TECNOLÓGICO DE MONTERREY®

INSTITUTO TECNOLÓGICO Y DE ESTUDIOS SUPERIORES DE MONTERREY
CAMPUS CIUDAD DE MÉXICO

ESCUELA DE INGENIERIA, DISEÑO Y ARQUITECTURA

EEG and facial signals classification on Real-Time using Neural Networks

MAESTRÍA EN CIENCIAS DE LA INGENIERÍA

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Mayo 2012

Resume

The following thesis deals with a method for acquiring and classifying electrical signals originated at facial skin. There is also analyzed the already implemented system by EMOTIV Epoc headset that is used for analyzing Electroencephalographs in order to improve the system. A new method is programmed in order to allow people to write with just looking the wished letter in a modified *qwerty* keyboard. All the system also enables communication with NI software and hardware, so it is possible to control devices trough the programmed system. The used method for the classification system was Neural Networks and the whole patterns are presented at the attachments of this document.

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Chapter I

1.1 Motivation

Since human interfaces began to be exploited in order to manipulate objects, it has been a challenge to control objects with the mind, further from only objects, the mind of other people. Nowadays, it is possible to identify the incoming electrical signals from brain. Although they are very noisy, a set of patterns can be identified by building them using different brain areas. By using electrodes, many headsets have been manufactured in order to offer mental control for devices like video games and hardware controls. However, it is still a challenge to have a quick system capable of being adapted to the majority of the users by training it only few minutes and having the less confusion from the signals.

These systems can be applied to a countless amount of devices and software. In order to make an inquiry about how different methods for pattern recognition can be applied, this research will deal with patterns recognition associated with stimulus induced over a human being classifying them on real time.

1.2 Background

Although there have been studies regarding the EPOC EMOTIV system, these studies are focused on describing the basic functions of the EMOTIV EPOC. These functions are related since the filtering process until classification process. There is not any proposal about a new system or configuration on the system that could be able to improve any layer of the system (Hoffmann, 2010).

Another work presented on the last year introduces various applications for testing and performing demo applications. There is used a Support Vector Machine which is used for classification of the EEG patterns. There are also tests regarding the performance of the algorithm classification (Varol, 2010).

Clearly the most advanced and best classificatory system is the one implemented on the Toyota Mind Controlled Wheelchair. Announced on 2009, the Toyota wheelchair enhances the system fuses RIKEN's blind signal separation and space-time-frequency Filtering[1] technology to allow rapid brain-wave analysis and display the results on a panel so quickly that drivers do not sense any delay. The new system has succeeded in having drivers correctly give commands to their wheelchairs with an accuracy rate of 95%, one of the highest in the world (Abolfathi, 2009).

Researches regarding gyroscopes include a huge amount of controllers for 3d games and entertainment devices (Dan Ionescu, Sept.2011). A mixture of Real Time image processing was developed in order to manipulate video games but also gestures and facial may extend gamer's degrees of freedom, but for these systems, the core is based on hand gestures so they are not available for people with tetraplegia. The system allows reaching extended precision (Algrain, Nov. 1991), so accurate movements might be developed by the user for controlling any device in a 3D world.

Recently, more researches have been developed regarding Apples's devices that include a gyroscope for controlling video games. It was also designed for aiding face recognizer algorithms (Scheuermann, 2011) in order to adjust angle deviations caused due user's hand-orientation in portable devices like iPod and iPhone.

The gyroscopes and accelerometers may also being used as (Schindhelm, 2011) inertial systems for indoor positioning: knowing an initial position, all subsequent positions can be calculated using various sensor data, which do not require any infrastructure and ensure the user's privacy.

By other hand, Brain Machine Interface researches have had many approaches in order to look for mental diseases and controllers for manipulating other devices like Lego Mindstorm robots (Liarokapis, 2011). Mental diseases researches in many cases just get focused on reporting EEG for patients that present any brain's malfunction; indeed, there are researches that report the possible zones where there might be damage by applying supervised conditions. In order to record

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[1] As a matter of fact there were used patented filtering methods by Toyota. *Blind signal separation (BSS) is a technology that separates the noise components and useful signal components from brain signals that can be used to control the wheelchair. It utilizes only on-line-recorded EEG signals. Space-time-frequency filtering is a technology which extracts space and time patterns and frequency oscillation data from EEG electrodes to discriminate significant features and components which are able to reliably control the wheelchair.*

EEG for limbs, subjects were instructed to walk on the treadmill at their comfortable speed while receiving real time visual feedback of their lower limbs (Alessandro Presacco, 2011)

Dynamic data-driven brain-machine interfaces or DDDBMI, are systems that have great potential to advance the understanding of neural systems and improve the design of brain-inspired rehabilitative (Ming Zhao, 2008). DDDBMI were developed in order to face two critical challenges:

1. The concurrent execution of many BMI models requires a tremendous amount of computing power and storage capacity.
2. Resources for effective brain-inspired motor control demand stringent timing requirement because of the need for low latency between brain signaling and sensory feedback.

However, these systems need huge workstations that demand real time processing and infrastructure compared to research labs requiring space and huge investment.

EMOTIV EPOC device allows acquiring fast EEG and is an inexpensive interface that is used for quick-training applications. Previous researches indicate that EPOC headset sacrifice accuracy for price (G. Michael Poor, 2011). These reports also indicate that EMOTIV EPOC training is difficult for being trained.

As a matter of fact, projects that focus on people with any disability are really scarce. A large amount of researches get focused on special cases that explain mechanism developed for that specific case. Indeed, devices just like EMOTIV EPOC, have more applications for video games and controls for interaction between users and consoles than for aiding people.

1.3 Framework

In the 20's, the psychiatrist Hans Berger published the first of twenty articles related to electrical activity in the brain and how it is possible to acquire an Electroencephalography. Since that time, this electrical acquisition technique has been used for medical applications (About Encephalograms on Human Beings, 1999).

An electroencephalography is defined as graphical representation of electrical activity in the brain between two different locations plotted on defined time. Common EEG (Electroencephalography) yields images that must be interpreted by medical staff or by image analysis accomplished by computers. In order to reach a better medical diagnosis, it is also necessary to implement an invasive method that requires inserting devices directly connected to brain tissue. Based on both analyses as the most reliable procedure, it is not always possible to implement invasive processes due they are really expensive and dangerous.

Although EEG was focused on finding possible brain damage, nowadays it is also used for real-time thought's classification. In order to reach this goal, portable hardware has been developed; the number of electrodes was reduced based on the main brain activity regions obtaining a reduced amount of incoming signals in the range of micro-Volts. These signals may be processed in real time and classified by using algorithms capable of differentiating the electrical signals ending the process with Boolean values representing an individual pattern of thoughts.

On these devices, several training methodologies are applied for adjusting the classification algorithms. However, they are really inefficient and the training period is really long emptying on non-reliable systems for accurate applications. By means of incoming signal, noise is introduced preventing accuracy. Among the causes of noise, is the fact that EEG signals have a big resolution on time (great changes on short periods of time) preventing an appropriate signal processing. Another consideration implied on an EEG is the fact that the signals are not sensed by working with single neurons, which means that an average per brain area must be calculated.

Although previous implications, EEG is the most efficient Brain-Computer Interface (BCI) for sensing brain electrical activity. On recent research, IT companies have developed BCIs including software and hardware drivers. Modular EEG, EmotivEpoc and TeunisOEEG are the most common devices for EEG acquisition on real time. In order to implement Real-Time classification algorithms, on this thesis will be implemented Artificial Intelligence classification algorithms; by using rough incoming signals from the EMOTIV EPOC system, the purposed system will be able to classify different kinds of thoughts and execute a pre-programmed action.

EMOTIV EPOC's projects include a wide range of applications, since autonomous cars to brain-controllers cell phones. Autonomos Labs at Germany modified a gasoline-driven car in order to be controlled with EMOTIV's gyroscope. The Car works with digital data, depending on the side where user spins the head the steering wheel will be rotated a fixed angle. Just in case of stopping or advancing the will be manipulated by moving the head up or down. There were used Artificial

Intelligence algorithms in order to reach differentiation between inputs (Rojas, 2011). New researches use neural signals to control mobile phones (Choudhury, 2010), a brain-controlled address-book dialing app, which works on similar principles to a P300-speller: the phone flashes a sequence of photos of contacts from the address book and a P300 brain potential is elicited when the flashed photo matches the person whom the user wishes to dial. The goal is to best understand how firing neurons can drive mobile applications and what the current limitations in already mobile phones applications.

1.3.1 Aiding people with disabilities

Living with a disability sets in patient's common activities an inordinate cognitive and social challenge. The patient gets his life reduced in professional and social opportunities; therefore the performance of common activities is a big challenge. In developed countries, the quest for a job is a challenge that may result in constant failures. Michelle Howard, a patient with tetraplegia, was kicked off by a solicitor when he asked her: *'Can you tell me, Miss Howard, how you would explain to a client about your disability?' She replied: 'You were sitting behind a desk when I came in. Would I be doing any different?'* (MacDonald, 1994) In underdeveloped countries just to think about jobs for subjects with tetraplegia is right now a dream. Even at home the subject with any disability gets physically but also socially limited. In several cases for subjects with Tetraplegia, they did not born this way, else they got this condition at mature ages so it is possible for the patient to work on intellectual activities.

Small Office Home Office (SOHO) is a proposed solution for working at home. An amount of devices is adapted based on diagnosis realized by a therapist in order to control a ball mouse, a touch mouse and a trackball. The personalization is based on how patient's skills are better with his hand, finger or a suggested extremity by the physiologist. However, on researches it has been concluded that digital controls work better for people with Tetraplegia than analog do (Yoshio Tanimoto, 2003).

Techniques that involve invasive methods are now considered as an option (Sung-Phil Kim, 2011). In Sung-Phil research, a Point-and-Click Cursor is tested: a computer interface extracts discrete (click) and continuous (cursor velocity) signals from a target amount of neurons in human motor cortex. A multi-state probabilistic decoding algorithm that simultaneously decodes neural spiking activity; the algorithm combines a linear classifier, which determines whether the user is intending to click or to move the cursor. The results reflected that *"single implanted microelectrode array might be useful for neural cursor control applications"*, however due the danger that implies an invasive method, it is not a reliable method for being implemented. In cases where the patient is not capable to afford the necessary adjustments this is not an option.

1.4 Problem statement

Although the proposal of this research is that the developed system would be used for as many people as possible, the system is designed for people who have non-pathological damage developed at brain cortex.

Due the brain is the most complex organ on the body and besides the usage of low-pass filters, there are many possible sources of noise, these sources of noise may be electrode's placement, electrode's humectation and external noise from brain-machine interface. Therefore the programmed algorithms must be robust.

By working with the incoming signals from the EPOC Emotiv system and considering all the rough different signals detected by the electrodes, it can be applied Neural Networks algorithms; this is due to its high training speed and noise tolerance in comparison with the already implemented systems like wavelet maps, sine-cosine diagram and support vector machine classification algorithms. Considering previous works (Abolfathi, 2009), there will be designed low-pass filter according to the natural frequencies of the brain, which will reduce noise disturbance and time for training the system.

1.5 Objectives

Even though there are plenty researches regarding electrical activity in the brain, few investigations have been done regarding signals classification. In the researches and for public works, it is possible to identify linear methods for classifying mental out coming signals. However it is the objective of this thesis applying non-linear techniques which may help to identify electrical patterns.

Pattern recognition at this research hardly depends on signal filtering and noise reduction, underway to reach a fast classification, it is the objective in this research to implement, according to the brain area, an efficient filter. By using efficient filters, it will be possible to reach the main objective: integrate a fast-trainable system able to compute different patterns reaching the most efficiency as possible. The hypothesis that supports this thesis can be inferred since for some brain illnesses there exists some patterns and for people with no-disease these patterns might be detected with the EPOC EMOTIV headset by following the already classified areas for previous researches.

1.6 Methodology

Pattern recognition involved on signals generated by human beings, used in the encephalograms, deals with nerve conduction studies and most often used to detect epileptic activity, but it is also a sensitive detector of encephalopathy and other types of brain dysfunction (Lee & Khoshbin, 2008). In many circumstances there are used Evoked Potentials, that are thoughts influenced over the human being in order to look for patterns. Specific procedure must be followed to reach better EEG signals. Common schedules include to avoid consuming any food or drinks containing caffeine for 8 to12 hours before the test and avoid fasting the night before or day of the procedure, since low blood sugar may influence the results.

