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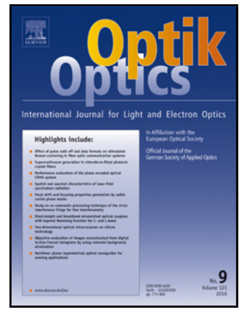

Title: Individual Identification based on Neuro-signal using Motor Movement and Imaginary Cognitive Process

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Individual Identification based on Neuro-signal using Motor Movement and Imaginary Cognitive Process

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Abstract- Neuro- signals are being widely used for clinical purpose to detect and diagnosis of mental disorders. Its uniqueness and consistent characteristics in human being made it feasible protocol identify the individual. In this paper we have investigated another cognitive process to identify an individual by that motor movement and imagination cognitive process would also be a eligible parameter to identify a person like others mental task , object recognition and listen audio etc. In order to it technically we have chosen a well defined method for non-stationary signal analysis method called wavelet transform and neural network classifier. In conclusion we have received that motor imagination based cognitive task performed by subject has better applicability motor movement based cognitive task.

Keywords: EEG signal processing, Energy features, wavelet transform and authentication

1. Introduction

The society is transforming into the digital world and every individual are now living with digital identities. Digital identities are having intensive values that should be pre- recorded to help machine for user authentication. The most popular tool for authentication is Biometric which uses human physical and behavioral characteristics of the human being, based on their unique features humans are identified and authenticate. A brainwaves authentication system is another addition to the wide range of authentication systems, but with the brand new concept. The electrical activity in human brain is used to confirm the identity instead of physically writing a password, one can think simply think about it.The password or “cognitive task” can be anything that a human mind may perform or think about, like a colour, a feeling, an image, text or something else.An human brain contains about 100 billion neurons that each generate and electrical charges. The sum of all these very small electrical charges contributes to the generation of an electric field with fluctuating electrical potentials around our scalp**[19].**The potentials are measured between two or more points called electrodes or sensors, , which is placed on the scalp at different locations. The measurements have been named Electroencephalography (EEG) and resemble waves.

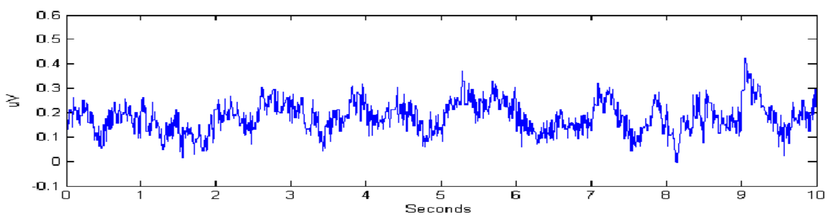

Fig.1: Brain Wave Signal (EEG)

2. Literature Review

In literature review survey, several methods have been proposed for feature extraction of EEG signal. Among the most recently published works are those summarized follows: Aris, S.A.M **[1]** have used data segmentation and linear regression model is used to extract the EEG Features Shiliang Sun **[2],** presents a novel method for feature extraction of EEG signal called extreme Energy Ratio (EER).Shiliang Sun ,Changshui Zhang**[3],** proposed an adaptive feature extractor namely adaptive common spatial patterns and multi-class common spatial patterns(CSP).Shiliang Sun, Changshui Zhang **[4],**proposed a new type of features based on kernel transformed space using whitening transform and projection transform.Poulos, M et al **[5],** presents feature extraction using parametric spectral analysis of the EEG signal. Auto regression (AR) parameters are estimated from a signal contained only alpha rhythm of the EEG.

Eswari, C. et al. **[6]** have investigated the use of brain activity for person authentication and person identification to reduce the fake pattern of Biometrics. L.citi and R. poli **[7],** have developed a technique or method where numbers on the screen were flashed randomly and recorded EEG signals of the subjects. The subjects were asked to concentrate on give target number and keep mental count of target flashes, When a target number is flashed, a positive potential about 300-600 ms after stimulus onset in evoked and shows up in recorded EEG signal. Total five trails were conducted in one session. Data set created and divided into two classes' one target and non-target. Neural Network was used for classification.

R.palanippan **[8],** presented In this paper, the gamma band feature spectral was computed from their visual evoked potential signals recorded from 61 electrodes while subject perceived a picture. R.palanippan et al [**9],** they have recorded VEP signals from 61 electrodes cap while subject is seeing a picture and compute their spectral features, it consists gamma band of signal. Gudmundsson S. et al. **[10],** presented autoregressive coefficient, channel spectral powers, inter-hemispheric channel spectral power differences, inter-hemispheric channel linear complexity and non –linear complexity (approximate entropy) values were used as EEG features. Abhishek vaish and Pinki Kumari **[11]** have been used statistical features for human emotion discrimination using ECG signals with different machine learning techniques.

