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Deep Learning for Mind Wave Electroencephalographic Biometric Security

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ABSTRACT

Brain generates various signals according to the situation and activates. The frequency of the brain is different as per the level of action taken place by the person it may be either imaginary or motor imagery activities. From the brain signals imaginary signals are captured using MindWave Mobile Portable device. Frequency wise channels are separated and categories as Delta, Theta, Alpha and Beta. These channels are indicated emotions, movement, sensations, vision, etc. Features are extracted of each channel using Power Spectral Density (PSD) function. Feature level fusion is used for pattern matching. The Novelty of this work is a single electrode device is used to capture an Electroencephalography (EEG) imaginary data & feature level fusion of channels. The results are proven that these EEG imaginary signals could be used as better biometrics based authentication system.

Keywords : EEG, Mindwave, Identification, Verification, Biometric

I. INTRODUCTION

An electroencephalography (EEG) is a branch of Neuroscience. Recently, researchers in a Neuroscience and computer science attracted towards novel and innovative type of biometric based on neural activity of brain signals, such as EEG signals instead of the biological traits of the human body like face, fingerprint, iris, retina, voice, etc. EEG Signal biometric trait are very difficult to duplicate, break or guess. A novel approach is used for processing brain signal data through an EEG. The EEG gives various types of information about a person that is emotional, mediation and sad state. We can analyze EEG Signal and find out the human Concentration, Mathematical solution power, Letter Composition method, Rotational style. These parameters are considered to person identification and verification purpose. This research work is divided into mainly Introduction, Related research work, Proposed Methodology, Experimental Result and Conclusion.

II. RELATED RESEARCH WORK

An EEG signals, data feature measurement through two types of algorithm these are Discrete Fourier Transform (DFT) and Wavelet packet decomposition (WPD). The distinct features of EEG signal are consider with four feature set. The EEG signal data result was 93%, 87% and 93% classification rates of three feature set. By using Multilayer Perceptron Neural Network classifies EEG signal feature data gives 100% recognition rate but limited subjects only three. In this experiment subject has to seat normally with calm and quiet with closed eyes without any physical activity while collecting the datasets 4 channels are used [1].

In the recent research, identification & prediction of Motion Sickness (MS) of a driver in real life while driving the vehicle is very interesting and very important task because it can save the life of so many peoples in traveling. MS provide one type of security to the drive as well as passengers. Prediction of emotions in real time through EEG signals is a challenging task, while performing any activity human brain produces signals and the signals are coming from various parts of our brain. In case of emotions which is comes from occipital, parietal, somatosensory, etc. identification of generating signals according to the power of signals such as alpha, theta bands. Identification of emotions from the signals in a certain band as per the frequency level is possible through various feature extraction techniques and classification algorithm such as PCA, LDA, BFS, FFS, KNN, SVM, NWFE, ML, etc. apart from that LDA and ML gives 95%. Therefore, it can be used more or less robust techniques for the prediction of MS very effectively [2].

This work presents a novel approach for biometric identification using electroencephalogram (EEG) signals using Hilbert-Huang Transform (HHT). The amplitude and frequency were computed immediately after the HHT produce for the classification using salient characteristics. The proposed system was evaluated using two publicly available databases in these scenarios, single electrode of an EEG device which used for biometric data acquisition. A first database consists of 122 subjects and second having total 109 subjects, at the time of collecting the database were subject had shown with a sequence of images on the screen and some mechanical activity or screening works got the 96% and 99% success rate respectively. These results are compared favorably with recent research articles by the various algorithm and classification [3]. A research on biometric using motor imagery EEG signals and Auto Regressive Moving Average (ARMA) are used to construct an estimated model. From that they have used ARMA based classification system on the basis of Artificial Neural Network (ANN) approach. The extracted features are stored in the specific vector for the identification & verification on the basis of classification. Three persons, four types of the motor imagery EEG data signals were captured & perform the comparative results. Therefore, on the basis of the outcomes of [4] shows that it can be successfully exploited for purpose of person authentication and identification.

Therefore, an EEG data signal which belongs to motor imagery strongly provides a strong biometric based authentication and identification system will be used for security purpose. At the time of EEG based development of the system, classification played a vital role. They have compared the results of the system for the identification of imaginary movements of the persons using 3 different classifiers. H. Jian-Feng has compared Linear Discrimination Analysis (LDA), Artificial Neural Network (ANN) and Support Vector Machine (SVM) for classification of EEG signals, in this result LDA outperforms well as a better classifier than other algorithms [5]. The analysis of EEG data for the biometrics is concentrated on functional connectivity and measurement of time-domain statistical data which is co-dependent on each other. These two approaches are complex relations in EEG data measurement [6]. M. Abo-Zahad, et. al.[7] discusses challenges facing while practical implementation of biometric system based on the signals received from the brain for the identification of the person in a real life application.

