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Automatic Person Authentication Using Fewer Channel EEG Motor Imagery

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***Abstract* — A biometric person authentication system using brain waves or Electroencephalogram (EEG) signals recorded using a minimum number of channels ranging from 2 to 6 is presented. The task for EEG recording consists of simple motor imagery movements that the subject has to imagine. The system uses an effective time-frequency based feature extraction method using the short-time Fourier transform (STFT) or spectrogram. Energy, variance, and skewness features are computed on the spectrogram. These features are used to train a support vector machine and neural network classifier. The classifiers are tested for person authentication with testing data using cross-validation. Results using a different number of channels with optimum features are presented.**

***Index Terms*— biometric person authentication, time frequency analysis, EEG motor imagery, support vector machine, neural network**

I. Introduction

Biometrics is the measuring and statistical analysis of people's physical and behavioral attributes. This technology can be used to define an individual's unique identity, often employed for security purposes. The traditional biometric traits are face recognition, retina or iris scanning, fingerprints, hand geometry, palm print signature, keystroke entry pattern, and voice recognition [1]. However, many of these traits can be forged or stolen. Fingertips, for example, can be damaged by an injury or can be forged by a gummy finger. Disguises can trick face recognition applications. Brain waves or Electroencephalogram (EEG) are the electrical activity of an individual's brain that is unique and cannot be tampered with. Hence, EEG is proposed as an alternative or an additional way of securing biometric applications [2].

EEG signals are gathered from electrodes that are placed in several locations on the scalp. Because everyone's brain is structured differently each EEG signal is unique for each person. EGG uniqueness makes the biometric un-forgeable or un-duplicable. The main disadvantage of using EEG signals is the setup for data acquisition. This setup can take up to 15 minutes to complete. This is impractical for an identification system that needs immediate results.

There have been a few but not many papers that have studied EEG signals as biometrics [2-10]. Most of them use more than 32 electrodes and have a complicated data acquisition procedure using images or other sensory inputs to stimulate the brain. This process is time-consuming and makes it impractical to implement a real-time biometric system based on EEG. In this paper, we reduce the number of electrodes to 2 and use simple motor imagery features of the body without compromising the results. This involves minimal setup time and makes a more practical identification system. This paper is organized as follows. Section II reviews biometric identification methods. Section III reviews previous related work on EEG motor imagery and its use in developing brain-computer interfaces (BCIs). Section IV presents the method of EEG-based biometrics using a minimal number of channels. Section IV presents the experimental setup. Section V presents the results and Section VI presents the conclusions.

II. BIOMETRIC IDENTIFICATION

There a few types of biometric systems:

- **Fingerprint:** Determined during the first 7 months of fetal development, each human has their own fingerprint. While this can be an adequate identification system it suffers from minor errors, the first is that they require computation power to be able to identify the person. Other factors like aging and bruises may cause the system to have errors.
- **Face Recognition**: Since birth human beings have been able to identify people by their face. Today systems use face recognition methods for identifying "mug-shots" to identifying an individual in a cluster of people. Unfortunately, a system is not safe from a person changing their appearance and the system not being able to identify them.
- **Signature:** Each person has a unique signature, how the person signs his names varies from person to person. While signatures may be hard to forger there are professionals that can do it which doesn't make for a good identification system.

III. EEG MOTOR IMAGERY

The current EEG-based biometric procedures are based on eye blinks, visual stimuli and rest states [3]. Most of these methods use 30 to 64 channels for recording EEG signals. These methods also use complex classifiers such as artificial neural networks and autoregressive models [3,4] that may require longer training time. Presenting visual stimuli and asking the subjects to recollect the scene are time-consuming tasks and may not be reliable over a period as the subjects brain learns and exhibits plasticity in cognitive tasks such as memory and recognition. Motor imagery tasks are straightforward and easy to perform and have been successfully used in Brain-Computer Interfaces for motor rehabilitation [11]. EEG-based motor imagery classification has been done with 8, 6, 4, and even with a single channel. Single channel EEG accuracy has been reported to be around 80% [12]. This paper explores the use of fewer channels from 8 to 2 for EEG recording motor imagery signals and then use it for successfully identifying the subjects.

