Analysis of Electroencephalogram (EEG) signals

Shayela Nausheen Aziz[1], Naveen Kumar Dewangan[2] , Vinni Sharma[3]

[1,2,3]*Dept of Electronics Engineering, BIT, Durg, C.G., India*

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Abstract: *The electroencephalogram (EEG) popularly known as brain waves represents the electrical activity recorded via electrodes on the scalp. The pattern of electrical activity is useful for diagnosing a number of conditions that affect the brain. The conditions may be epilepsy, dementia, brain tumour etc. In this project EEG signals are analyzed on the real time basis. The signals are extracted from 30 people. The people were of 18 to 25 years of age group with no abnormalities, illness or any disease. The signals for each of the emotions is taken from every person at different time interval. The EEG waves are extracted using the device called Neurosky Mindwave sensor. This sensor captures the brain waves through the electrodes attached to it. This is the four electrode device. The captured data is sent to the ATMEGA 328 where the incoming analog data is converted to digital form to make it compatible with the computer so that it can be further processed. The signal values lies in the range of microvolts. The extracted datas undergoes feature extraction process. The parameters that are used for feature extraction are continuous wavelet transform coefficient (CWT), probability distribution function (PDF), peak plot, and fast Fourier transform (FFT). The extracted EEG signals are displayed and the feature extraction process is done in the LabVIEW software. The accuracy yielded is 90.69% and sensitivity obtained is 85.55%.*

KeyWords: EEG, analysis, continuous wavelet transfer coefficient (CWT), probability distribution function (PDF), peak plot, fast Fourier transform (FFT)

I. INTRODUCTION

The Electroencephalogram popularly known as the brain waves is the electrical activity of the brain. Physiological control processes, thought process and external stimuli generate signals in the corresponding parts of the brain that may be recorded at the scalp using surface electrodes.[15] EEG potentials have random appearing waveforms with peak to peak amplitudes ranging from less than10μV to over 100μV.The bandwidth of the EEG signal is from below 1Hz to 100Hz.[8],[25] The brain wave is extracted and the signal undergoes various processes like data acquisition, filtering, feature extraction and then analysis for analysing the signal in any of the aspect. In data acquisition the recorded signals are converted in the form that can be further processed. Any signal other than that of interest could be termed as noise. These are removed using filters. The EEG is a non-stationary signal the feature extraction from the filtered data is done either in time domain or in frequency domain. Ones the feature is extracted the signals are studied and compared with the normal EEG signal. After undergoing the above processes the brain waves can be compared and detected in any of the perspective. Bioelectric events are picked up from the surface of the body before they can be put into the amplifier for subsequent record or display. This is done by using electrodes.[15]. In this project the classification of EEG signals using an experimental setup is done. The analysis of EEG signal is done on real time basis. This system uses four electrode system. This will be done by placing the electrodes on the forehead, above the ears and placing the ear clip on the left ear of the person whose EEG signal is going to be analysed. These electrodes extract the waves from the brain and sends analog value to controller which is ATMEGA 328 which processes the data of electrodes and makes it compatible to be worked further on the computer. The data from the ATMEGA 328 is fed in the LabVIEW using USB to TTL converter in which this data is compared and analysed to determine the emotion of person.

Table 1.1: Components of brain waves

S no.	Brainwave Type	Frequency Spectrum (Hz)	Amplitude (μV)
1.	Delta	0-3	100-200
2.	Theta	4-7	<30
3.	Alpha	8-12	30-50
4.	Beta	13-30	<20
5.	Gamma	30-50	<10

II. METHODOLOGY

The aim of the project is to do analysis of EEG signals for detection and comparison of brain waves for different emotions i.e. neutral, happy and sad. In order to accomplish this brain waves are extracted from the person using electrodes. The electrodes extract the brain waves and pass this analog signal to the ATMEGA 328 which process the data of the electrodes and makes it compatible to be worked on the computer. The ATMEGA 328 performs analog to digital conversion. This converted data is fed to the computer using USB to TTL converter. The data is fed to the LabVIEW software where the signal of the brain is displayed. The signals displayed are in terms of the micro Volts (μV). The wave ranges from less than 10μV to over 100μV. The values depend on the kind of signal generated by brain. The waves generated by brain for a sad person are in the lower range.[8] For a neutral or normal person the value lies in the mid-range and for a happy person the data is extracted in the higher range of microvolts. The block diagram of the experimental setup is shown below in figure 2.1 and figure 2.2 depicts the experimental setup.

