Characterization of Human Brain's Yuragi(fluctuation)in neural signals recorded non-invasively

Major Project - II

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of
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by
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CERTIFICATE

DECLARATION

I declare that my Major Project II entitled 'Characterization of Human Brain's Yuragi (fluctuation)in neural signals recorded non-invasively' submitted to the Department of Biotechnology, Delhi Technological University, is a result of the work carried out by me at Nano-Bioelectronics Laboratory, Department of Biotechnology and Linux Android Network System Lab, Department of Computer Science as M.Tech Thesis.

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(Saumya Priyadarshini)
2K15/BME/08

ABSTRACT

Random noise typically described as undesirable disturbance has always been suppressed by spending large amount of energy whether it is the field of electronics, computer technology based artificial intelligence or robotics. In contrast the effect of noise on non- linear system like biological system has been found to be positive. Naturally existing noise in the environment is utilized by the biological system for their improved performance in information processing. Yuragi (in Japanese) is referred to as biological fluctuation. Inspired from this biological activity of exploiting noise for seeking the potential benefits of low power consumption, adaptive to the environment and stable, there has been significant progress in development of applications of Yuragi to robotic systems as a complementing work between robotics and biology. In order to develop the mathematical function of such beneficial noise that is biologically inspired its necessary to understand the structure of physiological noise. This thesis tries to demonstrate a newly adopted paradigm to retrieve the structure of noise from neural recording of human brain. EEG dataset has been recorded from a single channel, dry electrode device. The brains electrical activity recorded non- invasively from the device is contaminated by various types of noise, both of biological and non- biological nature. This work tries to characterize both type of noise and intends to find the emerging pattern from biological noise and reject non biological fluctuation which can potentially be from electrical interference present in environment and acquired while travelling through electrode.

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Chapter 1

Introduction

Engineers always put their efforts to reduce the noise in their circuits, and yet the best computing machine in the universe i.e our brain looks unpredictable and seems to work in a random fashion. The principle behind is referred as neural noise or neuronal noise[Ferster,1996 and Stein et al.,2005]. Noise is a phenomenon of unpredictable random fluctuations assumed to be undesirable as it can degrade performance. The present electronic system and computer technology have to eliminate noise by spending tremendous energy for improving the performance. This random perturbance can corrupt the transmitted messages by the genesis of electromagnetic interference in the field of communication. But in biology, noise has different principle and surprisingly has shown to have benefits in signal detection and information processing in non- linear systems[Pinneo,1996, Traynelis and Jaramillo,1998 and Faisal et al.,2008]. In, contrast the role of biological noise is poorly understood. Stochastic resonance is described as an instance of beneficial noise. This biological variation is referred to as Yuragi (in Japanese).The way biological system exploits noise naturally existing in the system, has given a new insight to the scienctific community[Yanagida and Kano,2016]. It has been found that organic system process information by using thermal energy to operate stochastically. And the energy consumed is same as the thermal noise. Inspired from this natural system there has been efforts to create novel devices equipped with biological functions and minimise power consumption. A master equation of stochastic resonance was proposed by researchers at Osaka University, Japan for creating this new type of devices that would have guiding principle of bio inspired system. Following is the proposed equation in which the yuragi parameter has to be controlled.

$$\frac{\mathrm{d}x}{\mathrm{d}t} = f(x)' + \delta(t) + \eta \tag{1.1}$$

$$\text{f(x)} = \text{Input signal}$$
$$\delta(t) = weak\ signal$$
$$\eta = Yuragi\ noise$$

Where biological systems uses power of 10 micro watts, same task performed by supercomputers require power of 10 megawatts. One kind of such biological noise could be that elicited by the brain which is referred as neural noise or neuronal noise. The next section discusses about the neural noise.

1.1 Neural Noise: Brain's Yuragi

Noise comes into picture when large number of signals of varying characteristics like amplitude, frequency etc. interact and get superimposed. Similarly, our brain generate noise when millions of neuron fire simultaneously and generate electrical signal of varying potential difference. Some neurons generate spike [Andrew,2003] and some neurons are non-spiking . Figure 5.2 shows how noise has impact on the transmission of signals during the propagation of signal by non-spiking neurons.

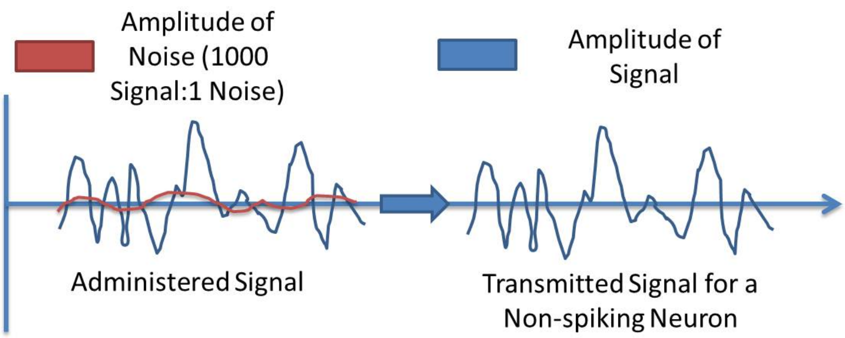


Figure 1.1: Signal and Noise

Neural noise [Ferster,1996] occurs due to the brains yuragi that refer to the intrinsic random electrical variability within neuronal network. Majority of noise generally occurs below a voltage-threshold required for generating an action potential but sometimes it can be in the form of action potential. When looked at microscopic level the neuronal activity exhibits stochastic characteristic due to the agitation and random atomic collisions which is referred as noise[Mandell and Selz,1993]. On one hand neural response variability exists which is defined as the different responses to specific neuronal input signals whereas on the other side groups of neuron will show different characteristic behaviour having highly irregular firing pattern [Softky and Koch,1993]. Typically noise is an obstruction to neural performance but new research suggests it does not always hold true in non-linear networks. Earlier it was considered to slow down [McDonnell and Ward,2011] and have a negative impact on processing power but now it has shown to have benefits to complex neural network upto a certain optima value [Parnas,1996].Study done by Anderson and his colleague supported the fact that noise has benefits and their theory showed that noise in visual cortex helps the threshold of action potential to linearize and make smooth [Anderson et al., 1968-1972]. Another research suggested that there is a positive relationship between interconnectivity and noise like activity [Serletis et al., 1768-1778]. There are numerous studies done to understand why noise is prominent in neuronal networks but still neuroscientist are not clear with the theory of existence. There is usually two kind of effects of neuronal noise i.e. either rise in variability to the neural response or more amusingly allow noise induced dynamical activity which cannot be seen in a noise free system. For example, in stochastic Hodgkin-Huxley model channel noise induced oscillations [Wainrib et al., 2012]

1.2 Using EEG to detect Yuragi Noise

The brain cells communicate through electrical impulses and are active every time even during sleep.Figure 5.3 shows the transmission of signal from one neuron to other. These

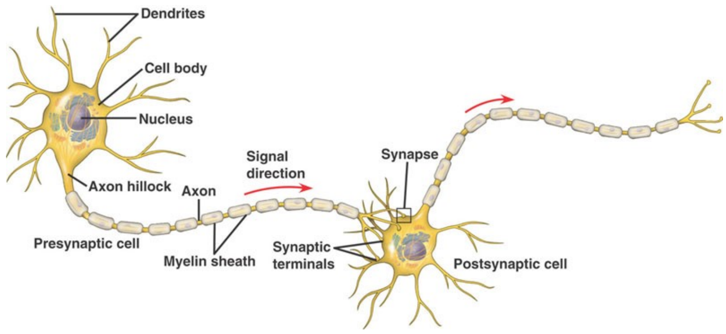


Figure 1.2: Signal Transmission in Neurons

electrical activity is the representation of potential difference that occurs during synchronized neural activity and it varies according to age, mental state and cognitive activity. An electroencephalogram (EEG) is the test that is used for the detection of electrical activity present in the brain generally done for diagnosis of medical condition. This technique uses flat metal discs called electrodes that is placed on scalp. Thus the electrode of EEG device senses and captures the average of all the electrical activities around the region of scalp where the electrode is placed which appears in the form of voltage signal. Since the neural activity is the coordinated firing of millions of neurons in the brain, the electroencephalogram shows a high frequency voltage fluctuation. Figure 5.4 shows the different frequency band of electrical activity which are associated with different regions of brain [Herrmann et al., 1979].

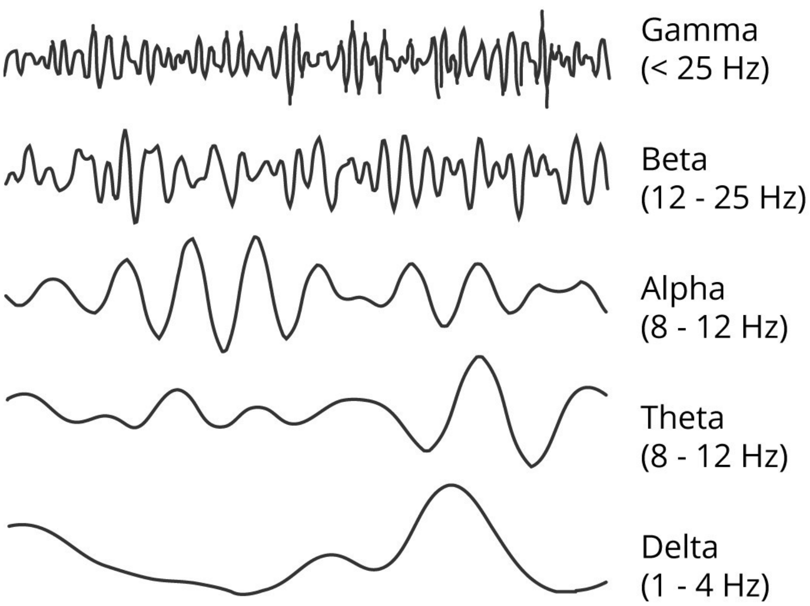


Figure 1.3: EEG Frequency Bands

Different regions of brain are associated with different frequency band of fluctuation and the EEG signal is used to measurably detect such variation. These electrical signals of brain rhythm are composed up of different frequency range which includes both type of noise, one with physiological origin and the other of non- physiological origin.

1.3 Low cost EEG Devices

Nowadays myriad of EEG devices are available ranging from single channel to multiple channel electrode EEG systems. In hospitals and laboratories medical grade EEG systems have been used for long time. But after the development of dry electrode EEG devices it has become feasible to take such technology from hospitals and laboratory to informal environment also. This technology has reduced the labour of montage placement thereby making it easy to use as well as making it affordable. Various types of low-cost EEG devices exist commercially in the market today are shown in the Figure 1.4 below.

Figure 1.4: Single and Multiple Channel EEG Device

It uses bluetooth technology to transfer the samples of signal wirelessly to the host computer.The single channel neurosky device measures the potential difference between the electrode resting at frontoparietal region Fp1 of forehead according to International 10-20 system [Jasper,1958] and the reference electrode attached at one ear [Zhang et al.,2010].

1.4 Goals and Contributions

In order to understand the biological phenomenon of exploiting noise goal of this thesis is to extends the work by characterizing the stochastic activity and analysing the changes in human brain electrical activity with age.[Stamoulis and Chang,2015]. For this experiment Neurosky Brainwave starter kit which is a single channel dry electrode EEG device has been used that can capture the EEG waves from Frontoparietal which is supposed to record the neural noise. From micro as well as macro level EEG signals are contaminated by various types of noise, both of biological and non-biological spectrum. The origin of physiological noise and stochastic neural behaviour is associated with membrane and synapse-level processes and/or neural network connectivity. On the other hand, origin of non-physiological noise is amplifier related and electromagnetic noise. Non-physiological noise are responsible for poor signal quality, poor source localization and may create difficulty in decoding input signals and in estimating electrophysiological parameters of interest.

1.5 Overview of Thesis

Figure 1.5 shows the workflow of adopted paradigm in this thesis. This thesis is prepared according to this paradigm.Chapter 3 presents the pilot study experiment and the dataset used in this work and the signal processing.Chapter 4 gives the description of methodology and features and the reason why that method is chosen with each step in detailed explanation. Chapter 5 shows the results and their discussion with analyses.

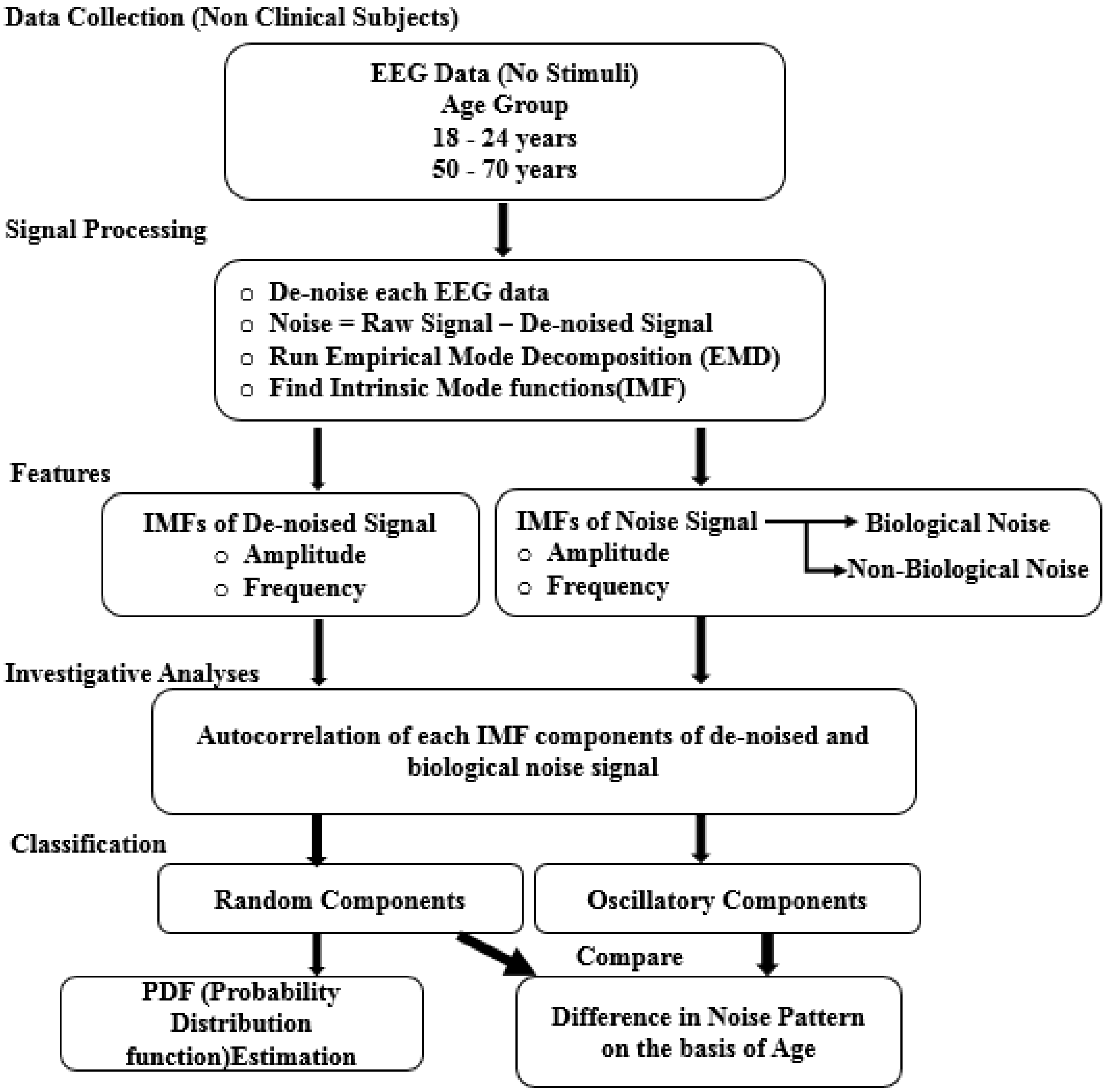


Figure 1.5: Workflow in the thesis

Chapter 2

Review of Literature

This chapter presents the background research and applications developed using Yuragi. It also highlights the principle behind Yuragi.