Working with brain incoming signals, it will be designed a graphics user interface that will allow plotting real time incoming signals as well as the classification results. This interface will be developed on C++ and LabVIEW. On a first stage, Neural Networks algorithms will be programmed in order to classify the signals. Considering that not all the electrodes are useful, heuristically it will be determined which signals may be avoided in order to improve signal analysis and classification.

Chapter 2

EEG

For the following thesis, there will be applied an Evoked potential which is a neurophysiological exploration that evaluates the function of the acoustic sensorial system, visual, somatosensory[2] and its communication ways due induced answers caused for a known and normalized stimulus. The Evoked potential was thought for setting a pattern that could be helpful for a further classification method which will help us to train with different patients the system. The Evoked potential indicates the modification of the electric potential induced by the nervous system in response to an external stimulus, especially sensorial (a sound, an image, etc...) but there may also be an internal event such as a cognitive activity (attention, memory, etc.) and it might be recorded by using the Electroencephalography.

Electroencephalography is the neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp or, in special cases, on the cortex. The resulting traces are known as an electroencephalogram (EEG) and represent so-called brainwaves. It is important to notice that difference of potential is measured with respect to a reference electrode, although this reference electrode is commonly omitted.

The EEG is tightly linked to cerebral metabolism. The action potential from a lonely neuron cannot be detected by measuring extracellular activity, due its amplitude is too small for being detected using only one EEG. It has the capacity for being alive at least 0.3rns, on this period, it accumulates enough power synchronously with surrounding cells in a range of 200 Hz. The release of neurotransmitters will be triggered until potential difference reaches the axon limit (axon terminal). There are two kinds of neurotransmitters: one causes an inflow of positive ions through the change of permeability on the post-synaptic neuron membrane. By this way the potential gap will be created; this case refers to the post-synaptic excitation potential (whenever it is positive).

Post-synaptic potentials vary its amplitude from 50 to 100 mV (on measurements realized on the scalp) and are the main source in an EEG.

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[2]It is a sensory system composed of the receptors and processing centers to produce the sensory modalities. They include touch, temperature, proprioception (body position) and pain.

2.1 Left and right hemispheres

Since this research looks for repeatable-patterns generated by as much subjects as possible, it could be the first step to classify EEGs depending on the hemispheres at the brain.

Structurally, the left and right cerebral hemispheres look broadly similar. Functionally, however, speech and language, stepwise reasoning and analysis, and certain communicating actions are based mainly on the left side in most people.[3] Although it is known that humans EEGs show these results, they may be affected by many circumstances: ingested food, prominent veins and stress disorders in the subject.

Although hemispheres classification based on EEGs might be used as reference, brain signals patterns just work for identifying whether the EEG comes from a woman or from a man. Researches purpose the usage of wavelet transform analysis and artificial neural networks for classifying (Sternickel, 2002). However, until now there is not a pattern or a convincing analyses that is able to set reliable results for being repeated with more than one subject, furthermore, conclusions just like *detection of late potentials has not achieved convincing results because only one wavelet has been used and the frequency bandwidth has not been optimally adjusted* (Sternickel, 2002) can be read in conclusions at research articles.

2.2 The cerebral cortex

Due this research works with a non-invasive method it is necessary to explain how skull's width affects sensing any incoming signal from brain's activity. Since signals are obtained from head, hair and sweat are common layers that interfere for obtaining strong and clean signals. The resistivity values of the different tissues of the head affect the lead field of electroencephalography. When the skull, including tissues that surround it, are modeled like a concentric sphere, the different resistivity values have no effect on the lead fields of the magnetoencephalography .

In order to investigate EEG detectors' ability to concentrate measurement sensitivity there must be introduced the term *half sensitivity volume*. This term is defined based on electrode's detecting area; its sensitivity is highest just under it. Since for this thesis, the brain is a homogenously

[3] Carter Rita, The human brain

distributed source, throughout the brain the neural sources have the same probability to activate in an instant of time and in direction; if this assumption is true then most of the signal comes from the region where the sensitivity is the highest: just under the electrode. It is possible to establish that sensitivity decreases as a function of the distance from the electrode but also the region where it comes is smaller so: *The HSV is the volume of the source region in which the magnitude of the detector' sensitivity is more than a half of its maximum value in the source region* (J. Malmivuo, May, 1997). Figure 1 shows two circles that surrounds a point X, this point represents the main contact between the soft part at the EMOTIV EPOC headset that absorbs the electrolytic substance and the first metallic layer that connects with the wire that carries the incoming signal. For a practical generalization, it is assumed that skull's width is distributed in measurements as shown in Figure 1.

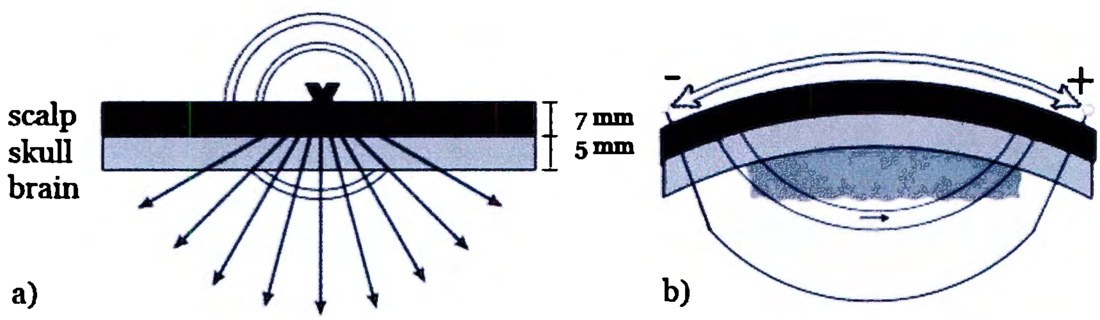

Figure 1. a) Levels at head for EEG acquisition. b) Dipole created by two electrodes. (Suihko, 2004).

Great part of the required signal for being sensed by the electrodes comes from brain cortex and for its examination it is classified depending on the resolution at brain's cortex.

Type	Characteristic
Gross anatomy	Sulci and gyri.
Microscopic anatomy	The shapes and types of cells and their connections.
Neurological Function	When small areas are simulated to study the sensations or movements this produces.

Emotiv EPOC headset acquires the incoming signals by working at level of *Neurological Function* but not just cerebrum signals, also voltages generated due muscles stretching and contracting. Now, since HSV is a volume, it can be inferred where it is possible to obtain de cubic units. By considering the area of the electrode and the depth at skull's user it can be determined. However for this research this factor could not be calculated due there was not used an invasive method.

2.3 Synapses

Synapses are communication sites where neurons pass nerve impulses among themselves. The cells not usually in actual physical contact, but are separated by an incredibly thin gap, called the synaptic cleft. Microanatomically, synapses are divided into types according to the sites where the neurons almost touch. These sites include the soma, the dendrites, the axons and tiny narrow projections called dendritic spines found on certain kinds of dendritic spines found more than 50 percent of all synapses in the brain; axodendritic synapses constitute about 30 percent. In bigger schematics (Figure 2) it is possible to appreciate

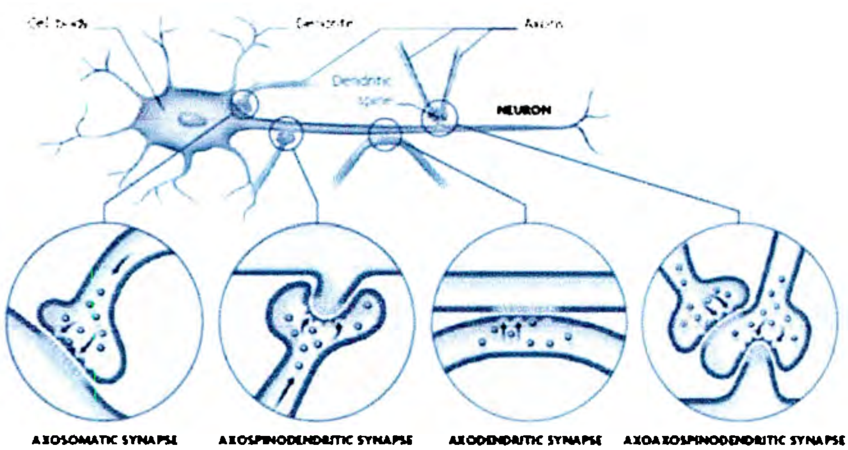

Figure 2. Different kind of synaptic activity in the brain (Carter, 2009).

Axosomatic synapse: one between the axon of one neuron and the body of another.

Axospinodendritic synapse: an axon to the spine (a bulge) on a dendrite.

Axodendritic synapse: axons which connect axon to dendrite.

Axoaxospinodendritic synapse: when the synapses is among two axons and a small membranous protrusion from a neuron's dendrite.

The incoming brain signals have this source as the main responsible for electrical activity in the brain. However, the signals have not simple common patterns which may be classified. In order to set an outline, the electrical shapes created in the brain were classified according to its frequency domains:

Delta waves (δ): from ½ to 4 Hz. Deep unconscious, intuition and insight. Having, the feature of deep sleep stage, this frequency band the δ activity is associated with some certain specific morphologies, location and rhythmicity has relation to different pathologies.

Theta waves (θ): 4-8 Hz. Subconscious creativity, deep relaxation. They are enhanced during sleep and play an important role in the brain electrical activity of infants and children. For the awake adults, high θ activity is considered abnormal and it is related with different brain disorders.

Alpha waves (α): 8-13 Hz. Mind is wandering and the subject is in a dreamy state, receptive and passive. They appear spontaneously in normal adults during wakefulness under relaxation and mental inactivity conditions. They are best seen with eyes closed and most pronounced in occipital locations.

Beta waves (β): 13-30 Hz. Conscious thought external focus. They are best observed in central and frontal locations and have less amplitude than α waves. They are enhanced upon expectancy states or tension. Usually they are subdivided into β_1 and β_2

Gamma waves (Υ): 30-100 Hz. Not quite defined, but linked to perception and alertness or anxiety.

These waves are related to different response of the human being for example, EEG alpha activity reflects attention demands, and beta activity reflects emotional and cognitive processes. On different researches it has been possible to set brain areas that determine specific reactions of the human being for specific stimulus as can be appreciated on Figure 3.

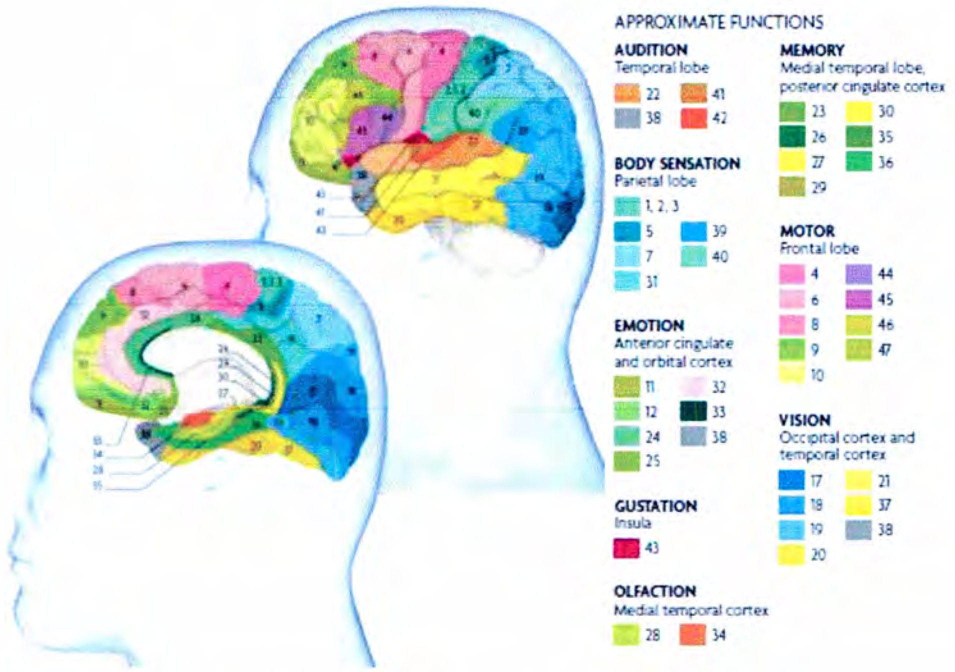

Figure 3. Cerebral division according to the induced sensations in the human being by the surrounding events (Carter, 2009).

