parametric 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 [17].

High-resolution method includes techniques such as Multiple Signal Classification and Eigenvector (MUSIC). 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.

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

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. For each trial in tasks, 12 and 24 frames were extracted for single channel and two channel respectively. Each trial per subject per task and each task is repeated ten times. 250 data samples from 25 subjects were obtained. The features are extracted to train ten trials and test the neural network.

Two neural network models such as Feed Forward Neural Network (FFNN) and Recurrent Neural Network (RNN) are used to identify 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 [18].

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. PSD features extracted from the signals are used to train and test the classifiers to identifying individuals. The data is divided into 4 datasets namely, read,relax, spell, maths. The four data sets were used as training and testing sets. Each dataset contained 250 patterns. The network is modelled using 24 and 12 inputs and 9 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 and FFNN is trained using Levenberg back propagation training algorithm. 48 network are modeled using data acquired for the four tasks. 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

Experiments are conducted to modal networks using four biometric tasks and six features and two networks for the signle channel and two channel data. 48 network models, each are analyzed for the single channel data and two channel data. The performance of the 96 network models are discussed below.

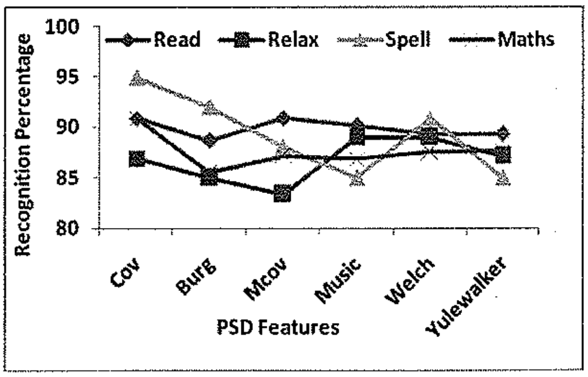

Figure 4: Mean Recognition performances of the FFNN using the two channel acquisition process

Fig3 shows the mean identification rates of the 24 network models using FFNN maximum recognition accuracy of 97% for the spell task using covariance algorithm was obtained. It is also observed that the network models have the minimum classification accuracy of 87% for relax task using burg algorithm.The lowest standard deviation 0.5 was obtained for read task. The overall standard deviation varied from 5.19 to 0.5.

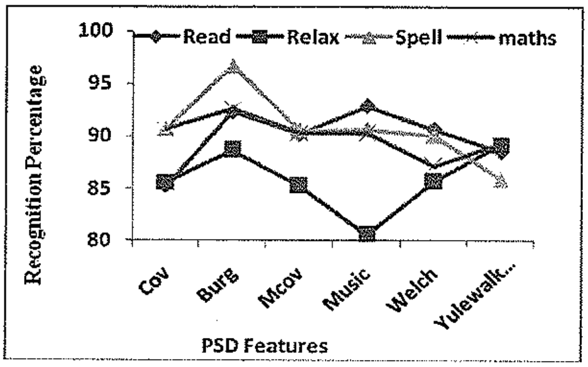

Figure 5: Mean Recognition performances of the RNN using the two channel acquisition process

Fig4 shows the mean identification rates of the 24 network models using the RNN it can be inferred that the maximum recognition accuracy of 98% for the spell task using burg algorithm was obtained. It is also observed that the minimum accuracy of 87.3% was achieved for RNN model using a covariance algorithm for the read tasks. The lowest standard deviation 0.61 was obtained for spell task. The standard deviation varied from 3.63 to 0.61 From the figure 4 it is observed that RNN model using covariance algorithm had highest recognization accuracy compared to the FFNN model

