# IMPLEMENTATION OF SHORT TERM FOURIER TRANSFORM ALGORITHM FOR THE CLASSIFICATION OF EEG SIGNALS TO VALIDATE HAND MOVEMENT

**By**

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## BONAFIDE CERTIFICATE

Certified that this project report entitled "**IMPLEMENTATION OF SHORT TERM FOURIER TRANSFORM ALGORITHM FOR THE CLASSIFICATION OF EEG SIGNALS TO VALIDATE HAND MOVEMENT**" is the bonafide work of **D.KARTHIK KUMAR** [Reg. no. 1020106008] who carried out the research under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

13/5/11

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# ABSTRACT

This project outlines the classification of EEG signals obtained during hand movement using Short time fourier transform algorithm to validate Mu-rhythm. Electroencephalography (EEG) is widely used in clinical settings to investigate neuropathology. Since EEG signals contain a wealth of information about brain functions, there are many approaches to analyzing EEG signals with spectral techniques. Mu rhythm is usually encompassed in the alpha range (8-12Hz), it is strongly suppressed during the performance of contralateral motor acts. Modulation of the μ rhythm is believed to reflect the electrical output of the synchronization of large portions of pyramidal neurons of the motor cortex which control the hand and arm movement when inactive.

The role of signal processing is crucial in the development of a real-time Brain Computer Interface. Until recently, several improvements have been made in this area, but none of them have been successful enough to use them in a real system. The goal of creating more effective classification algorithms, have focused numerous investigations in the search of new techniques of feature extraction. The main objective of this study is the establishment of STFT algorithm which allows EEG signal classification between given tasks. The extension is to interface to a prosthetic device to assist movements for the physically challenged and paralysed.

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# CHAPTER 1

# INTRODUCTION

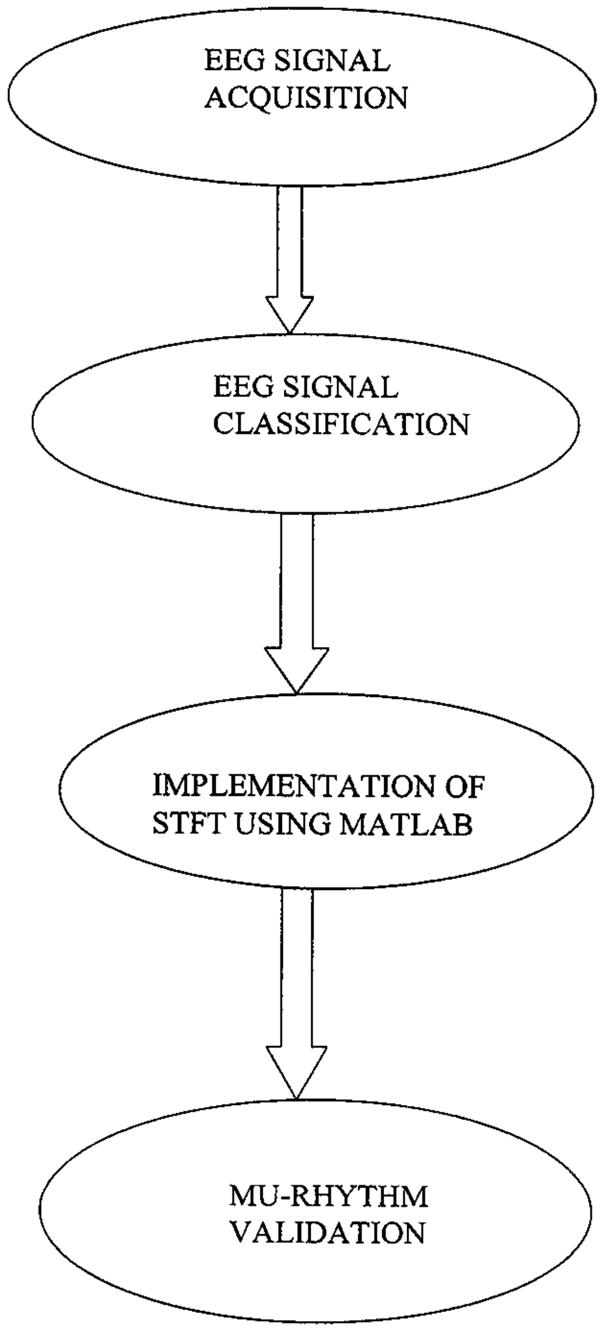
The EEG signals are used as a vector of communication between men and machines. It represents one of the current challenges in signal theory research. The principal element of such a communication system, more known as "Brain Computer Interface", is the interpretation of the EEG signals related to the characteristic parameters of brain electrical activity.

The role of signal processing is crucial in the development of a real-time Brain Computer Interface. Until recently, several improvements have been made in this area, but none of them have been successful enough to use them in a real system. The goal of creating more effective classification algorithms, have focused numerous investigations in the search of new techniques of feature extraction.

## 1.1 PROJECT GOAL

The main objective of this study is the establishment of optimal classification algorithms and methods which allows EEG signal classification between given tasks. The extension is to interface to a prosthetic device to assist movements for the physically challenged and paralysed.

## 1.2 FLOW DIAGRAM



## 1.3 ORGANIZATION OF THE REPORT

- **Chapter 2** discusses about the electrical activity of brain
- **Chapter 3** reports on EEG data acquisition during hand movement
- **Chapter 4** gives about Implementation of Short term fourier transform
- **Chapter 5** discusses about validation of Mu-Rhythm hypothesis.
- **Chapter 6** demonstrates the results that are simulated.
- **Chapter 7** gives the conclusion of the project.

# CHAPTER 2

# ELECTRICAL ACTIVITY OF BRAIN (EEG)

**Electroencephalography (EEG)** is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp.

EEG obtained from scalp electrodes is a sum of the large number of neurons potentials. The interest is in studying the potentials in the sources inside the brain and not only the potentials on the scalp, which globally describe the brain activity. Direct measurements from the different centers in the brain require placing electrodes inside the head, which means surgery. This is not acceptable because of the risk for the subject. Another possibility is to calculate the signals of interest from the EEG obtained on the scalp. These signals are weighed sums of the neurons activity, the weights depending on the signal path from the brain cell to the electrodes. Because the same potential is recorded from more than one electrode, the signals from the electrodes are supposed to be highly correlated. If the weights were known, the potentials in the sources could be computed from a sufficient number of electrode signals. Independent component analysis (ICA), sometimes referred to as blind signal separation or blind source separation, is a mathematical tool that can help solving the problem.

## 2.1 Wave patterns

### 2.1.1 Delta waves:

Delta is the frequency range up to 4 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow wave sleep. It is also seen normally in babies.