Although it is possible to link brain activity with emotions and actions, it is also possible to find multiple brains' areas associated with a single stimulus (Figure 4).

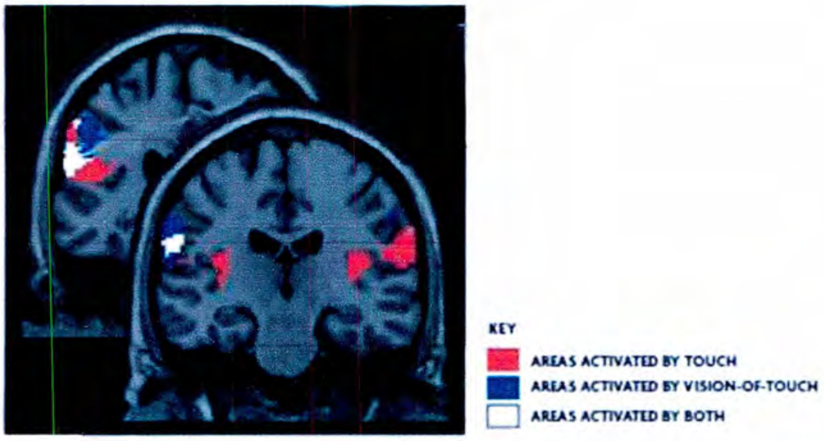

Figure 4. Common fMRI associated with areas activated by touch and vision of touch (Carter, 2009).

On the left hemisphere, a somatosensory area is the activity registered by both touch and vision touch. In the case of the overlapped fMRI (functional magnetic resonance image) at the right hemisphere, there are incoming signals representing direct touch but mirror neurons have been detected here in similar experiments.

- The ideal conditions for detecting an electrical signal:
- Many neurons must be triggered at the same time.
- These neurons must be aligned parallel so their action potential must be added and not cancelled.

2.4 EPOC EMOTIV System

The EPOC EMOTIV system detects and classifies incoming signals by using encrypted algorithms. Since electrical detection, signals are codified and processed in real time. Although, process time is really efficient, signals classification isn't. The references for acquiring the signals are appreciated at Figure 5 and the placement was established by international standards. In order to reach a better signal from each electrode, they must be wet with an electrolytic substance that improves electron's flow.

EPOC SDK includes:

1. 14 Channels with
    a. Common Mode Sense (active electrode) reference.
    b. Driven Right Leg (passive electrode) reference.
    c. P3/P4 Locations
2. Neuro-signal acquisition.
3. Processing wireless neuro-headset.
4. Real-time display of the Emotiv headset data stream, including EEG, contact quality, FFT, gyro, wireless packet acquisition/loss display, marker events, headset battery level.
5. Among others (EPOC, 2010).

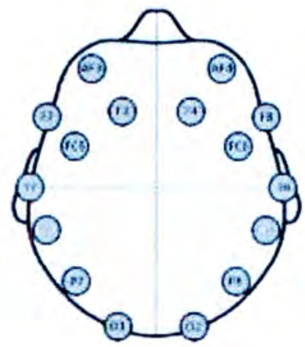

Figure 5. Electrodes placement: channel names based on the International 10-20 locations (EPOC, 2010).

Figure 6 shows a continuous fast EEG, according to the programed software, it displays 128 samples per second. The resolution is in micro Volts, in order to configure a pattern recognition algorithm, there will be extracted about 100 samples per signal to execute Real Time processing. As it can be appreciated the pattern recognition algorithm will have 14 entrances corresponding to each one of the electrodes. At this precise EEG, it can be appreciated how all the signals try to converge to zero, which indicates a state of no incoming signals receiving.

User's interface allows to the system to classify between different head signals:

1. Expressive Suite: facial movements or muscular stretching and contacting actions.
2. Affective Suite: it detects user's emotions.
3. Cognitive Suite: it detects influenced thoughts regarding pushing, pulling, moving up and moving down a virtual cube.

2.5 Rough data from headset

EMOTIV Epoc offers different headsets that can be upgraded depending on final user's needs. For this research a Developer's edition was used. The main advantage for this edition is the access that can be reached to rough incoming signals from fourteen electrodes. Since fourteen signals come from head, noise sources may appear for different reasons so it is recommendable to use the headset in a calmed environment and user must be focused in the task that must perform.

The incoming signals are delivered at 128 samples per second per channel as maximum. The samples taken will decrease depending on the programmed code by the user, which will vary depending on the time required by computer's processor in order to interact with the acquired data.

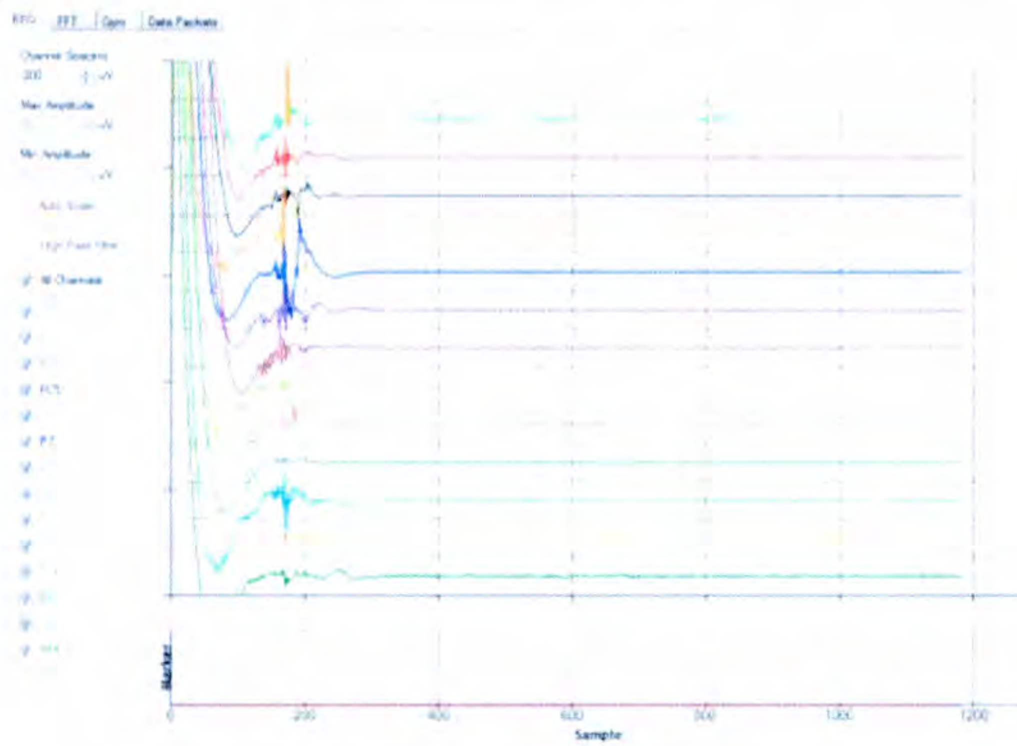

Figure 6. Raw incoming signals from EMOTIV system.

The whole system in the headset lets work with three different kinds of signals: Electroencephalographs, Electromyography and Gyroscope inputs. The interface also includes trainable software where the user may train different pre-established emotions or induced thoughts and face movements in order to control configured devices.

Although the software is configured for video games and interactive 3D scenarios, external codes may be useful in order to set communication and controlling more hardware. However there exists a huge range for researches in order to improve EEG classification. EMOTIV purposes a wide-range for thoughts in order to be trained therefore more actions may be performed.

Figure 7 and Figure 8 shows an EEG recorded in 15.632 seconds for two different users. The ECGs were taken at early morning and the users where asked to do not take breakfast previous to the analysis. ECG in Figure 7 was taken from a long-haired woman (user 1) and Figure 8 from a bald man (user 2).

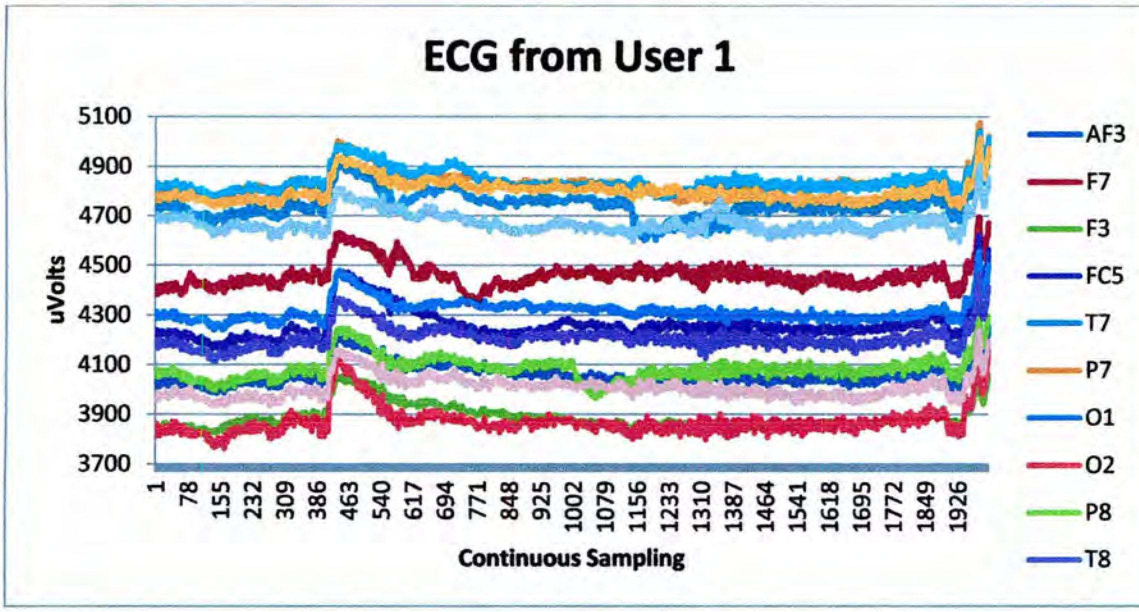

Figure 7. Rough ECG for an induced thought (User 1).

AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
4062	4462	3890	4262	4748	4833	4318	3873	4085	4209	4842	4803	4674	4009

Table 1. Average signals for each electrode for User 1.

More samples were taken from each user; the average per channel is shown in Table 1 and Table 2. For this average the whole samples were considered even though there where distortions. For these signals it can be concluded that for different times of sampling, the variation in average is almost null. Even for different users the variation is not considerable (Table 3).

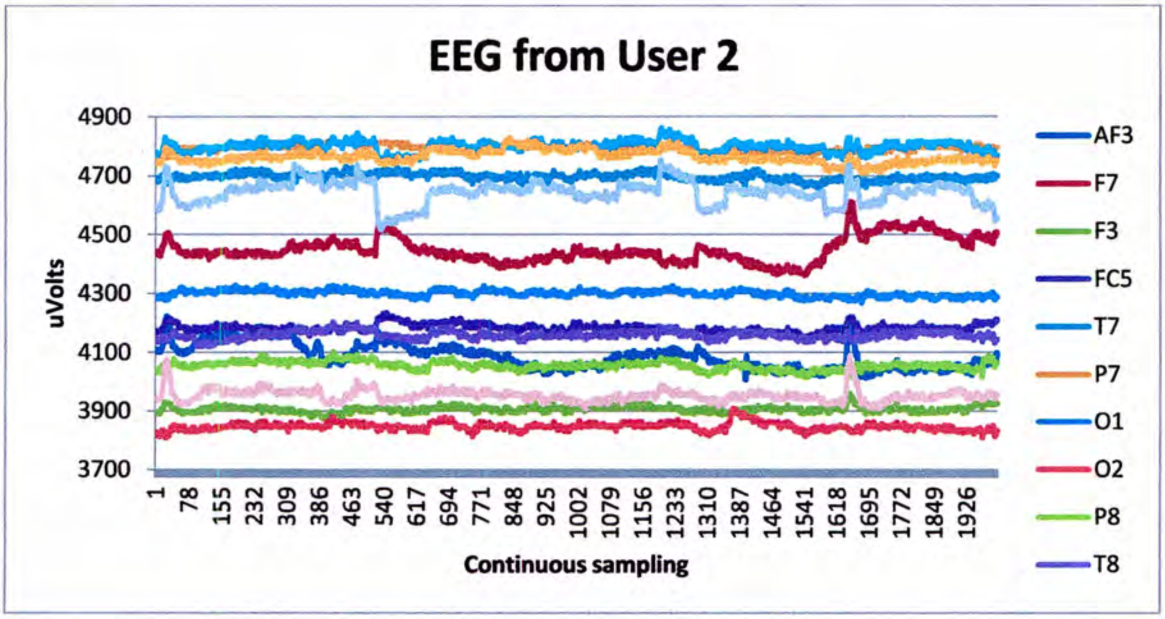

Figure 8. Rough EEG for induced thought (User 2)

AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
4087	4449	3907	4183	4698	4795	4301	3847	4056	4159	4800	4766	4644	3954

Table 2. Average for each electrode for User 2.

AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
25	12	17	79	50	38	17	25	29	50	42	37	30	55

Table 3. Difference of average between User 1 and 2.

Figure 9 displays contributions for different frequencies by using the Magnitude of its Fourier transform, this representation is for th whole set of 14 electrodes. It is appreciated that user's greatest amplitudes are concentrated in low Frequencies; regarding frequencies classification, they are associated to subconscious creativity, deep relaxation, mind is wandering but it is also in conscious thought for external focus. This is acceptable due the subject was influenced to remain in this state. However, it is also appreciated that since 70 Hertz there is an increment in the amplitude that is associated to awareness in the person and it is due the person did not reach a a bigger concentration.

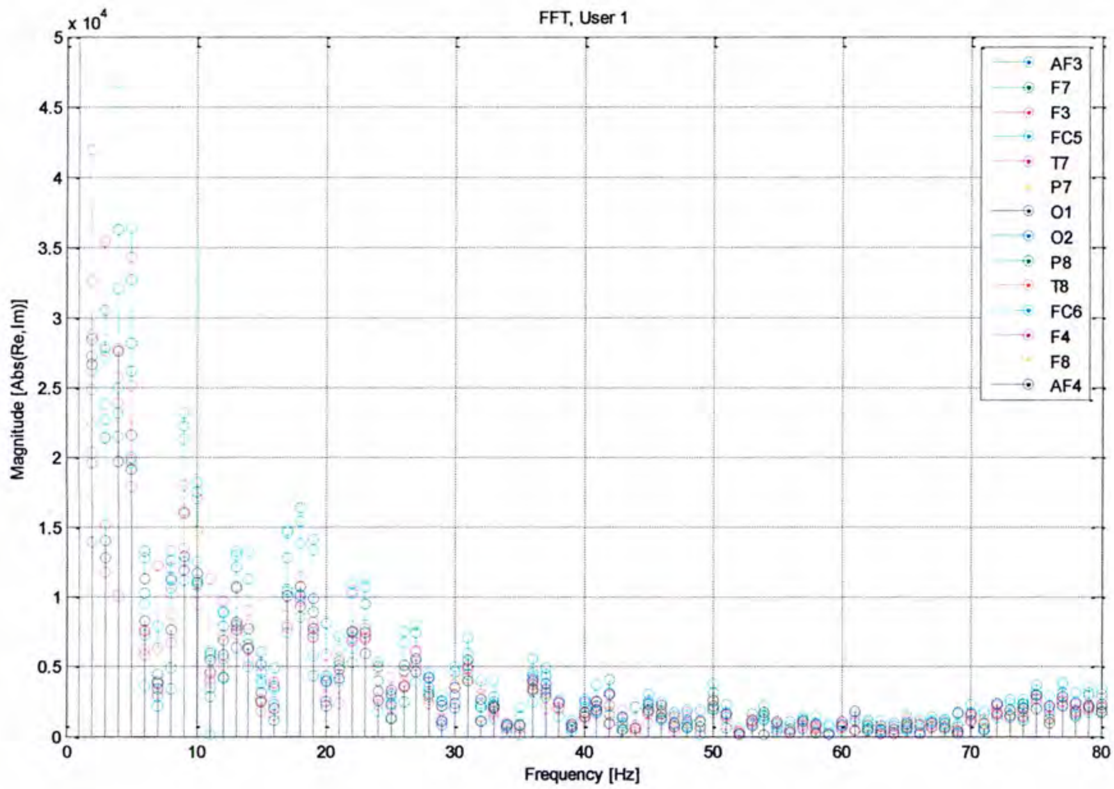

Figure 9. Fourier analysis for User's 1 EEG

Figure 10 shows ECG for User 2 but in contrast with User 1, there is not an increment at high frequencies and the amplitudes is general are lower than User 1, besides not all the channels reach amplitudes greater than 1Exp4. Since for reaching greater frequencies it is necessary to still hold lower frequencies, it can be said that User 2 reached greater concentration. In the case of both users, there appears a harmonic at 1Hz which amplitude cannot be appreciated. Although this frequency is considered in the range of Alfa Waves there also exist noise signals that contribute in the increasing of the signal.

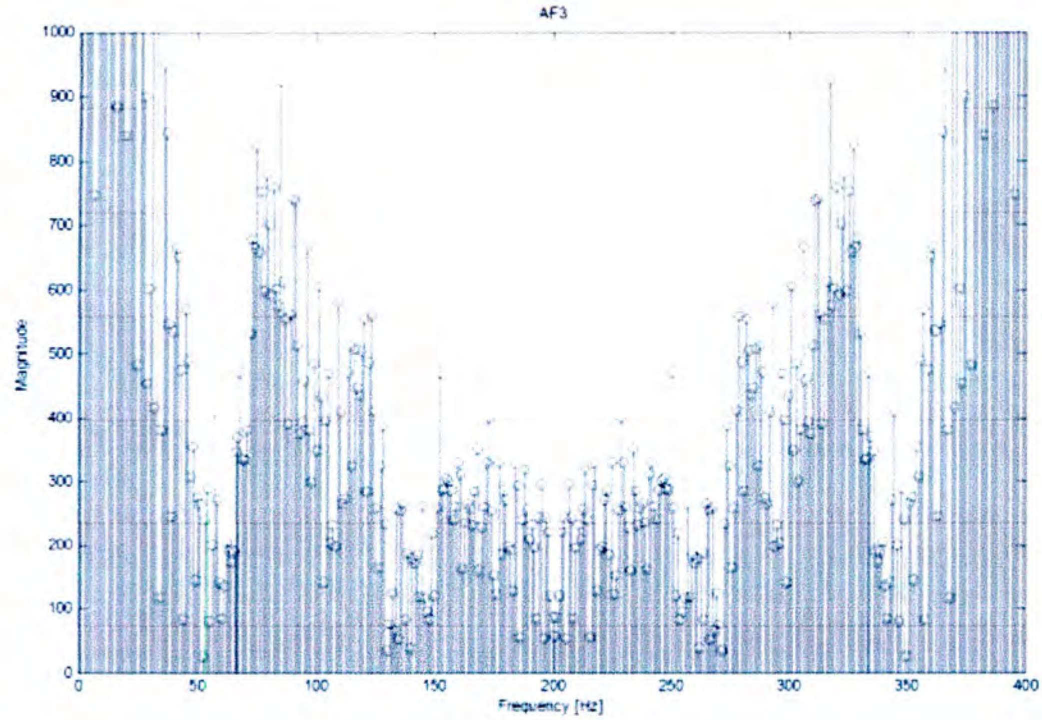

Figure 10. Fourier Analysis for AF3 electrode taken from User 1.

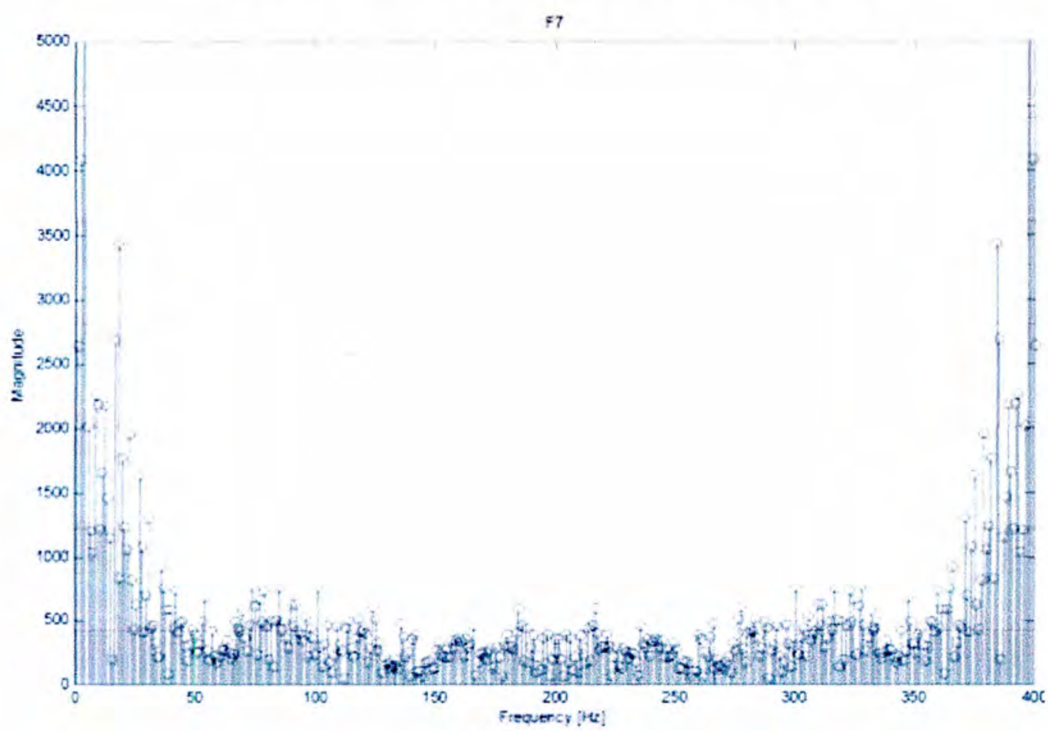

Figure 11. Fourier Analysis for F7 electrode taken from User 1.

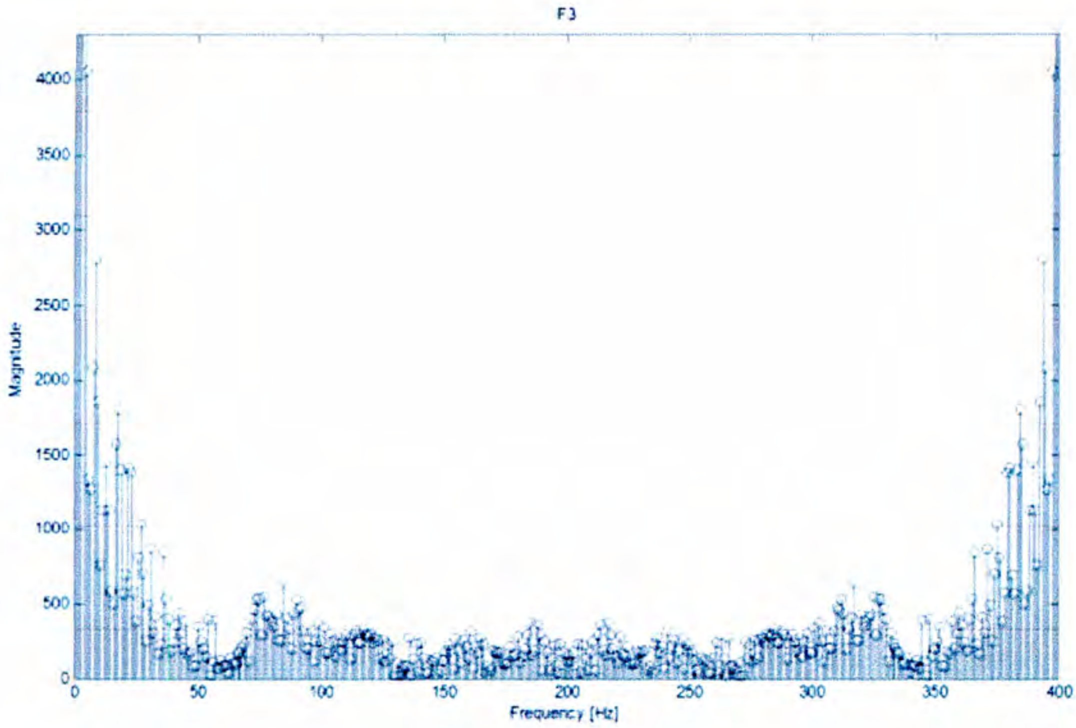

Figure 12. Fourier Analysis for F3 electrode taken from User 1.