2.1 Computational power of noisy neurons

It has remained unknown how brain which is a deviously complex biological computing device can process tremendous amount of information with a very low power requirement. Even the worlds fastest supercomputers fail to imitate the brain. Though there has been a large progress in simulating the brain functioning but even supercomputers cannot reach the efficiency that brain does. Simulating a single second of human brain activity in a powerful computer was made possible after the development of open source simulation software NEST software by the researchers at the Okinawa Institute of Technology Graduate University in Japan and Forschungszentrum Jlich in Germany [http://www.nest-simulator.org/installation/]. It was only possible with the access of worlds fourth fastest supercomputer the K computer at the Riken research institute in Kobe, Japan. With the utility of NEST software framework, creation of artificial neural network of 1.73 billion nerve cells connected by 10.4 trillion synapses took place successfully under the supervision of Markus Diesmann and Abigail Morrison. Still this was only a fraction of the neurons every human brain contains. It is believed that human brain consists of hundred billions of nerve cells. Its not amusing that simulating the brains activity in real time was next to impossible. The K computer with 82,944 processors took 40 minutes to get just 1 second of biological brain processing time. Also a large system memory of 1 PB was required to run the simulation because each synapse had individual model. The neurons had a random arrangement. Since the complexity and working of brain has not been completely understood there has not been any standard way to measure the computational power of brain unlike computers whose computational power is measurable. Osaka University, Japan developed a technology that measures the brain temperature at high resolution using MRI (Magnetic resonance Imaging) and MRS (Magnetic Resonance Spectroscopy). This helped to find the energy consumption difference between the resting state and active state of brain and it came out to be only 1 watt. Although being a complex system the brain cells uses merely 1 picowatt power for processing massive information which became clear when it was looked at cellular level. Numerous scientific evidences shows the ultralow power consumption of brain. For instance, a specialized computer program AlphaGo was designed to play the board game go that came into news when it beat a human opponent. 250 kilowatts of electricity was used to do this. Whereas on the other side human brain consumes about 20 watts that includes the energy to keep neurons alive [34]. It would take many centuries to understand this complex and delicate organ and when it becomes clear how such biological phenomenon is controlled using such small amount of energy, technology can be equipped with similar biological principles to create an ultra-low power consumption system and increasing the energy efficiency tremendously. These biological systems and even other simpler species have inspired robotics research [19] and led to the beginning of brain inspired computing technology and development of bioelectronics.

2.2 Underlying principle of Brains low power consumption

When researchers from many different fields worked together a powerful synergy was created that lead to the findings of underlying principles behind the brains usage of extremely low power for performing tasks and computation. Following sections defines two such important events the stochastic resonance effect and adaptive behaviour of organisms in thermally fluctuating environment.

2.2.1 Stochastic Resonance

Research in stochastic resonances started early for more than 25 years ago mostly by the physicists but may also be familiar to some biologists and researchers from other disciplines too. Stochastic resonance is said to be observed when increment in random fluctuations improves the signal transmission and detection instead of degrading the quality[McDonnell and Abbott,2009]. The unpredictable fluctuation and random noise is typically assumed to degrade and corrupt performance but it can sometimes improve information processing in non- linear systems. This stochastic facilitation was observed to enhance information processing both in experimental neuroscience as well as theoretical models of neural networks and systems [4]. But there is a gap between the two approaches which can be bridged only with designing new experiments based on new theory and models.

Ubiquity of stochastic noise in neural noise has its potential roles in facilitating information processing which deserves greater attention. To achieve progress in this area a common approach must be adopted by researchers from different backgrounds. Eventually hypothesis were produced for the better understanding of stochastic resonance and stochastic facilitation. Following figures gives a better understanding of classical stochastic resonance and the framework proposed for stochastic facilitation.

Figure 2.1 below depicts the necessary conditions for classical stochastic resonance. A weak periodic signal is considered to be the input to a non-linear system such that without the presence of noise it cannot be deciphered. Such signal is labelled as subthreshold in many cases. Now when this signal is detected only in the presence of noise stochastic resonance is said to be observed. Based on power spectral density i.e the spectral content, signal to noise ratio (SNR) can give the measure of the quality of output signal. As the power of noise is varied the SNR will manifest a single peak usually. But for non-classical stochastic resonance, the signal need not be periodic in nature. Also for a simple network of neurons, necessity for weak subthreshold signals has been discarded.

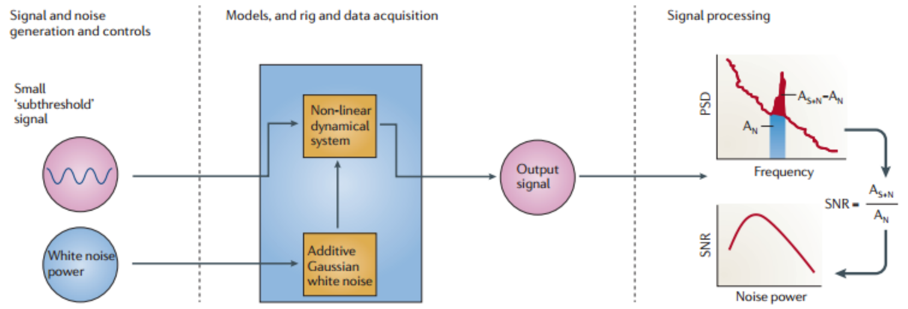


Figure 2.1: Classical stochastic resonance

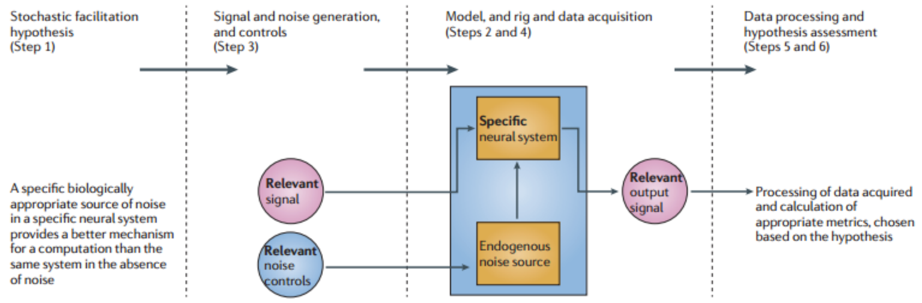


Figure 2.2: Proposed framework for stochastic facilitation

Figure 2.2 below presents a hypothetical framework to aid the progress in stochastic facilitation research. Step 1 states a hypothesis of beneficial biological noise. Next comes the computational model which can be stimulated by relevant input signal and the output response can be measured as specified in step 2. In step 3 those input signals are selected which are relevant to the hypothesis. Also the noise that is introduced or removed from the experimental model are chosen after analysing their relevance to the hypothesis. After selecting the input signal and noise it is introduced into the simulation of experimental model which is followed by acquiring the data in step4 and further processing in step 5.In past studies of stochastic resonance in neural system, similar steps have been followed in different sequence.

2.2.2 Attractor Selection Model

Attractor selection model is based on biological fluctuation [Tian et al.,2016] inspired from highly adaptable nature of E.coli in changing environment. It was originally proposed to simulate the behaviour of Escherichia coli in the flexible nutrition environment using the bistability equations. In different nutrition environments E.coli has an adaptive behaviour to regulate its metabolic state. In adequate nutrition condition the metabolism of E.coli usually becomes vigorous [Gong et al.,2017]. This results in increment of mRNA concentrations in E.coli which promotes growth and reproduction by producing enough nutrition materials. This state will be maintained only if nutrition is adequate. On the other hand the metabolism of E.coli deteriorate when nutrition is inadequate. In this condition mRNA concentration goes down inevitably. To make the E.coli shift to a stable metabolic state from the current state the concentrations change stochastically.

This adaptive nature of E.coli in changing nutrition environment can be mathematically modelled by the bistability equations where each attractor formulates a stable adaption state of mRNA concentrations.

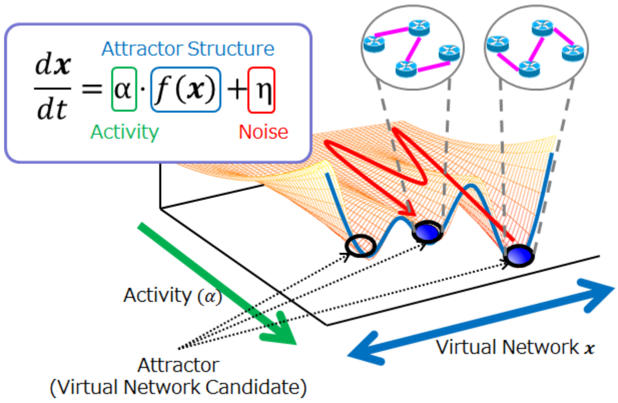


Figure 2.3: Attractor Selection Model

The bistability equations consist of two main parameters, one is activity and other is noise. Activity indicates adaption goodness of E.coli to the nutrition environment. Noise takes the stochastic effect on the mRNA concentrations. The relation between these two parameters is of ebb and flow. Stochastic effect of noise on mRNA concentration will decline when there is an increase in activity. Here the effect of noise on high activity will become negligible. In contrast, stochastic effect of noise will rise when the activity decreases. This implies that if mRNA concentrations cannot adapt to the nutrition environment, the noise will always affect the sufficiently low activity of inadaptable state. So, the adaptive attractor selection model can keep the E.coli in its adaptive state as far as possible. And with the stochastic effect of noise the in adaptable E.coli shift to the adaptive state.

2.3 Development of First Yuragi Algorithm

The world's first bio-inspired 'Yuragi(fluctuations)' algorithm originally proposed by Osaka University, Japan for virtual network control technology and later on was developed by Nippon Telegraph and Telephone Corporation, Osaka University, and The University of Electro-Communications in collaboration. It had a great service in providing rapid recovery to a network in case of unexpected disaster or congestion. A month after, using this developed technology researchers demonstrated an experiment to avoid congestion at an event sponsored by National Institute of Information and Communication Technology. The technology was developed to meet the demand of sudden traffic changes due to the rapid spread of cloud computing and other emerging application like M2M/IoT. Since, multiple logical network are operated on a common physical network infrastructure, it becomes important to operate such network in stable manner. The underlying principle behind the development of this technology is the adaptability like bio-organism as described in the previous section. The theoretical studies were carried out by Osaka University to develop the control algorithms. On the other hand, NTT improved the control algorithm to implement for an operational network. It also invented network control server for the demonstration of the developed technology.

The recent rapid spread of cloud computing and emerging applications such as M2M/IoT

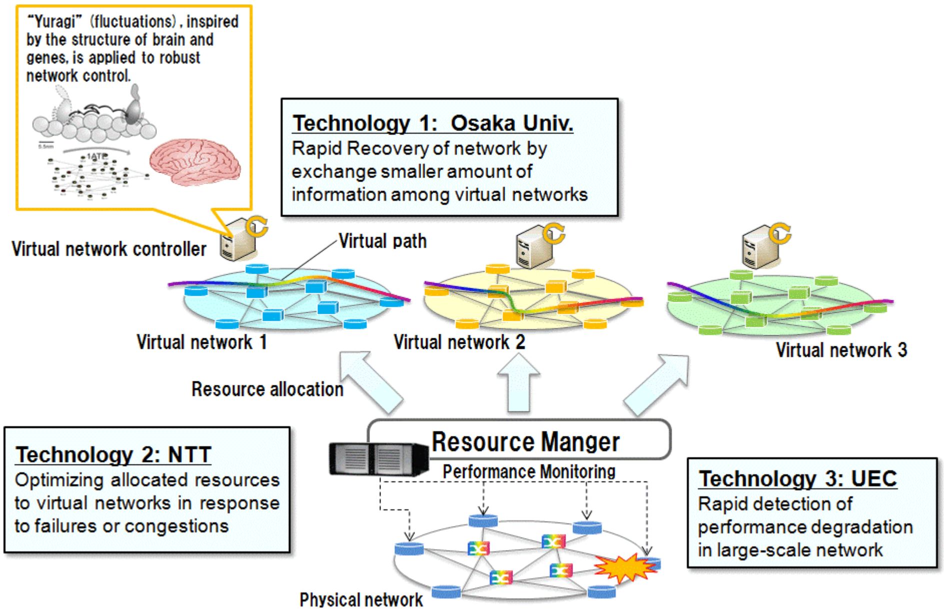


Figure 2.4: Worlds first development of bio-inspired Yuragi algorithm for network virtualization

has led to sudden traffic demand changes.The Figure 2.4 gives the structural glimpse of the technolgy. As multiple logical networks are operated on a common physical network infrastructure, it has become increasingly important to operate such networks in the stable manner in order to maintain the stability of each service from the view point of BCP (business continuity planning).