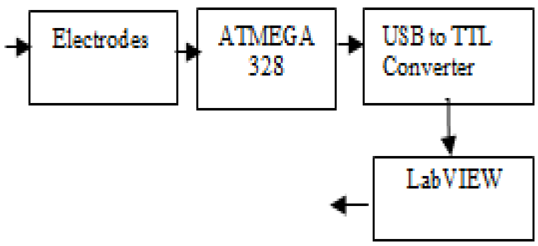


Figure 2.1: Block Diagram

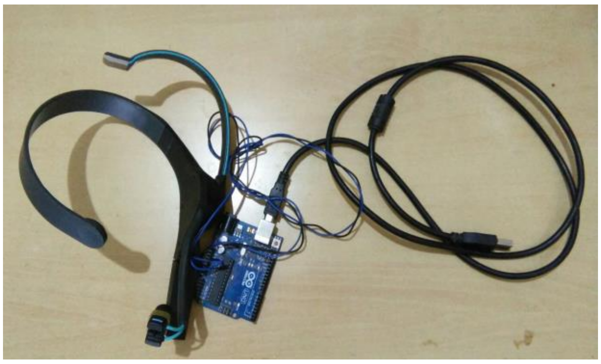


Figure 2.2: Experimental Setup

The extracted datas are stored in the .csv format in the excel sheet. For further processing the data is converted to the .tdms format. Ones the datas are stored the further processing is done of feature extraction. Feature extraction techniques are applied to get features that will be useful in classification. Following are the methods that are used for feature extraction:

- Continuous Wavelet Transform
- Probability Distribution Function
- Peak plot
- Fast Fourier Transform

Continuous Wavelet Transform: The following equation defines

$$CWT_s(a,\tau) = \frac{1}{\sqrt{a}} * \int_{-\infty}^{+\infty} S(t)\psi_o*\left(\frac{t-\tau}{a}\right)dt$$

Where S (t) is the signal, Ψo (t) is the mother wavelet function, a and τ are the scale and shift of the wavelet respectively. User defined scales are used to specify the scales, a can be any positive and real value. If not specified the VI selects a as 1, 2, 3…, scales and τ as 0, dt, 2dt, 3dt,..Ndt where dt is time step and N is approximately equal to the signal.

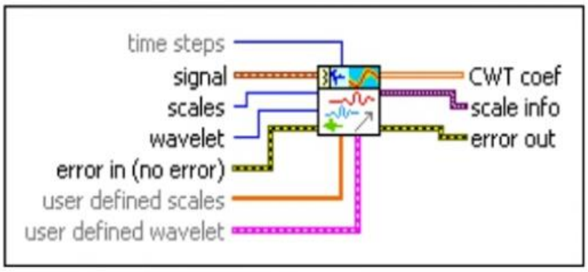


Figure 2.3: Block of CWT coefficient

Probability Density Function: In probability theory, a probability density function (PDF) is defined as a function whose value at any given sample or point in the sample space can be interpreted as providing a relative likelihood that the values of the random variable would equal that sample. The PDF is used to specify the probability of the random variable falling within a particular range of values as opposed to taking on any one value.

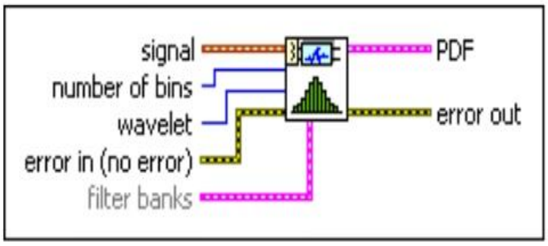


Figure 2.4: Block of PDF

Peak Plot: Peak defines the maximum value that a signal attains. Plotting of the peaks defines the interval at which the peak is attained by the following signal.