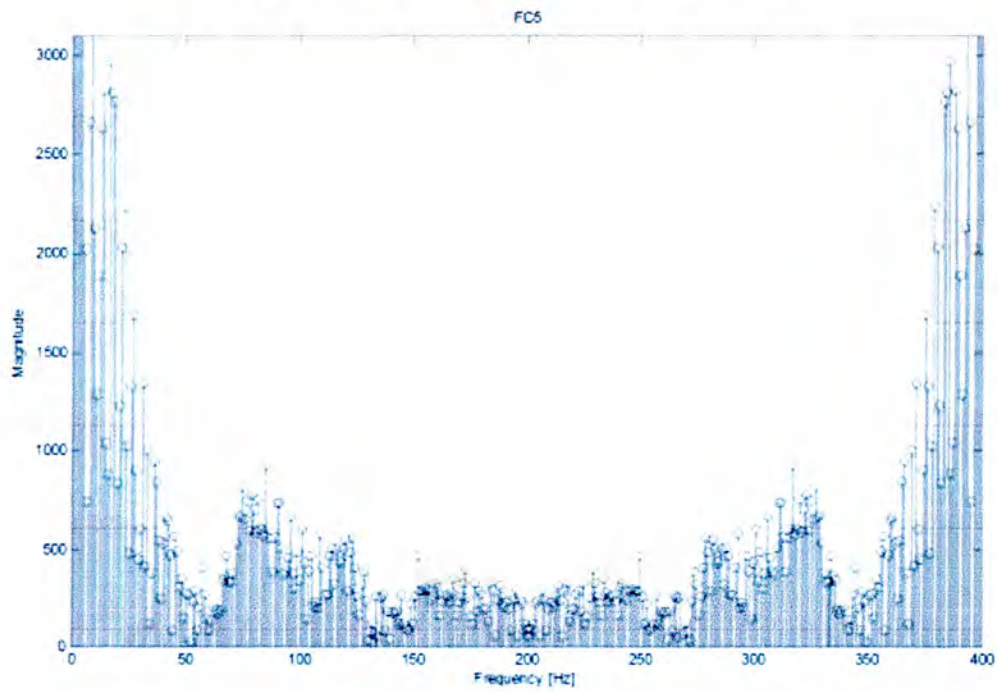

Figure 13. Fourier Analysis for FC5 electrode taken from User 1.

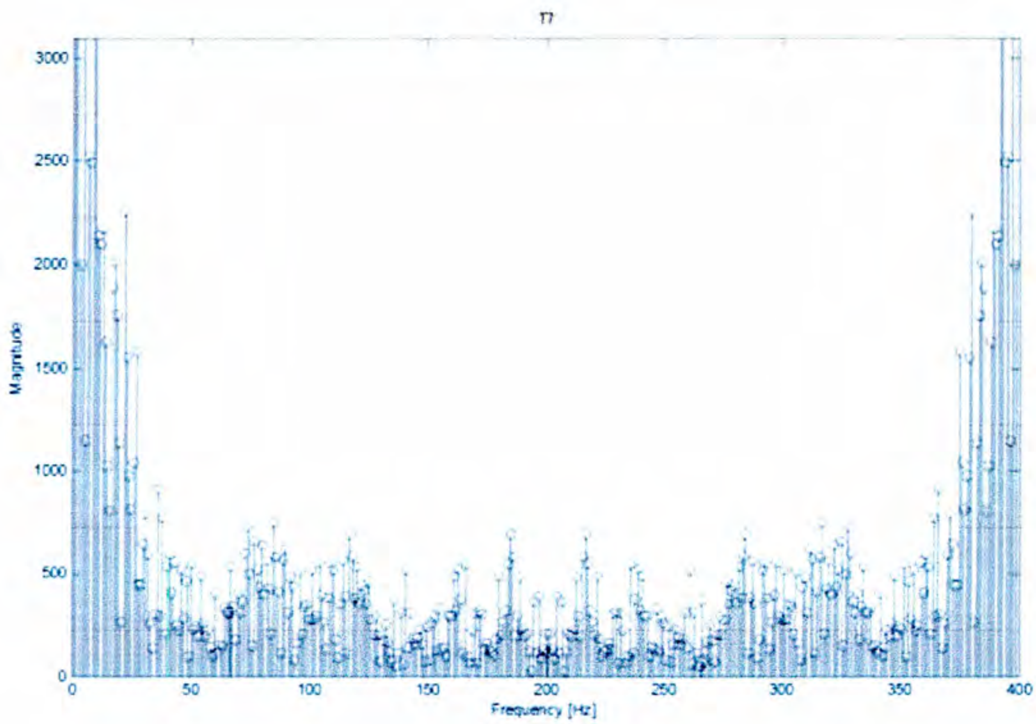

Figure 14. Fourier Analysis for T7 electrode taken from User 1.

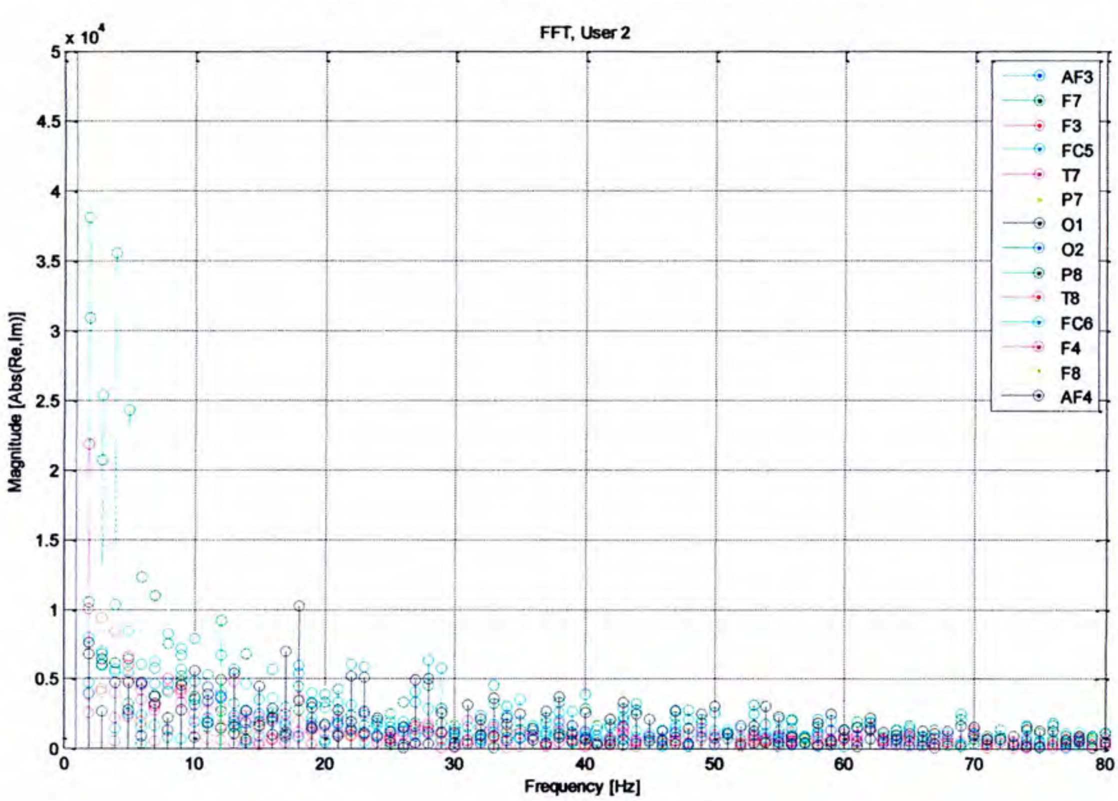

Figure 15. Fourier analysis for User's 1 ECG.

The software SDK works with C++ codes that allow simplifying some tasks. However, the code was not thought for working with the rough data, it just accesses properties that are used in the Expressive Suite, Affective Suite and Cognitive Suite.

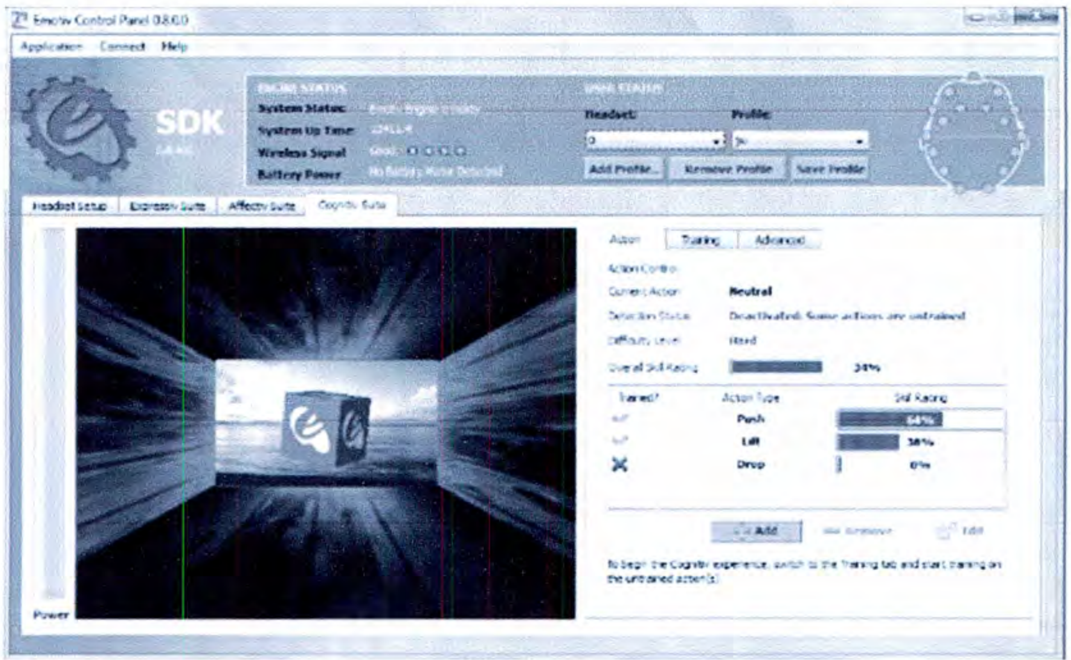

Figure 16. Cognitiv Suite.