2.4 Other Applications of Yuragi

After the development of first Yuragi algorithm many more applications followed. Some of them are described in the following section.

2.4.1 Yuragi Synthesis for Ultrasonic Human Brain Imaging, 2013

This was one of the application in the area of brain imaging. It was proposed to synthesize yuragi for barin imaging under the skull. The advantage of this technique was that image registration was not required like the conventional methods. Using Yuragi synthesis it became possible to get effective results. The requirement of image registration comes when there is a need to create more than two images into one image. Yuragi synthesis made the process easier by eliminating the image registration requirement. Also the efficiency of the method was verified by comparing its error rate and accuracy with other existing methods. The biological systems utilise the process of autoregulation. Similarly Yuragi performs autoregulation thereby leading to a simple and energy-saving system. This study comprised of utilising yuragi to an ultrasound based medical imaging technique for diagnosis. The results produced with the application wer far mor superior than other methods. Thus a new application of yuragi was developed for visualizing the brain.

2.4.2 Analysis for trans-skull brain visualizing,2011

Another application of yuragi was found in the area of brain anatomy. Measurement of skull depth and imaging the sulcus under it was done by employing ultrasonic waves. Additional waves were used and gaussian noise as the yuragi analysis. Firstly the thickness of skull was evaluated from both the synthesized waves. For determining the thickness two points were required one on the surface of skull and other on the bottom point. These waves were utilised for the bottom point based on fuzzy inference. From the B-mode images for both synthesized waves sulcus surface was extracted. Skull thickness was successfully calculated with the use of cow scapula as the skull and steel ditch as human sulcus. With the results produced the effectiveness using Yuragi analysis wave was found to be greater.

2.4.3 Analysis for detecting heart-rate by mat-type sensor in bed,2011

Yuragi analysis found its usefulness for detecting heart rate also by mat-type sensor. In this approach also Gaussian noise was considered as yuragi and based on fuzzy logic extraction algorithm were developed. Accuracy for various weight ratio was evaluated on the basis of 10 healthy subjects. Even the tiny accuracy difference makes a big change in the assessment of autonomous nervous system. The result showed the superiority of mat type sensor signal thus finding yuragi analysis useful in detecting heart rate.

2.4.4 Yuragi electronics inspired by living bodies

In biological system the information processing exploits thermal (organic)noise for its stochastic operation. It is characterized by its energy consumption level which is found to be same as thermal noise. There is a trade-off between processing speed and quantity of data processed.Individual Neuron cells are influenced by noise, as a group they are able to create a highly reliable information processing sytems. Morover, they are able to create new algorithms independently leading to a robust system even in a fluctuating environment. Indigenous to organic system a brain like information system can be created when elements that govern the natural fluctuation called yuragi will be systematized. There has been rigorous research in this area that clarifies the underlying principle of such exploitation. Bio-inspired robots are among such pioneering development. Based on this natural principle new type of electronic devices are proposed that will be governed by these guiding principles.

2.5 Signal Processing of EEG data

For linear, strictly periodic or stationary signals Fourier spectral analysis methods were used. But these limitations suggests that for analysis of non-stationary signals some more strict conditions are necessary.For investigating the characteristics of noise in EEG simple noise models like Gaussian noise will not be suitable because it does not account for non-stationary statistics whereas noise of neural origin are non-linear and difficult to identify. To overcome these issues a new analytic method was developed namely Hilbert-Huang transform [Huang et al.,1998]. This new method could analyze the non-linear and non-stationary signals. Empirical mode decomposition was the principle step which could decompose any complex signal into a finite small number of intrinsic elements. These elementary components are called intrinsic mode functions(IMF). These finite small number of elements had well-behaved property of Hilbert transforms. This algorithm has no specified basis which makes it different from the Fourier decomposition and wavelet decomposition methods. The basis of EMD is adaptively generated according to the signal which makes its decomposition efficiency very high.This gives much greater physical sense due to the localization of Hilbert spectrum much steeper in both time and frequency domain.Its excellent properties makes it widely useful for researchers and signal processing experts as well as other domain.

Although a powerful algorithm but to gain insight into the generating mechanisms of the set of simpler elements by the intended deconstruction requires some additional assumptions also. The IMF's are supposed to be fluctuating about their mean values aproximately symmetrically. The initial rows of the matrix contains the IMFs components and the last row is left with the residue. The residue contains all the non-symmetric contents of the time series process. The physical sense of implementing EMD algorithm depends on two factors. First is the character of the signal and secondly the analysis target. Without clarifying the type of signal and the task to be achieved it cannot be implemented blindly , a suitable stopping criteria must be analysed prior to decomposition.

2.5.1 EMD for non-stationary signals

As described in the previous section EMD is applicable to non-linear processes. It is based on the local time scale characteristics of the dataset. The underlying structures and sharp features of the signal is revealed in the intrinsic mode functions which yields real time frequencies as a function of time. These individual components have an energy- frequency-time distribution labelled as the Hilbert transform. The IMFs instantaneous frequencies are meaningful because it is based on the local properties of the signal.Other advantage is that there is no need to represent the non-linear signal with invalid harmonics. Because of its great significance to accurate the time-frequency analysis in different scale it has been extended from univariate to multivariate EMD (MEMD. following this, a new method was proposed recently to prevent the process of mode mixing. It is now called noise assisted EMD(NA-EMD).But this method is prone to unstable performance due to its highly complex computation. So a new method is proposed to resolve this issue called partial noise assisted EMD. To assist the decomposition process instead of white noise, a high frequency band limited noise will be used [Huang et al.,2017].

2.5.2 Intrinsic Mode Functions of EEG

IMFs extracted from EMD foe EEG signals gives a deep insight and information about the signal. Generally the low frequency IMF does not contain much information. For bandlimited signals the IMFs are even simpler and less in number. And the residue gradually comes closer to zero. In case of non-band-limited signal if the signal is contaminated with lot of noise the resultant of empirical calculation wont make much sense. It would be left in the residue. The meaningful information are present in the early IMFs. This proves the empirical nature of the algorithm. After the computation and sifting through a signal of interest, there is some small residue left which the algorithm has not confronted.So, it leaves in the residue. This is the reason why strict stopping conditions are required and very specific knowledge to the IMF definition in order to gain intuitive understanding of the empirical mode decomposition.

2.5.3 ANOVA

For statistical analysis and comparison of different datasets a technique called Analysis of Variance(ANOVA) is used. It also compares the means of different data and give the relation between them. To be more specific it examines the null hypothesis using the group mean and the number of groups. MATLAB provides the statistics and Machine Learning Toolbox which has the function to perform different variante analysis. It includes one-way, two-way and N-way analysis of variance.

Chapter 3

Data

This Chapter gives an overview of the data set, its format and how it was collected and further processed.

3.1 Data Set for pilot experiment

The data was collected from the college students and staffs in the laboratory itself. The nonclinical subjects participating in the experiment included 60 adults of age group 18-26 year old and 20 adults of age group 45 - 70 year old. No stimuli was included in the experiment. The Neurosky product used for recording brainwaves uses a technology called ThinkGear which enables the device to interface with the wearers brainwaves. The data from the headset is directed from the serial port to an open network socket by a background process that runs on the computer and is known as ThinkGear Connector (TGC). The device is equipped with the thinkgear module and consists of eeg sensor that touches the forehead at frontoparietal region(fp1) of the scalp as recommended by 10/20 electrode system. This is a unipolar device with the reference points located on the ear clip. The data is processed by the onboard chip which is contained in the thinkgear module(TGAM1). This processed data is provided to the software and applications in digital form. The raw brainwaves and eyeblink are calculated on the thinkgear chip.

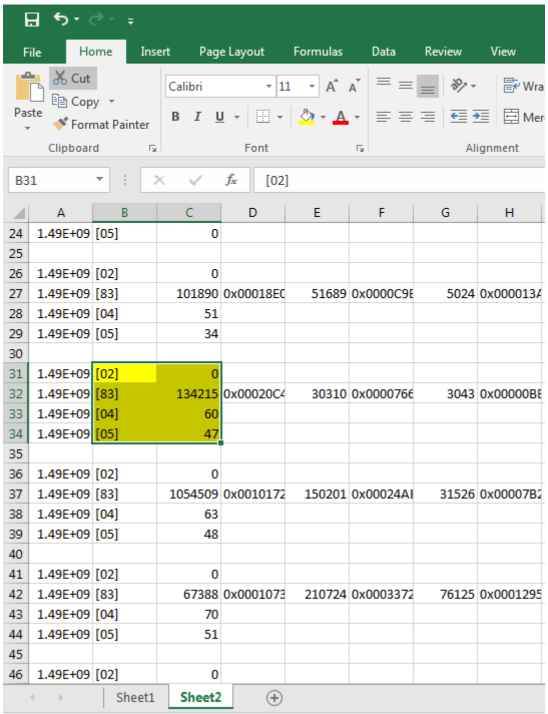
3.2 Overview of dataset

The format of recorded data set is .csv (comma separated value) and it can be saved as .txt file which appears like following :

1485887509.283: [80] 35, 0023, -2.794721

The parts before the ":" are time stamp information. The rest of the data is the RAW sample value expressed in 2 different forms. 34 is ASCII representation and 0022 is its hex value ,"80" = the data type. The frequency at which this RAW sample values are sent is 512Hz that means 512 samples each second which corresponds to the voltage measurement in microvolts at the sensor location. The graph of these Raw sample values gives a waveform corresponding to the voltage fluctuation at the sensor. The EEG and denoised signals and intrinsic mode functions for each trial were extracted from the respective subjects session. The software integrated with the device recorded timestamps at a resolution of 1 second and to give precise timestamps at a resolution of milliseconds for each discrete sample they had to be interpolated linearly.

There is a small loss of precision in timing for each sample but this loss can be ignored.

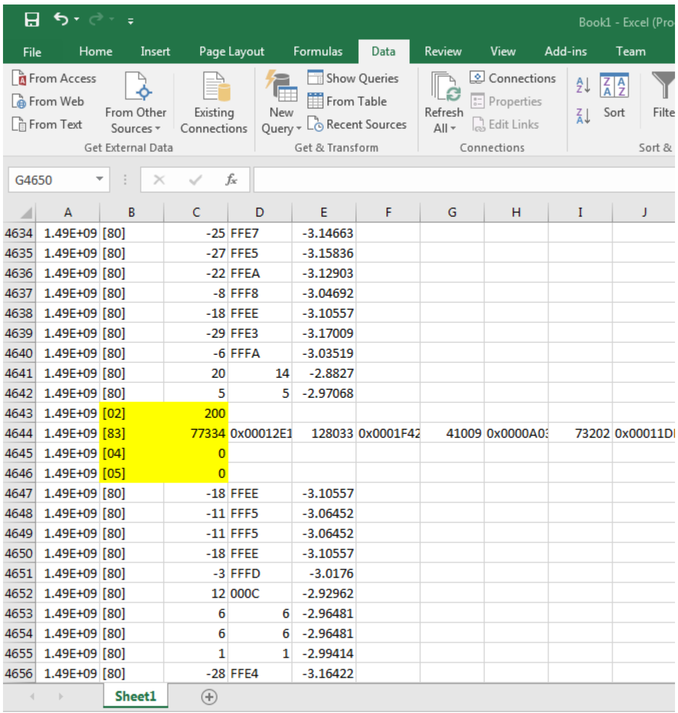


	A	B	C	D	E	F	G	H
24	1.49E+09	[05]	0					
25								
26	1.49E+09	[02]	0					
27	1.49E+09	[83]	101890	0x00018EC	51689	0x0000C9E	5024	0x000013A
28	1.49E+09	[04]	51					
29	1.49E+09	[05]	34					
30								
31	1.49E+09	[02]	0					
32	1.49E+09	[83]	134215	0x00020C4	30310	0x0000766	3043	0x00000BE
33	1.49E+09	[04]	60					
34	1.49E+09	[05]	47					
35								
36	1.49E+09	[02]	0					
37	1.49E+09	[83]	1054509	0x0010172	150201	0x00024AE	31526	0x00007B2
38	1.49E+09	[04]	63					
39	1.49E+09	[05]	48					
40								
41	1.49E+09	[02]	0					
42	1.49E+09	[83]	67388	0x0001073	210724	0x0003372	76125	0x0001295
43	1.49E+09	[04]	70					
44	1.49E+09	[05]	51					
45								
46	1.49E+09	[02]	0					

Figure 3.1: Highlighted section indicate good connection

Only those trial were acceptable in which the signal quality was good which in turn can be observed by a 0 value for the entire session otherwise the trial was discarded.This ensured a good trial but some artifacts like eye blink and muscle artifact can still get contaminated. These artifacts can still be considered as acceptable noise level. Out of 60 data collected 10 datas from age group of 18-26 years and 3 data from age group of 45-70 years participants had to be discarded due to poor data quality.They showed large amount of poor quality data as lucid by consistent non-zero samples.Following Figure 3.1 gives the overview of data. Highlighted value indicate good quality signal with a zero value. Also it gives attention value and meditation value. Here in the Figure 60 is the attention value measured on a scale of 100 and 47 is the meditation value measure on same scale.

The greater the deviation from zero , poorer the quality of signal. At the end of every second the device provides the attention and meditation value. These values help us analyse whether the previous second data is reliable or not. It may occur due to poor contact of electrode and forehead , electrical interference or a noisy environment too. This could be avoided by checking the electrode placement on forhead if it properly lie flat on the subject's head. Also, to minimize electrical interference switching off the phone and lights would be beneficial. One should ensure these environment constraints prior to reading. If not taken such care the data may seem to have significantly greater number of spikes and very noisy data.



