BRAIN FASTENER AS EEG BIOMETRIC AUTHENTIFIER

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Abstract - *Authentication is a crucial factor when protecting data or any information system of any sort. Electroencephalogram (EEG) brain signals contain a unique pattern for each individual and the potential for biometric applications. Non-invasively documented electroencephalographic human brain activity has gained popularity as an alternative person discriminative biometric due to its continuous usability, compliance with privacy and comparatively harder forgeability compared to the most prevalent biometric identification approach of fingerprint recognition. The system develops a novel method for an authentication process that uses EEG brain signals. Unique features of EEG data for distinguishing brain activities can eventually be used to authenticate a user. Deep learning methods for person authentication based on electroencephalographic brain activity address the challenge of manipulating the temporally correlated structures or recording session specific variability within EEG. Recent methods have also mostly trained and evaluated on the basis of EEG data from a single session. The system uses an adversarial inference approach to extend such deep learning models to learn session – invariant person discriminatory representations which can provide longitudinal usability robustness.*

Key Words: **Electroencephalogram, Deep learning, Convolutional Neural Network, Person authentication, Biometrics.**

1. INTRODUCTION

There are many drawbacks to authentication mechanisms currently in use. Although biometrics cannot be stolen, some systems are easily misled with fraudulent or fake replicas. Often, certain security procedures may be overridden by spoofing and pressuring. Fingerprints and palm-prints can be duplicated, and high-resolution images can trick iris scans. Using EEG signals, researchers are developing novel authentication types with state-of-the-art signal processing and machine learning techniques. EEG-based authentication is the strongest in data security applications, because it is unique and cannot be repeated. Due to its capacity to learn good feature representations from raw data, deep learning (DL) has shown huge potential in helping to make sense of EEG signals. EEG brain signals contain a unique pattern for each individual and the capability for biometric applications. EEG is a method of recording neural activity of the brain. Synaptic currents are produced when the neurons are activated. Those currents produce an electric field. The EEG is also divided into some frequency bands, to explain rhythmic behavior. In such bands behavior is correlated with different mental states [1].

- Delta waves (below 4 Hz) are associated with deep sleep.
- Theta waves (4–8Hz) are typical for dreamlike states and old memories
- The alpha band (8–13Hz) corresponds to a relaxed state recorded in the occipital brain zone.
- Sensorimotor (mu) rhythms (8–12 Hz) are associated with the sensory-motor cortex and can be used to recognize intention or preparation of movement and also imaginary motor movement.
- Beta (13–30Hz) waves are associated with alertness, arousal, concentration, and attention.
- The gamma band (30–50Hz) is characteristic for mental activities such as perception, problem solving, and creativity [7].

EEG can be obtained when a person participates in some form of cognitive activity or when the individual actually rests with their eyes open or eyes closed. The protocols can generally be divided into two types: resting state and cognitive tasks. Resting-state EEG is acquired while the subject is actually at rest when gathering data and does not perform any specific function. The participant undergoes specific tasks in cognitive protocols, while the EEG is acquired.

Data pre-processing is a key step towards improving the quality of data in order to facilitate the extraction of useful data information. Typically raw EEG is contaminated with electrical artifacts. The most popular of these are 50/60 Hz noises from surrounding electronics and muscle artifacts from face and eye movements. Preprocessing the EEG is common for reducing or eliminating these artifacts to enhance the signal strength. Artifacts may be either absolutely rejected on the basis of any criteria, or corrected [2].

Once the noise-free signals from the signal enhancement process were collected, important features were extracted from the brain signals. The extraction of features represents one of the most important steps in the processing and analysis of EEG signals because how well the extracted features represent the EEG signals affects the recognition system's performance. The adopted features can be classified into groups of domains (i.e., time domain, frequency domain, and time-frequency domain) or channels (i.e., single-channel and two-channel) [2]. The nature of EEG signals governs the search for suitable features for biometric recognition: features based on Fourier Transform (FT) are designed to capture the signals' energy/spectra; other features are designed to capture the EEG signals' time-dependent information; and wavelet-based features are built to capture both time and frequency characteristics of EEG signals [3].

