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Novel Algorithm for Feature Extraction and Classification of EEG signals

Mangala Gowri S G[1]
Assistant Professor
MSEC, VTU
Bangalore, India

Cyril Prasanna Raj P[2]
Dean of R & D
MSEC, VTU
Bangalore, India

Badarinarayan K S[3]
Principal
MSEC, VTU
Bangalore, India

Abstract- **This paper aims in developing an algorithm for feature extraction by using Discrete wavelet transform (DWT).Feature extraction from Electroencephalogram (EEG) signal for emotion recognition provides an adequate information. In this paper DWT is used to extract significant features representing emotion in Brain Computer Interface (BCI) in EEG signals. The EEG signals are acquired in real time using Neurosky Mind wave sensor and processed in real time using wavelets for feature extraction. For a given EEG signal brain waves are identified from DWT Spectrum. These brain waves quantify emotions. The proposed algorithm based on DWT, is modeled in Matlab and it is validated using 10 different EEG samples. Features such as energy are found to identify the intensity level of different bands of EEG signal .The best results were obtained by using Bior 5.5 wavelet for signal decomposition and to obtain the accurate frequency bands.**

Keywords: Electroencephalogram, Emotion recognition. Discrete wavelet transform, Feature extraction, Bior 5.5

1. INTRODUCTION

Brain-computer interfaces (BCI) are a system that allows the user to translate brain activities into a set of commands for the computer to understand to control any computer application or Neuro prosthesis [6]. Several methods are existing to detect brain activity such as magneto encephalography (MEG), Functional Magnetic Resonance Imaging (FMRI) and Electroencephalogram EEG).

But EEG signals have rapid response time and are inexpensive method relative to other methods, so it is widely used to monitor brain activity in BCI research.

In 2025, widespread applications will use brain signals as an important source of information. Routine applications in professional context, personal health monitoring, and medical treatment. [1].The upcoming future where humans and information technology are seamlessly and intuitively connected by integrating various biosignals, from brain activity. Game, health, education, and lifestyle companies will be associated to brain and other biosignals to develop applications and electronic gadgets for a wider community. People will want to monitor their brain states to provide them with reliable estimates of their mental capacity and performance level. But the EEG has rapid response time and is inexpensive method relative to other methods, so it is mostly used in the BCI research. The aim of human computer interaction (HCI) is to improve the interactions between human and computers. Because most computers lack understanding of user's emotions, sometimes they are unable to respond to the user's needs automatically and correctly. However human emotion plays a vital role in perception, cognition and social behavior [2].

The EEG signals are recorded as a weak potential by placing the electrodes on the scalp and analyze to establish a BCI system. The recorded EEG signals are processed offline to extract features and classify emotions. In this work EEG signals are recorded in real time and processed using wavelets to extract significant features for emotion analysis. The Fig.1 shows the block diagram for BCI.

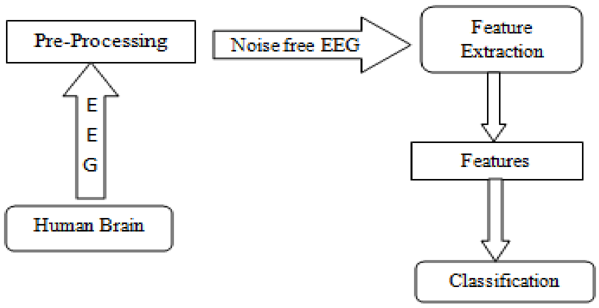


Fig. 1 Basic BCI Block Diagram

From the BCI signal analysis, it is observed that, EEG signal has been acquired from the scalp of the brain using EEG acquisition set-up. The acquired raw EEG signal is pre-processed. Preprocessing in EEG signal is to remove the baseline and performing its average of the signal from the original signal. The noise free EEG signal is analyzed by using wavelet transform to extract all the fundamental frequency components of EEG signal i.e. alpha, beta, gamma, delta and theta. The frequency sub band separation of EEG signal for emotion classification is based only on the decomposition of the signal to certain levels. This is followed by feature extraction from these sub bands. Classification of emotions is carried out on the basis of these features. Wavelets and Neural Networks are used for Classification and Detection of brain waves as they provide distinct features. However, selection of appropriate multilevel decomposition of brainwave signals in identifying the prominent features from the EEG signal provides a scope for development of Novel Algorithm.