	A	B	C	D	E	F	G	H	I	J
4634	1.49E+09	[80]	-25	FFE7	-3.14663					
4635	1.49E+09	[80]	-27	FFE5	-3.15836					
4636	1.49E+09	[80]	-22	FFEA	-3.12903					
4637	1.49E+09	[80]	-8	FFF8	-3.04692					
4638	1.49E+09	[80]	-18	FFEE	-3.10557					
4639	1.49E+09	[80]	-29	FFE3	-3.17009					
4640	1.49E+09	[80]	-6	FFFA	-3.03519					
4641	1.49E+09	[80]	20	14	-2.8827					
4642	1.49E+09	[80]	5	5	-2.97068					
4643	1.49E+09	[02]	200							
4644	1.49E+09	[83]	77334	0x00012E1	128033	0x0001F42	41009	0x0000A0:	73202	0x00011D
4645	1.49E+09	[04]	0							
4646	1.49E+09	[05]	0							
4647	1.49E+09	[80]	-18	FFEE	-3.10557					
4648	1.49E+09	[80]	-11	FFF5	-3.06452					
4649	1.49E+09	[80]	-11	FFF5	-3.06452					
4650	1.49E+09	[80]	-18	FFEE	-3.10557					
4651	1.49E+09	[80]	-3	FFFD	-3.0176					
4652	1.49E+09	[80]	12	000C	-2.92962					
4653	1.49E+09	[80]	6	6	-2.96481					
4654	1.49E+09	[80]	6	6	-2.96481					
4655	1.49E+09	[80]	1	1	-2.99414					
4656	1.49E+09	[80]	-28	FFE4	-3.16422					

Figure 3.2: Highlighted section indicate poor connection

The Figure3.2 above shows a non zero value 200 which indicates poor quality signal.

3.3 Data Collection from non-clinical subjects

The data were collected with the consent of participants by ensuring their saftey and no harm from the device. Each subject were made to fill a form to make sure patients have no neurological condition. So in this study EEG dataset were from healthy subjects.

3.4 Cleaning the Data

Cleaning the data refers to the process of rejecting the poorly recorded section of the entire data. As mentioned in the previous section that after analysing the quality of signal from the non zero values at the end of every second it becomes clear to realise the poor values of the signal. Thus that poor section can be discarded easily.

Chapter 4

Method

This chapter highlights a detailed explanation of all methods and techniques used in the analyses of the experiments, as well as the reasons behind using those methods.

4.1 MATLAB for EEG Signal Analyses

MATLAB- Matrix Laboratory is the language of technical computing that integrates computation and visualization and programming simultaneously in a moderately friendly environment harmonised for iterative experiments and scientific workflow. All the problems and solution are expressed in matrix based mathematical form using both symbolic as well as numeric calculations thereby making the code easier to read, write, understand and maintain. It has a vast library of prebuilt toolboxes, extremely helpful support and fully documented functionality that helps to get started with a chosen domain. For the processing and analysis of electrophysiological data several toolboxes can be utilised namely EEGLab, Wavelet, ERPLab, Fieldtrip along with other programs and in-build codes with an ease to adjust several parameters. Scientific analyses becomes very easy with the extensive set of built-in math functions and graphic features of 2D and 3D plotting functions enabling to visualise and interpret data. The analyses can run on large data sets and MATLAB code can be interfaced with other languages like C/C++, Java, Python, .NET, Microsoft Excel, Handoop, SQL when required for the deployment of algorithms and applications. One can switch to different toolbox packages at the same time as required. Also EEG Lab and other packages offers an expandable platform to develop new plugin functions.

4.2 Concept of Denoising and Filtering

There is a large intersection between these two concepts but they are not same. Denoising utilises filters so it can be said denoising is filtering but not all filtering is denoising. In order to preserve all the frequency we have used de-noising technique to specifically remove noise and no kind of filter.

4.2.1 Filtering

Every signal can be represented as a combination of sine and cosine wave as given by fourier series. So, the signals can be thought of as built up from a large number of different frequencies sine and cosine waves[put reference of Fourier series/transform]. In signal processing, a digital filter attenuates a signal for each of its frequencies differentially.Filtering implies one can apply any type of "filter(s)" into data depending on the purpose and application.Ideally, the passband frequencies will be made to pass without any change from input to output whereas stopband frequencies are completely attenuated at the filter output.This means there will be an infinetly steep fall-off gain at the cut off frequencies and in both the passband and stopband the amplitude characteristic will be flat. But this is an ideal case. There are several filters available to approximate these ideal behaviour having their own advantages and limitations. Two such filters are Finite Impulse Response (FIR) filter and IIR (Infinite Impulse Response) filters. The principle is that when a Dirac-pulse i.e. short unity pulse is presented at input the output will give impulse response of a filter. This operation does not necessarily removes noise. It can be used to select or reject certain frequency band by implementing various filters. The Neurosky recording device is equipped with advance filter for noise immunity. The brain signals first pass through the analog and digital low and high pass filters. The output signal is confined in the range of 1- 100 Hz. Aliasing may occur which is corrected and then finally sampled at 512Hz. For the processing of EEG data the most recommended filter is elleptical filters

4.2.2 Denoising

It is an operation for explicitly and specifically removing noise from source data sets. It can be achieved by filtering in combination with other operation like thresholding. The goal of de-noising is to recover the original clear and clean data from noisy environment. This technique attempts to remove the noise and retain the signal irrespective of the frequency content of the signal. This involves three stages [Reference -shrinkage denoisin stanford]:
o Linear forward wavelet transform
o Nonlinear shrinkage denoising
o Linear inverse wavelet transform

Our EEG signal recorded from neurosky device is a one dimensional signal since it has one independent variable i.e. time. So we apply 1-D de-noising function. The description of de-noising function available in MATLAB is described as follows:

Syntax:

XD = wden(X,TPTR,SORH,SCAL,N,'wname')

Description:

wden signifies one dimensional de-noising function. It runs an automatic de-noising process of one dimensional signal using wavelets.
X is the input signal which is supposed to be de-noised.
TPTR is a character vector that contains the threshold selection rule. These rules are based on the underlying model

$$y = f(t) + e$$
$$e = \text{white noise } N(0,1)$$

Non-white noise can be dealt by rescaling output threshold using the parameter SCAL. When a nonwhite noise is suspected, thresholds must be rescaled by a level-dependent estimation of the level noise. There are two kinds of thresholding method namely soft thresholding and hard thresholding.

Hard and Soft Threshold

Hard thresholding is the simplest method but soft thresholding has nice mathematical properties. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. The hard threshold signal is

$$x \; if \; x > thr, and \tag{4.1}$$

$$0 \; if \;\; x \leq thr \tag{4.2}$$

Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards 0. The soft threshold signal is

$$sign(x)(x - thr) \; if \; x > thr, and \tag{4.3}$$

$$0 \; if \; x \leq thr \tag{4.4}$$

The main difference between the hard and the soft thresholding methods is in the choice of the nonlinear transform on the empirical wavelet coefficients. As can be seen

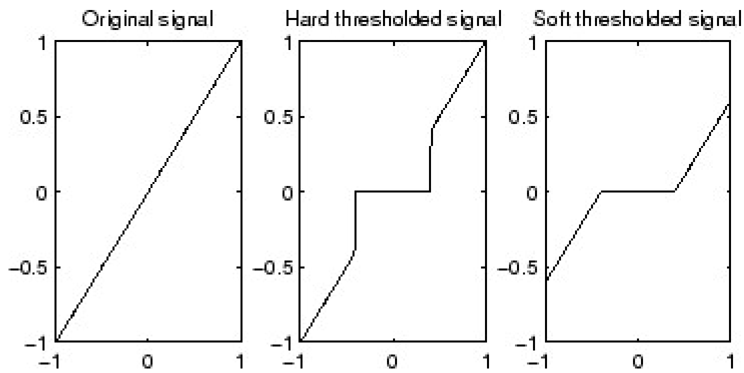


Figure 4.1: Hard and Soft Threshold

in the Figure4.1 above, the hard threshold impacts by creating discontinuities at x = t, while the soft procedure does not create any discontinuity.There are mainly four threshold selection rule namely rigrsure, minimax, sqtwolog and heursure. SURE and Minimax threshold selection rules are more suitable for implementation when minute details of signal lie near the noise range. So, these two rules become more conservative. The other two selection rules have been found to remove noise more efficiently.

4.3 EEG Noise Extraction

Once the raw signal is de-noised, unwanted noise can be looked by subtracting the output de-noised signal from the raw signal. so, the de-noised signal gives the EEG noise variance which is further investigated by using signal processing techniques. The characteristics of EEG noise is also affected by the de-noising techniques applied. So, it cannot be implemented blindly.Through literature survey the most efficient thresholding technique was found to be Heursure, so in this work this threshold selection rule has been applied for the best suitable outcome.

4.4 Empirical Mode Decomposition

EMD is basically an iterative algorithm (set of rules) which uses a method called sifting to extract intrinsic mode functions from any real signal. In other words, it recursively estimates the IMF components by decomposing the time series signal and can detect waves that are riding on other waves - the kth IMF rides on the (k+1)th IMF. . Behind this method there have to be certain assumptions in order to deconstruct the complex signal into a set of simpler components to gain insight into generating mechanisms. Clarification of the type of signal and given task must be done before running EMD and it is important to describe the stopping criteria in the software. For the output components to be sensible the analysis target as well as character of signal matters.

4.4.1 Sifting

It is a process of separating out components of a signal one at a time in context of wavelet decomposition in signal processing.

4.4.2 Intrinsic Mode Function

The IMF components are generated by proceeding through following steps:
(1) Identifying the local minima and maxima in the signal
(2)Generating the upper and lower signal envelopes associated with the extremas by fitting cubic splines.
(3)Mean of the upper and lower envelope is computed.
(4)This mean is subtracted from the raw signal.

These components are assumed to fluctuate about their mean values approximately symmetrically. All non -symmetric contents of the time series signal will remain in residue of the iteration. EMD first removes the high frequency components of the signal and then sifts down to the mean trend of the signal. By definition, IMFs will have well behaved Hilbert transforms. They will also have instantaneous frequencies associated with them, i.e. throughout the signal, there can be isolated such a time-window that within that time-window the signal oscillates with a unique frequency.

4.5 Feature Groups

This section describes different parameters for identifying the distinguishing features between the two age groups that could be extracted from the EEG signal for study trials.

4.5.1 Baseline for Pilot Study

Several parameters that shows distinguishing characteristics of the EEG noise dynamics between the two age groups will be used as features for this pilot study. Mean amplitudes of EEG Noise,Standard Deviation Autocorrelation for each of the Intrinsic Mode Functions (IMFs), Probability Distribution Function (PDF), are some of the features studied for both category of subjects. These features are computed across the entire duration of trial.

4.5.2 Mean EEG Noise Amplitude

In this thesis, the mean amplitude of EEG noise and standard deviation is the most simplest feature of all. The mean amplitude is computed across all sample points in the EEG noise.Thus, one trial will have two mean amplitude values one for each age group.

4.5.3 Standard Deviation and Q-Q Plot

A quantile quantile plot also called a q-q plot is a graphical tool that helps to visually evaluate whether a set of data whose underlying distribution is unknown has apparently come from a specified distribution like normal or exponential. For instance, if our dependent variable is assumed to be normally distributed, the normal q-q pot helps to validate the assumption. Its a subjective approach that allows us to know if the assumption is violated or not. If it is violated then we can visually assess which data points are responsible for the violation. It displays a quantile quantile plots of the quantiles of a sample data against the theoretical quantiles values from a normal distribution function. The plot is displayed in scattered form and if the distribution of sample data is normal then the plot will appear linear. In other words it allows to assess if two sets of sample data are from same distribution or not . The sample data is ordered from smallest to largest values in the q-q plot and then further plotted against expected value for any specified distribution at each quantile. The quantiles are based on the length of sample data. If the data has n number of data points then plot will use n quantiles. On the x axis appear the quantile values of first data set and the y axis has the corresponding quantile values for the second data set.

4.5.4 Autocorrelation and Cross Correlation Function

Autocorrelation, also known as serial correlation, measures the correlation of a signal with a delayed copy of itself as a function of delay called lag. In other words, it is the similarity between observations as a function of the time lag between them. The analysis of autocorrelation is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. It is often used in signal processing for analyzing functions or series of values, such as time domain signals. The autocorrelation (Box and Jenkins, 1976) function can be used for the following two

purposes:
1. Detection of non-randomness in sample data.
2. Identifying an appropriate time series model if the data are not random instead are oscillatory.
Autocorrelation is a correlation coefficient lying in the range of zero to one. However, instead of correlation between two different variables, the correlation is between two values of the same variable at times Xi and Xi+k. When the autocorrelation is used to detect non-randomness, it is usually only the first (lag 1) autocorrelation that is of interest. When the autocorrelation is used to identify an appropriate time series model, the autocorrelations are usually plotted for many lags. The autocorrelation function can be used to answer whether the sample data set generated from a random process and if the time-series or a non linear model is more suitable as compared to a simple constant plus error model. Randomness is one of the key assumptions in determining if a single variate statistical process is under control. If the randomness assumption is not valid,typically either a time series model or a non-linear model (with time as the independent variable) can be used.

4.5.5 Probability Distribution Function

Probability Distrubution Function gives information about the probability that a random variable X can take a value less than or equal to x. 'X' is a random variable and 'x' is one of the value that random variable can take. When the variables are descrete the term distribution is used whereas if the variables are continuous it is called probability density function.