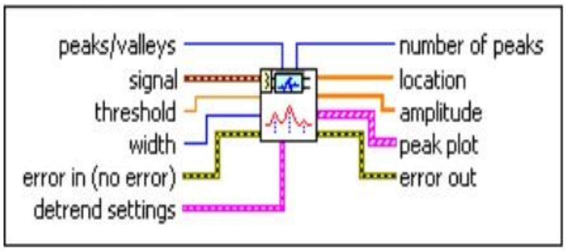


Figure 2.4: Block of Peak Plot

Fast Fourier Transform: Fast Fourier Transform is an algorithm that samples a signal over a period of time or space and divides it into its frequency components. These components are single sinusoidal oscillations at distinct frequencies each with their own amplitude and phase.

The FFT is given by following equation.

$Y_{k} = \sum_{n=0}^{N-1} x_n e^{-j2\pi kn/N}$ for n= 0, 1, 2……, N-1

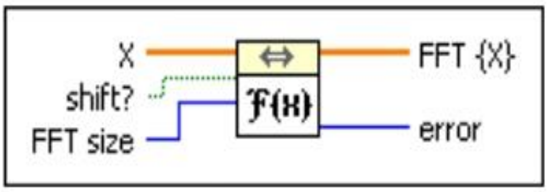


Figure 2.5: Block of FFT

2.1 Components Used

2.1.1 Hardware Components:

Table 2.1.1 Hardware Components

S. No.	Equipment	Device	Quantity
1.	Electrodes / Brainwave Sensor	Neorosky Mindwave Sensor	1
2.	ATMEGA 328	Arduino UNO	1
3.	Cable	USB to TTL Converter	1
4.	P.C.	Laptop	1

2.1.2 Software Components:

Table 2.1.2: Software components

S. No.	Software Used	Purpose
1.	LabVIEW	Display of signal and feature extraction
2.	Arduino IDE	Programming of ATMEGA 328
3.	MS Excel	Data Storage

2.2 Component Description:

2.2.1 Neurosky Mindwave Sensor: Device consists of two sensors which are used to detect and filter EEG signals. One sensor is placed on forehead and is used to detect electrical signals. This sensor also collects noise from environment generated by human muscle, computers, light bulbs, etc. Other sensor is clipped on ear and is used as ground and reference to filter out the electrical noise.

2.2.2 Arduino Uno: The Arduino UNO is a widely used open-source microcontroller board based on the ATMEGA 328 microcontroller and developed by Arduino.cc. It is programmable with the ArduinoIDE (Integrated Development Environment) via a type B USB cable.

2.2.3 USB to TTL Converter: USB to TTL Level Serial Converter Board, which provides a way to link from USB port on computer to connect 5V or 3.3V TTL level serial interface devices.

2.2.4 LabVIEW: LabVIEW (Laboratory Virtual Instrument Engineering Workbench), created by National Instruments is a graphical programming language that uses icons instead of lines of text to create applications. LabVIEW is consisted of Front Panel window and Block Diagram window. Front Panel window consists of controls and indicators that is, input and output/display, respectively. Block Diagram window consists of Terminals or Icons corresponding to front panel controls and indicators, as well as constants, function, SubVIs, structure, and wires that connect data from one object to another.