2. RELATED WORK

There are many methods for feature extraction and classification which is analyzed and adopted by different authors. In [2] EEG data base has been collected for four emotional states by giving an external stimulus that is by movie elicitation which is designed for acquiring subjects. Different Classifiers are used for statistical features in time domain and frequency domain. K-NN algorithm, Multilayer Perceptron and SVM are used as classifiers.

The Authors in [3] have developed a new feature extraction method for a user-independent emotion recognition system namely HAF-HOC from electroencephalograms (EEGs) is considered. Novel filtering procedure is used for the feature extraction Hybrid Adaptive Filtering (HAF), for an efficient extraction of the emotion-related EEG-characteristics was developed by applying Genetic Algorithms for six distinct emotions , is considered by providing a higher classification rates upto 85.17 percent.

The Author in [4] has analysed the EEG signals for 4 different participants from the dataset**.**The extracted data set is then decomposed into different subbands with the help of wavelet transform using matlab.Author has analysed the EEG signals for 4 different participants from the dataset**.**The extracted data set is then decomposed into different subbands with the help of wavelet transform using matlab.Different frequency ranges of EEG signals such as alpha, beta, gamma, theta &delta for classifying two classes of emotions named as High arousal (HA) and Low arousal (LA) are considered. In [5] EEG signals from 62 channels of 20 subjects is collected between the age group between 21-39 years.In [6] an optimal EEG-based emotion recognition algorithm based on spectral features and neural network classifiers is proposed. Wavelet transform and Gabor based spectral functions were implemented for classifying the EEG signals. Neural network classifiers such as improved particle swarm optimization (IPSO) and probabilistic neural network (PNN) are developed to determine an optimal nonlinear decision boundary between the extracted features from the six basic emotions like sadness , happiness , anger, fear , disgust and surprise.In [7] EEG signals are classified using two emotions (i.e., positive and negative) by giving an external stimulus. The power spectrum features, are analysed with an accuracy rate of about 85.41% by using SVM Classifier. In [8] it is proposed with two emotions happy and sad for the classification using EEG signals. The experimental results indiacte that the gamma band of about 100 Hz is suitable for EEG –based emotion classification,with an accuracy of 93.5% to 6.7% and 93.0% to 6.2 %. In [9] Varun Bajaj proposes the new features based on multiwavelet transform for classification of human emotions from electroencephalogram (EEG) signals. The EEG signal measures electrical activity of the brain, which contains lot of information related to emotional states. The proposed features are based on multiwavelet transform of EEG signals with Morlet wavelet kernel function of MC-LS-SVM has provided a better classification accuracy for classification of emotions. In [10] A modified adaptive filtering algorithm for signal preprocessing is proposed in this system for removing the noise and artifacts in EEG signal. The adaptive neuro fuzzy inference system is also proposed for classifying and analyzing the emotions based on the features selected. In [11].The efficacy of extracted features for classifying five types of emotional states relax, mental task, memory related task, pleasant, and fear. For this purpose support vector machine classifier was employed to classify the five emotional states by using salient global features. In case of statistical features the overall accuracy was obtained 54.2%, which is improved for FFT features of 55.00% and the highest accuracy was obtained by DWT features which was 60.15%.In [12] EEG data was collected by showing and playing different audio-video stimuli to acquire the proper emotions. For classification of data LDA Classifier was used with an classification rate of 84.37% for happiness and for relaxed state it is 92.70%.