IV. BIOMETRIC IDENTIFICATION METHODOLOGY

The methodology consists of EEG data acquisition for the motor imagery tasks of thinking movement in five parts of the body such as left hand, right hand, left foot, right foot, and tongue. Once sufficient trials of EEG signals for the above tasks are obtained from a subject, the spectrogram is computed on each of these signals. The feature extraction stage consists of calculating the energy features on the spectrogram. The workflow for the methodology is given in the figure below..

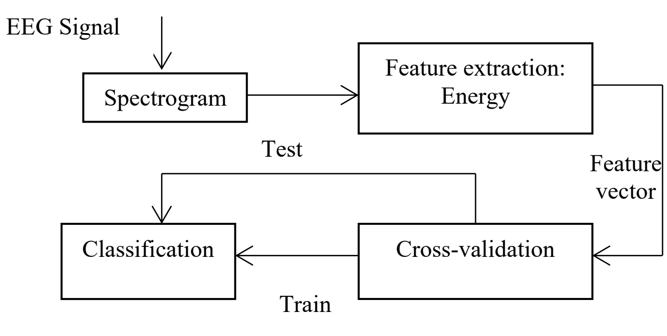

Fig. 1. Flow chart of the methodology.

A. Data acquisition

To collect the EEG from each subject an Easycap was used. An Easycap is an EEG recording device , the device uses 32 ring-shaped electrodes to collect 32 channels of data. Fig 2 demonstrates an illustration the location of the nodes in the Easycap. Using the Short Time Fourier Transform (STFT), we compute the spectrogram of the EEG signals that were recorded.

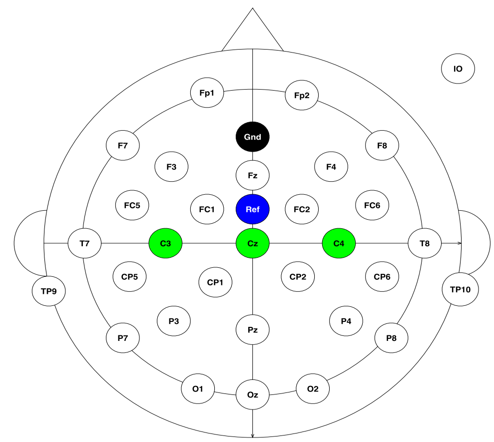

Fig. 2. Position of electrodes C3, C4 and Cz.

B. Spectrogram computation

The spectral content of the EEG signals is non-stationary, which means the signal changes over time. The Discrete Fourier transform (DFT) is a mathematical operation that decomposes a waveform into a sum of sinusoids components, where the coefficients represent the correlation between the signal and the particular frequency sinusoid. But applying the DFT, along the signal does not reveal the transitions in the spectra, it just shows the frequencies present. Hence, using the DFT over short periods of time (regular intervals) known as STFT is used. This approach allows identification of the interval of time at which all frequencies are present in the signal. The discrete STFT is computed using a window function w, x[n] is the signal to be analyzed and N is the frequency sampling factor. The resulting STFT is represented as a matrix with time and frequency $\omega=2\pi k/N$ information. The size of the window has the effect of changing the time-frequency resolution, with a wider window better frequency resolution but lower time resolution and vice versa for a narrow window are obtained.

C. Feature extraction

Energy defined on the spectrograms could characterize signal complexity with the changes in time, and also many of the characteristics in frequency domain such as time-frequency localization. A frequency of 500 with a window size of 128. The energy distribution of the spectrogram of imagining left-hand movement, imagine right-hand movement, imagine left leg movement, imagine right leg movement, and imagine tongue movement respectively were calculated

After calculating the energy distribution for each movement, the mean, the variance and the skewness were calculated for each energy distribution.