### 2.1.2 Theta waves:

Theta is the frequency range from 4 Hz to 7 Hz. Theta is seen normally in young children. It may be seen in drowsiness or arousal in older children and adults; it can also be seen in meditation

### 2.1.3 Alpha waves:

Alpha is the frequency range from 8 Hz to 12 Hz. It emerges with closing of the eyes and with relaxation, and attenuates with eye opening or mental exertion.

### 2.1.4 Mu-Rhythm:

Mu ranges 8–13 Hz, and partly overlaps with other frequencies. It reflects the synchronous firing of motor neurons in rest state. Mu suppression is thought to reflect motor mirror neuron systems, because when an action is observed, the pattern extinguishes.

### 2.1.5 Beta waves:

Beta is the frequency range from 12 Hz to about 30 Hz. It is seen usually on both sides in symmetrical distribution and is most evident frontally.

### 2.1.6 Gamma waves:

Gamma is the frequency range approximately 30–100 Hz. Gamma rhythms are thought to represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function.

# CHAPTER 3

# EEG DATA ACQUISITION

## 3.1 EEG DATA ACQUISITION:

EEG signals was taken at SRMC hospital for normal person using Neuroscan EEG machine. In our study, we took raw EEG data values for two persons at resting state and in moving state.

## 3.2 Electrode Placement:

EEG signals are measured at the scalp by affixing an array of electrodes positioned according to the 10-20 international system and with reference to digitally linked ears (DLE). DLE referenced voltages are obtained by using the average of voltages at both ear lobes as reference. The ear lobes are selected because they constitute an almost quiet reference. As a matter of fact, they present small influences due to temporal activity.

## 3.3 10/20 SYSTEM OF ELECTRODE PLACEMENT:

### 3.3.1 Overview:

From an electrical engineers perspective, EEG signals originate from the summation of a large number of events where small voltage pulses are generated by electrochemical activity. Each pulse can be seen as an electrical dipole having a vector direction. The electrical energy of the pulse travels through the conductive tissue and fluids of the brain, through the skull, scalp, and to our electrodes. The head can be modeled as a "volume conductor", with essentially equal conductance throughout. Electrical signals travel at the speed of light in a volume conductor. There are other neurological pathways that transmit information in an electrochemical chain can be considered for future work. From an EEG perspective, we can only measure that activity which results in significant electrical energy being released into the volume conductor.

### 3.1.2 Ground Electrode

With modern instrumentation, the ground electrode plays no significant part in the measurement. It is only necessary to provide "electronic housekeeping" for the amplifiers. Therefore it can be placed anywhere on the body. A conductive rubber wrist strap electrode for convenience.

### 3.1.3 Test Procedure

The following test was performed to measure the effects of electrode placement on signals originating in various parts of the brain.A fish bowel approximately the size of a human skull was outfitted with silver chloride electrodes epoxied to the sides of the bowel. Placements were at simulated left ear, right ear, and Cz. Additional electrodes simulated a narrow bipolar placement such as Cz-C4, and a wider placement such as C3-C4. The bowel was filled with a saline solution approximating that of biological fluids.An electronic signal source of approximately 10 Hz was connected to a "dip stick" consisting of a plastic rod with two silver chloride buttons on either side. This allowed simulating a dipole type signal with a know location and vector direction in the fluid. The electrode labels correspond to their position with respect to the brain zones, i.e. Fronto-polar(Fp), Frontal (F), Central (C), Temporal (T), Parietal (P) and Occipital (O). Odd indexes are located in the left hemisphere and even ones in the right hemisphere

### 3.1.4 Bipolar, Close Spaced

This type of placement emphasizes the area of the head immediately under the electrodes. It is most sensitive to dipoles oriented inline between the electrodes.

### 3.1.5 Bipolar, Wide Spaced

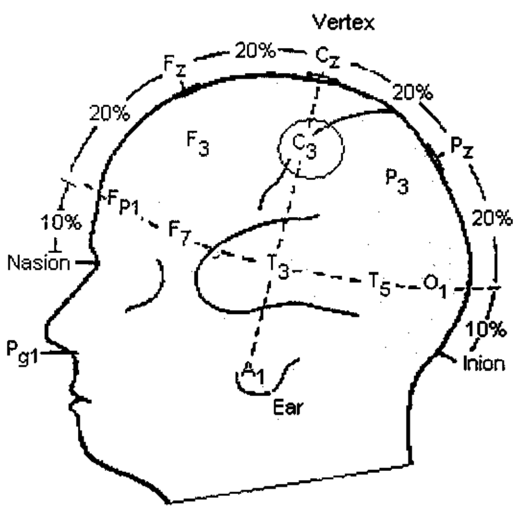
The two main differences in this placement is the deeper penetration into the head, and the tendency to emphasis the areas immediately under the electrodes.

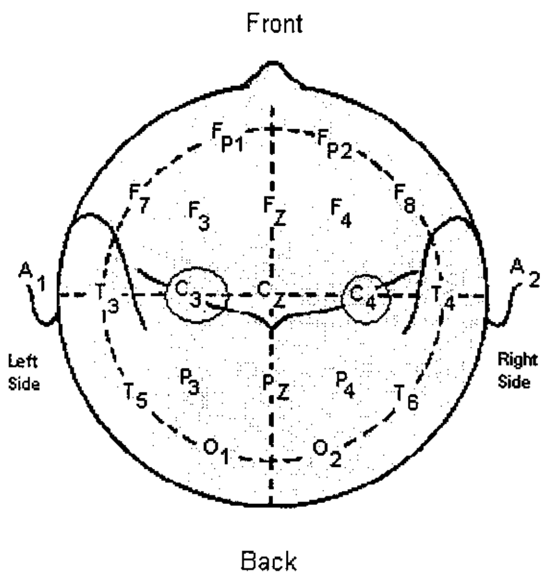
### 3.1.6 Right Ear to Cz

This placement is really the same as bipolar wide spaced, except that the ear is one of the electrodes. By moving the Cz electrode a short distance would probably not produce a significantly different result.

### 3.1.7 Linked Ears to Cz

Tends to spread pickup to the whole head. Again we get some emphasis of the areas just under electrodes. This small difference probably explains why we are able to do scanning with this configuration. With statistical analysis the small differences can be made significant. Of course, anything else that produces small differences would also affect the measurements.