Chapter 5

Results and Discussion

This chapter gives the description and analyses of output results. Following Figure 5.1 is the output raw signal at Fp1(Frontopareital) brain region of Subject 1 recorded from the single channel EEG device. This signal is contaminated with non-physiological noise that may have got acquired from other environmental factors. After implementing signal

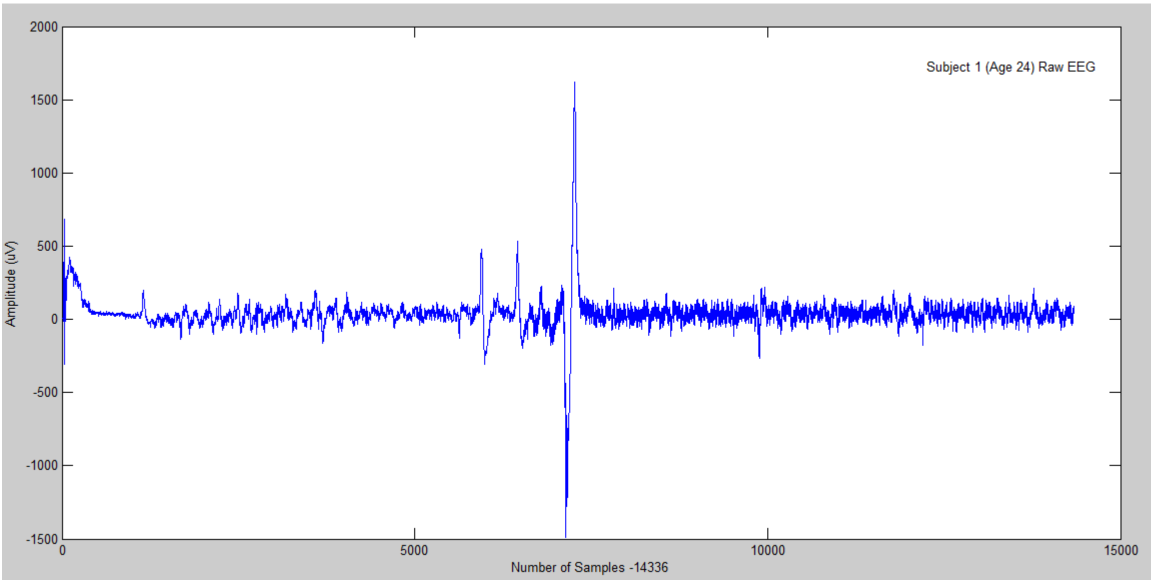


Figure 5.1: Raw EEG Plot of Subject 1

processing wavelet decomposition techniques in MATLAB, the raw signal was de-noised to get a clear signal. This resultant signal is the representation of EEG noise of subject 1 of age 24. For further analysis the signal was decomposed into 15 intrinsic mode functions. It is speculated that the mean amplitude of the basic signal and each of the IMF components will be significantly different from the other age group. Next portion of this chapter gives the diagram of EEG Noise and first IMF component compiled into one. This thesis is based on a verly preliminary exploration of the EEG noise structure and its statistics. For investigating their characteristics systematically and vigorously a larger study with wider range of cohort is a necessity. Nonetheless, this experiment highlights the different features of noise variability with age related transitions. The largest peak shows the eye blink in the dataset which has been considered as a part of EEG noise. When all the 15 components of raw EEG noise will integrated it is expected to give the

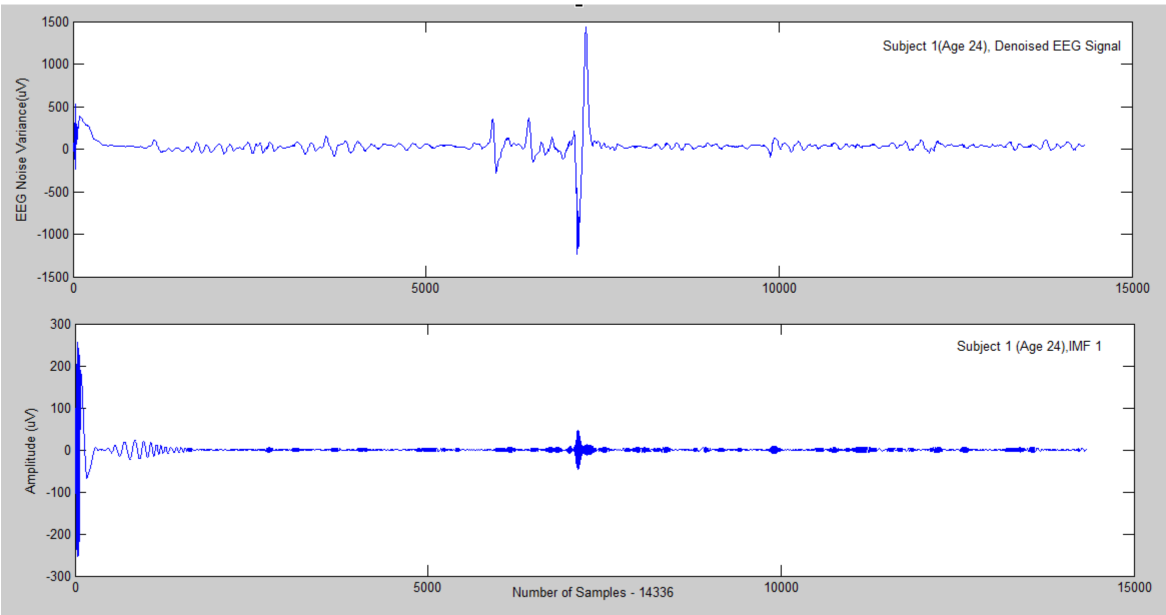


Figure 5.2: EEG Noise and IMF 1 of Subject 1

EEG noise signal. Above Figure 5.2 gives a glimpse of first IMF component of the first age group along with the clear EEG noise signal after removing the noise of non-biological origin. The amplitude has decreased significantly as expected.

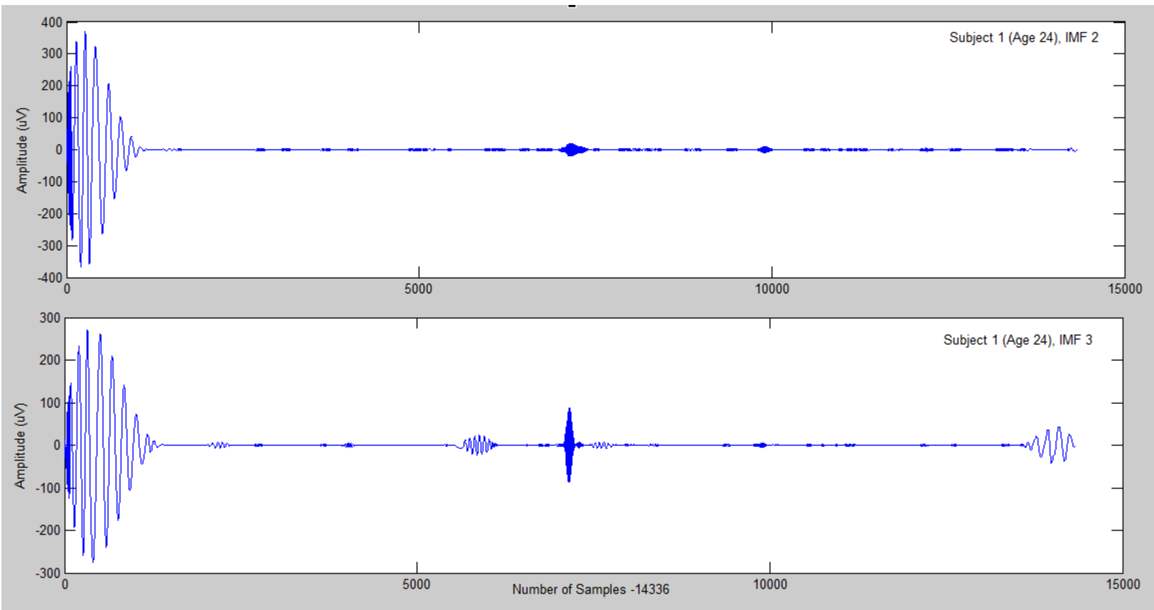


Figure 5.3: IMF 2 and IMF 3

Figure 5.3 shows the second and third elements of EEG Noise Signal. The empirical mode decomposition algorithm removes the high frequency noise first from the raw EEG noise signal for making the investigation easier. The proceeding sections are presented with all the IMFs of both age group. Finally , it was found that the standard deviation in subject 1 was significantly large from the subject 2.

The graph 5.24 reveals the distinguishing change in the varying age related volunteers.