D. Feature selection

This work used the same feature selection procedure as outlined in [13], to quantify the separation between classes. Let $\hat{Y}$ be the normalized matrix of the features while Y is the the feature matrix for each subject. The sum of the distance of the features from the mean is calculated as:

$$D_L = \sum_j |\hat{Y}_{i,j} - M_i | \qquad (1)$$

Where i is the feature index, L is the number of features, j is the class index, and J is the total number of subjects. The standard deviation for each feature is calculated as:

$$\sigma_L = \sqrt{\frac{1}{J}\sum_{j=1}^{J}\left(Y_{i,j} - M_i\right)^2} \qquad (2)$$

We sorting the results of equation (1)-(2) and the first 60 best features were selected. These were the features that were used for training the SVM and NN classifiers.

E. Classifiers: Support Vector Machine(SVM)

The SVM is one of the most recent and powerful classifiers used widely in pattern recognition. It uses a discriminative hyperplane that maximizes the margins, which is the distance between the closes instance to the hyperplane [14]. By maximizing the margins, the SVM reduces and selects the accurate hyperplane.

Because the SVM uses a hyperplane it would only be able to classify classes that can be separated, hence the problem has to be transformed to a higher dimension. This a done with a kernel function.

The SVM can use different kernel functions or kernel tricks, the most used are linear, polynomial, radial-basis function (RBF), and sigmoidal. In this research, the polynomial kernel was used. Which is defined as: let x be the training vector then the polynomial would be:

$$K(x_i, x_j) = (\gamma x_i^t x_j + r)^q \,, \gamma > 0 \qquad (5)$$

where q, r and γ are set by the user [15].

While the kernel function helps with the non-separable classes, SVM is still not a multi-class classifier. In other words, to make the SVM a muti-class classifier several algorithms have been used: one-versus-one and one-versus-all are the most popular.

In this research, the LIBSVM library that implements one-verse–one has been used [16]. Unlike the one-versus-all algorithm that makes n models for n classes, one-verses-one makes $[\frac{n(n-1)}{2}]$ model one for every pair of classes While one-verses-one has more models than one-verses-all it has been tested to be better with larger problems.

Neural Network (NN)

The other classifier that was used in this work is neural networks. The NN consists of 4-layers with 60 input nodes, 41 in the first hidden layer, 16 in the second hidden layer and 20 nodes in the output layer. Figure 3 shows a diagram of the neural network classifier.

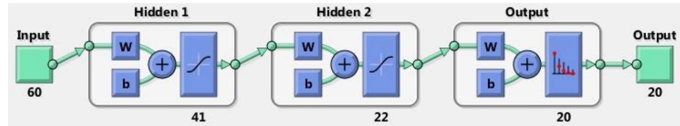

Fig. 3. Diagram of the neural network.

V. EXPERIMENTAL SETUP

Each of the 20 subjects was made to sit in a comfortable chair and asked to see the monitor. On the monitor, the words left, right, and up are displayed. For the first 120 trials the subject was told to imagine moving his left and right hand based on the word in the monitor, the next 120 trials the subjects were told to imagine moving their left and right leg based on the word in the monitor, and for the last 60 trails the subject were told to imagine moving their tongue up. Each subject was given several training sessions before the actual experiment. In each trial, the subjects imagine each action 11 times. Hence, the total data for each task is 1320.

After the data was collected, the STFT was computed and the energy features were calculated. This was followed by the application of the feature selection process. The first 60 features for a combination of 8, 6, 4, and 2 channels are used. A 10-fold cross-validation method for training and testing using the SVM and NN classifier was done.