## 3.4 EEG DATA ACQUIRED

### SUBJECT 1: EEG DATA VALUES AT RESTING STATE

Table 3.4.1 EEG data values at resting state of subject 1

TimePoints=5500 Channels=6 BeginSweep[ms]=0.00
SamplingInterval[ms]=2.000 Bins/uV=1.000 Time=12:07:04

| F4-A2 | C4-A2 | P4-A2 | F3-A1 | C3-A1 | P3-A1 |
|---|---|---|---|---|---|
| -7.76 | -8.05 | -9.77 | 0.50 | -0.25 | 0.91 |
| -7.15 | -6.93 | -8.71 | 0.59 | -0.28 | 0.94 |
| -6.00 | -5.58 | -7.48 | 0.49 | -0.40 | 0.84 |
| -4.26 | -3.75 | -5.69 | 0.29 | -0.55 | 0.67 |
| -2.79 | -2.23 | -3.53 | 0.09 | -0.67 | 0.56 |
| -2.08 | -1.02 | -0.82 | -0.14 | -0.81 | 0.52 |
| -3.20 | -1.51 | 0.75 | -0.58 | -1.14 | 0.28 |
| -5.82 | -4.22 | -0.71 | -1.19 | -1.70 | -0.21 |
| -8.01 | -6.88 | -2.94 | -1.69 | -2.13 | -0.63 |
| -8.78 | -8.09 | -3.74 | -1.97 | -2.27 | -0.75 |
| -7.61 | -7.55 | -2.88 | -2.19 | -2.26 | -0.64 |
| -5.52 | -5.93 | -1.29 | -2.21 | -2.05 | -0.27 |
| -3.66 | -4.45 | -0.19 | -2.19 | -1.87 | 0.04 |
| -2.46 | -3.23 | 0.43 | -2.18 | -1.76 | 0.27 |
| -1.62 | -1.84 | 0.72 | -2.22 | -1.67 | 0.45 |
| -1.31 | -0.72 | 0.54 | -2.20 | -1.53 | 0.64 |
| -1.54 | -0.22 | 0.09 | -2.24 | -1.46 | 0.69 |
| -0.82 | 1.37 | 0.33 | -2.20 | -1.31 | 0.85 |
| -0.58 | 3.71 | 1.16 | -2.00 | -0.98 | 1.24 |
| -1.65 | 4.10 | 1.18 | -1.74 | -0.64 | 1.59 |
| -2.70 | 2.81 | 0.22 | -1.36 | -0.26 | 1.91 |
| -3.51 | 1.49 | -0.95 | -0.89 | 0.13 | 2.18 |
| -4.33 | 0.14 | -2.14 | -0.55 | 0.43 | 2.31 |
| -5.38 | -1.62 | -3.59 | -0.32 | 0.59 | 2.29 |
| -5.95 | -3.46 | -5.12 | 0.13 | 0.94 | 2.47 |
| -5.45 | -4.92 | -6.33 | 0.87 | 1.57 | 2.88 |
| -5.12 | -6.48 | -7.41 | 1.58 | 2.16 | 3.12 |
| -5.56 | -8.34 | -8.60 | 1.96 | 2.37 | 2.97 |
| -6.08 | -9.95 | -9.62 | 2.12 | 2.37 | 2.63 |
| 7.34 | 9.46 | 6.08 | -2.21 | -1.70 | -3.88 |

## SUBJECT 1:EEG DATA VALUES AT HAND MOVING STATE

Table 3.4.2 EEG data values at moving state of subject 1

TimePoints=5500 Channels=6 BeginSweep[ms]=0.00
SamplingInterval[ms]=2.000 Bins/uV=1.000 Time=12:07:14

| F4-A2 | C4-A2 | P4-A2 | F3-A1 | C3-A1 | P3-A1 |
|---|---|---|---|---|---|
| -8.51 | -9.27 | -3.34 | -3.24 | -3.44 | -2.16 |
| -7.71 | -7.76 | -2.53 | -4.11 | -4.21 | -2.78 |
| -7.11 | -5.88 | -1.36 | -5.25 | -5.26 | -3.73 |
| -5.15 | -2.84 | -0.04 | -6.02 | -5.96 | -4.39 |
| -4.43 | -1.56 | -0.17 | -6.54 | -6.42 | -4.93 |
| -4.96 | -2.60 | -1.82 | -7.09 | -6.96 | -5.68 |
| -4.28 | -2.37 | -2.39 | -7.43 | -7.29 | -6.25 |
| -2.52 | -0.77 | -1.61 | -7.38 | -7.21 | -6.40 |
| -0.62 | 0.54 | -0.85 | -7.31 | -7.10 | -6.54 |
| 1.05 | 1.01 | -0.69 | -7.19 | -7.00 | -6.68 |
| 2.00 | 1.48 | -0.14 | -6.85 | -6.74 | -6.62 |
| 3.37 | 3.24 | 1.79 | -6.24 | -6.21 | -6.26 |
| 6.27 | 7.32 | 5.03 | -5.51 | -5.48 | -5.64 |
| 6.50 | 9.16 | 6.05 | -4.80 | -4.87 | -5.06 |
| 6.20 | 8.41 | 5.33 | -4.16 | -4.36 | -4.57 |
| 6.38 | 7.88 | 5.35 | -3.75 | -4.06 | -4.25 |
| 8.47 | 9.36 | 7.39 | -3.05 | -3.44 | -3.53 |
| 8.73 | 9.30 | 8.14 | -2.29 | -2.81 | -2.83 |
| 6.59 | 7.65 | 7.28 | -2.06 | -2.68 | -2.60 |
| 4.09 | 4.85 | 4.94 | -2.06 | -2.74 | -2.55 |
| 1.58 | 1.35 | 2.50 | -2.07 | -2.83 | -2.49 |
| 0.50 | -0.81 | 1.95 | -1.86 | -2.71 | -2.27 |
| 0.60 | -1.46 | 2.94 | -1.34 | -2.19 | -1.67 |
| 0.70 | -2.36 | 2.89 | -0.70 | -1.54 | -0.91 |
| -0.48 | -4.47 | 0.78 | -0.39 | -1.23 | -0.51 |
| -0.70 | -4.66 | -0.09 | 0.01 | -0.78 | -0.02 |
| 0.05 | -3.47 | -0.02 | 0.14 | -0.57 | 0.31 |
| 0.32 | -2.47 | -0.51 | 0.33 | -0.36 | 0.63 |
| 0.62 | -0.11 | 0.37 | 0.63 | 0.01 | 1.13 |
| 0.62 | 1.87 | 1.60 | 0.66 | 0.20 | 1.42 |
| -1.36 | 0.49 | 0.08 | 0.36 | 0.03 | 1.28 |
| -4.52 | -2.99 | -3.36 | -0.15 | -0.41 | 0.78 |