Figure 6 shows Cognitiv suite where a cube must be thought to be controlled in different directions: pull, push, move left, move right, get on or get down the cube, depending on how many thoughts were trained the level increases due there might be confusion between two different directions. For reaching the intermediate level, there are just necessary two directions to be trained; even with two directions the effectiveness in the system is really low. In test performed for this thesis, was observed that subjects must be in quite relaxation and no distraction must occur, even eye's movements are a source of noise. If it is considered manipulation for more directions, the system gets instable even in conditions where the subject is isolated. So for video games there is not a trustable interface that leads to real control. By other hand, Expressive Suite enables to set

2.5 EEG processing

On first stage and with the purpose to detect patterns on raw signals there were designed Matlab lowpass and bandpass filters .The first step consists on saving raw signals from five different subjects, these values were saved on csv files. Later the incoming rough values were filtered in the designed filters shown in Figure 17 and Figure 18. Following it is showed Matlab code:

```
FilterSpec = fdesign.lowpass('N,Fc,ap,Ast', 80,4,1,80,20)
disp(designmethods(FilterSpec))  ;
FilterObjLowpassdelta = design(FilterSpec);
```

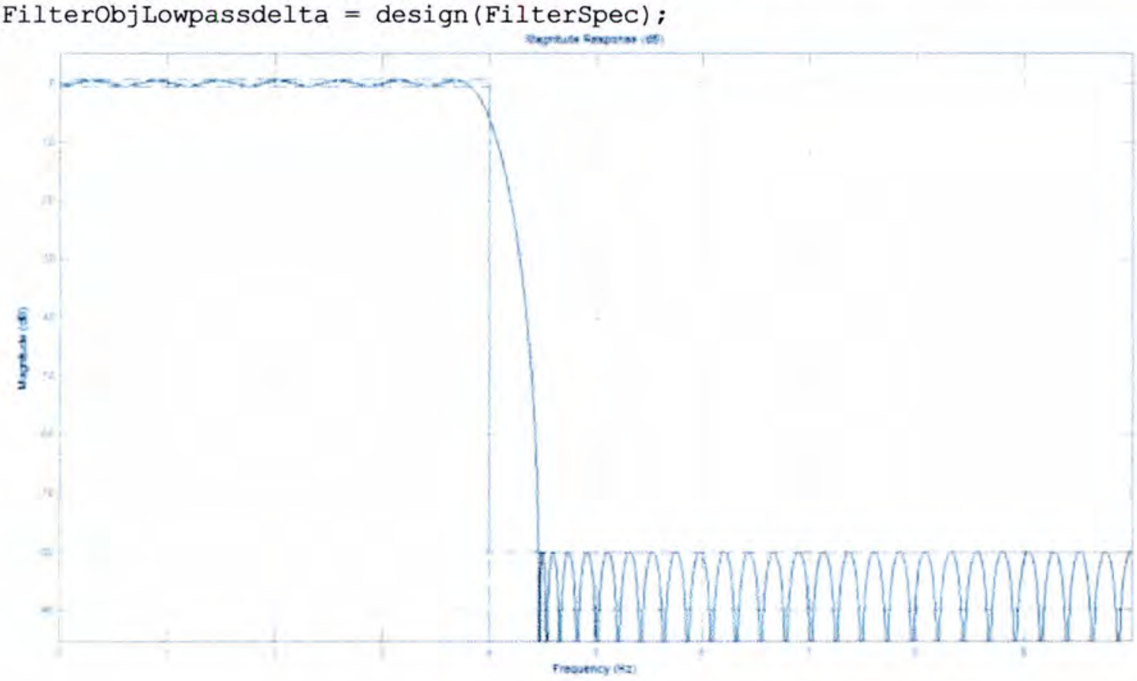

Figure 17. Lowpass filter designed on matlab.

```
FilterSpec = fdesign.bandpass('n,fc1,fc2', 80, 5, 10, 480);
disp(designmethods(FilterSpec))  ;
FilterObjPassbandtheta = design(FilterSpec);
```

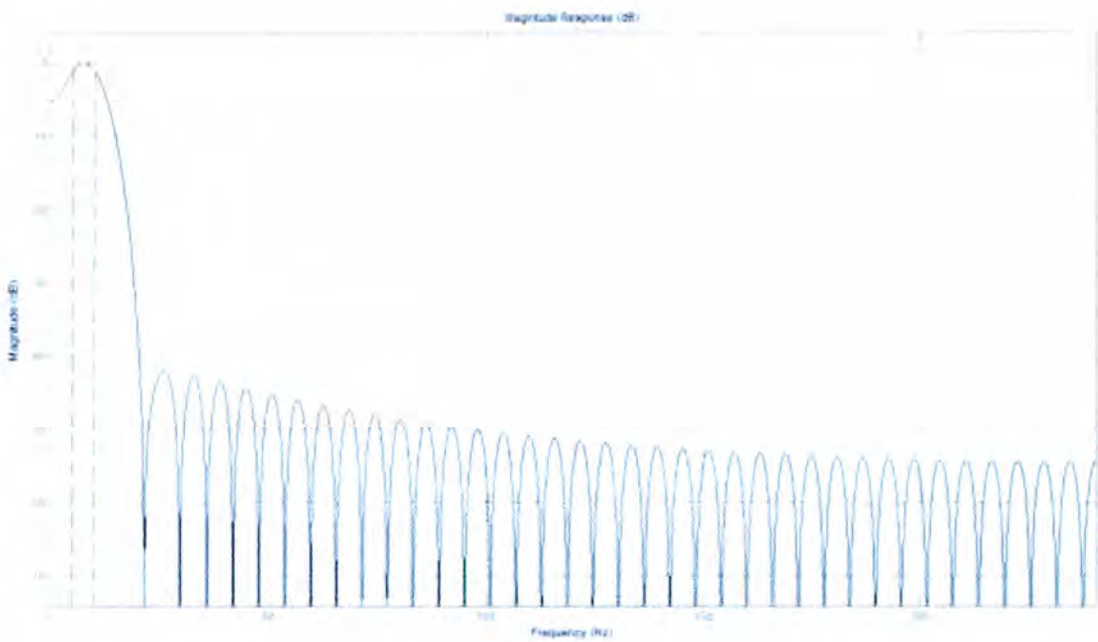

Figure 18. Passband filter designed on Matlab.

As already mentioned, brain output signals are classified according to their frequency domain, the range is among zero and one hundred Hertz. Depending on the excitement of the person this frequency will increase. On these tests it was avoided this excitement, the subject was placed on a relaxing environment and the subject was induced to think about saying a word: right or left. In both cases the fourteen incoming signals were normalized to be filtered. On filtered signals it can be appreciated that the most remarkable difference among both thoughts are on delta and theta waves. By simple comparison among each other of left and right signals, a different pattern can be set. However on other subjects, the patterns were not seamed, so it is possible to set a pattern by training and individual however such signal can't be applied, even if it is normalized, to another subject.

The signal acquisition method (Figure 19) was configuring according to the already set method for EPOC. The programmed Neural Networks were enough in order to reach a quick response in time.

Figure 19. Structure for data analysis.

Table 4 shows the data corresponding to the samples for two subjects, the samples were cropped from a 2000 samples in the electrode AF3 placed on the front side of the headset. Data is presented in the order of µVolts. Table 4 is divided in four sections; two columns represent two different samples for the same person. Statistical analyses indicate variance between data but not patterns. For each subject the standard variation is really low (Table 5) with respect to facial movements. However, it is possible to establish that for all the subjects the range for AF3 goes from 4023.81 to 4075.38 for all the subjects. This range allows setting a limit from which it will be possible to observe oscillations not only for induced thought but also for any perturbation occurred at skull's skin level.

Subject 1: Left		Subject 1: Right		Subject 2: Left		Subject 2: Right	
4067.179	4069.231	4049.231	4069.231	4024.615	4045.128	4028.718	4015.385
4074.872	4068.718	4054.872	4065.128	4024.102	4047.692	4020.513	4028.718
4078.974	4068.718	4060	4056.923	4041.026	4038.974	4025.128	4024.615
4077.436	4063.59	4065.128	4066.154	4043.077	4031.282	4041.026	4002.564
4075.385	4058.461	4068.205	4075.897	4044.102	4031.795	4040	4010.256
4077.436	4059.487	4058.974	4073.846	4048.718	4032.82	4035.385	4032.82
4082.051	4060	4042.564	4073.333	4037.949	4042.564	4049.231	4027.179
4080.513	4060	4043.077	4074.872	4027.179	4049.743	4051.795	4017.436
4074.359	4066.667	4054.872	4075.385	4029.231	4039.487	4032.82	4021.026
4076.41	4068.205	4060.513	4076.41	4029.231	4036.923	4032.308	4027.179
4079.487	4061.026	4058.461	4077.436	4029.231	4041.026	4047.692	4037.949
4076.41	4059.487	4052.82	4077.949	4032.82	4036.41	4041.026	4043.077
4076.41	4056.923	4048.205	4077.949	4030.769	4036.923	4030.256	4031.282
4073.846	4052.82	4047.179	4075.385	4024.615	4042.051	4033.333	4021.538
4070.256	4057.949	4052.308	4073.333	4022.051	4040	4031.795	4028.205
4069.743	4061.538	4058.461	4076.41	4026.154	4043.59	4027.179	4037.949

4070.256	4058.974	4062.051	4084.615	4033.846	4049.231	4030.256	4036.41
4068.718	4061.538	4061.026	4089.231	4043.077	4033.846	4026.667	4022.564
4066.154	4064.102	4055.385	4083.59	4046.667	4023.077	4018.461	4018.461
4068.718	4053.333	4051.795	4075.897	4042.051	4034.359	4021.538	4023.077
4077.436	4046.667	4056.923	4074.359	4034.359	4037.949	4027.179	4018.461
4076.923	4054.872	4062.564	4075.385	4029.743	4028.205	4022.564	4014.359
4062.564	4062.051	4056.41	4075.385	4031.795	4026.154	4019.487	4021.026
4059.487	4058.461	4049.743	4075.385	4027.179	4039.487	4023.59	4025.641
4073.333	4055.385	4050.769	4075.897	4012.82	4051.282	4031.795	4019.487
4080	4061.538	4052.82	4076.923	4017.436	4036.41	4036.923	4012.82
4075.897	4067.692	4057.949	4078.461	4040	4014.359	4037.436	4016.41
4073.333	4068.718	4063.59	4076.923	4045.128	4029.231	4033.846	4023.077
4073.846	4067.179	4060.513	4074.359	4034.872	4046.667	4028.718	4028.205
4075.385	4063.077	4052.308	4074.872	4034.359	4034.359	4030.769	4029.231
4076.923	4056.923	4049.743	4077.436	4038.974	4042.564	4035.897	4025.128
4074.872	4059.487	4050.769	4076.923	4035.897	4063.59	4031.795	4022.051
4071.282	4067.692	4050.769	4076.41	4017.436	4050.769	4025.641	4022.051

Table 4. Rough data from users.

Average	4073.81	4061.23	4055.15	4075.38	4032.74	4038.73	4031.84	4023.81
Standard Deviation	5.03	5.36	6.07	5.42	8.85	9.25	8.13	8.36
Percentage	8.10	7.58	6.69	7.52	4.56	4.37	4.96	4.82

Table 5. Statistical Analysis for induced thoughts.

Figure 6 draws the filtered signal for the fourteen channels. The signals were recorded while the person was induced to think about saying left or right. As previously indicated, the signals were classified according to the five different signals: alfa, beta, gamma, delta and theta. On the graphs the fourteen signals are overlapped. However, by trying to set the incoming signals to be a pattern the following information may be set:

1. The alfa, beta, gamma, delta and theta waves get their highest values at any brain activity, so the increment in the amplitude per frequency is considered for generating a control. However there exists dependence in the appearance of these signals and they are not relatives to only one kind of thought but also depends in the emotional state of the person and the digested food[4].

[4] Electrolytic substances, alcohol or food with chemical substances that may have high influence in the electrical activity at the brain.

2. Although it is possible to sense these signals and by considering this fact, great perturbations may occur, however the signal generated at skin level present patterns and greater oscillations.
3. Since EEG uses signals generated at brain core and not at skull level, it is recommendable to use an invasive method in order to record these patterns so, a non-invasive may be used later. Due the focus in this thesis and the used resources, it was not possible to work with an invasive technique but it is possible to track the position of the eye since the voltage signal generated at this area can be tracked from fourteen positions allowing references that aid to track eye's position.
4. Due voltage signals generated at brain core are uncountable; it can be assumed that voltage is taken by area, so what it is observable on graphics is a voltage average. Represented in Figure 3, if any motor activity is executed, what will be observable in a graphic are oscillations in all the already mentioned frequencies. For the actual GUI developed by EMOTIV, this condition is overriding for training the system and is the main reason why is so difficult to train more than one signal.

In order to look for a pattern there were performed tests on different subjects. The tests were performed at early morning with fasted subjects and the induced thought was related to repeat in their mind the word left or right. For avoiding any perturbation induced by eye´s movements each subject was told to avoid any eye movement or blinking. Although there were produced eye´s signals, the data range was isolated to samples that do not include these perturbations with a sampling that is configured to work with only 26 per second.

Figure 20 graphs the AF3 electrode for both subjects and for the whole acquisition data, the different signals were graphed using pass-band and low-pass-band filters (Figure 17 and Figure 18). However there was not possible to set a pattern.