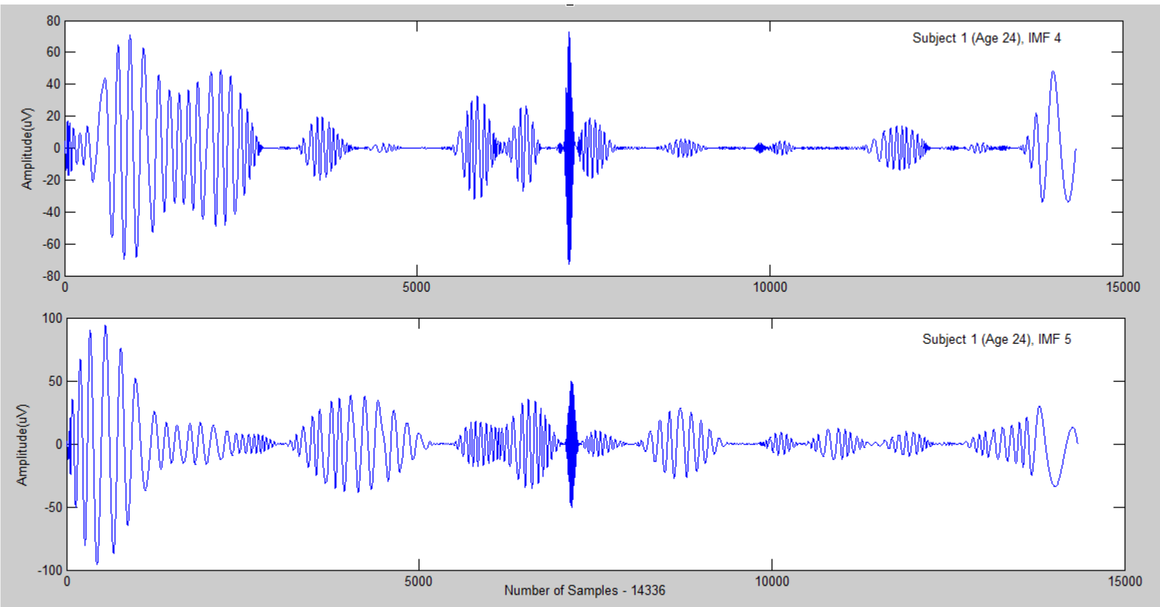


Figure 5.4: IMF 4 and IMF 5

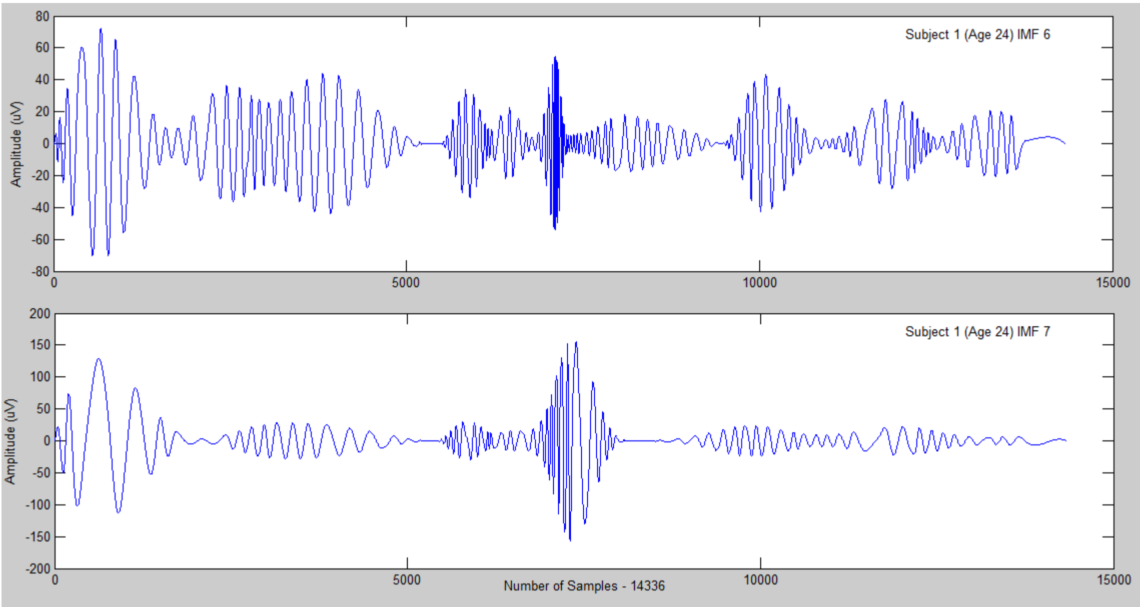


Figure 5.5: IMF 6 and IMF 7

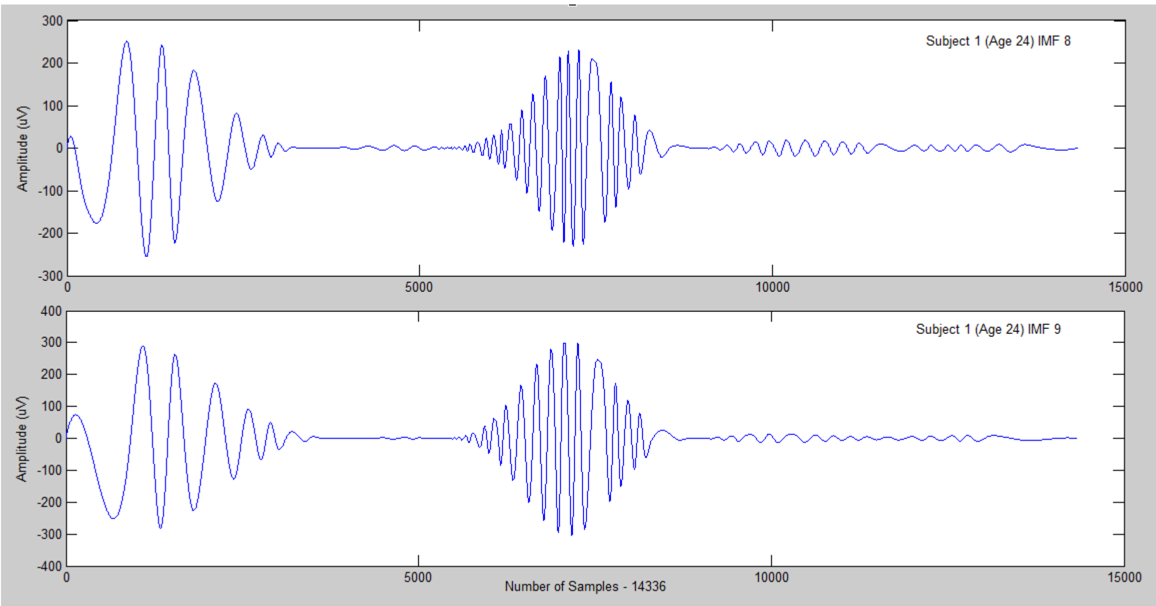


Figure 5.6: IMF 8 and IMF 9

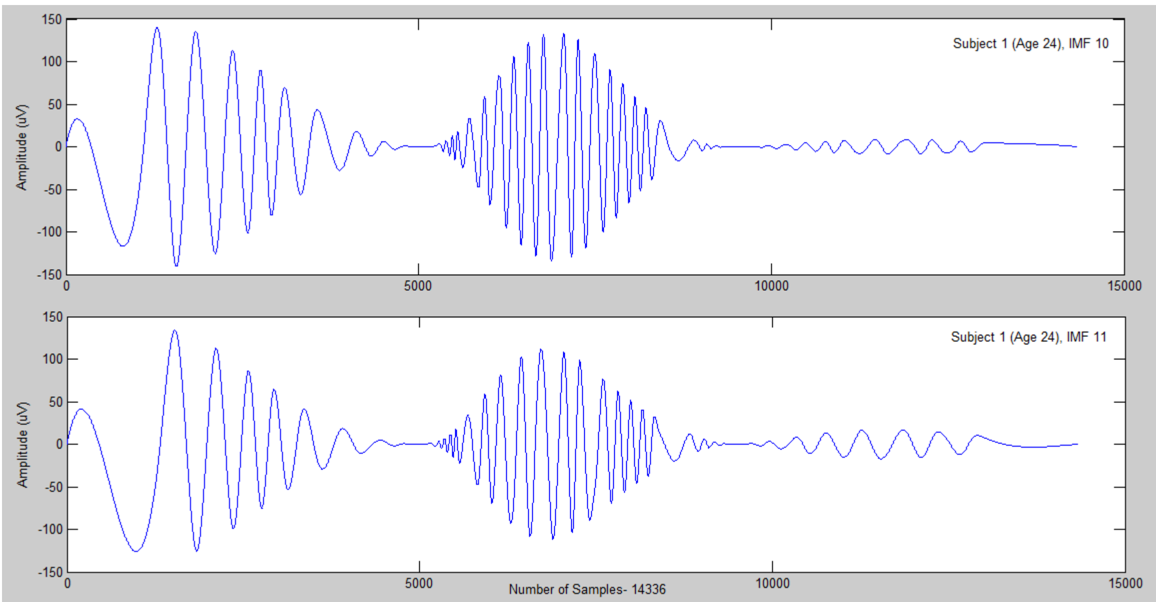


Figure 5.7: IMF 10 and IMF 11

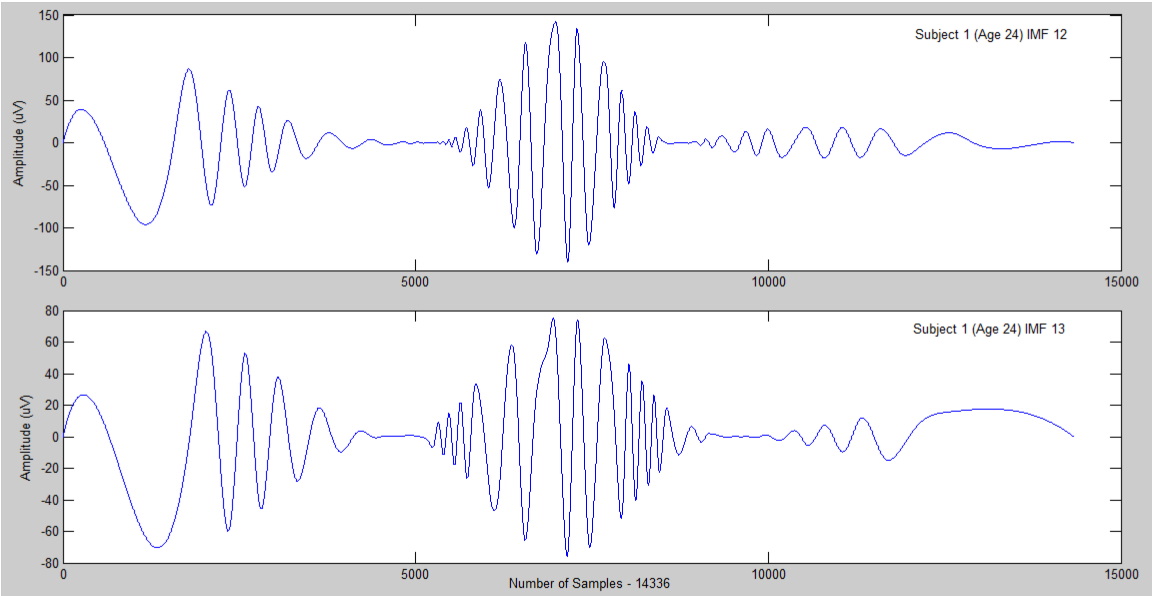


Figure 5.8: IMF 12 and IMF 13

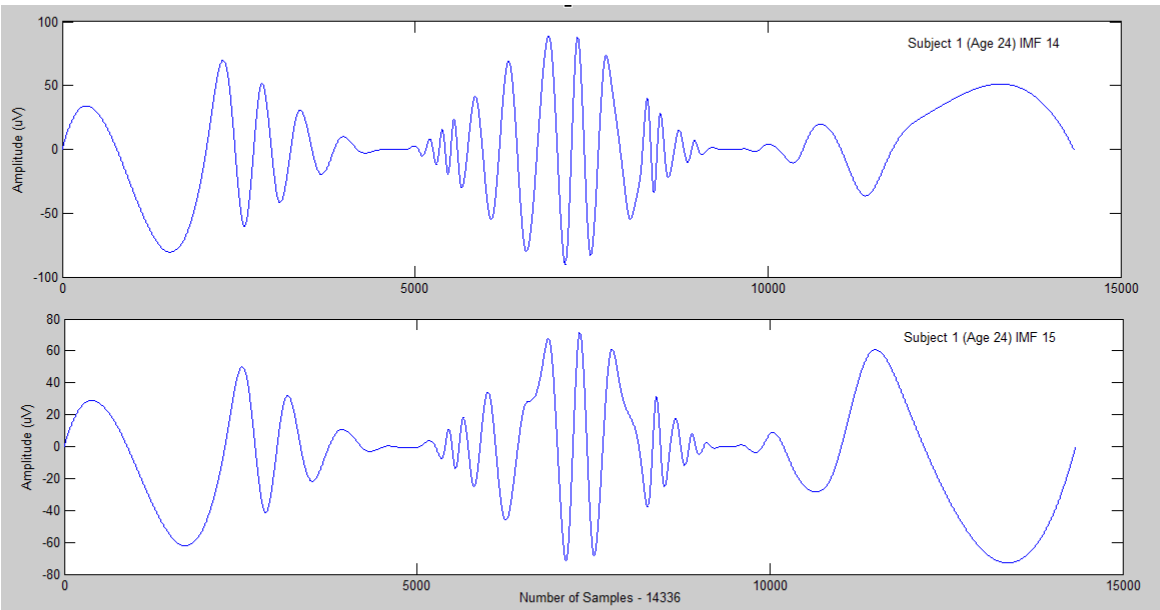


Figure 5.9: IMF 14 and IMF 15

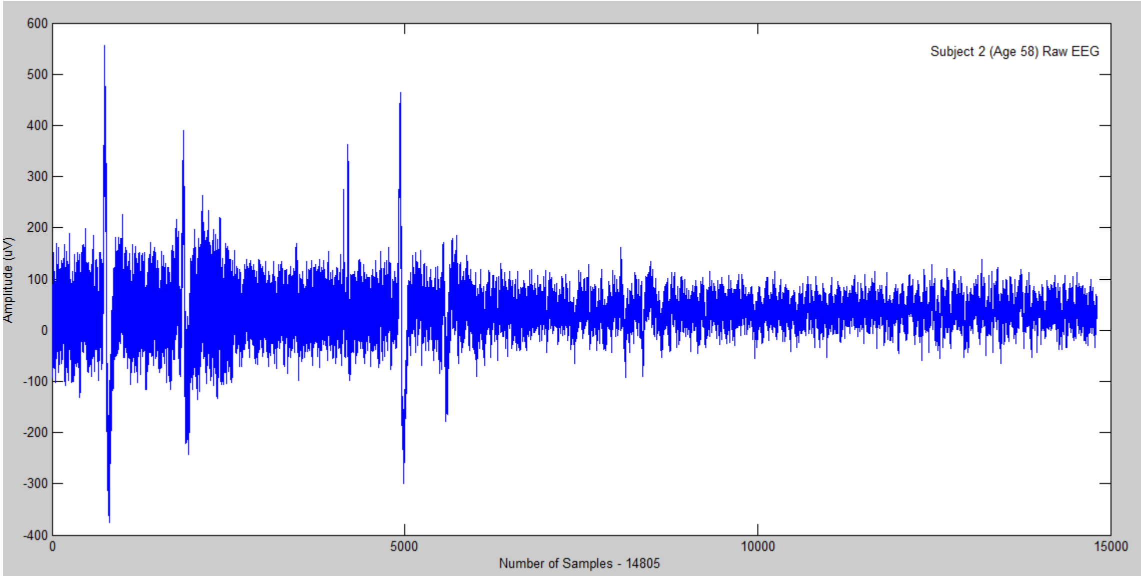


Figure 5.10: Raw EEG Plot of Subject 2

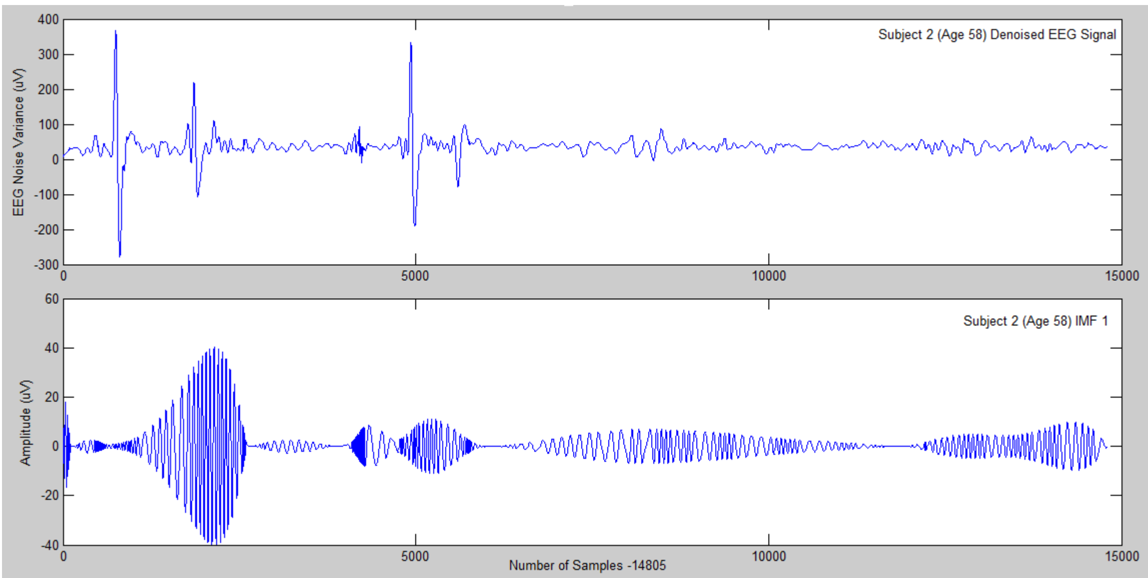


Figure 5.11: EEG Noise and IMF 1 of Subject 2

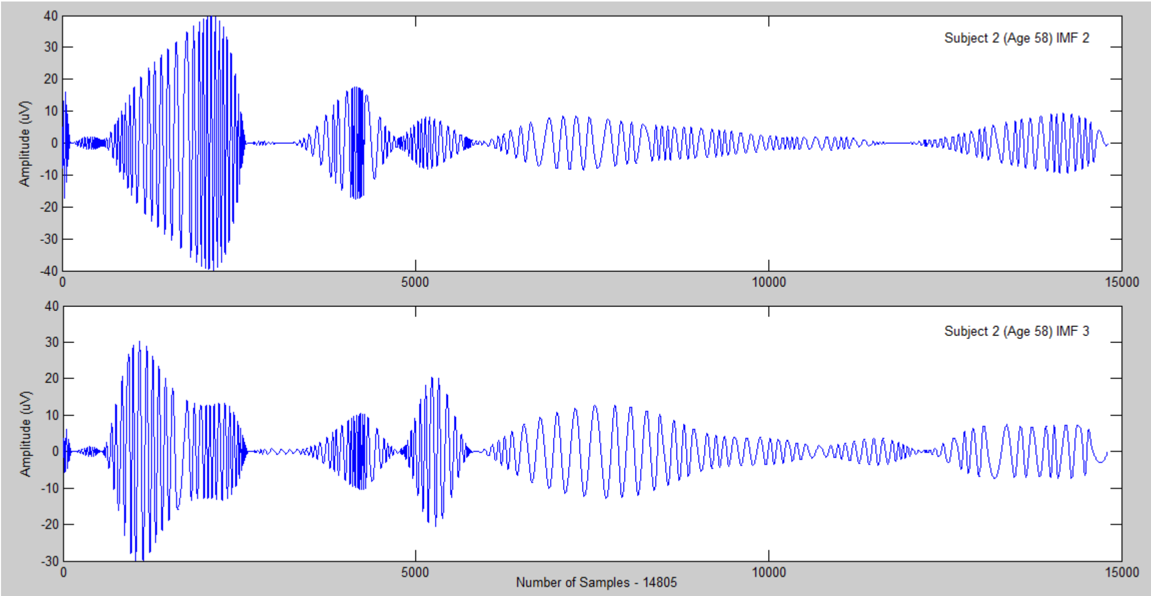


Figure 5.12: IMF 1 and IMF 2

Figure 5.12 shows the second and third elements of EEG Noise Signal.

