Artificial Intelligence based Modelling of Biometric User Authentication System using EEG Signals

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Abstract: Electroencephalography (EEG) is most commonly referred as brain waves. In brain computer and brain machine interfaces brain waves are used where authentication is the need of today's time. Pin, Password technique, retina, heart-rate, fingerprints etc. are used as biometrics to provide authentication. By using the uniqueness of brain waves of different persons a very integral and effective biometric authentication can be provided. This work describes the application of recording the brain wave and providing two level biometric user authentication. A system is modeled and implemented which allows user to set a predefined pattern of movement which is then used as brain wave pattern to get the access. The first level of authentication is pin and password with second level authentication as the brain waves. Identification of different subjects is done by minimal neural network classifier with minimum sensor inputs and the classification efficiency is found to be 93% to 100%.

Keywords: Electroencephalography (EEG), brain waves, authentication, neural network, ensemble averaging.

Introduction
Electroencephalography (EEG) equipment's are becoming more available on the public market and with the only requirement of attaching a headset on the client brain wave authentication systems can gain popularity due to its high security. Research directly related to authentication by means of brain wave is rather limited and hence an attempt is made based on using minimum number of sensors to record EEG signal. [1]The brain signals are determined by person's unique pattern and can be influenced by stress and mental state of the individuals which makes them very difficult to be obtained under force. It is also related to the individual's genetic information and therefore are more reliable and have been proposed for biometric authentication. This paper presents framework for EEG authentication with minimum number of sensor signals and reduced computational complexity. The focus has been in building a system which enables usage of the EEG device to 1) acquire the EEG signal 2) process and classify the EEG signal and 3) use the signal classification to identify the subject. Our work is organized in different sections. Section II presents the background ofthe work and section III discusses details of the proposed approach for feature extraction and classification section IV displays the results of experimentation carried out using dataset and finally in section V the conclusion and future scope is highlighted.

Related Work
Previous studies have found that the brain activity of an individual is determined by the individual's unique pattern of neural pathways and thus it can be used for biometrics. The main advantage of using brain signals as a biometric identifier is that it is one of the most fraud resistant. It is known that it is impossible to imitate the brain activity of any subject due to the fact that the neural pathways of subjects are unique. [1] P. Tangkraingkij, C. Lursinsap used the techniques which are standardized to identify the relevant signals; the signals considered are not directly identified but are cleaned first by applying independent component analysis. Then, a supervised neural network is used to test the accuracy of the identification process. According to Chulalongkorn Comprehensive Epilepsy Program, Locations FP1, P3 and C4 are the pertinent channels, which can be used for person identification.

[2]Sebastian Marcel and Jose´ del R. Millan proposed to adopt a statistical framework based on Gaussian Mixture Models and Maximum A Posteriori model adaptation, widely used in other biometric authentication approaches such as speaker authentication or face verification. Person authentication aims to accept or to reject a person claiming an identity, so called enrolment process stores one or more biometric samples or templates in a database or in a secure travel document and attribute them to a subject. For future identification or verification processes this reference data can then be used for comparison.

[3]C. Ashby, A. Bhatia, F. Tenore researched on person identification based on EEG wave was performed where the author used FFT to calculated spatial power and autoregressive parameters. These features sets are combined into a feature vector

that is then used by a linear support vector machine (SVM) with cross validation for classification in order to classify the subject.

[4]M. Poulos, M. Rangoussi N. Alexandris proposed neural network based person identification using EEG and uses spectral information extracted from the EEG non-parametrically via the FFT and employs a neural network (a Learning Vector Quantizer - LVQ) to classify unknown EEGs as belonging to one of a finite number of individuals. Neural network classification was performed on real EEG data of healthy individuals in an attempt to experimentally investigate the connection between a person's EEG and genetically-specific information. The proposed method produced correct classification scores at the range of 80% to 100%. These results are in agreement to previous research showing evidence that the EEG carries genetic information.

[5][6]Later back propagation NN based classifier was also adopted by Palaniappan where evoked potential signals were used based on 61 electrodes, which resulted in average accuracy of 99.06%. [7]HU also used neural network with seven failure and listed for 3 subject with true acceptance rate varying from 80%-100%. [8]Power spectral density feature were adopted by Hema with six individuals and the average accuracy was 94.4 to 97.5%.