From the analysis, above all the related works. In this paper, a novel algorithm for feature extraction and emotion classification is proposed, modeled and developed based on DWT. An experimental setup is developed for capturing brain activity of 10 students when they were really excited during the cultural fest conducted in our College. Real samples were extracted from the students, when they were happy and excited.

3. PROPOSED WORK

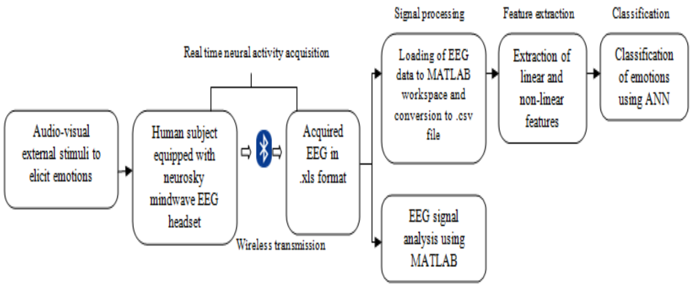


Fig. 2 Overall Proposed Block Diagram

From the proposed block diagram, EEG samples are acquired by using the Neurosky Mind wave EEG headset.

The Neurosky Mindwave sensor is a low cost single-electrode EEG headset, and it has been proven effective in detecting users mental states.

A. NEUROSKY MINDWAVE

The NeuroSky Mind Wave is a device for monitoring the electrical signals generated by neural activity in the brain. This headset was launched in 2010/11 and has been designed to identify and monitor electric signals generated by neural activity in the brain, which has been used to research ADHD, Alzheimer's and Cognitive Stress. The Mind Wave consists of a headband, with a sensor arm containing the EEG electrode which rests on the forehead above the eye (FP1 position in accordance with the American Electroencephalographic Society's (1994) 10-20 system of electrode placement). The device consists of eight main parts, ear clip, flexible ear arm, battery area, power switch, adjustable head band, sensor tip, sensor arm and inside think gear chipset.

B.TECHNICAL BACKGROUND OF MINDWAVE SENSOR

Mind wave sensor basically works with think gear technology. NeuroSky Think Gear ASIC Module (AM) is the world's most popular EEG technology. Together with a dry electrode, it senses the faint signal from the human brain, filters out extraneous noise and electrical interference and converts to digital to power games, apps, toys, and research.
Think Gear is the technology inside every NeuroSky product or partner product that enables the device to interface with the wearers' brainwaves. It includes:

- The sensor that touches the forehead
- The contact and reference points located on the ear pad, and
- The onboard chip that processes all of the data

Fig. 3 Think gear chip

The above figure shows the Think gear chip. Both the raw brainwaves and the eSense Meters (Attention and Meditation) are calculated on the Think Gear chip. The calculated values are output by the Think Gear chip, through the headset, to a PC.Types of data output from Think Gear chips: Raw sampled wave values (128Hz or 512Hz, depending on hardware), Signal poor quality metrics, and eSense Attention and Meditation meter values, EEG band power values for delta, theta, alpha, beta, and gamma

C. *DEVICE DESIGN*

The principle of operation is quite simple. Two dry sensors are used to detect and filter the EEG signals. The sensor tip detects electrical signals from the forehead of the brain. At the same time, the sensor picks up ambient noise generated by human muscle, computers, light bulbs, electrical sockets and other electrical devices. The second sensor, ear clip, is a grounds and reference, which allows think gear chip to filter out the electrical noise .The device measures the raw signal, power spectrum (alpha, beta, delta, gamma, theta), attention level, mediation level and blink detection. The raw EEG data received at a rate of 512 Hz. Other measured values are made every second. Therefore, raw EEG data is a main source of information on EEG signals using Mind Wave