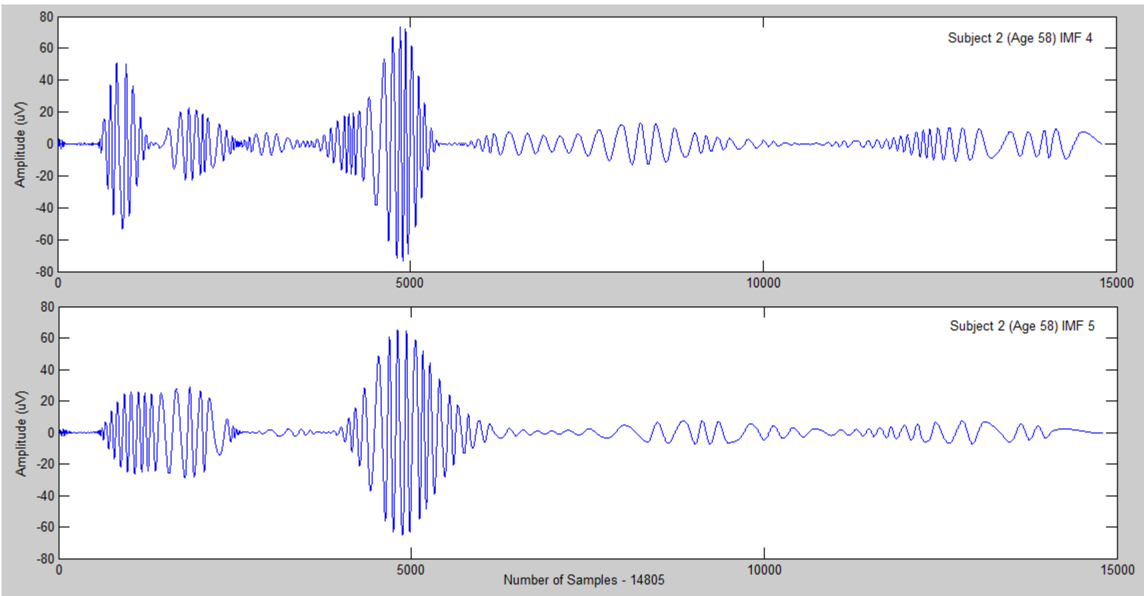


Figure 5.13: IMF 4 and IMF 5

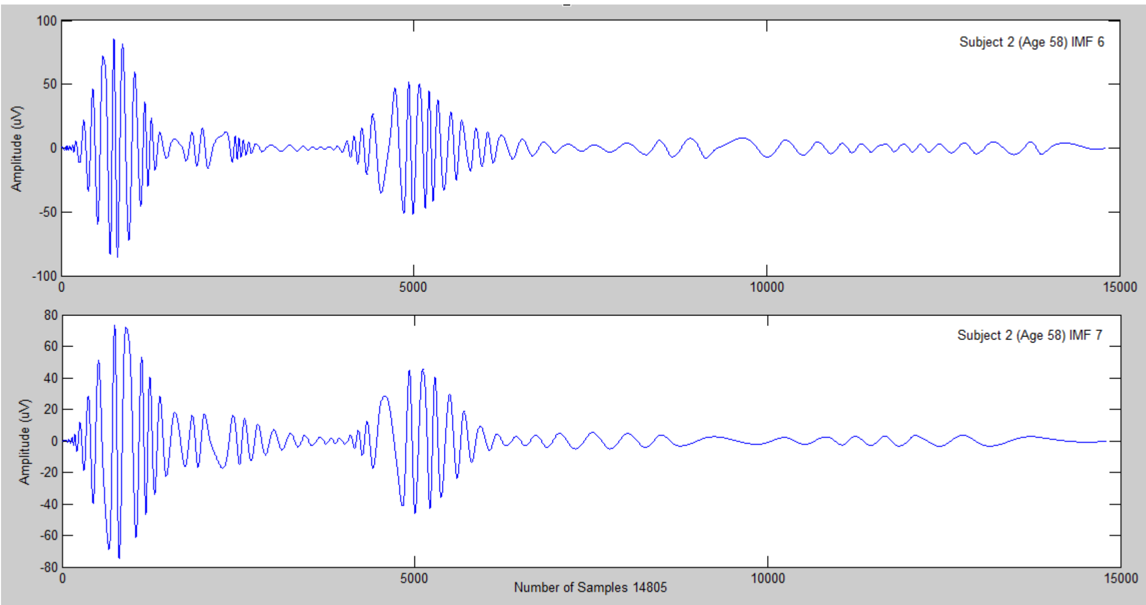


Figure 5.14: IMF 6 and IMF 7

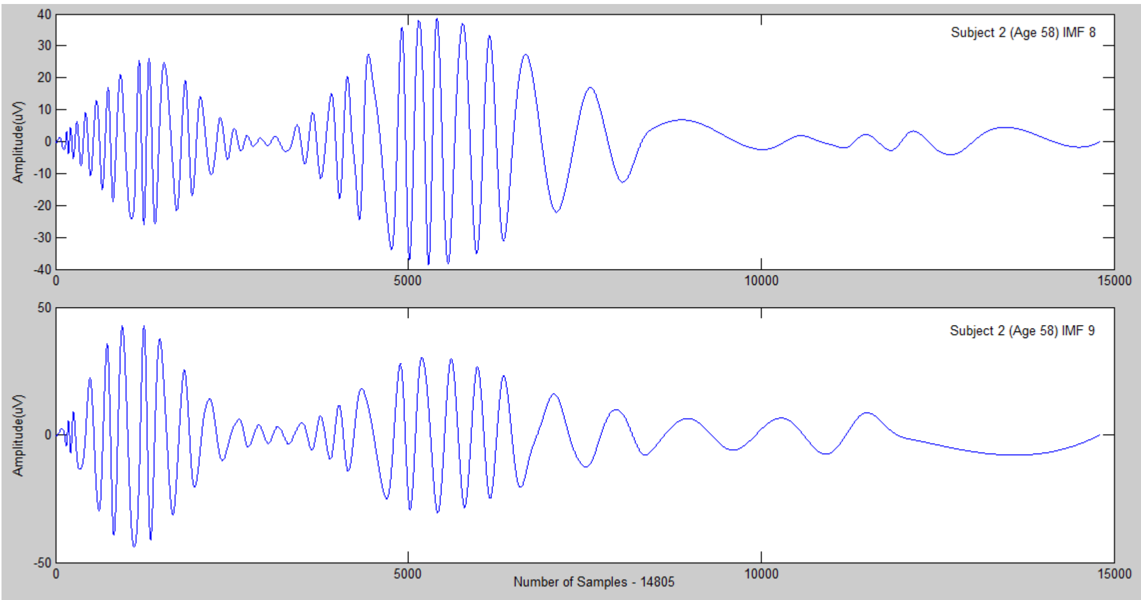


Figure 5.15: IMF 8 and IMF 9

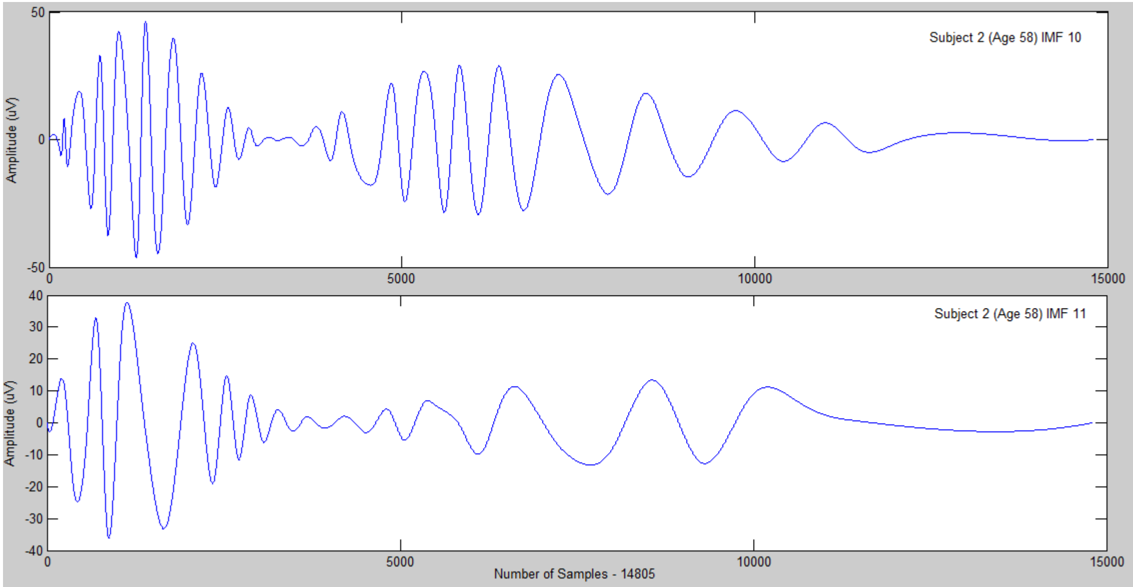


Figure 5.16: IMF 10 and IMF 11

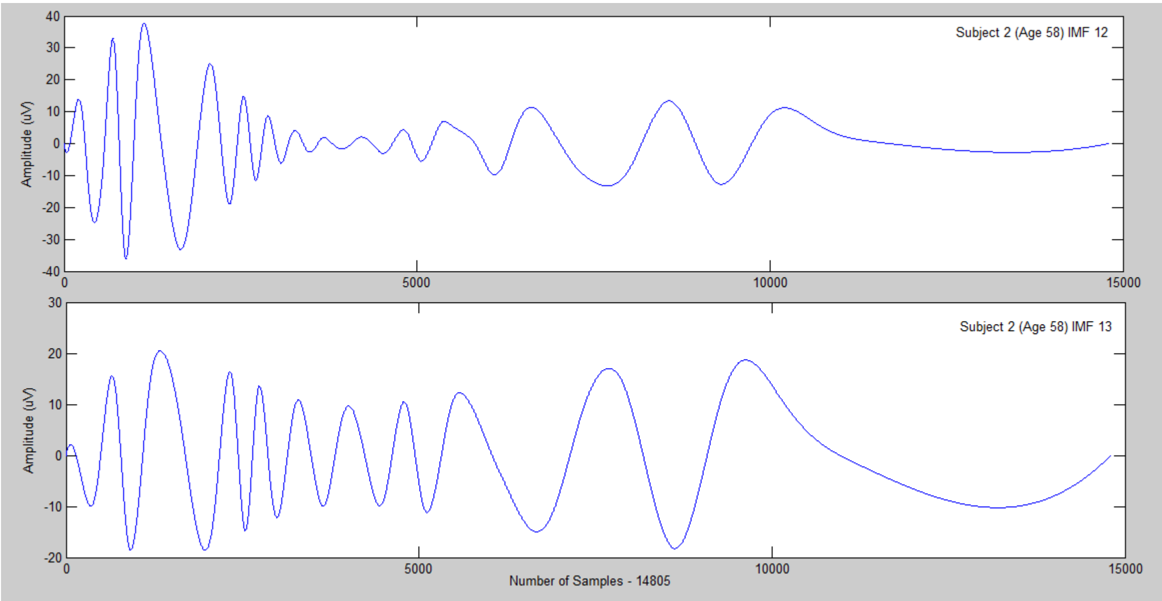


Figure 5.17: IMF 12 and IMF 13

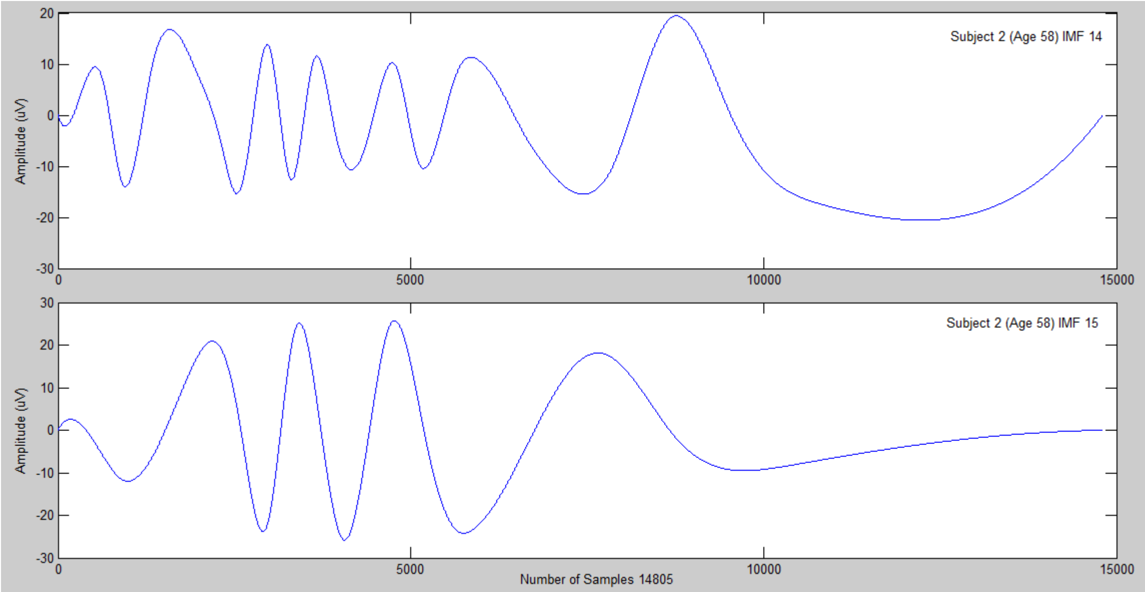


Figure 5.18: IMF 14 and IMF 15

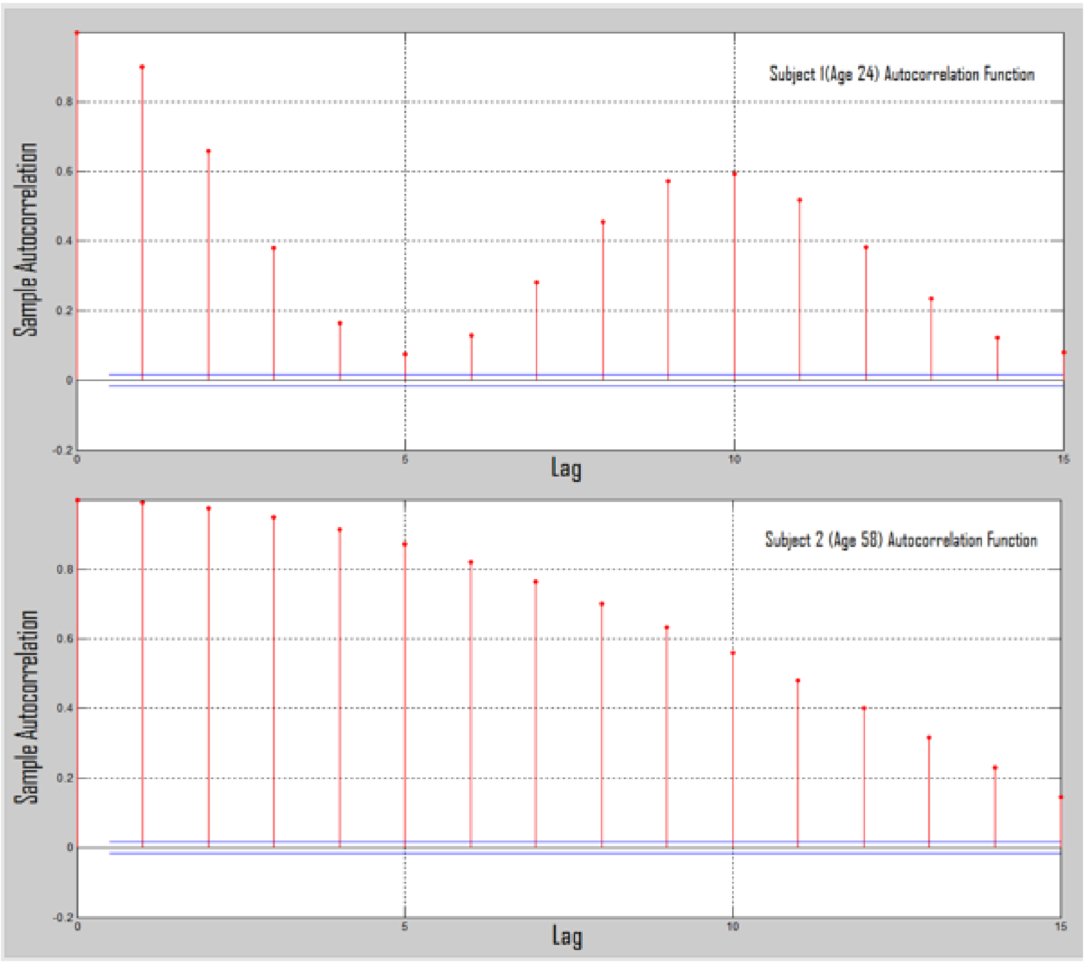


Figure 5.19: Autocorrelation Function of Subject 1 and Subject 2

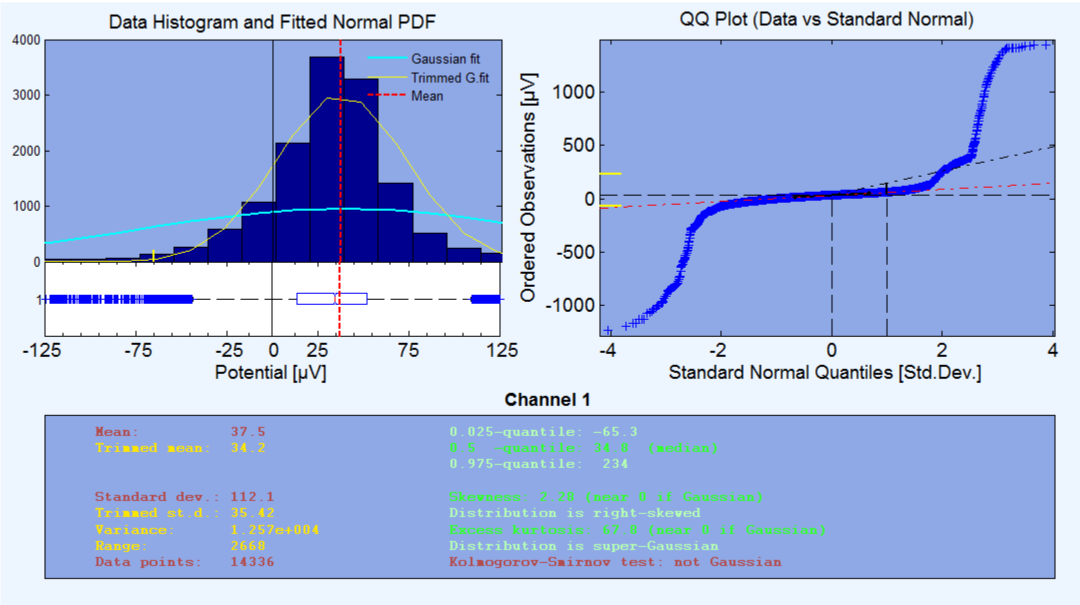


Figure 5.20: Probability Distribution Function of Subject 1

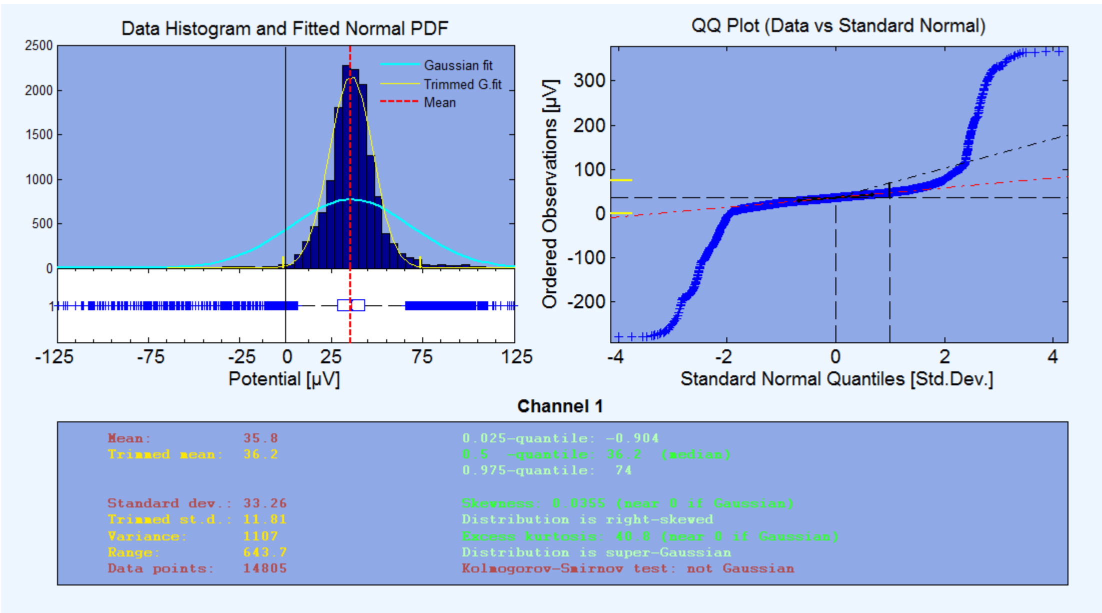


Figure 5.21: Probability Distribution Function of Subject 2

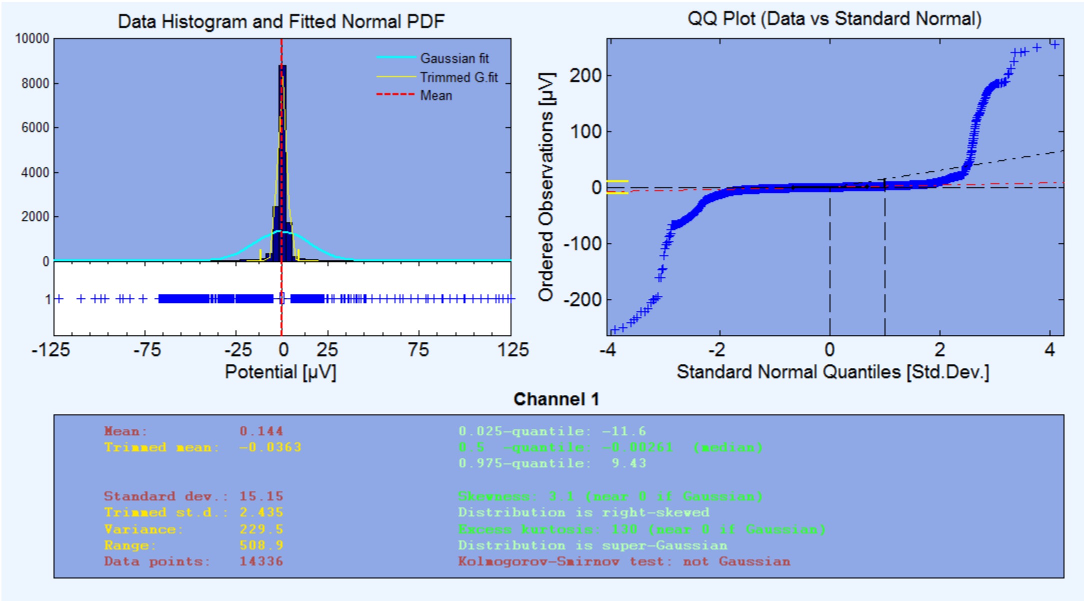


Figure 5.22: Probability Distribution Function of IMF 1 of Subject 1

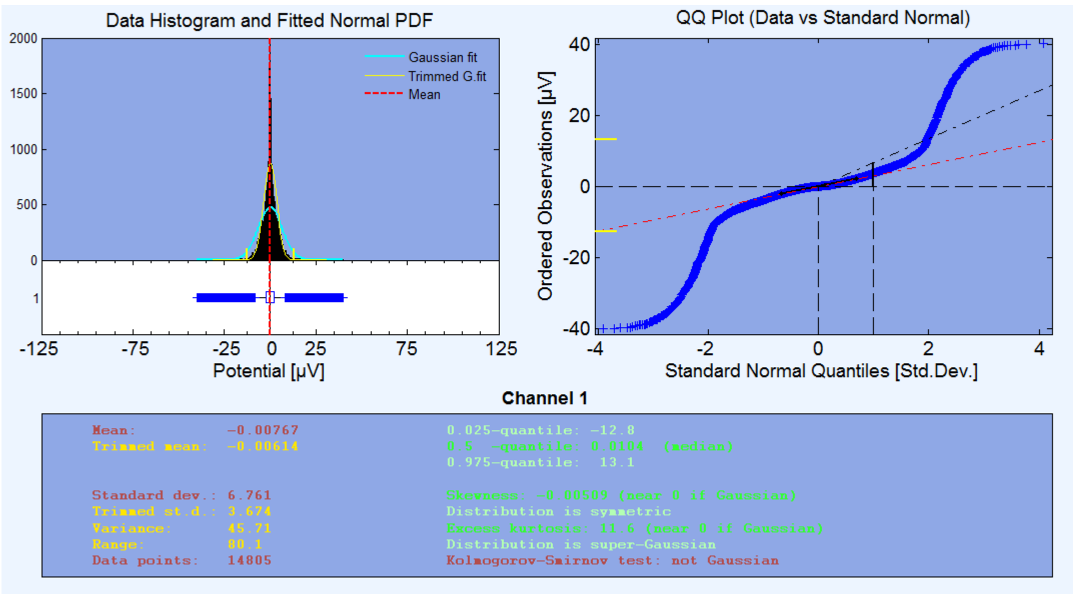


Figure 5.23: Probability Distribution Function of IMF 1 of Subject 2

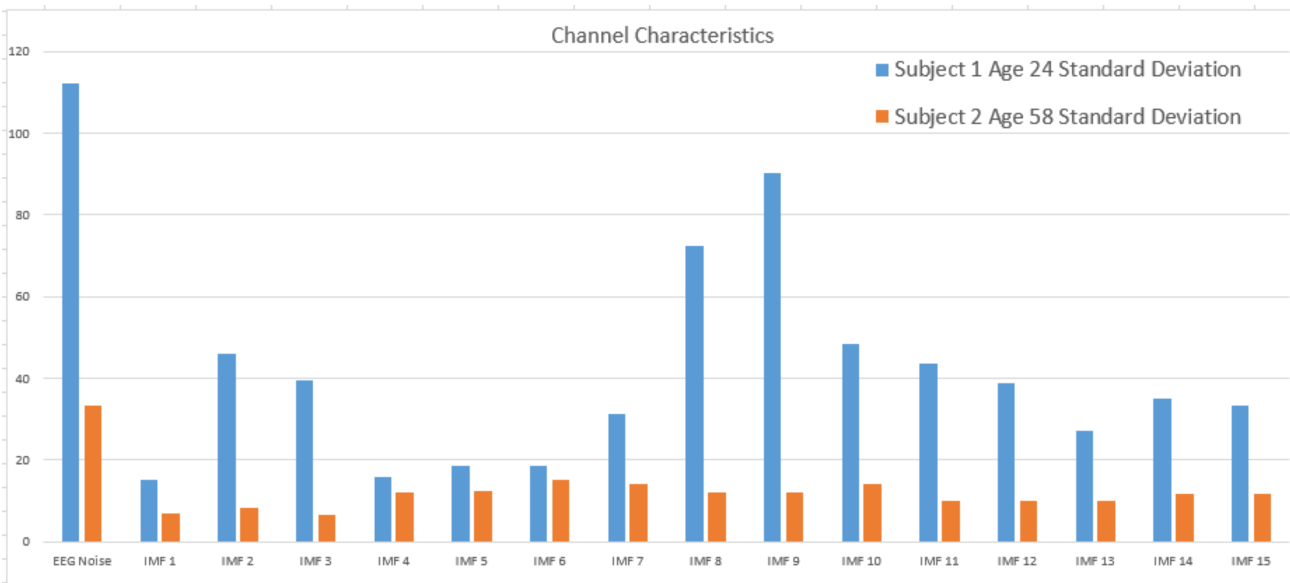


Figure 5.24: Channel Characteristics Graph

Chapter 6

Conclusion

From the study done so far it can be concluded that the standard deviation among the two age groups is significantly large. First subject of age 24 years shows a larger deviation than the second subject of age 58 years. But the mean amplitude was very close in each of the intrinsic mode functions. Other statistical parameter that is the autocorrelation function was seen to be high in the second subject. This suggest that the randomness is less and more of oscillatory nature. Whereas in the first subject the autocorrelation was found to be close to zero in the first lag. Based on this pilot experiment various predictions can be derived from this priliminary study. There is a decrease in the effective signal-to-noise ratio. For identifying the age related difference the change in mean amplitude of each of the IMFs failed to appear. So, more effort should be made to devise new methods and experiment for investigating the noise behaviour for a more reliable hypothesis. However earlier it was suspected that this noise would decline with age because with the growth and cognitive development mental processes become more efficient. But new research suggest that noise actually increases with age which is an indication of greater complexity in the brain.With a memory task experiment conducted by Randy McIntosh between children and adults it was discovered that brain maturity leads to more stable and accurate behaviour in memory task but with an increment in signal variation.Adults had more noise than the children. Nonetheless, this study opens up new perspectives to see the age related changes between child, adult and old age volunteers.There are some evidence as mentioned by McIntosh that noise levels go down with diseases like Alzheimer's and go up with disorders such as schizophrenia.It is still not clear at which level the noise is optimum. So, this moment to moment variability in brain signals can be studied more deeply by designing effective experiments to find that optimum level of noise when the brain efficiency is at peak.

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