VI. PERSON IDENTIFICATION RESULTS

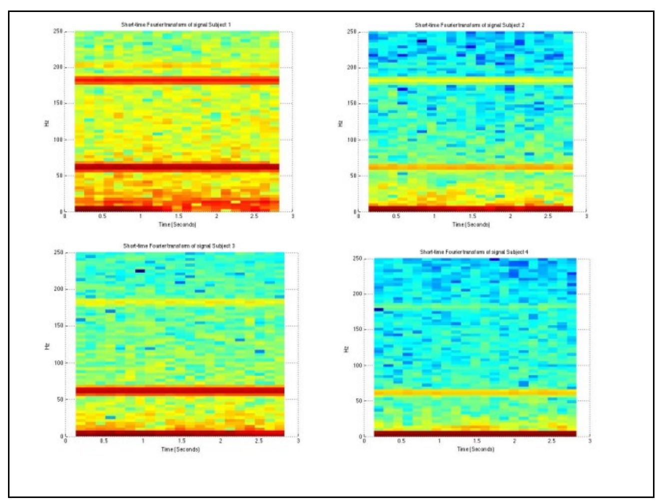

Fig. 4. Spectrogram plots of 4 different subjects' left hand motor imagery data.

TABLE I: SVM results for channels: C3 and C4

Subject	Accuracy	Subject	Accuracy
1	86.14%	11	93.86%
2	95.76%	12	75.30%
3	98.71%	13	88.56%
4	99.47%	14	93.18%
5	98.86%	15	84.32%
6	74.39%	16	98.18%
7	97.65%	17	93.26%
8	84.09%	18	80.45%
9	99.85%	19	99.85%
10	75.45%	20	87.20%

TABLE II: NN results for channels: C3 and C4

Subject	Accuracy	Subject	Accuracy
1	87.65%	11	93.64%
2	94.85%	12	80.15%
3	98.56%	13	85.83%
4	99.17%	14	94.24%
5	57.50%	15	86.97%
6	69.02%	16	48.18%
7	96.52%	17	92.73%
8	82.95%	18	77.20%
9	97.95%	19	99.47%
10	74.85%	20	86.29%

Figure 4 shows spectrogram plots for 4 different subjects imagining left-hand movement. The x-axis is the time and y-axis is the frequency in Hertz. It can be seen that the spectrogram is able to capture the differences in the imagination of individual subjects. The spectrogram signatures for left-hand movement imagination is quite distinct from each subject. Similarly, spectrograms are computed for imagination of right-hand movement, left leg movement, right leg movement and tongue movement.

TABLE III: SVM results for channels: C3, C4, Cz

Subject	Accuracy	Subject	Accuracy
1	88.71%	11	98.03%
2	99.09%	12	79.85%
3	99.55%	13	99.55%
4	99.77%	14	99.85%
5	98.48%	15	86.36%
6	86.59%	16	99.39%
7	94.62%	17	97.20%
8	92.95%	18	83.18%
9	99.77%	19	100.0%
10	98.71%	20	95.68%

TABLE IV: NN results for channels: C3, C4, Cz

Subject	Accuracy	Subject	Accuracy
1	90.91%	11	97.20%
2	97.95%	12	84.02%
3	98.71%	13	98.94%
4	99.62%	14	99.47%
5	98.33%	15	89.70%
6	85.61%	16	29.77%
7	95.68%	17	97.05%
8	94.47%	18	87.12%
9	99.85%	19	99.47%
10	98.11%	20	93.64%

Tables I to V gives the accuracies obtained for a different number of channels for each of the 20 subjects using the SVM or NN classifier. The accuracies are obtained from 10 fold cross-validation.