Itai, A et al **[12]** have proposed a new method of feature extraction using a spectrum intensity ratio and shows classification reaches up to 90%. Shi-Liang Sun **[13],** presented mixtures of common spatial patterns for feature extraction of EEG signals. Pinki Kumari et al **[14]** used the Local binary pattern for features extraction for human attributes discrimination. Estrada, E et al [**15]** have presented relative spectral band energy, harmonic parameters, and Itakura distance for feature extraction methods.

R. planiappan **[16],** used energy features extracted from the EEG signals to analyze the difference among the people. Hu Dingyin et al. **[17]** have presented wavelet packet decomposition and wavelet packet energy of special sub-bands is employed as the original features.

In the view of above methods for feature extraction, we have proposed variation of Energy features using wavelet decomposition methods: Symlet decomposition, Daubechies decomposition and Coifet decomposition method and calculated the *Energy, Recoursing Energy Efficiency (REE), Logarithmic Recoursing Energy Efficiency (LREE), and Absolute Logarithmic Recoursing Energy Efficiency (ALREE)* of each bands of the EEG signals

3. Neuro –Signal Background:

Neural Signals are the electrical potential carrying the information to be transmitted between neurons/dendrites. They also initiate chemical stimulation on the synapses to transfer/carry forward the message from/to brain. These electrical activities can be detected by the medical equipment Electroencephalogram (EEG), measures the electricity levels over areas of the scalp. In 1929, Hans Berger performed the first noninvasive measurements of bioelectrical activity in the brain. During the last seven decades, electroencephalography, or EEG, has been established as a tool for monitoring brain dynamics and brain function. The combination of electrical activity is known as Brainwaves pattern [21] [22].

3.1 Neuro-signal Acquisition-

In this study we, have used motor movement/imaginary dataset which has been developed by BCI 2000 for general purpose [23] [24]. This dataset is freely available in the website name www.physionet.org. This dataset consists of over 1500 records of 109 subjects. Each subject were asked to perform motor/imaginary tasks which is synchronized with target appears

Task 1: A target appears on either the left or the right side of the screen. The subject opens and closes the corresponding fist until the target disappears. Then the subject relaxes.

Task 2: A target appears on either the left or the right side of the screen. The subject imagines opening and closing the corresponding fist until the target disappears. Then the subject relaxes.

We were only interested with cerebral signal because the cerebral region has high impact when person perform some motor movement task therefore, we only collected the Cz channel which placement over the scalp has been shown in the following picture all electrodes montage style based on 10-20 system.

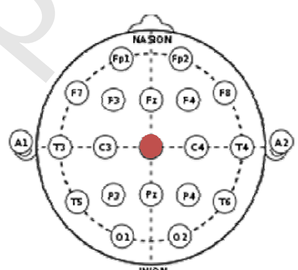

Fig.2: Cz Signal position over the scalp area

4. Debauchees' Wavelet Decomposition:

A family of wavelet transforms discovered by *Ingrid Daubechies* Concepts similar to Haar *(trend* and *fluctuation*) Differs in how scaling functions and wavelets are defined The mathematical formulation of this has described below:

The wavelet expansion of signal x (t) has following expansion

$$x(t) = \sum C_{j_0k} \; \varphi_{j_0k} \; (t) + \sum_{j=k_0} \sum_k d_{jk} \;\; \psi_{jk}(t) \quad \text{--(1)}$$

Equation (1) shows that there are 2 terms. The first one is the 'approximation' and the second one is the 'details'. The details are represented by-

$$d_x = \int x(t)\psi^*_{jk} \; (t)\,dt \qquad \text{--(2)}$$

and $\psi_{jk}(t)$ called the wavelet function is given by-

$$\psi_{jk}(t) = \frac{1}{\sqrt{2^j \, \psi\left(\frac{t-k2^j}{2^j}\right)}} \qquad \text{- (3)}$$

The approximation co-efficient are given by:

$$C_{jk} = \int x(t)\,\varphi^*_{jk} \; (t)\,dt \quad \text{-(4)}$$

$\varphi_{jk}(t)$ is called scaling function and given by:

$$\varphi_{jk} = \frac{1}{\sqrt{2^j \, \varphi\left(\frac{t-k2^j}{2^j}\right)}} \quad (5)$$