[9]Liang et al used neural network with signals from 6 channels to classify 7 individuals and achieved accuracy between 42.87% to 50.14%. [10]Mu also used back propagation neural network to identify autoregressive and fisher distance from 6 channels for 3 individuals and got an accuracy of 80.7% to 86.7%. [11]A. Sundarayan et.al introduced the concept of wavelet based feature extraction that uses visual and auditory evoked potential. [12]Dan et al used the polynomial kernel SVM based on wavelet transform (WT) and AR from single channel. The average accuracy was 85% on 13 subjects.

[13][14]Seul-Ki Yeom, Heung-II Suk, SeongWhan Lee proposed EEG-based person authentication system which recorded relatively lower performance compared to other widely used traits, namely, face, iris, and fingerprints, it is still meaningful as a biometric system due to its immunity to forgery and the impossibility of duplication. Also, unlike other biometrics, the proposed technique is even applicable for physically disabled persons whose brains are still working. Also signal difference and least square error of time derivative features on 18 channels with the Gaussian kernel SVM was implemented on 10 subjects which resulted in accuracy of around 86%.

Proposed Approach

In this work, it is proposed to develop a neural network based pattern classifier for identification of the different subjects after the user confirms the pin and authentication using minimum number of sensors and computationally efficient classifier. Then the process goes through the second level, for identifying the subject based on the acquired EEG signal. The enrollment process starts with the acquisition of the EEG signal and after ensemble averaging the signal parameters are extracted. During authentication process, the extracted parameters are given as an input to the classifier producing the output indicating the presence of the legitimate user as shown in fig1.

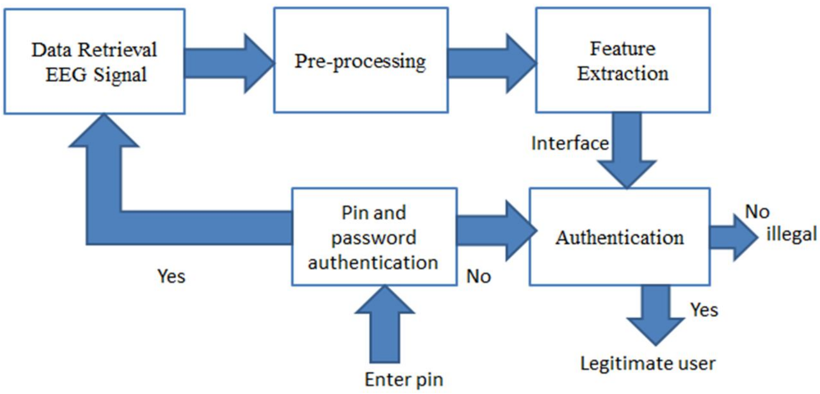

Fig1: Block diagram of Proposed Approach

This first block receives wireless data and performs relevant data extraction from raw data that is captured. A program is developed in MATLAB whose objective is to extract the data, preprocess and interpret from brain waves that are received. A specific pattern of brain waves is pre-defined after training the neural network for authentication. User needs to generate the authentic pattern to get the access. It is a two-level authentication system, in which user confirms the pin condition first before brain wave is used. Once pin passes to the system it matches with pre-defined pattern and if the pin entered is wrong, it displays the message as 'Unauthenticated'. A sub-system is developed to provide second level of authentication using brain wave after successful pin condition is achieved.

Dataset

[15]EEG data from ten subjects were used for this study from UCI Machine Learning Repository which is publicly available. The description of the data and recording procedures are as follows. An electrode cap was used to record EEG signals from sensor positions defined by the 10–20 system of electrode placement. The data were sampled at 250 Hz (3.9-msec epoch) for 1 second. The system was calibrated before each recording. Signals were recorded for 10 control subjects, with 10 runs per subject per paradigm. The test data used the same 10 control subjects as with the training dataset.