## SUBJECT 2: EEG DATA VALUES AT RESTING STATE

Table 3.4.3 EEG data values at resting state of subject 2

TimePoints=5500 Channels=6 BeginSweep[ms]=0.00
SamplingInterval[ms]=2.000 Bins/uV=1.000 Time=12:04:11

| F4-A2 | C4-A2 | P4-A2 | F3-A1 | C3-A1 | P3-A1 |
|---|---|---|---|---|---|
| -8.17 | -5.87 | -4.84 | -1.61 | -0.69 | -3.44 |
| -8.21 | -5.77 | -5.02 | -1.84 | -0.92 | -3.11 |
| -8.31 | -5.80 | -5.26 | -2.25 | -1.48 | -3.45 |
| -8.26 | -5.74 | -5.30 | -2.74 | -2.12 | -3.98 |
| -8.02 | -5.41 | -5.17 | -2.92 | -3.18 | -4.74 |
| -7.46 | -4.91 | -4.86 | -2.11 | -3.95 | -5.48 |
| -6.45 | -4.39 | -4.42 | -0.87 | -4.11 | -5.87 |
| -5.41 | -3.92 | -4.10 | -0.05 | -3.74 | -5.74 |
| -4.51 | -3.31 | -3.64 | 1.41 | -2.45 | -5.29 |
| -3.56 | -2.57 | -2.85 | 2.34 | -1.45 | -5.23 |
| -2.29 | -1.59 | -1.82 | 2.44 | -0.81 | -5.01 |
| -0.91 | -0.45 | -0.89 | 2.91 | 0.09 | -4.21 |
| 0.32 | 0.63 | 0.06 | 4.12 | 1.64 | -2.86 |
| 1.37 | 1.69 | 1.12 | 5.33 | 3.47 | -1.42 |
| 2.46 | 3.03 | 2.31 | 5.31 | 4.60 | -0.35 |
| 3.36 | 4.29 | 3.38 | 5.06 | 4.97 | 0.85 |
| 4.17 | 5.07 | 4.12 | 4.42 | 4.91 | 2.57 |
| 4.82 | 5.73 | 4.77 | 3.14 | 4.98 | 4.53 |
| 5.38 | 6.43 | 5.49 | 3.41 | 6.28 | 6.46 |
| 5.75 | 6.95 | 6.27 | 4.67 | 8.66 | 9.22 |
| 5.95 | 7.05 | 6.62 | 3.75 | 8.51 | 10.21 |
| 6.14 | 7.04 | 6.66 | 2.68 | 8.01 | 10.47 |
| 6.00 | 6.94 | 6.70 | 2.97 | 8.24 | 10.77 |
| 5.53 | 6.59 | 6.69 | 3.44 | 8.21 | 10.64 |
| 4.92 | 6.20 | 6.56 | 3.58 | 7.82 | 10.28 |
| 4.27 | 5.82 | 6.33 | 4.19 | 7.81 | 10.14 |
| 3.62 | 5.25 | 6.05 | 3.87 | 7.15 | 9.08 |
| 3.00 | 4.69 | 5.73 | 2.65 | 5.69 | 6.78 |
| 2.32 | 4.31 | 5.44 | 1.02 | 3.79 | 4.28 |
| 1.64 | 3.92 | 5.24 | -0.29 | 1.51 | 2.02 |
| 1.42 | 3.62 | 5.19 | -1.14 | -0.28 | 0.44 |
| 1.42 | 3.58 | 5.09 | -1.39 | -0.56 | 0.12 |
| 1.09 | 3.49 | 4.93 | -1.27 | -0.11 | 0.50 |

## SUBJECT 2: EEG DATA VALUES AT HAND MOVING STATE

Table 3.4.4 EEG data values at moving state of subject 2

TimePoints=5500 Channels=6 BeginSweep[ms]=0.00
SamplingInterval[ms]=2.000 Bins/uV=1.000 Time=12:04:21

| F4-A2 | C4-A2 | P4-A2 | F3-A1 | C3-A1 | P3-A1 |
|---|---|---|---|---|---|
| -0.14 | 0.73 | -1.65 | 9.39 | 4.77 | 0.82 |
| 0.99 | 1.36 | -1.18 | 11.52 | 6.94 | 3.41 |
| 2.12 | 1.82 | -0.78 | 12.05 | 7.94 | 4.81 |
| 2.75 | 1.91 | -1.00 | 10.77 | 7.22 | 4.12 |
| 2.86 | 1.69 | -1.53 | 9.76 | 6.77 | 3.34 |
| 2.98 | 1.51 | -1.90 | 10.51 | 7.47 | 3.53 |
| 2.95 | 1.23 | -2.45 | 11.05 | 7.88 | 3.74 |
| 2.53 | 0.81 | -3.22 | 9.84 | 6.92 | 2.88 |
| 2.22 | 0.40 | -3.73 | 8.97 | 6.53 | 2.28 |
| 1.97 | 0.03 | -4.09 | 8.09 | 6.70 | 2.06 |
| 1.55 | -0.29 | -4.44 | 6.58 | 7.10 | 2.23 |
| 0.99 | -0.68 | -4.69 | 4.23 | 5.54 | 1.39 |
| 0.49 | -1.16 | -4.78 | 1.66 | 2.69 | -0.16 |
| 0.06 | -1.28 | -4.61 | -1.05 | 0.51 | -0.49 |
| -0.34 | -1.22 | -4.21 | -3.22 | -0.86 | -0.24 |
| -0.71 | -1.25 | -3.74 | -4.84 | -1.83 | -0.21 |
| -0.65 | -0.91 | -2.96 | -5.39 | -2.06 | 0.32 |
| -0.74 | -0.49 | -2.18 | -4.32 | -1.46 | 1.06 |
| -1.11 | -0.35 | -1.50 | -3.69 | -1.02 | 1.58 |
| -1.24 | -0.18 | -0.66 | -2.59 | -0.36 | 2.53 |
| -0.97 | 0.42 | 0.43 | -1.31 | 0.26 | 3.38 |
| -0.70 | 0.98 | 1.53 | -1.62 | -0.64 | 2.61 |
| -0.46 | 1.36 | 2.66 | -2.30 | -1.84 | 1.05 |
| -0.49 | 1.46 | 3.27 | -3.45 | -3.21 | -0.82 |
| -0.44 | 1.65 | 3.83 | -3.73 | -3.82 | -1.83 |
| -0.54 | 1.66 | 4.35 | -3.05 | -3.92 | -1.94 |
| -0.70 | 1.62 | 4.77 | -2.13 | -3.75 | -1.14 |
| -1.21 | 1.51 | 4.95 | -0.42 | -2.84 | 0.97 |
| -2.01 | 1.00 | 4.75 | 0.37 | -3.01 | 2.19 |
| -2.67 | 0.34 | 4.39 | 0.34 | -3.34 | 2.49 |
| -3.03 | -0.06 | 4.06 | 0.56 | -2.54 | 3.06 |
| -3.55 | -0.54 | 3.64 | 0.64 | -2.11 | 2.99 |

- Total of 5000 data points obtained for 10 s EEG recordings.
- Each Notepad file contains data for 6 channels-C3, C4, F3,F4,P3,P4.
- Import of data for 1 channel is done at a time.