Daubechies wavelets are a family of wavelets to have highest number A of vanishing moments for a given support width N=2A, and among the 2^{A-1} possible solutions the one is chosen whose scaling filter has external phase. This family contains the Haar wavelet, db1, which is the simplest and certainly the oldest of wavelets. It is discontinuous, resembling a square from. Except for db1, the wavelets of this family do not have an explicit expression. The names of Daubechies family wavelets are written dbN, where N is the order, and 'db' the 'Surname' of the wavelet, as mentioned above, is the same as Haar wavelet. Here are the wavelet functions ψ of the next nine members of the family as shown in the below figure:

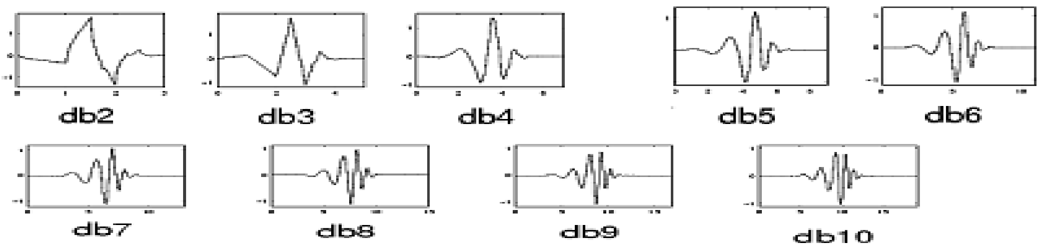

Fig.3: Daubechies Wavelet Family members

The original signal passes through the low pass filter called the approximation (A) and includes the high scale (low-freq) components and the signal passes through the high pass filter is called Details (D) and contains (high frequency) components. The low frequency filter output fed into another identical QMF filter pair. This process can be repeated recursively as a tree pr pyramid algorithm yielding group of signals that divides the spectrum of the original signals into small bands. To get the differences among the different subjects we have applied different method of decomposition of wavelet Family

The separating points are usually halfway between 0Hz and half the data sampling rate (Nyquist frequency).The first outputs of the QMF filter pair are de- sampled by the factor of two.

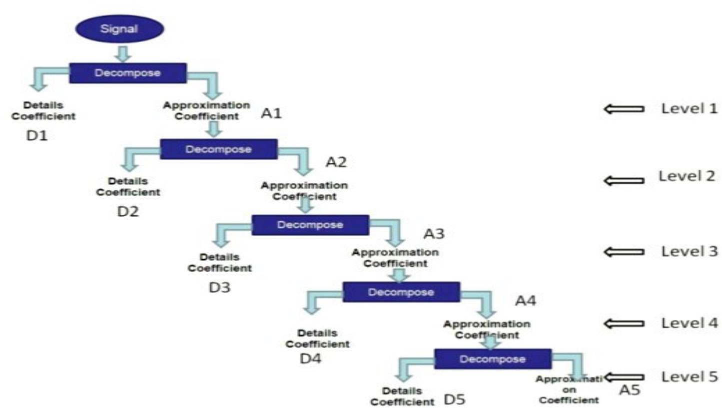

Fig.4: Decomposition levels of the original signal

Table.1. Relationship between Decomposition levels and EEG frequency Bands

Frequency Range	Decomposition level	Frequency band	Frequency Bandwidth(Hz)
0-4	A5	Delta	4
4-8	D5	Theta	4
8-14	D4	Alpha	6
14-32	D3	Beta	18
32-64	D2	Low Gamma	32
64-128	D1	High Gamma	64

5. Research Setup and Results

5.1. Neuro-signal based identification system:

In last five decades, there are several types of physical characteristics of the human are being used in information technology such as face, fingerprints, plamprint, and speech of the person. In continuation of this work researcher has started the evaluation of human neuro signal for person discrimination. The neuro-signal features of each individual are unique and have the potential use in person identification. Security can be enhanced by employing as many EEG features of individual as possible. The following architecture stating how EEG neuro signal can be used for the human identification