D. THINKGEAR MEASUREMENTS

The single dry sensor and reference pick up potential differences (voltages) on the skin at the forehead and the ear. The two are subtracted through common mode rejection to serve as a single EEG channel, and amplified 8000x to enhance the faint EEG signals. The signals are passed through analog and digital low and high pass filters to retain signals generally in the 1-50Hz range. After correcting for possible aliasing, these signals are ultimately sampled at 128Hz or 512Hz. Each second, the signal is analyzed in the time domain to detect and correct noise artifacts as much as possible, while retaining as much of the original signal as possible, using NeuroSky's proprietary algorithms. A standard FFT is performed on the filtered signal, and finally the signal is rechecked for noise and artifacts in the frequency domain, again using NeuroSky's proprietary algorithms. The acquired EEG signal which is in the format of .xls is loaded to the MATLAB workspace and converted to .csv format for further processing. The formatted EEG dataset is analysed by using wavelet transform to extract all the fundamental frequency components of EEG signal i.e. alpha, beta, gamma, delta and theta. EEG frequency bands which relate to various brain states. The aggregate of these electric voltage fields create an electrical reading which electrodes on the scalp are able detect and record. The prominent features from the EEG signal are extracted by using multiwavelets and with the help of these features the different emotions are classified and detected by using a novel algorithm with the help of Neural Networks.

4. EXPERIMENTAL SETUP

The experimental Setup for acquiring the EEG Signal is shown below in Fig. 4

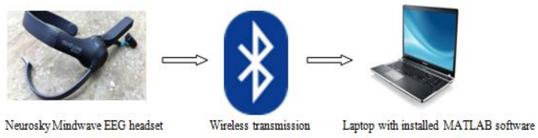


Fig. 4 Flow diagram of Experimental Setup

The above experimental setup shows the mindwave sensor which is made available to wear on any subject for acquiring the EEG data on the scalp of the subject, with all the proper settings and its totally harmless, then corresponding EEG signal will be displayed on the computer via bluetooth.

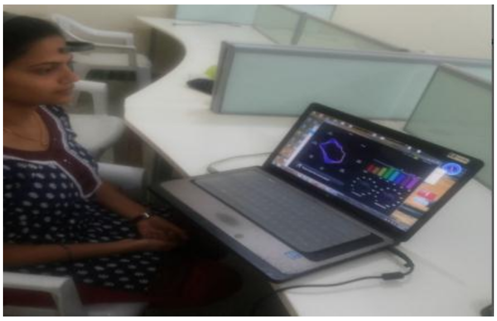


Fig. 5 EEG Signal Acquisition Setup

In the above EEG acquisition setup, the subject is made to wear the mindwave sensor on her scalp. Brainwaves are tiny electrical impulses released when a neuron fires in the brain. Neurosky's brain-computer interface technology works by monitoring these electrical impulses with a forehead sensor. The neural signals are the input to think gear chip, which is interpreted. The measured electrical signals and calculated interpretations are then displaying as output digital messages to the system, allowing to see the brainwaves on the screen. The analysis of any subject depends on the attention and meditation, which gives an affect on the brainwaves and the visualize to acquire the signal will be displayed on the computer via bluetooth.

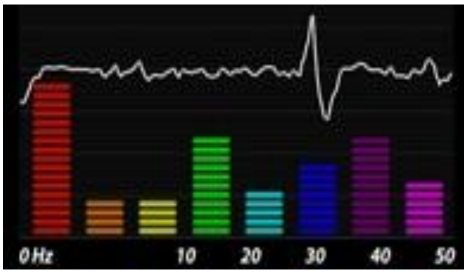


Fig. 6 EEG acquisition by Neurosky Mind wave

The EEG signal which is displayed in the visualizer can be loaded into excel sheet in the form of samples by using python code. The reason behind using python code is to interface the mindwave sensor with the PC. Since python is a scripting language which is very efficient to interface the hardware device with the computer. The language provides constructs intended to enable clear programs on both a small and large scale. Python supports multiple programming paradigms, including object-oriented, imperative and functional programming or procedural styles. It features a dynamic type system and automatic memory management and has a large and comprehensive standard library. The Fig. 7 shows the algorithm flowchart of python code for interfacing the mind wave sensor with the computer