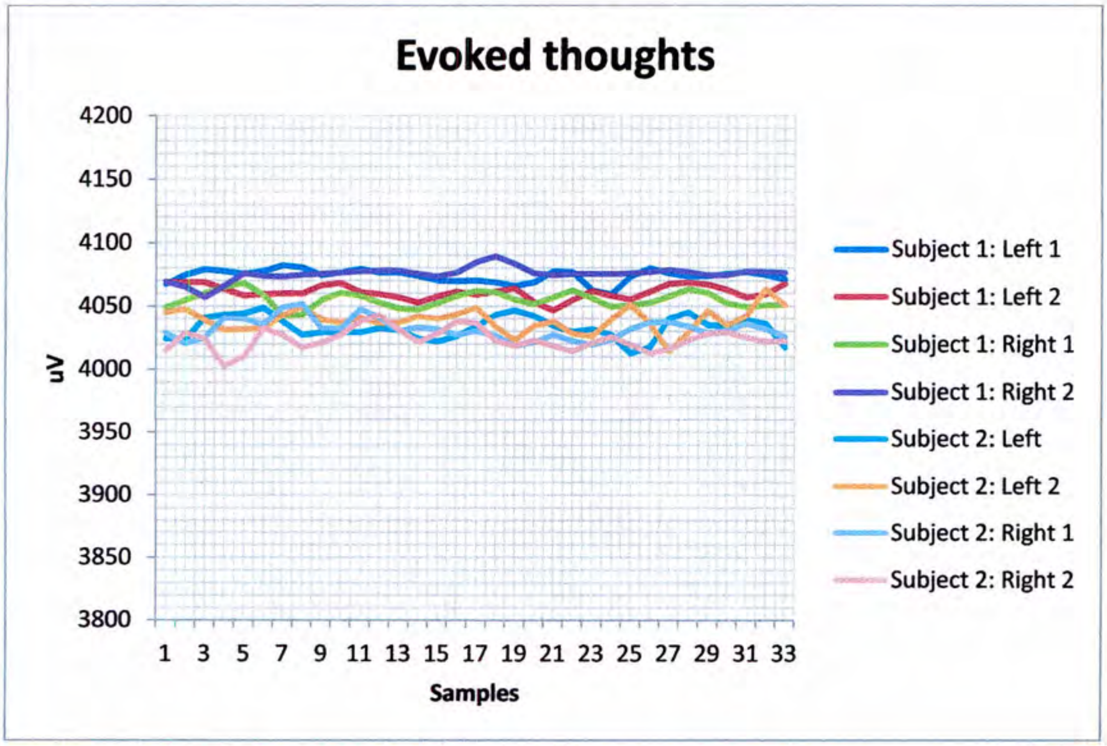

Figure 20. Rough incoming signals from EEG.

The following signals were chosen from different samples taken at different times from subject 1. These signals have short oscillations and are the most significant patterns recognized in both subjects. As a matter of fact, subject 1 was short haired and electrode's placement was easier than subject 2.

Although the acquired signals reflect oscillations, there was not possible to establish relationships between data acquired with subject one and subject two even between the signals generated by the same person.

A whole sampling set was taken from four subjects in order to look for patterns and identify similarities between signals from different subjects. The following charts show the answer for the sampling taken with low pass filter implemented. **Since amount of samples depends on processors task's state, and sampling was taken each second, *x* axis represents continuous sampling taken while approximately 15.62 seconds.**

Evoked thought corresponding to left

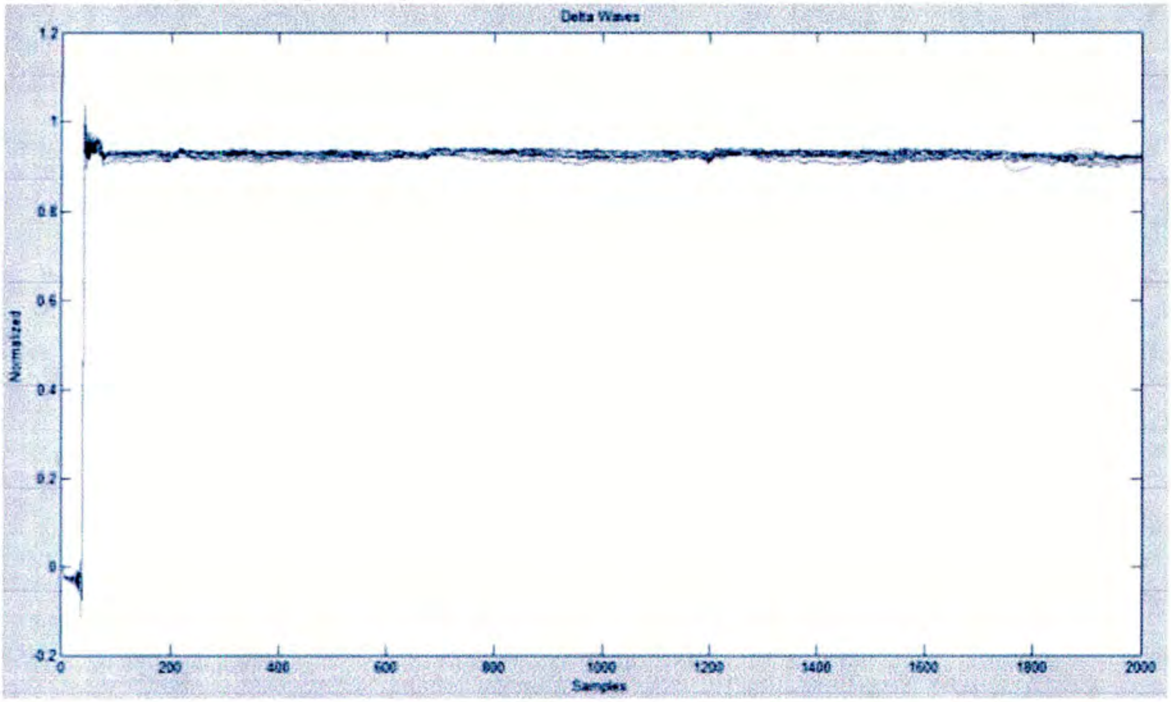

Figure 21. Delta Waves, filters for incoming signals less than 4 Hz.

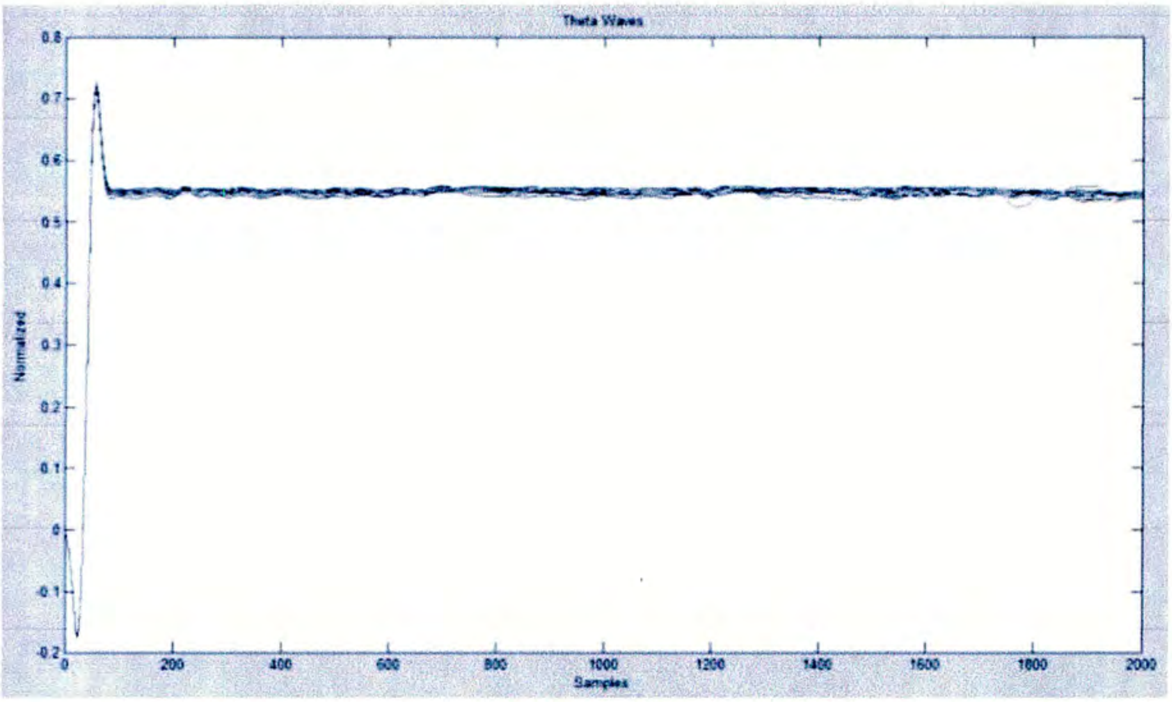

Figure 22. Theta Waves. Signals among 4 and 8 Hz.

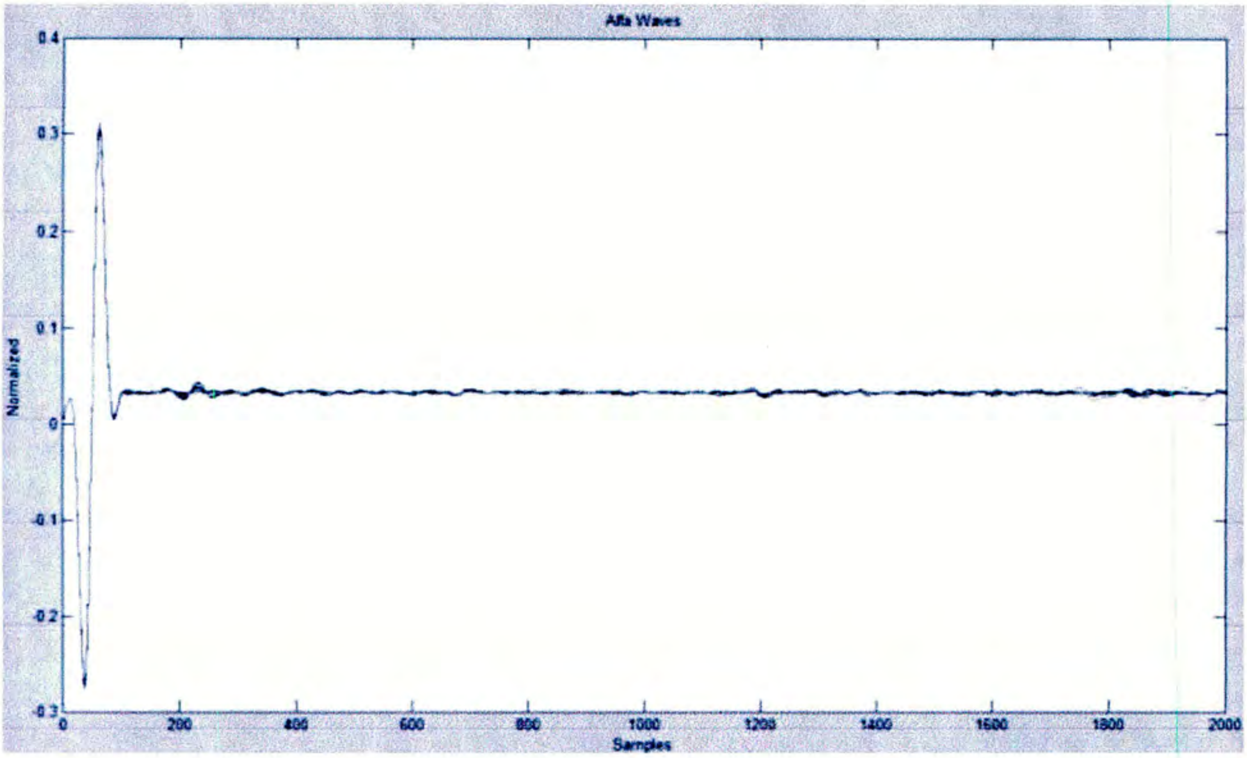

Figure 23. Alfa Waves. Signals among 8 and 13 Hz.