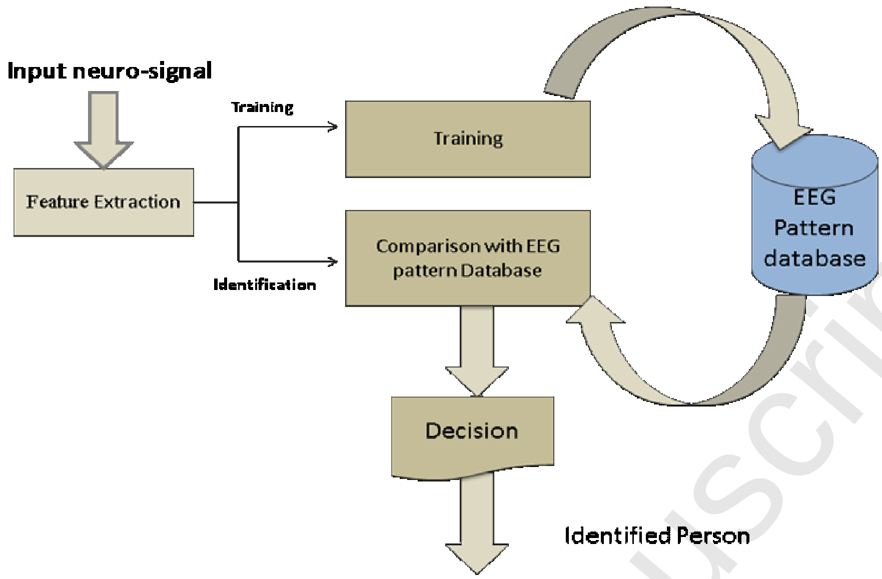

Fig.5: Block diagram of EEG (Neuro-signal) based identification system

5.2. Dataset for training and testing :

The performance of the classifier always depends upon the how we manage the quantum of dataset for training and testing of the classifier and good feature extraction. In the light of this we have created our dataset of five healthy subject which EEG signal has been collected from the online repository of clinical signals such EEG , ECG and EMG etc.

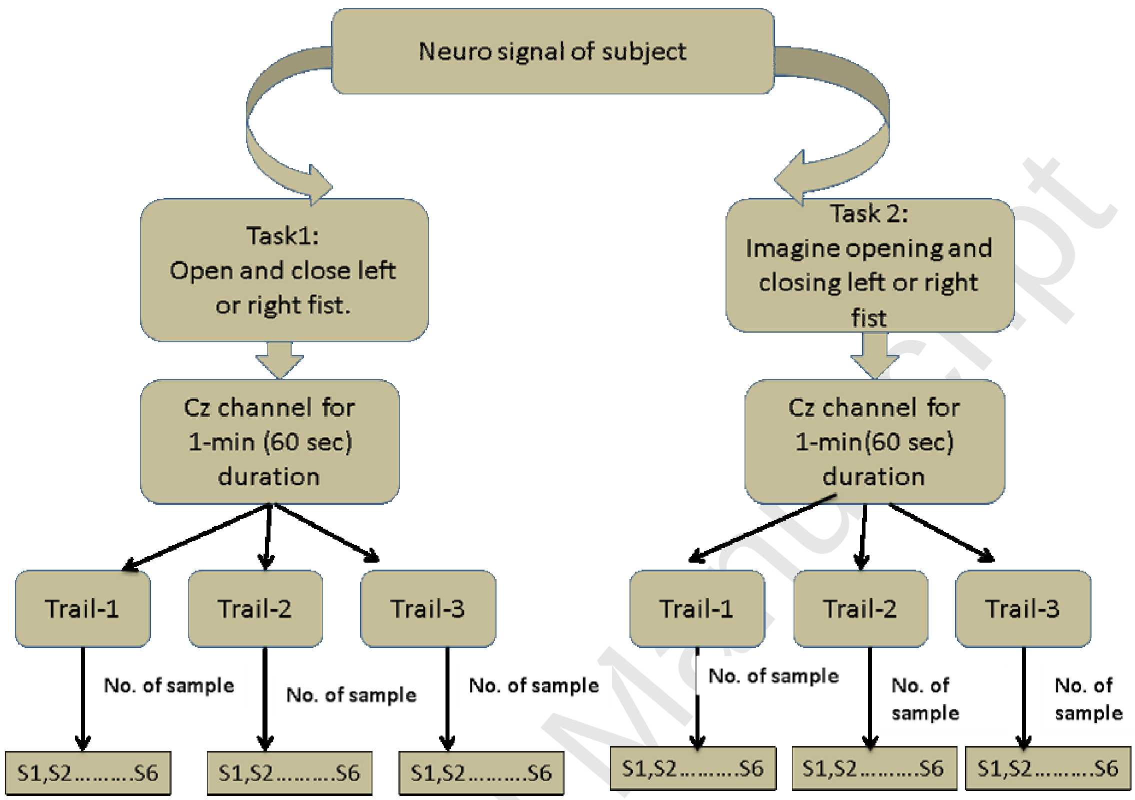

Fig.6: Flowchart of dataset creation for training and testing

Table.2. Details the no. of samples used

Number of subjects	Number of samples each trial per task	Total number samples
Five	Six	6 samples*3 trails* 5 subjects* 2 tasks = 180 samples