2.3 Program

2.3.1 LabView program for displaying the brain EEG signal

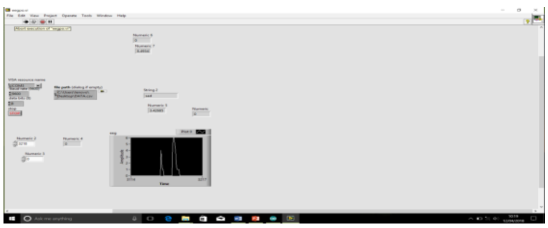


Figure 2.3.1.1: Front Panel for displaying the EEG signal

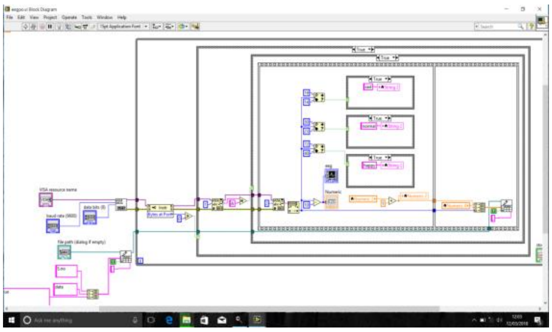
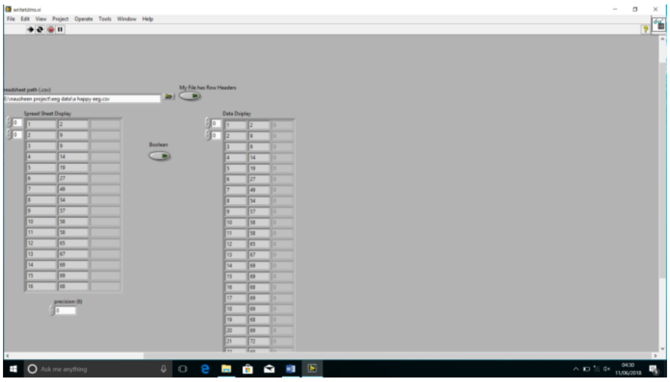
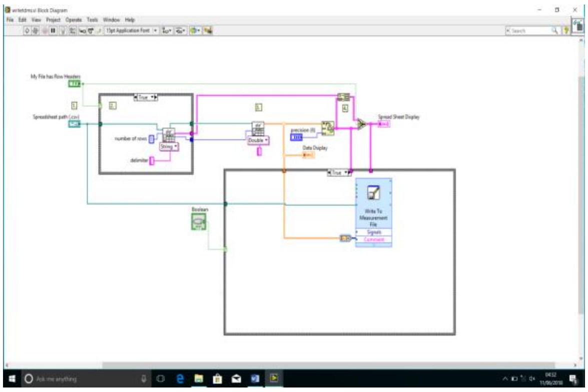


Figure 2.3.1.2: Block Diagram for displaying the EEG signal

2.3.2 LabVIEW program for conversion of .csv file to .tdms file

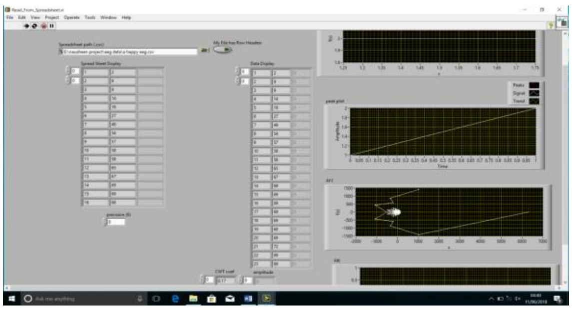


2.3.2.1 Front Panel for conversion of .csv file to .tdms file

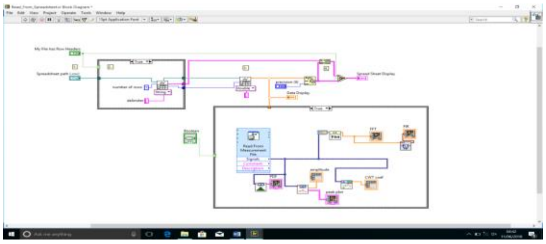


2.3.2.2 Block diagram for conversion of .csv file to .tdms file

2.3.3 LabVIEW program for feature extraction of the EEG signal



2.3.3.1 Front Panel for Feature Extraction



2.3.3.2 Block diagram for feature extraction

III. RESULT

3.1 Values of the signal generated by brain:

The EEG signals of 30 people are extracted. Brain waves for all the three emotional states i.e. neutral, happy and sad are extracted from each of the persons in different time interval. After the analysis following are the values that has been extracted

Table 3.1.1: Values of signal generated by brain for different emotions

S. No.	Emotions	Range (in microvolts)
1.	Neutral	23-30
2.	Happy	40-72
3.	Sad	14-19

3.2 Feature Extraction:

The following parameters for feature extraction has been applied on data extracted of one person for each of the emotional states. For each of the states there are 200 datas after removing zeroes.