# CHAPTER 4

# IMPLEMENTATION OF SHORT TERM FOURIER TRANSFORM

## 4.1. Analysis of EEG signals

In order to detect frequency composition of the EEG signals and identify the abnormalities, spectral analysis of the signals is performed. In this way, frequency band activities in EEG signals are determined and the low-frequency content of band which is the most important part of signal according to epileptic seizure is visualized. To be able to achieve this aim, EEG signals are analyzed by the STFT .For the application of these analysis methods, EEG signals in time domain are sampled at an appropriate frequency. Sampled signals are grouped as frames that contain evident sample numbers. The signals were processed and reconstructed by a system. For this purpose a developer program using Matlab software which is an application development program.

## 4.2. Short-time Fourier transform

Spectral analysis of the EEG signals is performed using the short-time Fourier transform (STFT), In which the signal is divided into small sequential or overlapping data frames and fast Fourier transform (FFT) applied to each one. The output of successive STFTs can provide a time–frequency representation of the signal. To accomplish this, the signal is truncated into short data frames by multiplying it by a window so that the modified signal is zero outside the data frame. In order to analyze the whole signal, the window is translated in time and then reapplied to the signal. Fourier analysis decomposes a signal into its frequency components and determines their relative strengths. This transform is applied to stationary signals, that is, signals whose properties do not evolve in time. When the signal is non-stationary we can introduce a local frequency parameter so that local Fourier transform looks at the signal through a window over which the signal is approximately stationary. Therefore, we applied the STFT to the EEG signals under study. When the window (t) is a Gaussian function, the STFT is called a Gabor transform. The basic functions of this transform are generated by modulation and transformation of the window function(t),where modulation and translation parameters, respectively. The fixed time window is the limitation of STFT as it causes a fixed time–frequency resolution.

Time Frequency distribution was constructed from short-term Fourier transform (STFT).The spectrogram is the squared magnitude of the windowed short-time Fourier transform. It considers the squared modulus of the STFT to obtain a spectral energy density of the locally windowed signal.*Short-Time Fourier Transform* (STFT), maps a signal into a two-dimensional function of time and frequency. The STFT represents a sort of compromise between the time- and frequency-based views of a signal. It provides some information about both when and at what frequencies a signal event occurs. However, you can only obtain this information with limited precision, and that precision is determined by the size of the window. While the STFT compromise between time and frequency information can be useful, the drawback is that once you choose a particular size for the time window, that window is the same for all frequencies. Many signals require a more flexible approach , where we can vary the window size to determine more accurately either time or frequency.

$$x(u)h^*(u-t) \rightarrow \text{Equation (1)}$$

h(t) is a short time analysis window located around $t = 0$ *and* $f = 0$.Thus, we can interpret the spectrogram as a measure of the energy of the signal contained in the time-frequency domain centered on the point $(t, f)$.

# CHAPTER 5

# VALIDATION OF MU-RHYTHM

**Mu rhythm** (μ rhythm) is kind of brain wave rhythm measured using Electroencephalography that has a maximal amplitude of somatosensory cortices at rest. It reflects the synchronous firing of motor neurons in rest state. Mu suppression is thought to reflect motor mirror neuron systems, because when an action is observed, the pattern extinguishes, possibly because of the normal neuronal system and the mirror neuron system "go out of sync", and interfere with each other. It is also called arciform rhythm because of the shape of the waveforms. Usually encompassed in the alpha range (8-12Hz), it is strongly suppressed during the performance of contralateral motor acts. Modulation of the μ rhythm is believed to reflect the electrical output of the synchronization of large portions of pyramidal neurons of the motor cortex which control the hand and arm movement when inactive.

In 1950 Gastaut and his coworkers reported desynchronization of these rhythms not only during active movements of their subjects, but also while the subjects observed actions executed by someone else. These results were later confirmed by additional research groups, including a study using subdural electrode grids in epileptic patients. The latter study showed mu suppression while the patients observed moving body parts in somatic areas of the cortex that corresponded to the body part moved by the actor. Current research concerning the mu rhythm is concerned with the development of this rhythm in infancy, it is possible links to the human mirror neuron system, and the implications of the sensorimotor origins of this rhythm.

# CHAPTER 6

# RESULTS AND DISCUSSION

The Matlab software was used to compute the STFT algorithm to perform the time-frequency analysis for the EEG signals, during resting state and hand movement of two persons. The results computed are shown below.

**SUBJECT 1: AT ELECTRODE POSITION C3**

EEG AT RESTING STATE: EEG AT MOVING STATE:

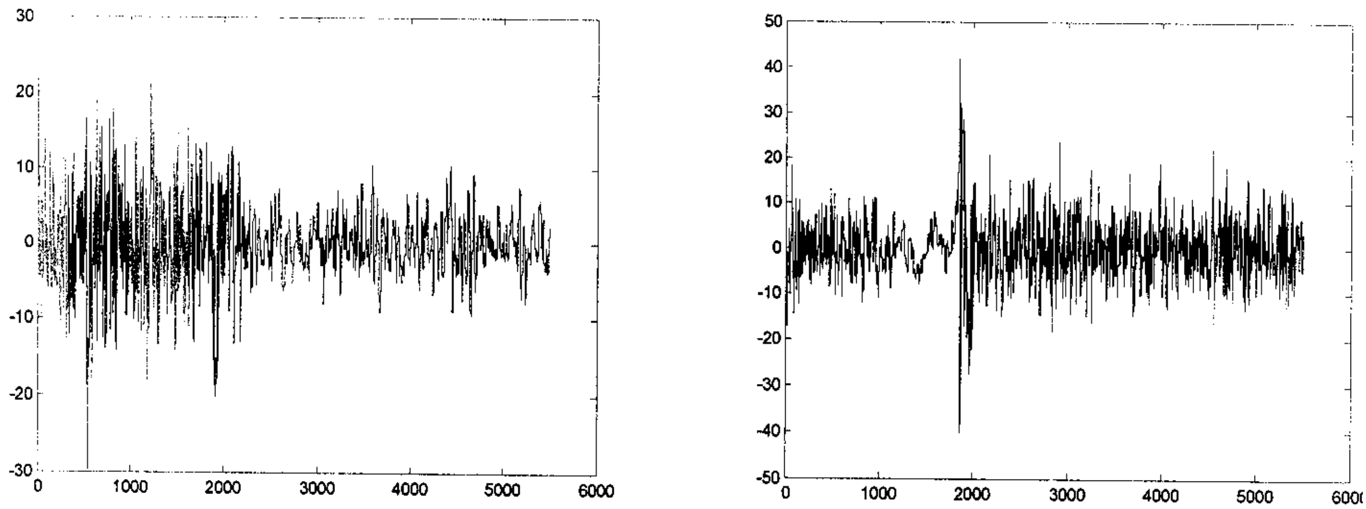


**Figure 6.1 Data samples of EEG at resting and moving state in C3**

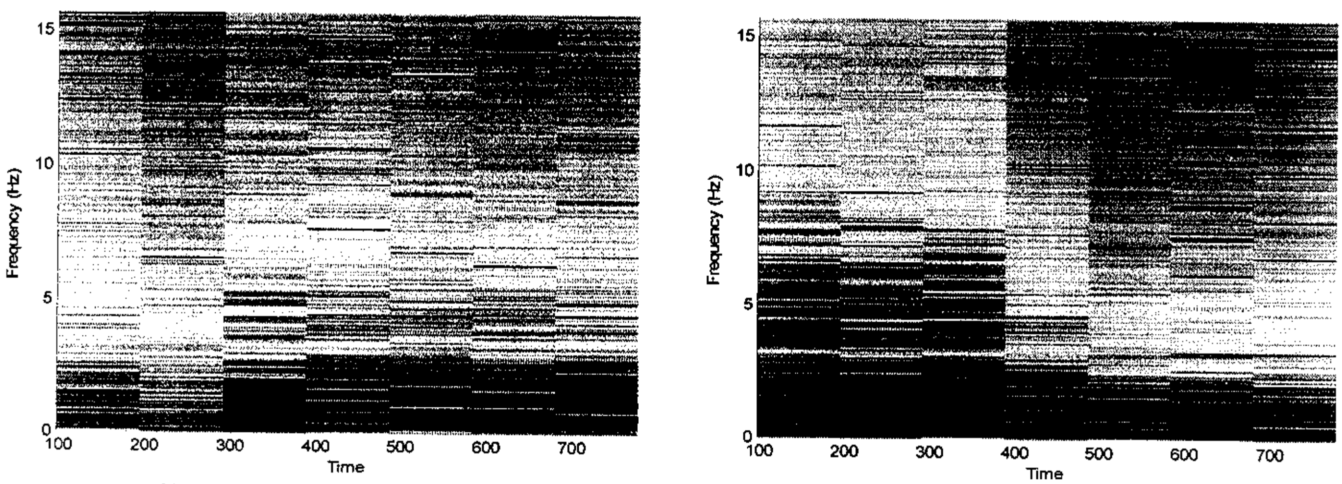



**Figure 6.2 Spectrogram at resting and moving state in c3**

➢ So from the above figure, we can conclude that in resting state the frequency is very low and in the moving state Mu-rhythm(8-13Hz) suppression takes place. This EEG data values are taken from electrode position C3 for subject 1(i.e. Sample of 1$^{st}$ person).

## SUBJECT 2: AT ELECTRODE POSITION C3

EEG at resting state: EEG at moving state:

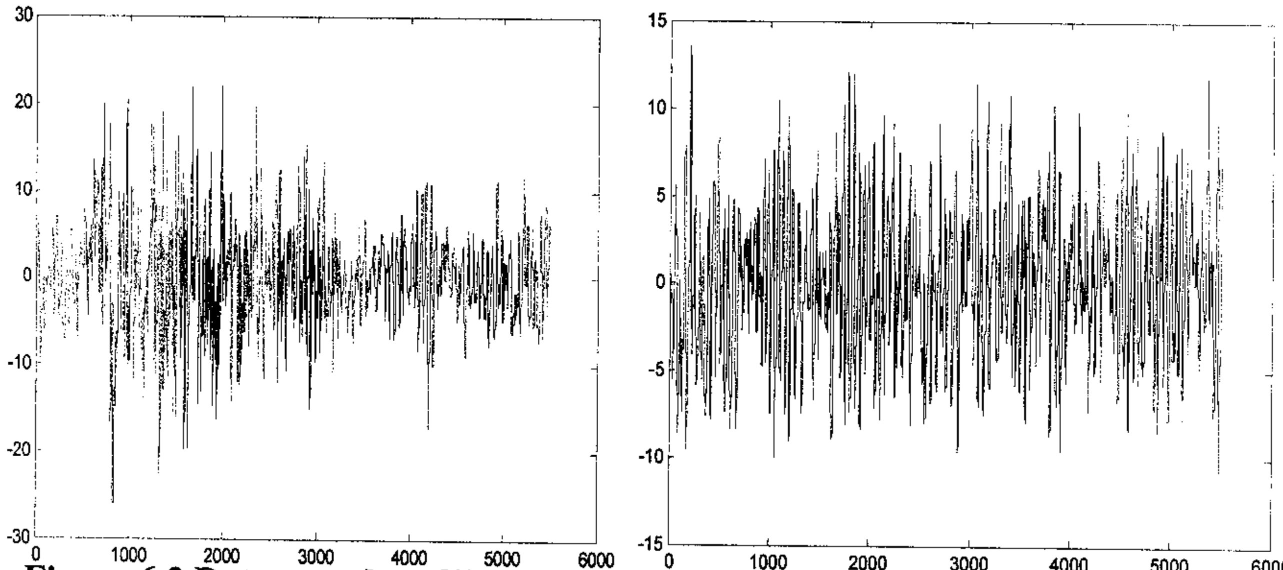



**Figure 6.3 Data samples of EEG at resting and moving state in c3**

Spectrogram at resting state Spectrogram at moving state

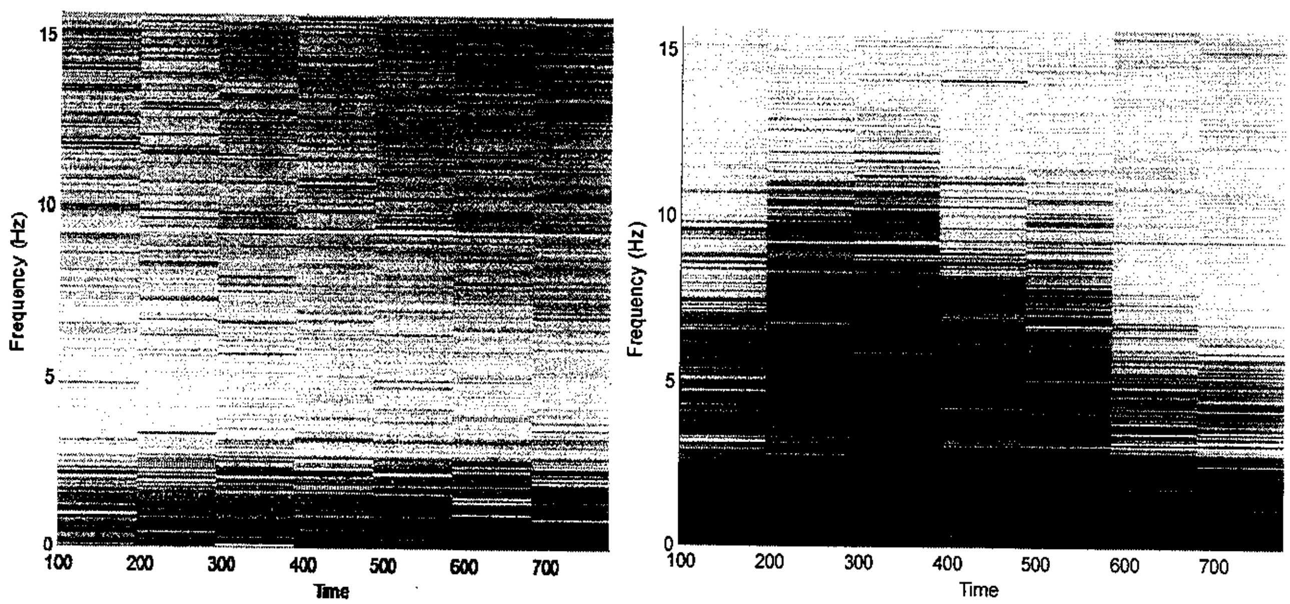



**Figure 6.4 Spectrogram at resting and moving state in c3**

➢ So from the above figure, we can conclude that in resting state the frequency is very low and in the moving state Mu-rhythm(8-13Hz) suppression takes place. This EEG data values are taken from electrode position C3 for subject 2(i.e. Sample of 2nd person).