Pre-Processing

The recorded EEG signal is noisy and therefore ensemble averaging is done for multiple measurements to reduce random fluctuation in the signal on multiple trials which can be interpreted as multiple signals from different sensors. This simple technique is helpful in filtering noise where the signal-to-noise ratio can be improved in proportion to the square root of the number of repetition of the signal. Thus by applying ensemble averaging even smaller peaks can be safely recognized. EEG signals have five major bands: delta, theta, alpha, beta and gamma and for different persons, the energy distributions of the required components are different and hence can be used as feature to represent individual persons.

Feature Extraction

Feature extraction is a mathematical transformation that extracts distinguishing and reproducible data from the sample. These data are a concise representation of the original information and are defined as biometric features. Statistical parameters are used to extract features that were fed into a neural network in order to classify subjects. 64EEG recordings from 10 subjects were available in the dataset. [1]In order to develop a practical system with minimum number of EEG sensors, selecting relevant EEG signal locations per person identification was important. Hence from 64 EEG signals, three relevant locations FP1, P3 and C4 are selected. Also too many signals may degrade the performance of the classifier. The recorded EEG signals from 3 sensors were then subjected to feature extraction process. The extracted features include min, max, mean, standard deviation, variance, median, correlation coefficient, conventional coefficient, energy, kurtosis and zero crossing rate. These statistical parameters were extracted to analyze the artifactual activities of the subject.The identification process based on extracted feature is captured by using neural network where the number of output neurons are set according to the number of subjects.

Experimentation

The EEG signals were processed and the extracted features formed the input to the neural network. The signals of 10 samples of each 10 subjects were used to train the network. The neural network used a 3 hidden layer network 12,10,10 neurons and output layer consisting of 10 neurons. The network was trained with Levenberg Marquardt back propagation algorithm was evaluated using mean squared error. The role of the activation function in a neural network is to produce a non-linear decision boundary via non-linear combinations of the weighted inputs**.** Also the interest is to consider the problem of approximating a function which is known only to have a certain number of smooth derivatives. The question of deciding which activation function will require how many neurons to achieve a given order of approximation is also investigated for allsuch functions. The smoother the activation function, the better is the rate of approximation. Since the change made to a weight using back propagation depends on both the output of the hidden layer neuron and on the derivative of the activation function, so using the logistic activation function can have both go to zero at the same time, it can end up with the hidden layer unit becoming frozen.. The number of nodes needed is dependent on the used activation function. As more nodes are required, the number of weights that need to be trained also grows this expands the search space of the training algorithm, and extends convergence times. After extensive simulation based on input data distribution the conclusion, is drawn that using log sigmoidal forcing function for hidden units the network converges with less number of nodes with respect tothe resulting network errors. The problem of vanishing gradient can be solved and learning can be faster. Variationsof theseparameters were tested, but it did not have any great impact on the results. All the signals from the selected channels were grouped for the training set, validation set and testing set. In order to explore the other architectures of neural network, radial basis functions (RBF) were also used to train the network and develop an efficient classifier which requires short training time. RBF network constructed is of single hidden layer consisting of 84 neurons. RBFN'S is trained in two phases: one is unsupervised learning on the hidden layer and supervised learning on the output layer to estimate the weights.

Results

The EEG dataset were processed for feature extraction and the extracted feature values were applied to back propagation neural network with three hidden layers for subject identification. The learning algorithm performance is depicted in fig2,3 and 4 which shows the performance for training, validation and testing patterns. The network converged with the identification accuracy of 97%. Also the network was tested with test data set comprising of 100 samples for 10 subjects and the identification accuracy was found to be 93% to 100%. The neural network architecture is given in fig5.