5.3 Feature Extraction:

Feature extraction plays the vital role for the classifier performance; it creates the unique characteristics each and every input which would help the classify this input correctly. There are several types of feature extraction methods are available in the area of signal processing. In our proposed work we have used variation of energy features six sub-bands of EEG signal[20] which has been extracted from below described mathematical tool:

$$ED_i = \sum_{j-1}^{N} |D_{ij}|, i=1,\ldots,l \quad \text{--(6)}$$

$$REE = \frac{\text{Energy of sub-band}}{\text{total energy of the signal}} * 100 \quad \text{--(7)}$$

$$LREE = Log(\frac{\text{Enger of Sub-band}}{\text{Total energy of the signal}} * 100) \quad \text{--(8)}$$

$$ALREE = Abs(Log\,\frac{\text{Energy of sub-band}}{\text{Total Energy of the signal}} * 100) \quad \text{--(9)}$$

$$\text{Total number of features} = 6\ \text{samples} * 3\ \text{trails} * 5\ \text{subjects} * 2\ \text{tasks} * 6\text{subband} * 4\ \text{features} \quad \text{--(10)}$$

The following tables shows the various energy distribution among subjects

Table.3. Energy values of subject-1 with different features

Feature Name	Energy feature	REE	LREE	ALREE
Gamma High	59.4053	0.5941	-0.2262	0.2262
Gamma Low	1.0849	0.0108	-1.9646	1.9646
Beta	1.6666	0.0167	-1.7782	1.7782
Alpha	3.2495	0.0325	-1.4882	1.4882
Theta	4.8435	0.0484	-1.3148	1.3148
Delta	29.7502	0.2975	-0.5265	0.5265

Table.4. Energy values of subject -2 with different features

Feature Name	**Energy feature**	**REE**	**LREE**	**ALREE**
Gamma High	2.5243	0.0252	-1.5979	1.5979
Gamma Low	2.7285	0.0273	-1.5641	1.5641
Beta	2.7208	0.0272	-1.5653	1.5653
Alpha	4.1291	0.0413	-1.3841	1.3841
Theta	6.6759	0.0668	-1.1755	1.1775

Delta	81.2215	0.8122	-0.0903	0.0903

Table.5. Energy values of subject -3 with different features

Feature Name	Energy feature	REE	LREE	ALREE
Gamma High	7.2796	0.0728	-1.1379	1.1379
Gamma Low	11.8066	0.1181	-0.9279	0.9279
Beta	8.0317	0.0803	-1.0952	1.0952
Alpha	12.1676	0.1217	-0.9148	0.9148
Theta	11.3635	0.1136	-0.9445	0.9445
Delta	49.3511	0.4935	-0.3067	0.3067

Table.6. Energy values of subject -4 with different features

Feature Name	Energy feature	REE	LREE	ALREE
Gamma High	6.3215	0.0632	-1.1992	1.1992
Gamma Low	19.7263	0.1973	-0.705	0.705
Beta	16.3466	0.1635	-0.7866	0.7866
Alpha	13.5622	0.1356	-0.8677	0.8677
Theta	10.1229	0.1012	-0.9947	0.9947
Delta	33.9204	0.3392	-0.4695	0.4695

Table.7. Energy values of subject -5 with different features

Feature Name	Energy feature	REE	LREE	ALREE
Gamma High	1.8233	0.0182	-1.7391	1.7391
Gamma Low	3.2734	0.0327	-1.485	1.485
Beta	6.0918	0.0609	-1.2153	1.2153
Alpha	8.387	0.0839	-1.0764	1.0764
Theta	12.0386	0.1204	-0.9194	0.9194
Delta	68.3859	0.6839	-0.165	0.165