The next most important factor for an EEG biometric system after feature selection is the choice of the classifier and the technique used to train it for a particular application. Classification is the final stage in the processing of EEG signals. The statistical features (mean, median, mode, variance, standard deviation, minimum and maximum) were obtained from output of feature extraction were used as input of classifier. The different types of algorithm which are commonly used for classification include K-Nearest Neighbor Algorithms, Linear Discriminate Analysis, Naive Bayes Classifier etc. [6] [5] [4]

2. PROPOSED METHOD

The system implements one of the best methods for human identification by using an EEG pattern to enhance security systems, since it is different for every subject. In other words, with the EEG signal the inter-subject variability is very high. The system follows several steps to get exact outcomes. The fig 2.1 shows block diagram of person authentication using EEG signals.

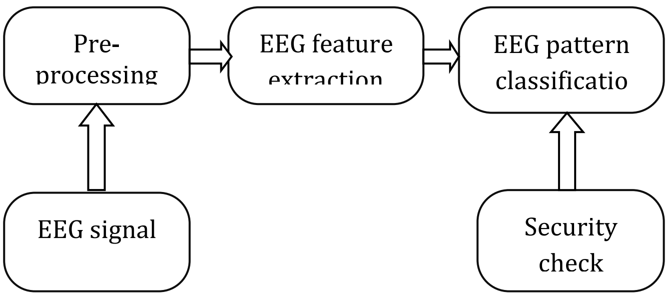

Fig - 2.1: Block diagram of person authentication using EEG signals.

Firstly, the system have to acquire a signal from the subject it is the EEG signature of the subject then find out which feature suits for the application and find out the method for extraction of the same from the signal and then it will be given to the classifier which classifies it in the different class depends upon its algorithm. Selection of a classifier is also essential and it also depends upon application as well.

2.1 Data Acquisition

Acquisition of signal or data is the most important step, since other steps depend on the data. The EEG data is taken through the electrode (sensors) from the subject's scalp. Superconductive gel is placed between the sensor and scalp, because there are very weak signals coming from the brain via the scalp. It is in terms of micro volt. Therefore, better reception of the signal conductive gel is used. And the measured signal from the particular node is not the signal from the particular location where the node is located but it is the average of the scalp's total relative potential.

Raw EEG data is too noisy for further analysis so it needs to be filtered and amplified. Subjects are advised to rest in quiet room with the closed eye this condition makes easy to yield required rhythm. Like that the system focus on experimental tasks such as eyes open, eyes close, left eye open ,Right eye open, open and close left or right fist. The system uses dataset collected using similar method.

2.2 Signal Pre-processing

At the time of data acquisition signal amplification and filtration process is applied to that data.
Here the system uses pwelch function,

$$pxx = pwelch(x)$$

pwelch returns the power spectral density (PSD) estimate, pxx, of the input signal, x. When x is a vector, it will be treated as a single channel. If window is a vector, pwelch divides the signal into segments equal in length to the length of window. Additional digital band pass filter is applied in second stage because the system need specific band of the EEG signal, signal band is 0.5 to around 90 Hz. The application requires signal of 0.5 to 64 Hz. To acquire the same band Butter worth band pass filter is applied and due to this operation some line interference and noise is also removed from the signal.

2.3 Feature Extraction

Feature extraction is the method of extracting desired output from the EEG pattern. Rather than apply the operation on EEG pattern the reason behind the feature extraction is classification process is easy with the extracted feature because, with help of feature we can easily identify the person. There are various methods are available for feature extraction. The system framework is trained using wavelet packet decomposition method for feature extraction of EEG signal. Fig 2.2 shows the feature extraction of the test person.

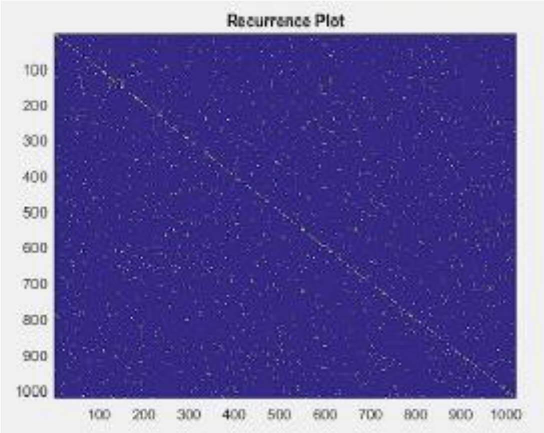

Fig - 2.2: Extracting the features of the test person

Wavelet packet decomposition (WPD) can provide signal decomposition over multi-level time-frequency. It allows for the simultaneous use of long-time interval for information of low frequency and short-time interval for information of high frequency. Selection of the correct wavelet and number of decomposition level is very critical when analyzing EEG signals using the WPD.