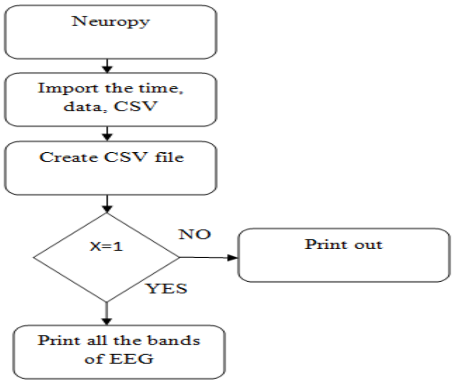
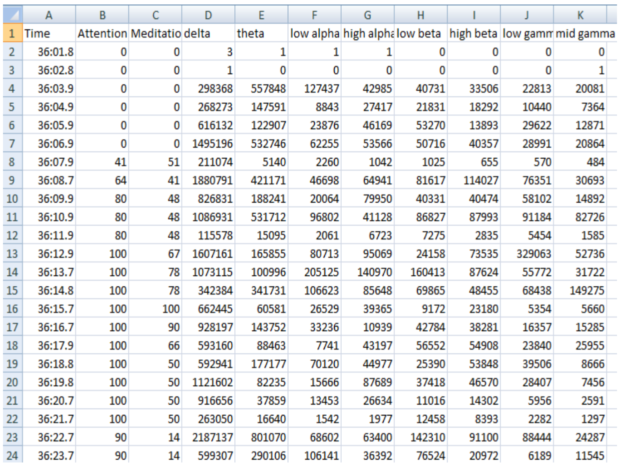


Fig. 7 Algorithm flowchart of python code

Thus the EEG Signal Loaded in the Excel Sheet contains Sample set for each and every Bands of EEG that is Alpha, Beta, Gamma, Detla and theta in separate columns which is shown in Fig. 8



	A	B	C	D	E	F	G	H	I	J	K
1	Time	Attention	Meditatio	delta	theta	low alpha	high alpha	low beta	high beta	low gamm	mid gamma
2	36:01.8	0	0	3	1	1	1	0	0	0	0
3	36:02.8	0	0	1	0	0	0	0	0	0	1
4	36:03.9	0	0	298368	557848	127437	42985	40731	33506	22813	20081
5	36:04.9	0	0	268273	147591	8843	27417	21831	18292	10440	7364
6	36:05.9	0	0	616132	122907	23876	46169	53270	13893	29622	12871
7	36:06.9	0	0	1495196	532746	62255	53566	50716	40357	28991	20864
8	36:07.9	41	51	211074	5140	2260	1042	1025	655	570	484
9	36:08.7	64	41	1880791	421171	46698	64941	81617	114027	76351	30693
10	36:09.9	80	48	826831	188241	20064	79950	40331	40474	58102	14892
11	36:10.9	80	48	1086931	531712	96802	41128	86827	87993	91184	82726
12	36:11.9	80	48	115578	15095	2061	6723	7275	2835	5454	1585
13	36:12.9	100	67	1607161	165855	80713	95069	24158	73535	329063	52736
14	36:13.7	100	78	1073115	100996	205125	140970	160413	87624	55772	31722
15	36:14.8	100	78	342384	341731	106623	85648	69865	48455	68438	149275
16	36:15.7	100	100	662445	60581	26529	39365	9172	23180	5354	5660
17	36:16.7	100	90	928197	143752	33236	10939	42784	38281	16357	15285
18	36:17.9	100	66	593160	88463	7741	43197	56552	54908	23840	25955
19	36:18.8	100	50	592941	177177	70120	44977	25390	53848	39506	8666
20	36:19.8	100	50	1121602	82235	15666	87689	37418	46570	28407	7456
21	36:20.7	100	50	916656	37859	13453	26634	11016	14302	5956	2591
22	36:21.7	100	50	263050	16640	1542	1977	12458	8393	2282	1297
23	36:22.7	90	14	2187137	801070	68602	63400	142310	91100	88444	24287
24	36:23.7	90	14	599307	290106	106141	36392	76524	20972	6189	11545

