Brain Signatures: A Modality for Biometric Authentication

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Abstract

In this paper we investigate the use of brain signatures as a possible biometric authentication technique. Research on brain EEG signals has shown that individuals exhibit unique brain patterns for similar tasks. In this paper we use brain EEG signals recorded during the performance of three mental tasks to identify six individuals. PSD features using Welch algorithm is extracted from the EEG Beta waves. A feed forward neural classifier is used to identify the six individuals. The performance of the neural network is appreciable with an average accuracy of 94.4 to 97.5%. Results validate the usage of brain signatures as a possible modality for biometric verification.

1. INTRODUCTION

A biometric system is used in two different modes. Identity *authentication* occurs when the user claims to be already enrolled in the system; in this case the biometric data obtained from the user is compared to the user's data already stored in the database. *Identification* occurs when the user's biometric data is matched against all the records in the database as the user can be anywhere in the database or he/she actually does not have to be there at all. Although both methods share the same preprocessing and feature extraction, however they target distinct applications. In the verification applications the people are supposed 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 in two main classes: Physiological and behavioral, physiological is related to the shape of the body. e.g. fingerprints, face recognition, voice, hand geometry retina, hand veins, ear recognition, facial thermo gram, DNA, odor, palm prints and iris recognition and behavioral is related to the behavior of a person. E.g. signature, gait, more modern approaches are the study of keystroke dynamics and of voice [1]

EEG as a biometric is relatively new compared to other biometrics. (1) This modality has several advantages: It is confidential (as it corresponds to a mental task). (2) It is difficult to mimic (as similar mental tasks are person dependant). (3) It is almost impossible to steal (as brain activity is sensitive to the stress and the mood of the person, an aggressor cannot force the person to reproduce his/her mental pass-phrase).

Paranjape et al [2] propose an EEG based biometric system using AR modeling of EEG with discriminant analysis to identify individuals with a classification accuracy ranging from 49 to 85%. In our earlier work [3] a mental task classification algorithm using band power features and feed forward neural network was proposed with maximum accuracy of 98 %

EEG is a technique that reads scalp electrical activity generated by brain structures. The EEG is measured directly from the cortical surface. When brain cells or neurons are activated, the local current flows are produced. EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. Only large populations of active neurons can generate electrical activity recordable on the head surface; weak electrical signals detected by the scalp electrodes are to be massively amplified. 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 position [4].

In this paper we propose an algorithm for biometric authentication using power spectrum and feed forward neural networks. EEG signals are extracted for three mental tasks namely relax, reading and multiplication tasks, from six subjects, Welch power spectral features (PSD) of the beta waves are extracted from the raw EEG signals to train and test the neural network.

2. METHODOLOGY

A. Data Collection

The EEG signals are acquired with an ADI Power lab EEG Amplifier using three noninvasive electrodes. The electrodes are gold plated cup shaped discs placed at F_4, O_2, F_{p1} locations based on the International 10-20 Electrode Placement System. [5]. F_{p1} is the earth electrode. Figure 1 shows the electrode position for data collection. The

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subjects were seated comfortably in a noise free room. The subjects did not make any overt movements and perform the tasks mentally. The subjects were requested to perform three mental tasks and data from the two electrodes F_4 and O_2 were recordered for 5s during a given task and each task was repeated ten times per session. Data was collected for two sessions on different days. The sampling frequency is 200 Hz. Following is the description of the tasks performed by each subject is describe as follows

Task 1- Relax:
No mental task is performed, subjects are told to relax and try to thing of nothing in particular. This task is used as a baseline measure of the EEG.

Task2- Multiplication:
The Subject is given a nontrivial multiplication problem to be solved mentally without vocalization and overt movements.

Task3- Reading:
The Subject is shown a typed card with tongue twister sentences and they were requested to read the sentence mentally without vocalizing.