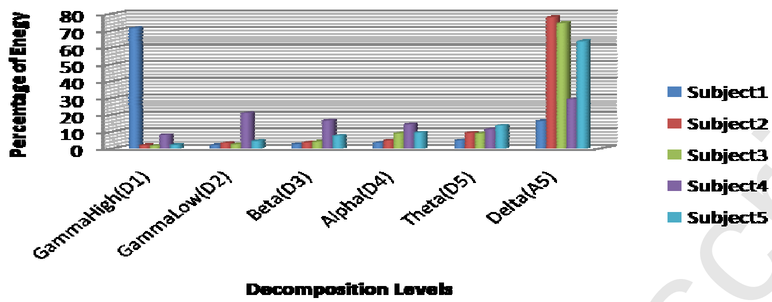

Fig.7: Distribution of Energy over EEG sub-bands for Task 1

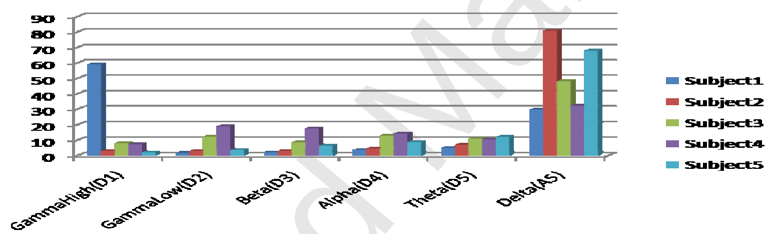

Fig.8: Distribution of Energy over EEG sub-bands for Task 2

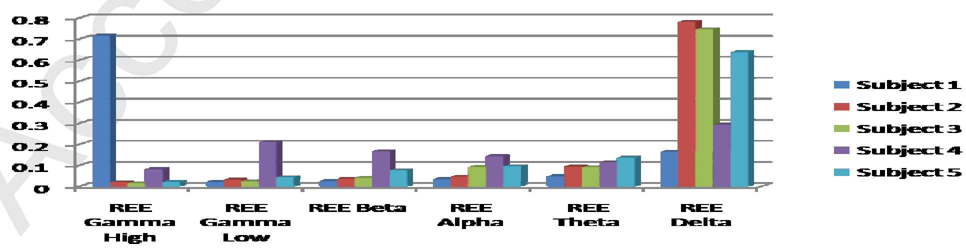

Fig.9: Distribution of REEnergy over EEG sub-bands for Task 1

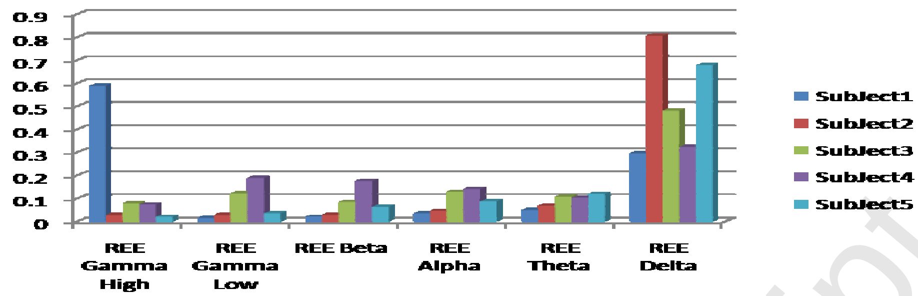

Fig.10: Distribution of REEnergy over EEG sub-bands for Task 2

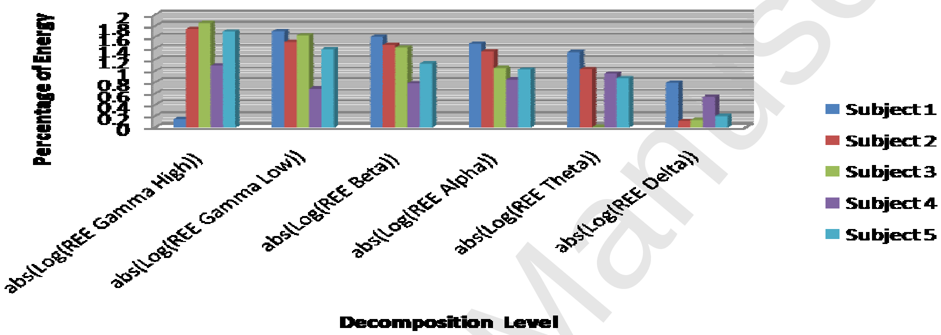

Fig.11: Distribution of absolute REEnergy over EEG sub-bands for Task 1

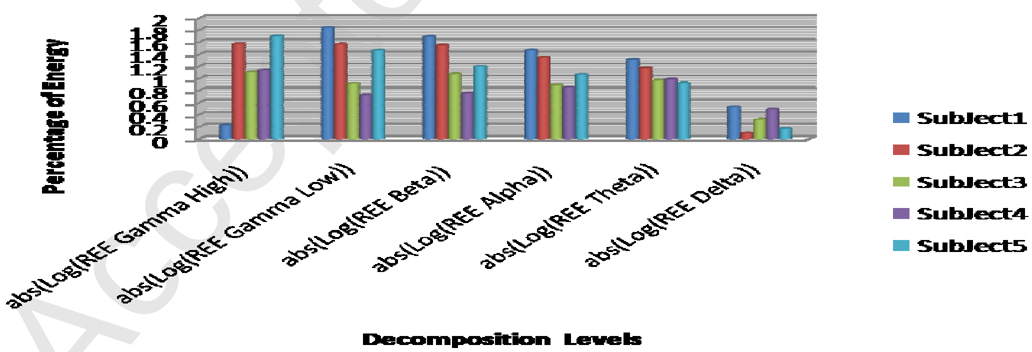

Fig.12: Distribution of absolute REEnergy over EEG sub-bands for Task 1

5.4 Neural Network Classifier: Numerous of paradigms and classification architectures have been developed to distinguish feature vector and sequence of data into distinct categories. Neural network is one of the popular classifier for pattern recognition .its architecture basically inspired from biological structure and tried to replicate the human brain structure, the classification protocol of this paradigm pretty similar to human brain.

In this proposed study, we have basically been focused on how variation of energy features is effective in person classification. We have used neural network pattern recognition tool for classification task and designed a network with 24 input features vector of each subject and 32 hidden layers and 5 output layer which has been successfully classifying the individual.

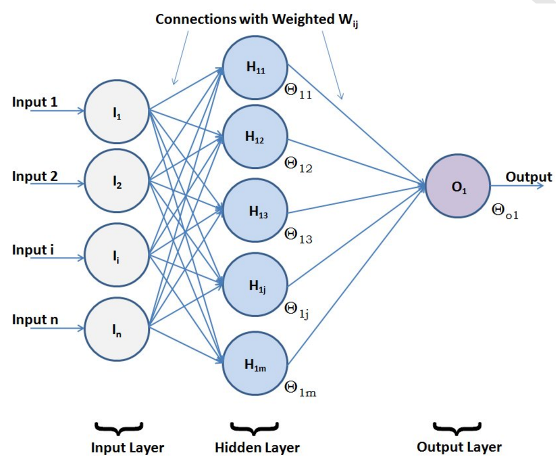

Fig.13: Multi-Layer Back Propagation ANN

5.5 Performance Matrix/measure:

The main performance indicator for any classification or biometric identification system is (receiver operating characteristic) ROC. It is basically, the curve of true acceptance rate (TAR) against false acceptance rate (FAR)., which is the measure of no of false instance classified as positive among all intruder and imposter cases.

FRR (False Rejection Rate):– The probability that a biometric system will fail to identify the legitimate claim. A statistic used to measure a biometric performance when operating in the verification task.