Fig. 8 EEG samples with all five bands of subject 1

5. ALGORITHM IMPLEMENTATION FOR FEATURE EXTRACTION

A. DISCRETE WAVELET TRANSFORM

When the input data to an algorithm is too large to be processed and it is suspected to be redundant then it can be transformed into a reduced set of features (also named features vector). This process is called feature extraction EEG feature extraction is done by using wavelet transform. But there are multiple wavelets available in the wavelet family therefore a suitable wavelet has to be chosen for the efficient extraction of different feature of EEG. EEG features mainly contains the different frequency bands they are:

- Alpha
- Beta
- Gamma
- Theta
- Delta

Wavelet transforms has the advantages of time frequency localization, multi-rate filtering, and scale-space analysis. Wavelet transform uses a variable window size over the length of the signal. The DWT is often introduced in terms of its recovery transform:

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k,l) 2^{-\frac{k}{2}} \psi(2^{-k}t - l) \qquad (1)$$

Here k is related to a as: a = 2k; b is related to l as b = 2k l; and d (k,l) is a sampling of W(a,b) at discrete points k and l.

B. BIORTHOGONAL WAVELET

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Among the different wavelets bior 5.5 has been chosen for the EEG feature extraction. The properties of Bior wavelet are discussed below

Let f_k and g_k belongs to H then f_k and g_k are said to be biorthogonal if

$$(f_j, g_k) = \delta_{jk} \qquad (2)$$

In order to construct two sets of wavelets that is

$$\psi_{j,k} = 2^{\frac{j}{2}} \Psi(2^j x - k) \qquad (3)$$

$$\widetilde{\psi_{J,k}} = 2^{\frac{j}{2}} \psi(2^j x - k) \qquad (4)$$

To construct (3) and (4) g, h, gbar, hbar filters are needed.

The two decomposition sequences are g_n and h_n and two sequences to act as a reconstruction sequences If C^1_n is a data set, then it can be decomposed as

$$c_n^0 = \sum_k g_{2n-k}\, c_k^1 \qquad (5)$$

$$d_n^0 = \sum_k h_{2n-k}\, c_k^1 \qquad (6)$$

For reconstruction

$$C_l^1 = \sum_n \widetilde{h_{2n-l}}\, c_n^0 + \widetilde{g_{2n-l}} d_n^0 \qquad (7)$$

The condition for the perfect reconstruction is

$$g_n = (-1)^{n+1} \widetilde{h_{-n}} \quad \text{and}$$

$$\widetilde{g_n} = (-)^{n+1} h_{-n} \qquad (8)$$

The scaling function is defines as

$$\phi(x) = \sum_n \sqrt{2} \sum_n h_n\, \varphi(2x - n)$$

and

$$\tilde{\phi}(x) = \sqrt{2}\, \sum_n \widetilde{h_n}\, \phi(2x - n) \qquad (9)$$

C. ANALYSIS BY USING DWT

The different bands of raw EEG signal are extracted by using bior 5.5 wavelet functions. The flowchart of the DWT algorithm is as shown in the Fig. 10 The algorithm flow chart for EEG feature extraction contains the following steps:

1) Collecting the Raw EEG signal from the EEG acquisition set up.
2) Raw EEG signal is converted into CSV format that is comma separated values in the Excel sheet.
3) Load the signal into the MATLAB platform.
4) Set the sampling frequency (fs)
5) Use bior 5.5 wavelet for decomposition and reconstruction of a signal to extract the frequency components. Bior 5.5 at 8 levels is used for the decomposition.

After 8 level decomposition the coefficients which lies in the suitable frequency bands off EEG only those coefficients are selected and they represents the different frequency bands of EEG.