Database acquisition is a time consuming procedure, in device setup time is varying when selecting no. of channels in the devices. In this case 64 channels were used to collect 109 people's data; it passes the signals in the middle range called as band pass filtering for the establishing functional connection amongst the sensors is calculated by the Phase based Lag Index system. From this connection data matrix is used to build the network to train the system and calculated

Eigenvectors. Brain resting state in performing well, but functional connectivity gives proper results, hence it can be a next generation technique for the classification of the data. EEG based biometric systems and biometric systems based on high-frequency scalp EEG features should be interpreted with caution [8].An explicitly investigated and assessed the permanence of the non-volitional EEG brainwaves over the course of time. Specifically, we analyzed how much the EEG signal changes over a period of six months, since any drastic change would make it unusable as an authentication method. The results are very encouraging, yielding high accuracy throughout the six-month period [9]. The amplitude of the brain signals is the indication of circadian rhythm which is tactless of the random changes for measuring features bi-variant measure Magnitude Squared Coherence (MSC) are used and reduced the number of channels of EEG signals for identification without any affect on the accuracy of the system.

The multidimensional data classification accuracy is better for fewest numbers of samples per person by using distance based classifier like KNN (K-Nearest Neighbor). In the previous literature, it is found that 64 channel data of 108 subjects gives 100% accuracy, in this case instead of 64 channels only 10 channels are used and also gives 100% recognition rate using 109 subjects' data with eye open resting position, environment for biometric identification [10].

III. PROPOSED METHODOLOGY

3.1 EEG Signal

In this research database is developed using a cost effective device that is Mindwave mobile and Micromax Canvas A114 mobile phone. The aged isomer programming LLC, free downloadable software in Android OS utilized. It is a portable system used for record database of the forehead with ear reference for database developers. The imaginary activity of letter Composition is captured with 5 iterations of 30 second.

Table 1. KVKRG Database Specification [13][14]

Database	Specification
Name	KVKRG EEG database
# Subject	200
Language	Marathi, English
Type	.csv
Session	3 (Morning, Afternoon, Evening)
Season	3 (Summer, Winter, Rainy)
Sampling Frequency	150 Hz
Activity (Task)	Imaginary closed eye: Baseline, Imaginary Mathematical, Geometric Figure Rotation , Mental Letter Composition Actity
Region	Maharashtra
Subjects Age	16-40
Gender	Male and Female
Environment	Controlled (Laboratories)

3.2 Feature Extraction

In this research work we used EEG Raw Value, eegRawValueVolts, Attention Level, meditation level, Blink strength, Delta (1-3Hz),Theta (4 -7 Hz), AlphaLow (8-9Hz), Alpha High (10-12 Hz), BetaLow (13-17 Hz), Gamma Low (31-40 Hz), Gamma mid (41- 50 Hz) these 7 features .

Apart from above features 5 features are selected for experiment because we are dealing with normal subject database these features are accept), Gamma Low (31-40 Hz), Gamma mid (41- 50 Hz).

Mean sample value (MSV)

Mean of all sample values

$$\mathrm{MSV} = \frac{1}{N} \times \sum_{1=n}^{N} x_n \quad (1)$$

Signal consisting of a discrete-time sinusoid with an angular frequency of π/4 radians/sample with additive N (0,1) white noise. Create a sine wave with an angular frequency of π/4 radians/sample with additive N (0, 1) white noise. The signal is 320 samples in length. Obtain the Welch PSD estimate using the default Hamming window and DFT length. The default segment length is 71 samples and the DFT length is the 256 points, yielding a frequency resolution of 2π/256 radians/sample. Because the signal is real-valued, the period gram is one-sided and there are 256/2+1 points [11].