TRR (True Reject Rate):- Biometric performance in verification task. The percentage of times a system (correctly) rejects a false claim of identity.

TAR (True Acceptance Rate):- The percentage of times a system (correctly) verifies a true claim of identity.

FAR (False Acceptance Rate) – The percentage of times a system produces a false accept.

In the biometric literature, FAR is sometimes defined such that the "impostor" makes zero effort to obtain a match.

$$TAR = 1 - FAR$$

Where TAR-true acceptance rate and FRR-false rejection rate

To verify the result of biometric system we have four matrix terms True Acceptance Rate (FAR), True Rejection Rate (FAR), False Acceptance Rate (FAR), False Rejection Rate (FAR),.

Verification results are reported in terms of the True Acceptance Rate (TAR), False Accept Rate (FAR), and ROC. The TAR is measured as the number of occurrences when genuine biometric identity are matched correctly, whereas, FAR is the measurement of the number of occurrences when imposter

identity are matched falsely. EER is the point where FAR and FRR are equal, where FRR is the False Reject Rate and measured on the basis of number of false rejections of genuine matches and also given as,

FRR = 1 – TAR

$\mathrm{ROC} = \mathrm{TPR}\ \mathit{vs}\ \mathrm{FPR}$

The following tables describing the true acceptance and False acceptance rate while person performing the Task 1 which described fig 6

Table.8. Confusion matrix Data Set Size {11 training and 7 testing}

	Sub1	Sub2	Sub3	Sub4	Sub5	TAR
Sub1	6	1	0	0	0	6/7=0.85
Sub2	0	6	1	0	0	6/7=0.85
Sub3	0	0	7	0	0	7/7=1
Sub4	0	2	0	5	0	5/7=0.72
Sub5	0	0	0	0	7	7/7=1
FAR	0	3/9=0.33	1/8=0.12	0	0	

$$\mathrm{TAR} = \frac{\left(\frac{6}{7}+\frac{6}{7}+\frac{7}{7}+\frac{5}{7}+\frac{7}{7}\right)}{5} \times 100 = 88.57\%$$

$$FAR = \frac{\left(\frac{3}{9}+\frac{1}{8}\right)}{5} \times 100 = 3.33\%$$

Table.9. Confusion matrix Data Set Size {10 training and 8 testing}

	Sub1	Sub2	Sub3	Sub4	Sub5	TAR
Sub1	7	1	0	0	0	7/8=0.875
Sub2	1	7	0	0	0	7/8=0.875
Sub3	0	0	8	0	0	8/8=1
Sub4	0	1	1	6	0	6/8=0.75