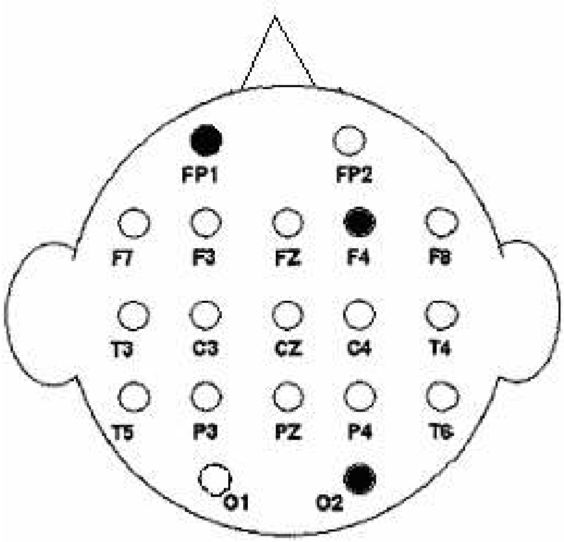

Figure 1. Electrode placement location for data collection

All the subjects were university students aged between 16 to 28 years. All were male except one female. During signal acquisition it was ensured that the subjects did not smoke few hours prior to data collections and all subjects were healthy and free from any medication. The signals were recorded in two sessions each session comprises of ten trials per task. Twenty samples are collected per subject per task.

B. Feature Extraction

The brain EEG activity can be broken down into four distinct frequency bands namely delta (0-3 Hz), theta (4-7 Hz), alpha (8 – 13 Hz) and beta (14- 20). Among the four, delta and theta occur during sleep while alpha (eyes closed) and beta (active) is seen in the conscious state of a human. Hence In this work we consider only the beta frequency band which is exhibited when the individual is actively thinking.

Raw EEG collected from the two electrodes are preprocessed initially to extract the beta waves which have a frequency range of 14 to 50 Hz, the beta waves are chosen as they are generated during functions like analytical problem solving, decision making and processing information, these waves are seen in the frontal and occipital regions of the brain. The extracted beta waves are processed using the Welch algorithm to extract power spectral density features. No signal artifacts were removed in this experiment.

C. Estimating the power spectral density using Welch's method:

PSD analysis provides the basic information of how power distributes as a function of frequency. In this study, PSD was calculated by using Welch's method. The input signal x is segmented into eight sections of equal length, each with 50% overlap. Any remaining (trailing) entries in x that cannot be included in the eight segments of equal length are discarded. Each segment is windowed with a Hamming window that is the same length as the segment. An FFT is applied to the windowed data. The (modified) periodogram of each windowed segment is computed. The set of modified periodogram is averaged to form the spectrum estimate. The resulting spectrum estimate is scaled to compute the PSD. 129 PSD features were extracted per trial per subject per task. 360 data samples are used in this experiment.

D. Feed Forward Neural Network Architecture

Three neural network models are developed classification of the individuals using the three mental tasks. The neural classifier used in this experimentation is a simple feed forward network with three layers trained by the conventional back propagation algorithm [6]. The hidden layer neurons are chosen experimentally as 10. All three networks have 129 input neurons representing the EEG features and 6 output neurons to classify the EEG features into six individuals. 360 data samples are used in this experiment. The NN is trained with 80% of the data samples and tested with 100 data samples. The training and testing samples are normalized between 0 to 1 using binary normalization algorithm. The feature data are normalized using the equation

$$x_{n\_i} = 0.8\left[\frac{x_i - x_{min}}{x_{max} - x_{min}}\right] + 0.1 \qquad , i = 1,2,3,\ldots,n \qquad (1)$$

The training data are chosen randomly. The initial weights that are connected to any of the hidden or output neuron are normalized in such a way that the sum of the squared weight values connected to a neuron is one. This normalization is carried out using equation (2) which is used to implement the weight updation.

$$w_{1j}(new) = \frac{w_{1j}(old)}{\sqrt{w_{1j}^2 + w_{2j}^2 + \ldots + w_{nj}^2}} \text{ , j=1, 2, 3… p} \qquad (2)$$

where n - number of input units
p - number of hidden units

A sum squared error criteria as defined by equation (3) is used as a stopping criteria while training the network. The sum squared tolerance defined in equation (3) is fixed as 0.001. The network is trained by the conventional back propagation procedure [6]. The cumulative error versus epoch plot of the trained neural network is shown in Figure 2. The cumulative error is the sum squared error for each epoch. Equation (3) gives the formula for determining the sum squared error.

$$\text{Sum squared error} = \sum_{p=1}^{p}\sum_{k=1}^{m}(t_k - y_k)^2 \qquad (3)$$

where

t_k is the expected output value for the kth neuron

y_k is the actual output value for the kth neuron

m is the total number of output neurons

p is the total number of input neurons

Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 15000.