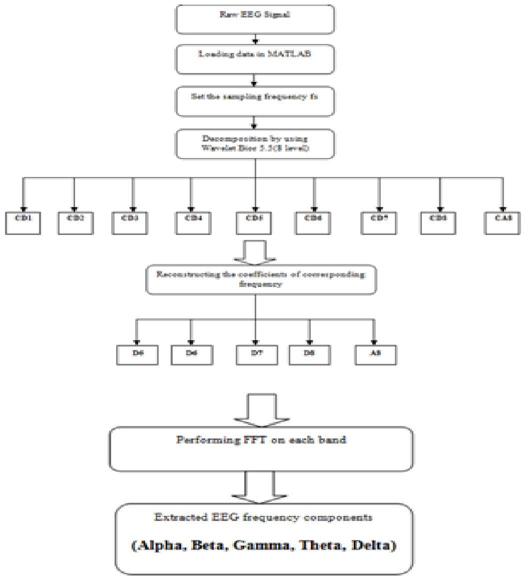


Fig. 10 Flow chart for EEG feature extraction

The Fig. 11 shows the 8-level decomposition tree. Table I describes the frequency range of extracted bands in EEG by using wavelet transform.

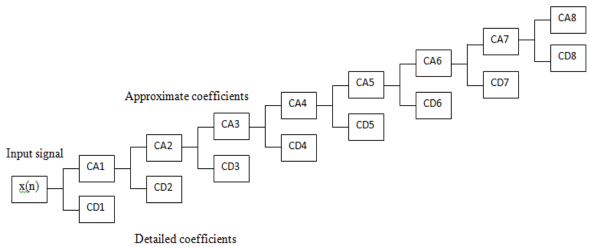


Fig. 11 8- level DWT

DWT successfully analyses the multi-resolution signal at different frequency bands, by decomposing the signal into approximation and detail information. The method for frequency band separation is implemented in MATLAB 2013.EEG requires feature extraction from the acquired signal in specific frequency range of delta, theta, alpha, beta, and gamma. After a first level decomposition, two sequences representing the high and low resolution components of the signal are obtained. The low-resolution components are further decomposed into low and high resolution components. After a second level decomposition, seven more decompositions are done as CA1, CA2, CA3, CA4, CA5, CA6, CA7 and CA8 are the approximate coefficients and CD1,CD2,CD3,CD4, CD5, CD6, CD7 and CD8 are the detailed coefficients obtained after successive decomposition. The multi-resolution analysis, using five levels of decomposition, yields five separate EEG sub-bands. The main objective of the proposed method of is Wavelet Transform the division of the original EEG signals into different frequency bands.

Table I. Decomposition of EEG signals with the sampling frequency of 500 Hz

Frequency range	Frequency bands	Decomposition level
0-4	Delta	A8
4-8	Theta	D8
8-16	Alpha	D7
16-32	Beta	D6
32-64	Gamma	D5

6. RESULTS

In this section, we evaluate the performance of EEG analysis for feature extraction using Bior5.5. First the performance measures the quality of the wavelet used for feature extraction. The Fig.12 shows the extracted frequency bands of EEG in time domain by using Bior 5.5 wavelet and Fig.14. shows the frequency spectrum of EEG bands. Also it is found that precision and quality of the waveform is good by using Bior 5.5 wavelet. Also the frequency bands of EEG lies in the suitable bands as shown in the Fig.13.