## SUBJECT 1: AT ELECTRODE C4

EEG at resting state | EEG at moving state

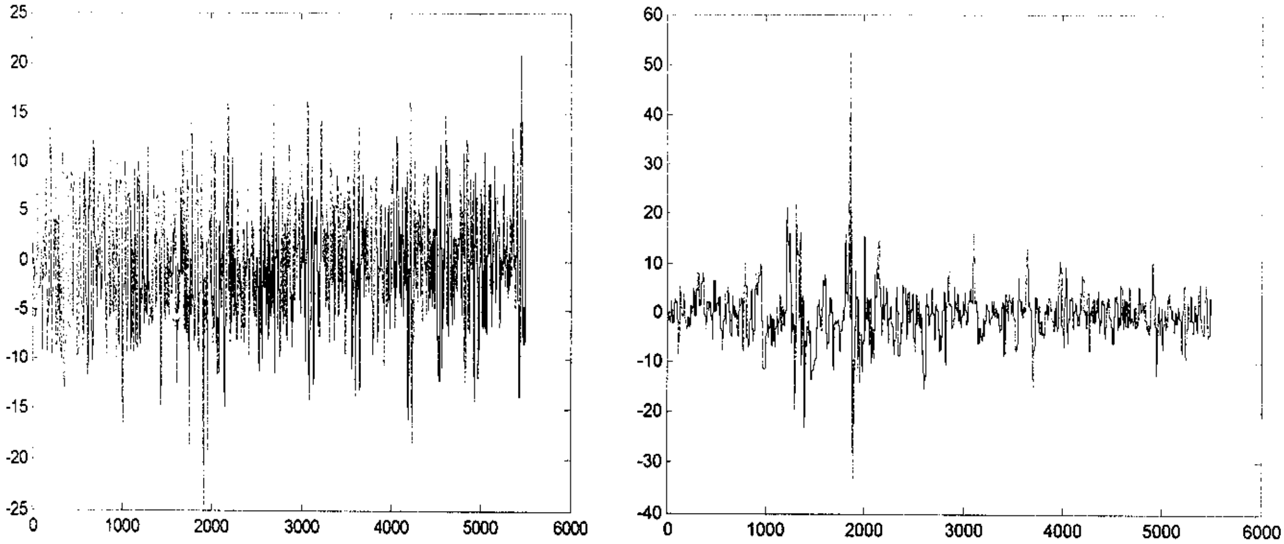



**Figure 6.5 Data samples of EEG at resting and moving state in c4**

Spectrogram at resting state | Spectrogram at moving state

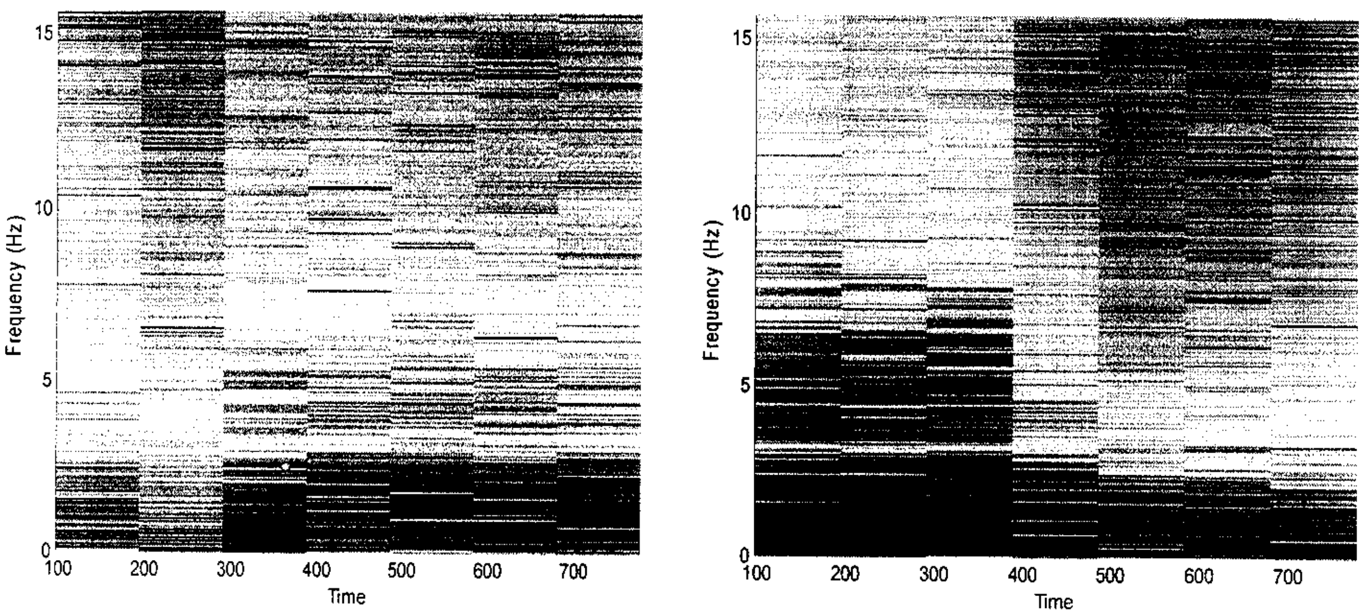



**Figure 6.6 Spectrogram of resting and moving state in c4**

➢ So from the above figure, we can conclude that in resting state the frequency is very low and in the moving state Mu-rhythm(8-13Hz) suppression takes place. This EEG data values are taken from electrode position C4 for subject 1(i.e. Sample of 1st person)