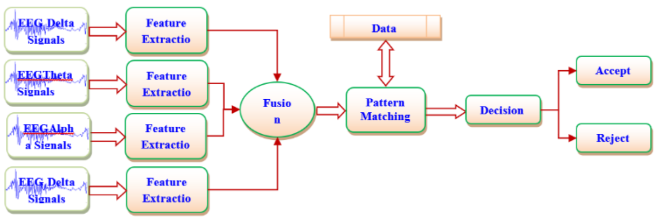

Fig 1: Proposed Methodology

Power Spectral Density (PSD)

The Power Spectral Density (PSD) to each frequency band is extracted from EEG signals as shown in the following. Wavelet translate of 4 levels was applied to decompose the filtered EEG data into five frequency bands, as shown in Table I, which reflect the physical activities. For each second (128 samples) in all channels and bands, a Fast Fourier Transform (FFT) with non-overlapping window was applied to find the PSD per band. Then the PSD is estimated as the average of the squared absolute value of the magnitude of the FFTs, as in equation (2)

$$PSD = \frac{1}{Nyq}\sum_{f=1}^{Nyq} |FFT|^{\wedge 2} \qquad (2)$$

(2), Nyq is the Nyquist frequency (sampling frequency/2), and fis the frequency in Hz. To investigate the influence of use windowing with FFT, Hamming window with length 128 was applied before FFT producing another type of PSD named PSD with hamming Because Mindwave device has 1 electrode wish gives Delta (1-3Hz),Theta (4 -7 Hz), AlphaLow (8-9Hz), Alpha High (10-12 Hz), BetaLow (13-17 Hz), Gamma Low (31-40 Hz), Gamma mid (41- 50 Hz) these 7 features channels, obtained (5 bands * 1 electrode) .Obtain the Welch PSD estimate of an input

Feature level fusion Σ

Concatenate the feature set of multiple channel of EEG signal. In this research work the Delta, Theta, Alpha, Beta signal channel of EEG biometric. Let δ= {δ1, δ2, δ3…………. δn} an extracted feature of Delta signal, θ= {θ1, θ2, θ3…… θn} an extracted feature of Theta signal, α= {α1, α2, α3,….. αn} an extracted feature of Alpha signal and β= {β1, β2, β3,…… βn} an extracted feature of Beta signal obtained by concatenating augmenting normalize feature vector and performing feature selection on resultant fused feature vectors. We conduct extensive experiments to evaluate the effectiveness and robustness of the proposed system [13][14][15][16]. Convolution Neural Network (CNN)

Convolution Neural Network (CNN)

After normalization of EEG signal we have provided input to the CNN, i.e. NE X NT where NE is electrode (1) NT is time

NT = time * sampling rate.

Convolution Neural Network (CNN) consist of multilayer neural network perceptron (MLP) it has a special topology with multiple hidden layers. We can use for feature extraction and pattern classification like biological neural network like small cell input can be proceed. It can be used to process the row information without processing the row data.

Network Topology (NT)

It is the model which is used for prominent feature extraction as well as pattern classification. There are five layers included in the network topology which are two convolutional layer, two pooling layer and one fully connected layer [12]. The input data matrix has structure of 1* 150. The Convolutional layers convolve that input data matrix via six 5-by-5 filter and output the filtered data map.

The filtered data maps are then entered into the average pooling layer, which divides the input-filtered data maps into sets of 2- by-2 rectangles. For each of these sub-regions, the average-pooling layer outputs the average value. The filtered data maps are then down-sampled and feature maps are obtained. During this step the computational complexity for upper layers is reduced. - The second convolutional layer uses the feature maps as input data. Through this and the second average-pooling layer, the first two steps are repeated. As a result, the features become more abstract and the computational complexity is further reduced. - Finally, the features obtained by the second average pooling layer are transferred to the fully connected layer. Ultimate classification is based on these features, Softmax activation function is used.

TABLE NO. 1. EEG DATA FEATURE SET

eegRawValue	Delta	Theta	Alpha		Beta		gammaLow	gammaMid
			alphaLow	alphaHigh	betaLow	betaHigh		
51	16745434	16750096	10235	9371	6354	4364	4869	3224
102	665851	91047	30130	7637	7995	25956	16752974	12957
19	206082	51834	4173	24355	14860	16748314	24462	18314
28	301085	38758	8633	24707	16746703	16759024	16537	17825
-279	1992969	99204	15682	68362	26465	27213	16761920	13203
89	483475	46766	68636	70677	16752442	83017	16597	6303
-349	16759164	16756526	16770661	12770	5000	18091	30031	8256
-300	285723	23618	2533	8622	4811	4421	3809	3397
24	16765681	28861	16745500	9428	17691	23362	16747113	16853
77	206582	10057	1356	5975	6416	5912	11819	4438
48	60769	16746334	16744346	16767015	15636	26680	23915	6900
51	364775	16773343	16749070	16756417	8894	22048	16496	10577
17	1446025	16769628	24715	14403	16756180	16766368	22151	8556
-264	97468	12890	10171	5712	8070	6106	10326	8207
34	273061	158117	83732	26191	8947	22988	25866	6478
17	616108	19593	14400	16751418	16755278	30792	15253	12013
39	75894	103275	16749335	23289	21902	22061	17374	8294