TABLE V: SVM results for channels: C3, C4, FC1, FC2, FC5 and FC6

Subject	Accuracy	Subject	Accuracy
1	89.77%	11	100.0
2	99.62%	12	96.36
3	99.7%	13	95.23
4	99.85%	14	88.33
5	99.17%	15	97.80
6	98.33	16	100.0
7	99.92	17	99.09
8	98.18	18	96.74
9	99.92	19	100.0%
10	98.56	20	98.56

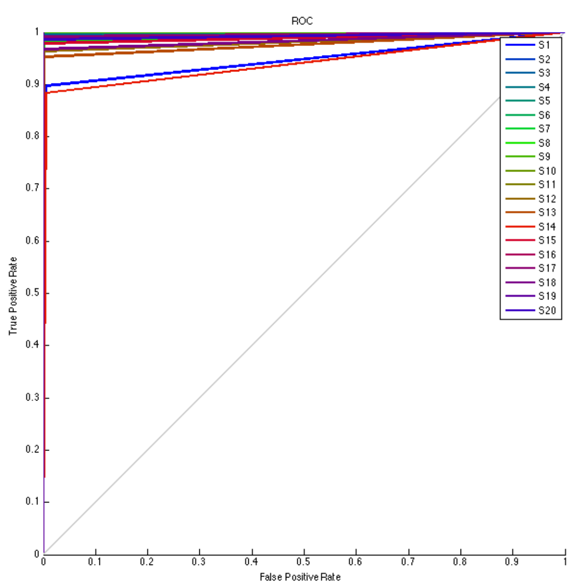

Fig. 5. ROC curve for SVM with 6 channels.

TABLE VI: NN results for channels: C3, C4, FC1, FC2, FC5 and FC6

Subject	Accuracy	Subject	Accuracy
1	90.68%	11	99.55
2	98.86%	12	94.62
3	99.92%	13	95.15
4	100.0%	14	91.74
5	98.79%	15	99.17
6	98.11	16	99.85
7	99.7	17	99.17
8	98.11	18	96.82
9	99.47	19	100.0%
10	97.65	20	99.7

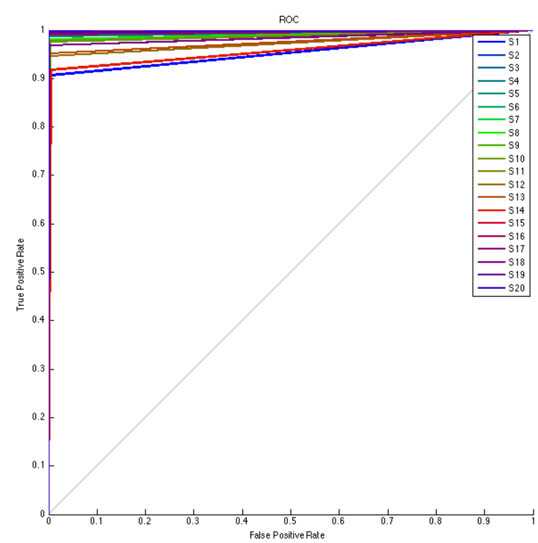

Fig. 6. ROC curve for NN with 6 channels.

Using only 2 channels reduces the average identification accuracy to about 90%. From the Tables, it can be seen that the SVM performs better than NN classifier in most of the cases. The NN performs well only in 6 channel case, in the rest it is over fitted, hence does not give good results. Figures 5 and 6 give the Receiver Operating Characteristic (ROC) curves for the SVM and NN classifiers.

VII. CONCLUSIONS

The goal of this research was to develop a system that can be implemented quickly for person authentication using EEG. Hence, a minimal number of channels was used. About 96% accuracy was obtained using only 3 channels and using 6 channels resulted in an average accuracy of about 98% and 90% with 2 channels. This shows that a simple task such as motor imagery can be used for automatic person authentication compared to other EEG-based systems that use more than 8 channels and require the subjects to recollect images or perform other sophisticated tasks. The system presented here can be used for person authentication with a hand-held smart device and a simple sensor. It requires placement of only two, four or six electrodes which can be done using individual electrodes instead of the full EEG cap which is uncomfortable. This system has minimal subject preparation time and can be implemented similarly to a fingerprint based system. The EEG motor imagery based person identification system can also be used along with face, iris or fingerprint based biometric authentication systems.

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