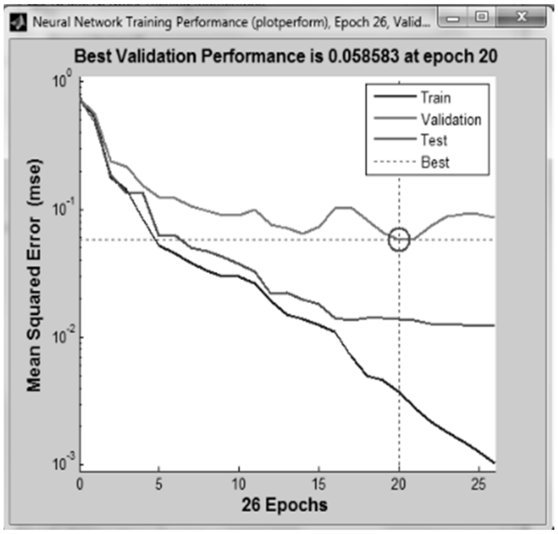

Fig2. Performance curve for back propagation neural network

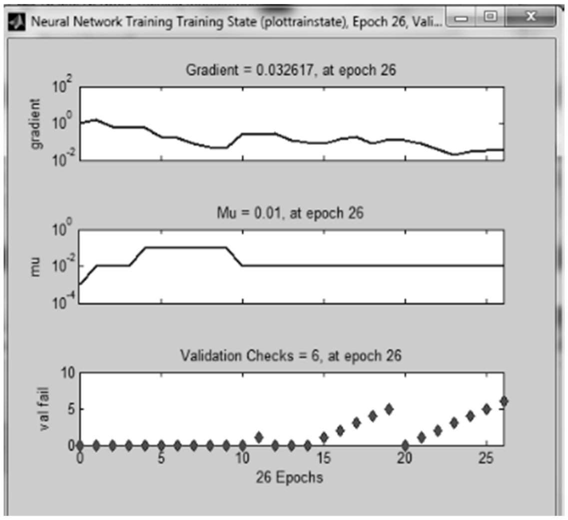

Fig3. Training state for back propagation neural network

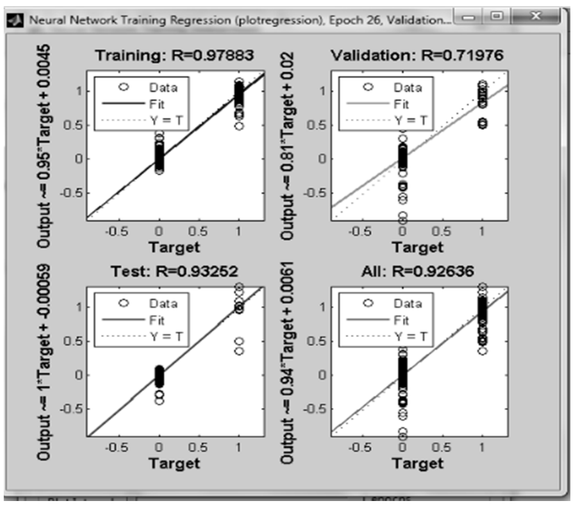

Fig4. Regression plot for back propagation neural network

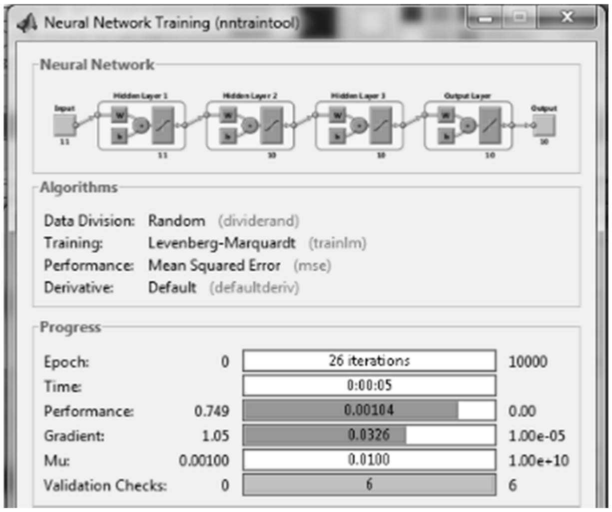

Fig5. Architecture of back propagation neural network

Also in order to achieve faster convergence, small extrapolation errors and higher reliability, radial basis function neural network is also implemented and the identification accuracy for the same was found to be 100%. Numbers of simulations were carried out to evaluate the efficiency and stability against the presence of outliers is shown in fig7. The RBFN'S with hidden neurons 84 converge to obtain higher accuracy. The architecture for radial basis fewer neurons network is shown in fig.7 and training results are given in fig6.