Sub5	0	0	0	0	8	8/8=1
FAR	1/8=0.125	2/9=0.22	1/8=0.125	0	0	

$$TAR = \frac{\left(\frac{7}{8}+\frac{7}{8}+\frac{8}{8}+\frac{6}{8}+\frac{8}{8}\right)}{5} \times 100 = 90\%$$

FRR=1-TAR

$$FAR = \frac{\left(\frac{1}{8}+\frac{2}{9}+\frac{1}{9}+\frac{1}{7}\right)}{5} \times 100 = 3.92\%$$

The following tables describing the true acceptance and False acceptance rate while person performing the Task 1 which described fig 6

Table.10. Confusion matrix Data Set Size {11 training and 7 testing}

	Sub1	Sub2	Sub3	Sub4	Sub5	TAR
Sub1	7	0	0	0	0	7/7=1
Sub2	1	6	0	0	0	6/7=0.85
Sub3	0	0	7	0	0	7/7=1
Sub4	0	0	1	6	0	6/7=0.85
Sub5	0	0	0	0	7	7/7=1
FAR	1/8=0.125	0	1/7=0.14	0	0	

$$TAR = \frac{\left(\frac{7}{7}+\frac{6}{7}+\frac{7}{7}+\frac{6}{7}+\frac{7}{7}\right)}{5} \times 100 = 94.28\%$$

FRR=1-TAR

$$FAR = \frac{\left(\frac{1}{8}+\frac{1}{8}\right)}{5} \times 100 = 5\%$$

Table.11. Confusion matrix Data Set Size {10 training and 8 testing }

	Sub1	Sub2	Sub3	Sub4	Sub5	TAR
Sub1	8	0	0	0	0	8/8=1
Sub2	1	7	0	0	0	7/8=0.87
Sub3	0	0	8	0	0	8/8=1
Sub4	0	0	1	7	0	7/8=0.87
Sub5	0	0	0	0	8	8/8=1
FAR	1/8=0.125	0	1/9=0.11	0	0	

$$TAR = \frac{\left(\frac{8}{8}+\frac{7}{8}+\frac{8}{8}+\frac{7}{8}+\frac{8}{8}\right)}{5} \times 100 = 95\%$$

FRR=1-TAR

$$FAR = \frac{\left(\frac{1}{9}+\frac{1}{9}\right)}{5} \times 100 = 4.44\%$$

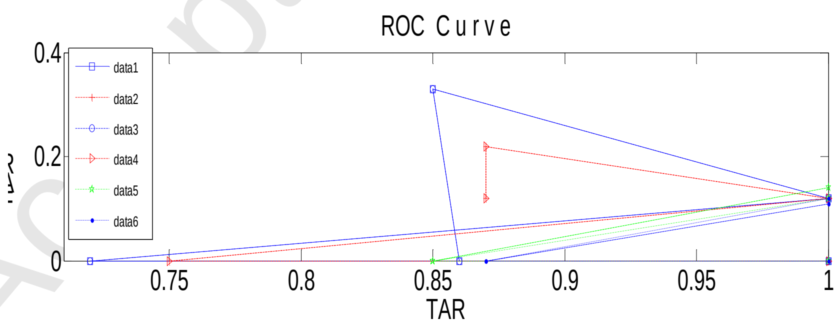

Fig.14: ROC Curve

Conclusion

The aim of this preliminary study was to investigate the ability of energy features obtained by using wavelet function from the EEG differentiate or identify a person from another person.

1. First finding of these results is energy distribution over the sub-bands of EEG signal corresponding to delta , theta, alpha , beta, gamma waves found to differentiate the person from the person from another while subjects were doing cognitive task which have mentioned above section.

2. The second finding of this results suggest that variation could potentially be used as new or additional features in order to authenticate or identify a legitimate person using their brainwaves which has been proved by using neural network classifiers.

3. The third finding of this study that while person imaging the already done task that cognitive process helped classifier to classify the individual. It perform much better in imagination state in comparison to physical state

4. In future, we would like change the feature extraction process and cognitive task to explore this area more .

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