3.2.1 CWT Coefficient

With time step as -1, at 64 scales and no error, wavelet function db02 is taken which yields the following output for different states

- For Neutral State- 0.29
- For Happy State- 0.17
- For Sad State- -0.18

3.2.2 Probability Distribution Function

Number of bins taken is 0 with wavelet function and no input error. The PDF obtained for three different emotional states are as follows

- For Neutral State- A valley is obtained at f(x) = 0.33, x = 2
- For Happy State- A constant plot at f(x) = 2
- For Sad State- A constant plot at f(x) = 0.182

The plot for PDF of three different states is given below.

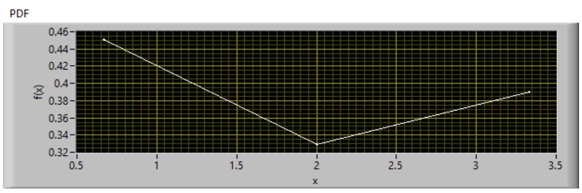


Figure 3.2.2.1 PDF for Neutral State

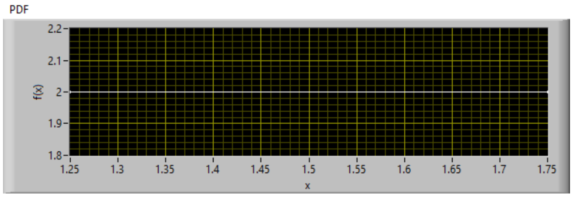


Figure 3.2.2.3 PDF for Happy State

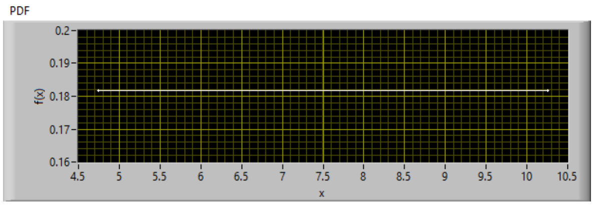


Figure 3.2.2.4 PDF for Sad State

3.2.3 Peak Plot:

Threshold is kept at 0, width is 8 and without any input error following are values obtained for the peak plot for different emotional states

- For Neutral State- Peak Amplitude = 4 at Time = 2
- For Happy State- Peak Amplitude = 2 at Time = 1
- For Sad State- Peak Amplitude = 13 at Time = 1