2.4 Classification

Classification of any signal or input is to verify or categorize in the pre-define classes. Classification is the mechanism by which information is classified into various ranges. The system adopts CNN for classification. Adam Optimizer algorithm is used in the system to accelerate network attenuation, the batch size is set to 128, and the learning rate is attenuated once in every 10,000 steps, so the model could converge to the optimal value. The model loss value converted to the minimum value in the training process of the CNN network when the training proceeded to 100,000 steps, and the training accuracy set (Acc) reached 99 percent. In time sequence, the cut EEG signal is entered into the BILSTM network, and the hidden unit information output is saved at each point in time. The characteristic matrix of time series is formed by splicing the cut heartbeat signal into a matrix vector. At the fusion level, the space characteristic matrix of CNN network and the time series characteristic matrix of BILSTM were fused and spliced, and the loss value is calculated and weight parameters are updated by back propagation. Here the system uses the 5x1 layer architecture.

Table - 2.1: The 5x1 layer architecture

1.	'sequenceinput'	Sequence Input	Sequence input with n dimensions
2.	'bilstm'	LSTM	BiLSTM with 100 hidden units
3.	'fc'	Fully Connected	9 fully connected layer
4.	'softmax'	Softmax	softmax
5.	'classoutput'	Classification Output	crossentropyex with 3 clases

3. RESULT AND ANALYSIS

The system mainly focuses on the accuracy of the authentication system. The CPU of the system is used for the computation and learning. The optimizer gives vital importance to the person's EEG for 3 persons with 100% accuracy in the test level and also within 25 epochs of the network the training network attains maximum accuracy with minimum loss. Elapsed time of training is less than 60 seconds with single CPU. Fig 3.1 and 3.2 shows the accuracy and loss graph of the training progress respectively.

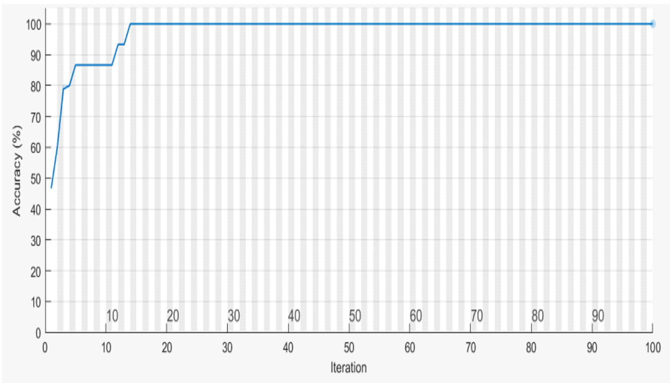

Fig - 3.1: Accuracy graph of the training progress

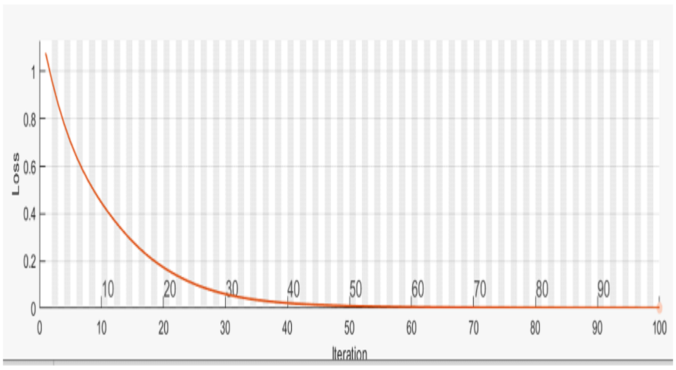

Fig - 3.2: Loss graph of the training progress

4. CONCLUSION

The system adopts an adversarial inference approach to expand deep learning based EEG biometric identification models, to learn session-invariant person-discriminative representations. Ensemble digital band pass filter and Butter worth band pass filter were used for noise reduction and wavelet packet decomposition was used for feature extraction. The convolution neural network was used for classification. Experimental study with biometric identification produced by 15 subjects yielded good TP levels over 40 different time trials conducted. With this lower error rate, the proposed EEG biometric identification system is particularly advantageous over other biometrics due to its robustness to resist fraudulent attacks.

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