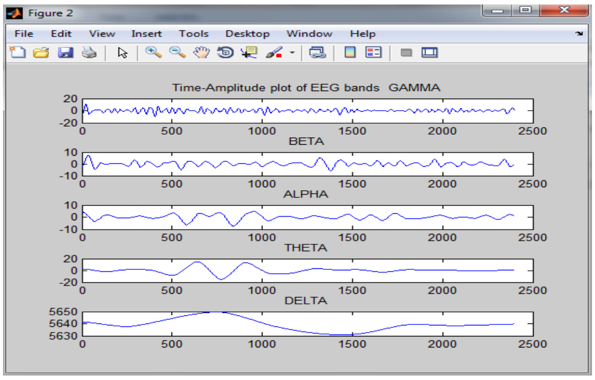


Fig.12. EEG frequency band (time-domain)

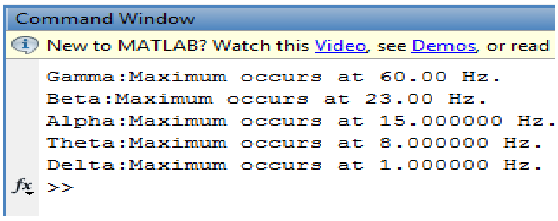


Fig.13 Maximum frequency occurrence of EEG bands

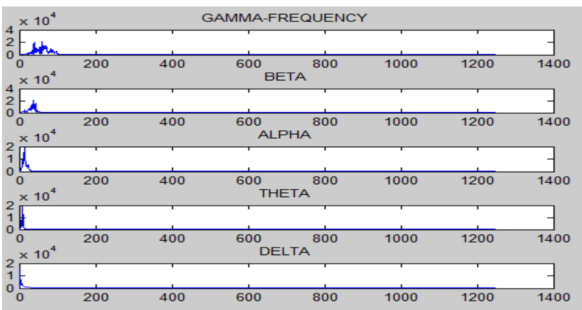


Fig. 14 EEG frequency band (frequency-domain)

From the extracted bands of EEG that is Alpha, Beta, Gamma, Delta and Theta some additional features such as energy properties were found which is tabulated in the below Table II.

ENERGY

Energy is defined as the square root of the average squared instantaneous signal values and it can be calculated by using the formula.

$$X_{energy}=\sqrt{\frac{1}{N}}\sum_{i=1}^{N} x_i^2 \qquad (10)$$

Where N is the number of samples and x is the input signal. The calculated energy of each bands of EEG are Alpha, Beta, Gamma, Theta, Delta of Real 1 subject is shown in the below Table II. It is found that gamma band has higher energy than compared to any other bands. Because the gamma band is high frequency band and its frequency per amplitude is high. Since theta and delta are low frequency bands they found to be having lesser energy.

Table II: Calculated energy of different EEG bands

Name of the subjects	Calculated Energy of different EEG bands				
	E_{Delta}	E_{Theta}	E_{Alpha}	E_{Beta}	E_{Gamma}
Real 1	8.740	15.260	8.328	7.961	21.366

The average energy level graph is shown in Table II for Real 1 subject. Fig.15, represents the Energy level graph of EEG bands.

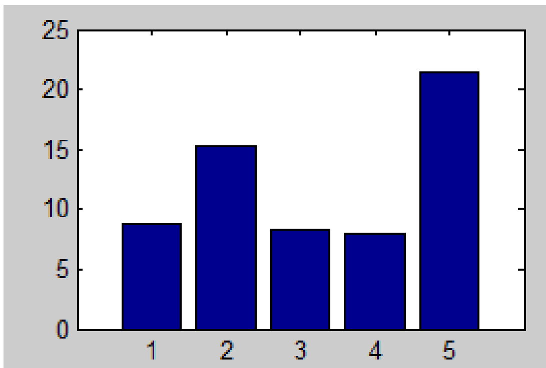


Fig. 15 Energy level chart for EEG bands

7. ACKNOWLEDGMENT

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8. CONCLUSION

In this work, Discrete wavelet transform (DWT) algorithm is proposed for EEG feature extraction, by using a Bior 5.5 wavelet, for classifying the EEG signals. Bior 5.5 wavelet is considered to be a better wavelet, compared to other filters in terms of the frequency bands and precision. So EEG signal acquisition is done using mind wave sensor. Further this work can be implemented using neural network for classification and can be proposed for developing a Brain Computer Interface System.

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