The plot is shown below

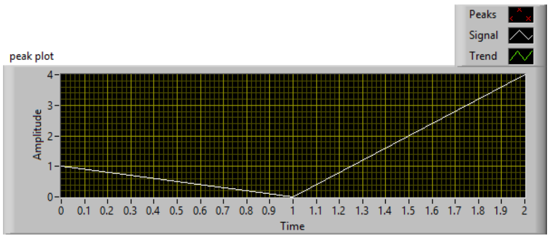


Figure 3.2.3.1 Peak Plot for Neutral State

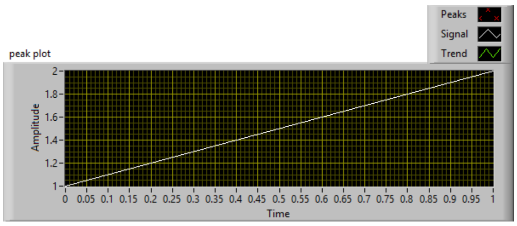


Figure 3.2.3.2 Peak Plot for Happy State

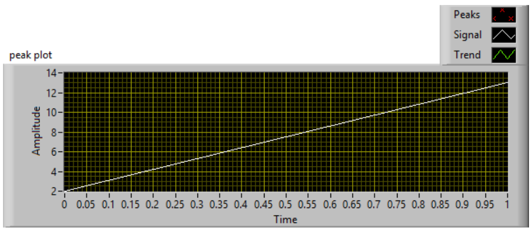


Figure 3.2.3.3 Peak Plot for Sad State

3.2.4 Fast Fourier Transform:

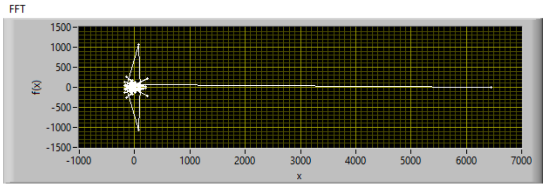


Figure 3.2.4.1 FFT for Neutral State

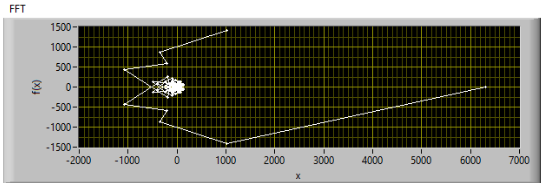


Figure 3.2.4.2 FFT for Happy State

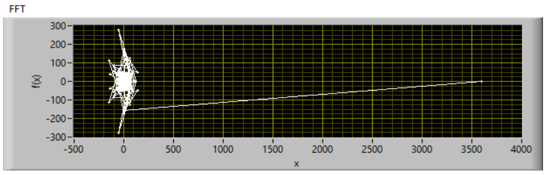


Figure 3.2.4.3 FFT for Sad State

3.3 Parameter Estimation:

Table 3.3.1: Testing Confusing Matrix

Emotion States	No. of testings	Normal	Happy	Sad
Normal	30	N→ N	N→ H	N→ S
Happy	30	H→ N	H→ H	H→ S
Sad	30	S→ N	S→ H	S→ S

True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) obtained for different states are:

Normal State:

TP = (N →N)

FP = (H →N) + (S →N)

FN = (N →H) + (N →S)

TN = (H→H) + (H →S) + (S →H) + (S →S)

Happy State:

TP = (H →H)

FP = (N →H) + (S →S)

FN = (H →N) + (H →S)

TN = (N →N) + (N →S) + (S →N) + (S →S)

Sad State:

TP = (S →S)

FP = (N →S) + (H →S)

FN = (S →N) + (S →H)

TN = (N →N) + (N →H) + (H →N) + (H →H)

Accuracy (Acc) =

{(TP + TN) / (TP + TN + FP + FN)} * 100

Sensitivity (Se) = { TP / (TP + FN) } * 100

Table 3.3.2: Parameters

Emotion States	TP	FP	TN	FN	Se (%)	Acc (%)
Normal	25	7	53	5	83.3	86.6
Happy	26	4	58	4	86.6	92.3
Sad	26	2	58	4	86.6	93.3

Average accuracy obtained is 90.69% and average sensitivity obtained is 85.55%.

IV CONCLUSION

Electroencephalogram (EEG) opens a window for exploring neural activity and brain functioning. Changes in brain electrical activity occur very quickly and extremely high time resolution is required to determine the precision at which these electrical events take place. By analyzing the EEG signal we can get the knowledge about the kind of signals generated in brain for different emotions, in case of brain injury or in case of any brain disease and compare it from normal EEG signal. Today's EEG technology can accurately detect brain activity at a resolution of a single millisecond. Careful analysis of the EEG records can provide valuable and improved understanding of the brain electrical mechanisms.

In this work the EEG signals from 30 people have been taken and classified into three emotional states i.e. happy, neutral and sad. These signals for different emotional states have been taken from each of the person at different time interval. The features of these classified signals are extracted using CWT coefficient, PDF, peak plot and fast fourier transform. The accuracy yielded is 90.69% and sensitivity obtained is 85.55%.

Future Scope:

- The method described by using the NeuroSky Mindwave Sensor will be helpful in governing the mental state of the ADHD patients and also of the patients in coma.
- This can be also used for detection and comparison of brain waves for any kind of brain injury or mental illness.
- By using the NeuroSky Mindwave Sensor a Brain Computer Interface can be developed which will be helpful for the paralytic patients who cannot move.

V ACKNOWLEDGEMENT

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