TABLE NO 2. DISTANCE MATRIX

0	7730991.949	6116394.356	7370273.39	7853236.593	11985746.02	14089220.78	8682605.441	12744309.83	9393457
7730991.949	0	6763899.424	5456663.712	8466063.153	9447346.576	11974204.53	7077255.627	8097867.78	8597073.966
611639	676389	0	924612	794019	700349	141643	880819	106202	967513

4.356	9.424		3.441	9.695	3.119	68.76	3.254	65.41	7.186
737027 3.39	545666 3.712	924612 3.441	0	640428 8.186	965399 6.695	111839 44.17	912647 8.661	999829 1.153	655913 1.78
785323 6.593	846606 3.153	794019 9.695	640428 8.186	0	530673 6.475	680372 3.034	531797 3.017	722036 3.339	808702 8.678
119857 46.02	944734 6.576	700349 3.119	965399 6.695	530673 6.475	0	834801 9.847	684105 1.085	716048 0.356	993682 8.949
140892 20.78	119742 04.53	141643 68.76	111839 44.17	680372 3.034	834801 9.847	0	707941 1.068	984453 2.915	142727 66.22
868260 5.441	707725 5.627	880819 3.254	912647 8.661	531797 3.017	684105 1.085	707941 1.068	0	832634 3.407	111333 25.08
127443 09.83	809786 7.78	106202 65.41	999829 1.153	722036 3.339	716048 0.356	984453 2.915	832634 3.407	0	899886 4.424
939345 7	859707 3.966	967513 7.186	655913 1.78	808702 8.678	993682 8.949	142727 66.22	111333 25.08	899886 4.424	0

3.3 Pattern Matching

Manhattan Distance Metric

Distance is measured of two points X (x1, y1) and Y(x2, y2) along with the axes of the plane with right angles, it is

$$\text{Distance} = |x1 - x2| + |y1 - y2| \quad (2)$$

3.4 Data Model

The extracted features of the data are stored in the data model using .mat file for pattern matching.

3.5 Decision

After pattern matching here used accept or reject decision on the basis of data available in the data model.

In this experiment we have used 200 subjects with two sessions, but here we show only 10 subjects data in the above table because of space limitations [15][16].

IV. RESULT AND DISCUSSION

In this experiment the KVKRG EEG database consist of 200 Subject with 5 iterations and two session i.e. summer and rainy. Calculated 13 EEG features which are shown in the Table No.1 & 2. i.e EEG Raw Value, eegRawValueVolts, Attention Level, meditation level, Blink strength, Delta (1-3Hz),Theta (4 -7 Hz), Alpha Low (8-9Hz), Alpha High (10-12 Hz), Beta Low (13-17 Hz), Gamma Low (31-40 Hz) and Gamma mid (41- 50 Hz),all these channels are considered as a feature. At the first time we have selected Delta (1-3 Hz) for the training of each subject and one of the single subjects to test but the result is not satisfactory. In the second experiment the Theta(4-7Hz) signal is considered for training features and one by one Theta signal is measured in testing but result not so good.

In the third experiment the alphaLow (8-9 Hz) signal is considered for training features and one by one alphaLow signal is considered for testing it gives good performance. In the successive experiment alphaHigh (10-12 Hz) uses for training feature it sounds better result as compare to earlier experiment. BetaLow (13-17 Hz), Gamma Low (31-40 Hz), Gamma mid (41- 50 Hz) is also exploit on same experiment but not considerable result.

In experiment no. 8 fusion of low alphaLow and alphaHigh features give better performance, therefore it is suitable for biometric.

Classification of the EEG feature is most important to biometric security. The pattern recognition is the best technique for this EEG feature classification. In this experiment the Manhattan Distance Metric gives 61% classification and recognition rate, i.e. shown in table Table No 3. Distance Matrix.

V. CONCLUSION

The innovative is in this novel area, developed EEG data using cost effective mindwave mobile device for biometric purpose. Developed our own database of 200 people in two sessions. Features are extracted of EEG channels using PSD. Feature level fusion of Delta, Theta, Alpha and Beta channels. Manhattan distance measurement is used for classification gives 61% accuracy of classification of distinct personalities. CNN Provide better feature extraction and classification rate that Manhattan. In future we will increase the data size and one winter session data, and again we will find the unique pattern from that data to person identification.

VI. FUTURE WORK

The fusion of many electrodes or features may increase the recognition rate for biometric identification and verification purposes. We can perform the fusion approach for fusion of multichannel it may increase the recognition rate.

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