Hence it is evident that the proposed neural network requires fewer computation units as compared to the work done by other researchers [4][5][9][10][12][13][14] giving classification accuracy between 93% to 100% with minimum number of sensors. This will facilitate the use of low cost EEG headsets for practical purposes and the user would be comfortable in wearing the same. The details of the comparison of the work done by other researchers are summarized in table 1.

Table1. Comparative study of performance parameters

Name of author	**Type of neural network**	**No. of sensors**	**Identification accuracy**
Poulos et al. [4]	Learning vector quantizer classifier	1	72% to 84%
Palaniappan [5]	Classic fed forward and back propagation neural network	16	99.06%
Liang et al. [9]	Support vector machine classifier	8	45.52% to 54.96%
Liang et al [9].	Back propagation neural network	5	42.87% to 50.14%
Mu and Hu[10]	Back propagation neural network	6	80.7% to 87.6%
Dan. et al [12]	Support vector machine classifier	1	85%
Yeom et al. [13,14]	Support vector machine classifier	18	86%
Proposed approach	Levenberg Marquardt Back propagation neural network	3	93% to 100%
Proposed approach	Radial basis function neural network	3	100%

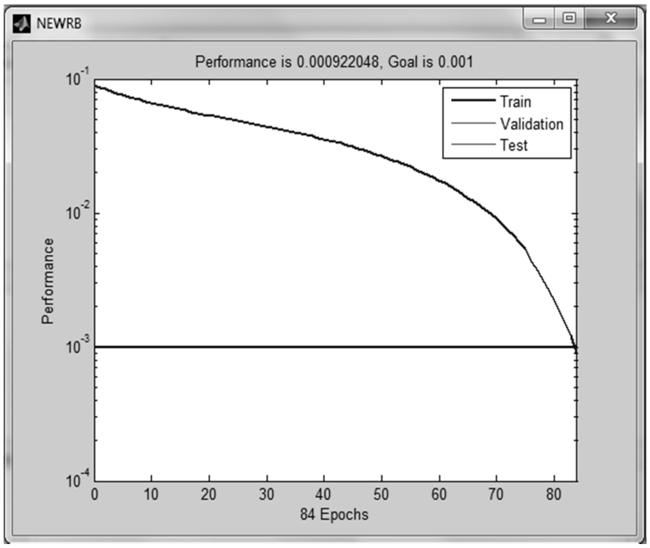

Fig6. Performance curve for RBFNN training

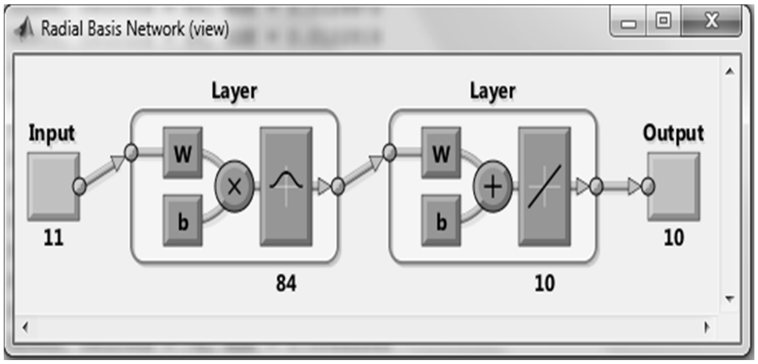

Fig7. Architecture of radial basis function neural network

Conclusion and Future Work

The practical technique with minimum sensor signals for identifying the subject based on EEG signals is proposed using supervised and unsupervised learning mechanism. The three identified location of the sensors were helpful in efficiently using EEG signal per subject. The radial basis function network is usually considered due to its short training time in comparison to back propagation algorithm, although the computation and storage requirements for classification of inputs after the network is trained are usually greater. However the back propagation neural networks converged with lesser computational units and also require less storage. Hence the concept of using EEG as a measure of uniqueness in a person is validated and it can be a potential candidate for biometrics market in future. Future work could be directed towards introducing randomness by exposing user to different type of stimuli and making use of minimum no of features to further reduce computational complexity.

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