3. RESULTS AND DISCUSSION

The results of the FFNN classification are summarized in Table 1 for different the three mental tasks. The classification accuracies of the neural classifier are shown in terms of minimum, mean and maximum classification. The multiplication and reading tasks are observed to show good performance of 97.5% and 97.3% respectively in identifying the individuals. Hence these tasks can be used in designing biometric verification systems. The average classification results is appreciable than a similar work using VEP signals and Neural networks reported in [7] the authors have reported an average classification of 96.63% with 61 electrodes used in their experiment. Figure 2 shows the Cumulative Error versus Epoch plot of the FFNN and Figure 3 shows the Classification performance versus training rounds for the three tasks.

4. CONCLUSION

A novel method using minimal electrodes and mental tasks is presented for biometric verification using brain signatures. EEG signals recorded from six individuals were used in the experimentation. PSD features extracted using the Welch algorithm was used in this study. A maximum average classification of 97.5 % is achieved, which shows that brain signatures can be used as a modality for biometric authentication. The minimum number of electrodes required also makes it ideal for implementation as a stand alone system.

ACKNOWLEDGMENT

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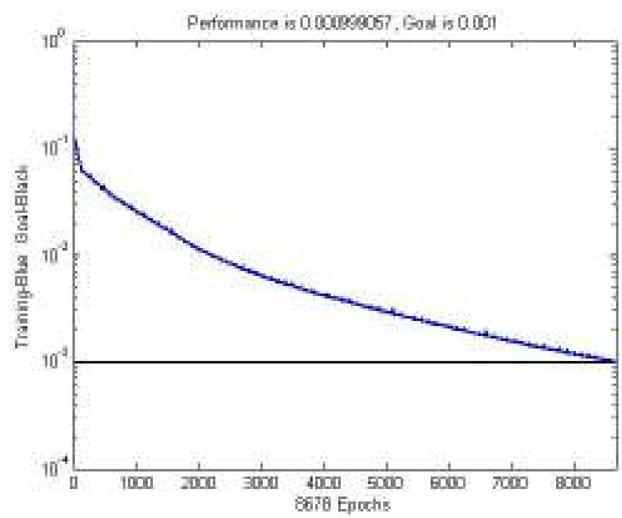

Figure 2. Cumulative Error versus Epoch plot for the FFNN

Table 1 Classification Performance of the FFNN

Classification Performance	Reading Task	Relax task	Multiplication Task
Min Classification	93.3	91.6	96.67
Mean Classification	97.3	94.4	97.5
Maximum Classification	100	98.3	100

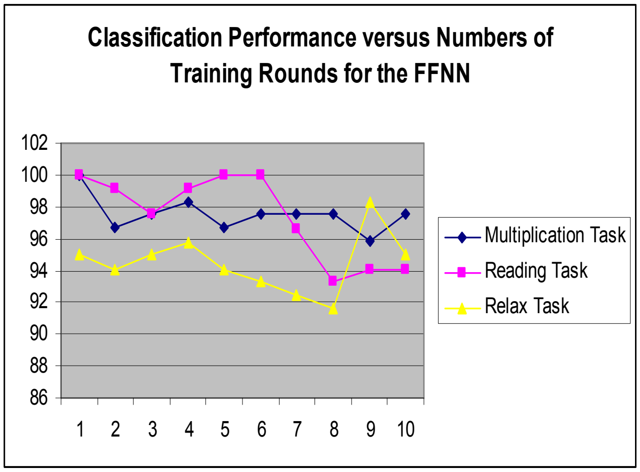

Figure 3. Classification performance vs. training rounds for the three tasks.

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