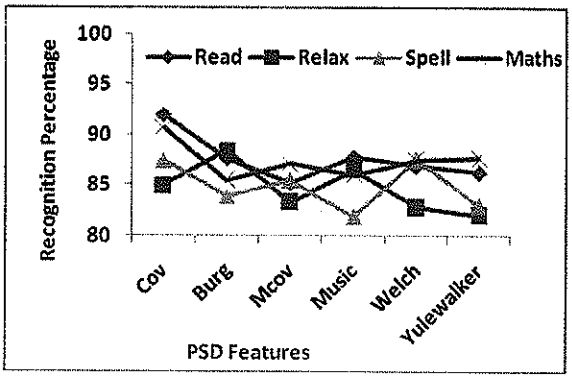

Figure 6: Mean Recognition performances of the FFNN using the single channel acquisition process

Fig5 shows the mean identification rates of the 24 network models using the FFNN, the FFNN model has a highest recognition accuracy of 94.89%, for the spell task using covariance algorithm was obtained. It is also observed that the network models have the minimum recognition accuracy of 85% was obtained for relax task using Pyule-walker. The lowest standared deviation 2.61 for read task . The standard deviation varied from 3.19 to 2.61.

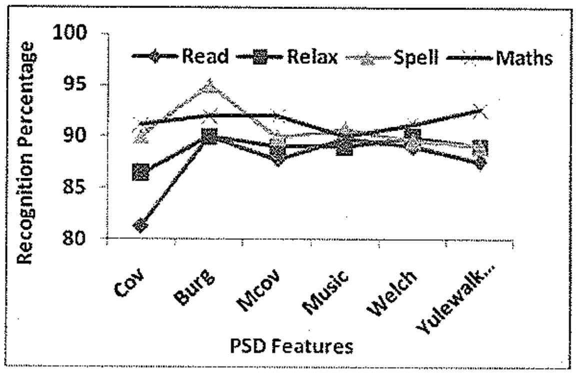

Figure 7: Mean Recognition performances of the RNN using the single channel acquisition process

Fig6 shows the mean identification rates of the 24 network models using the RNN it can be inferred that the network model has obtained a highest recognition accuracy of 96.71% was achieved for the spell task using burg algorithm with RNN. It is also observed that the lowest accuracy of 85.21% was achieved for RNN model using Pcovariance algorithm for the read task. The lowest standared deviation 0.21 was obtained for read task. The standard deviation varied from 4.61 to 0.21.

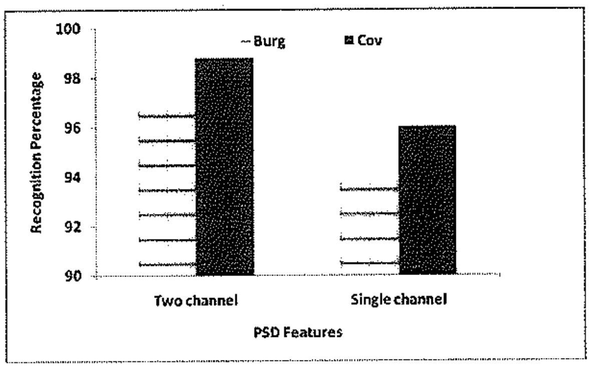

Figure 8: Recognition performances of the RNN for single channel and two channel process using the burg and covariance features

The experimental analysis of the 98 network models shows that two channel acquisition methods give marginally better recognition rate compared to the single channel acquisition method the power spectral. Maximum recognition rate of 98% was obtained using the burg algorithm and the RNN method.

V. Conclusion

This paper proposed biometric authentication using brain signatures. Biometric data from 25 subjects is used in this experiments. Six feature extraction methods and two network modals are used in this study. The study also compares the single channel and two channel acquisition process. Result validate that two channel acquisition proves gives marginally better recognition rate for person authentication. Experiments conducted on the 98 network modals show that the RNN has the better performance rate. Among the four biometric tasks proposed in the study, the spell task has outperformed the other three tasks and hence is found to be more suitable for biometric authentication. It can be concluded that single channel acquisition process can be recommended for EEG biometric studies on the acquisition process is less recommented. Better algorithm is to be developed to improve the recognition tasks which will be the focus of our features studies. Online real time study is to be conducted to evaluate the algorithm for real time application which will also be proposed in our future work.

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