## SUBJECT 2 – AT ELECTRODE C4

EEG at resting state EEG at moving state

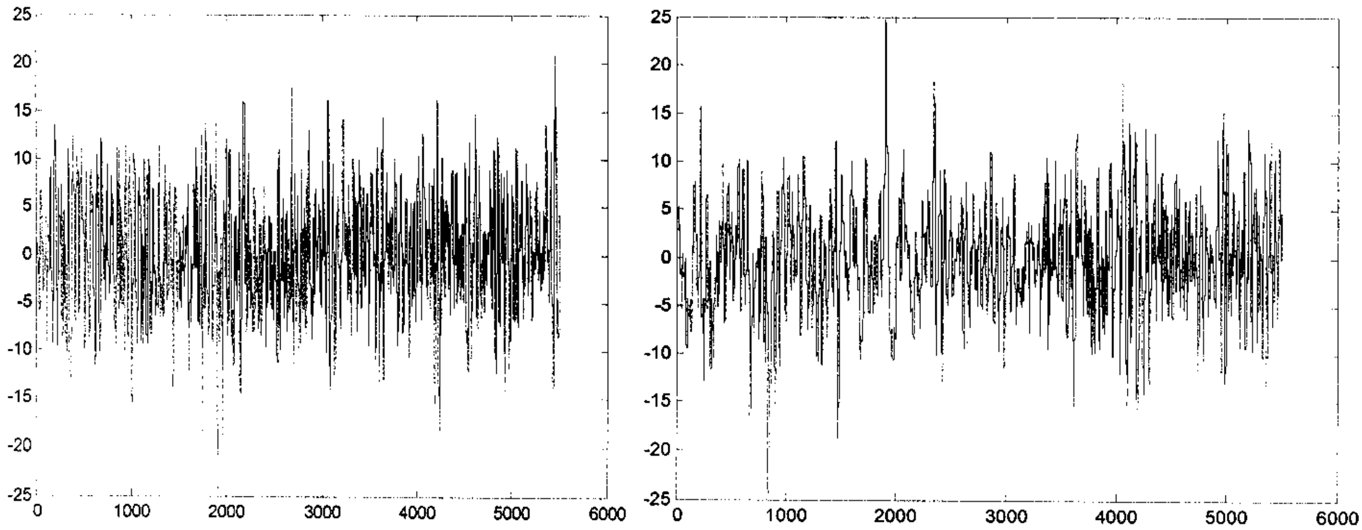


**Figure 6.7 Data samples of EEG at resting and moving state in C4**

Spectrogram at resting state Spectrogram at moving state

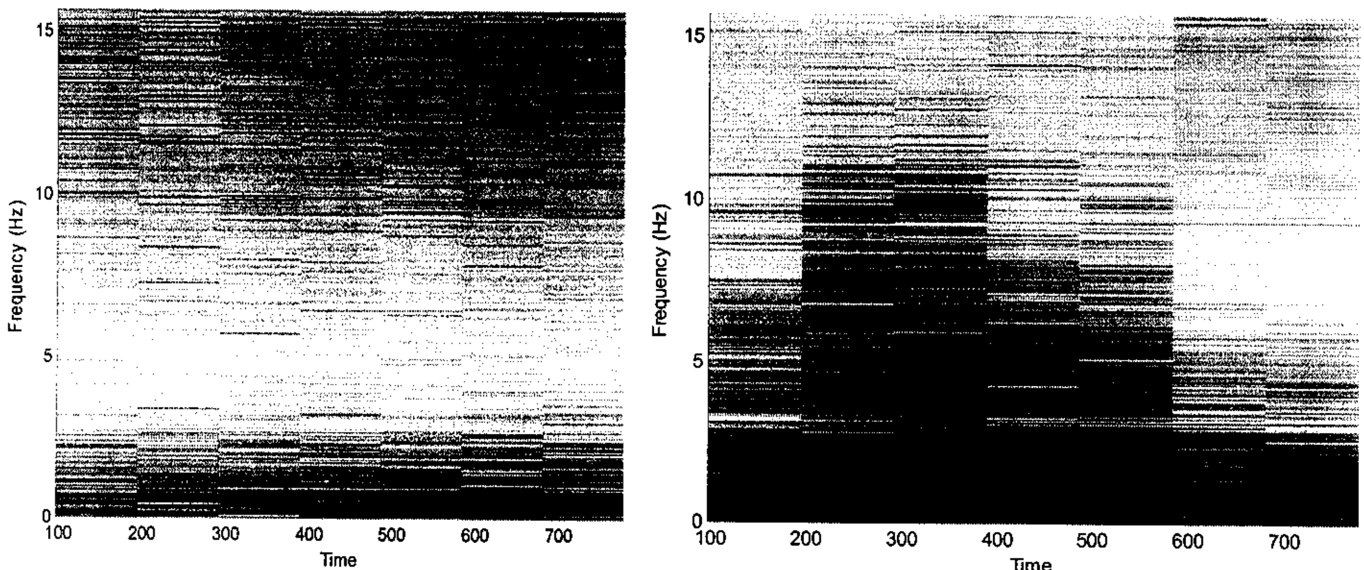



**Figure 6.8 Spectrogram of resting and moving state in C4**

- So from the above figure, we can conclude that in resting state the frequency is very low and in the moving state Mu-rhythm(8-13Hz)suppression takes place. This EEG data values are taken from electrode position C4 for subject 2(i.e. Sample of 2nd person).

## CONCLUSION

The aim of the study is to classify the EEG signals obtained during the hand movement at resting state and moving state. The Mu-Rhythm ranges 8–13 Hz., and partly overlaps with other frequencies. It reflects the synchronous firing of motor neurons in rest state. Mu suppression is thought to reflect motor mirror neuron systems, because when an action is observed, the pattern extinguishes, possibly because of the normal neuronal system and the mirror neuron system "go out of sync", and interfere with each other.

The experiment was carried out to obtain the TF distribution (TFD) constructed from short-term Fourier transform (STFT), which used function Spectrogram in Matlab toolbox.It is evident from the experimental results that the spectrogram obtained during the resting state at electrode c3,c4 does not show much variation in the energy distribution, but during the moving state the pattern extinguishes possibly from 12Hz-6Hz.

The transition of energy distribution between the two states signifies that the Mu-Rhythm has been suppressed when the hand movement was imagined.

# CHAPTER 7

## CONCLUSION

The objective of this study was centered in the search of a time-frequency method, which allows us to classify the EEG signals and further study the possibility of extension to all the different tasks. In order to quantify their spectral content as a function of time, STFT algorithm was implemented to obtain Time-frequency representation (TFR) methods which are well suited as tools for the study of spontaneous and induced changes in oscillatory states was evident.

**FUTURE SCOPE**

Feature extraction and classification of EEG signals is core issues on EEG-based brain computer interface (BCI). Typically, such classification has been performed using signals from a set of selected EEG sensors. Because EEG sensor signals are mixtures of effective signals and noise, which has low signal-to-noise ratio, motor imagery EEG signals can be difficult to classification.

This study can be extended in future for the classification and analysis of EEG signals for feature extraction using different algorithms and Real time interfacing with prosthetic devices.

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