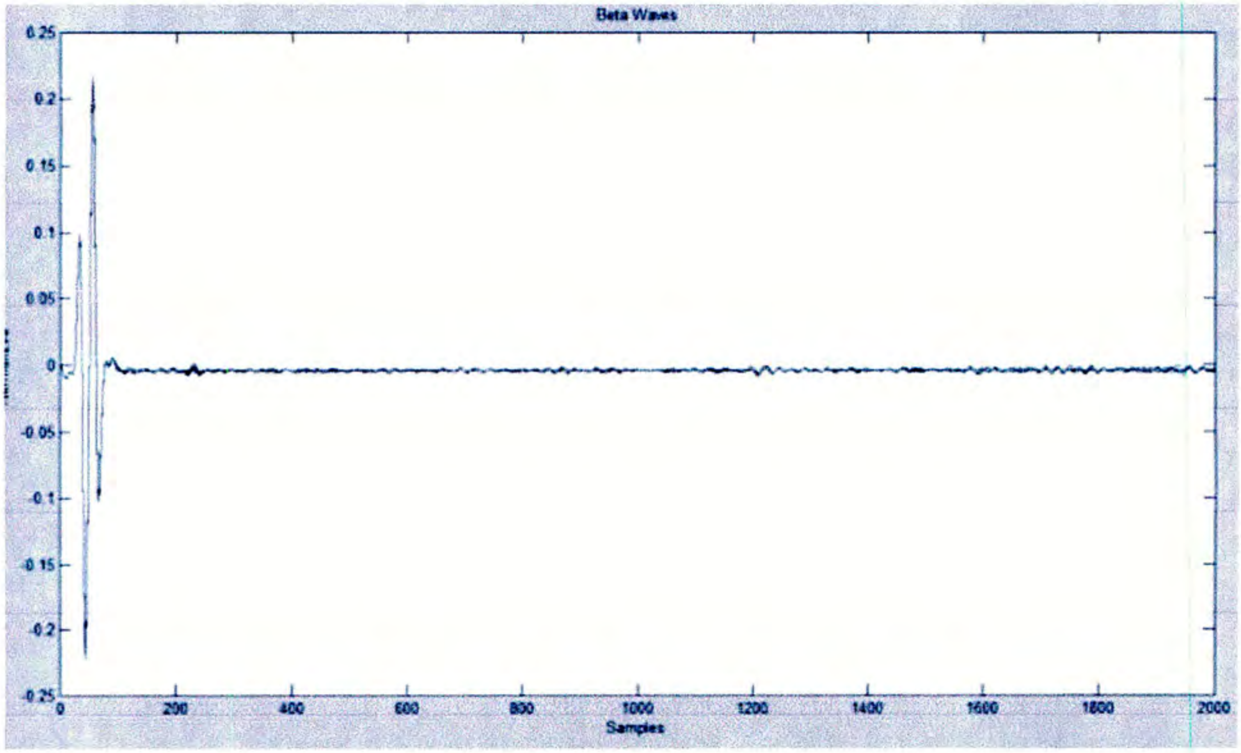

Figure 24. Beta Waves. Signals among 13 and 30 Hz.

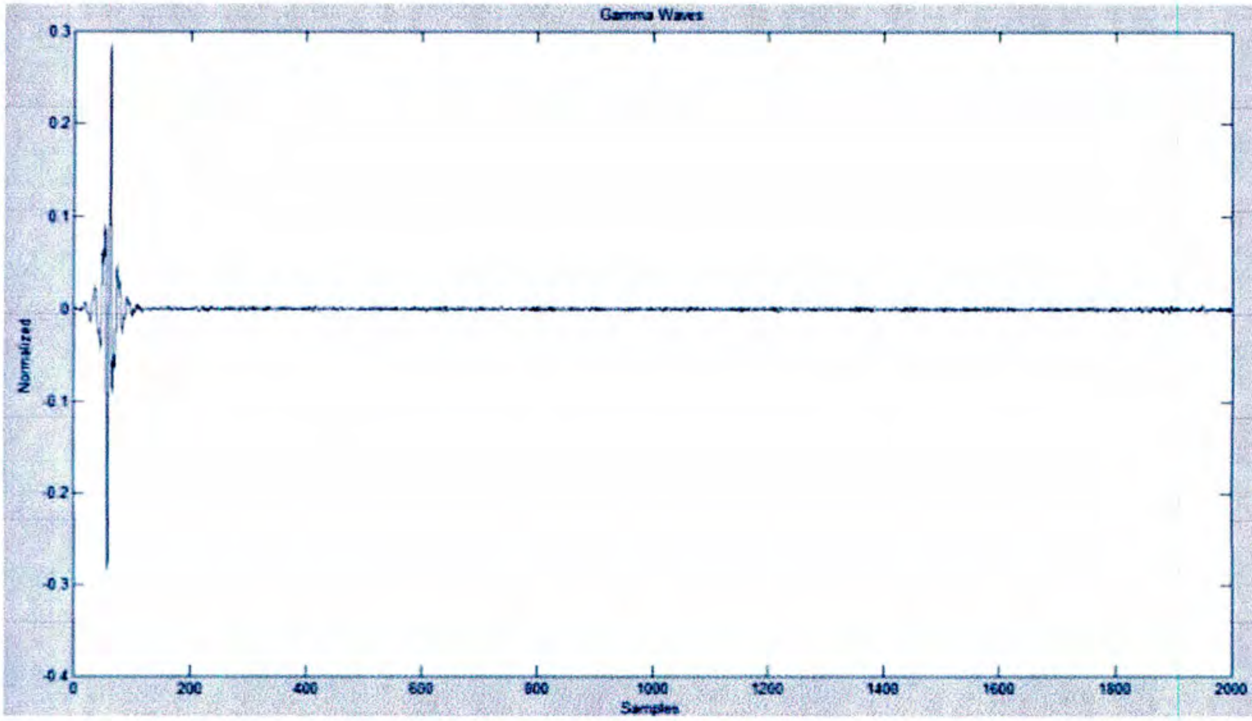

Figure 25. Gamma waves. Signals among 30 and 100 Hz.

Thought corresponding to Right

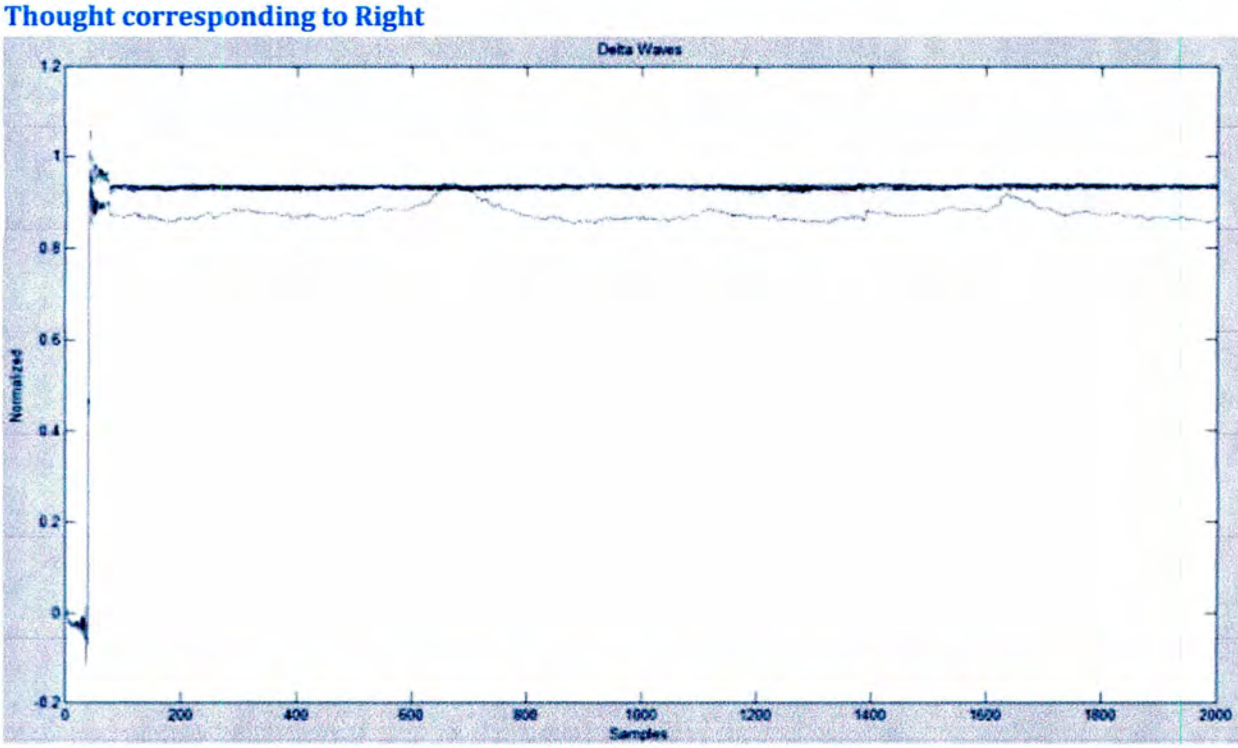

Figure 26. Delta Waves. Lowpass filter for signals less than 4 Hz.

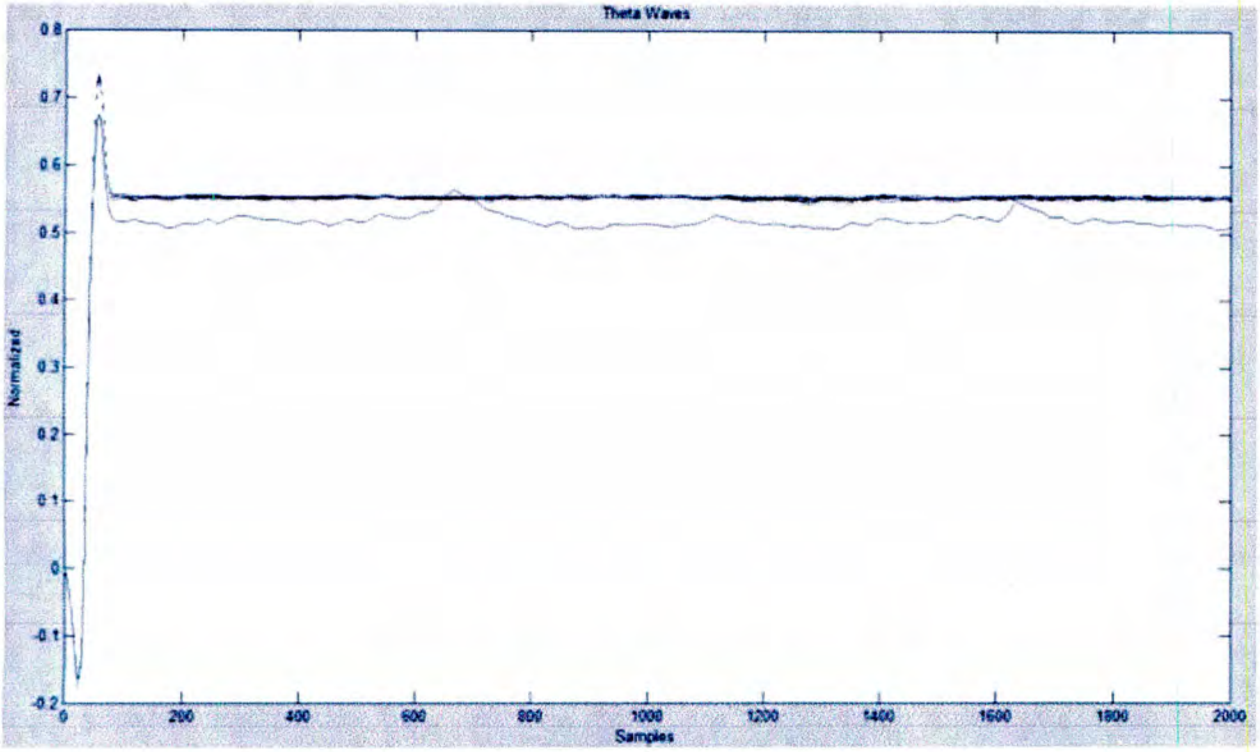

Figure 27. Theta Waves. Passband filtered signal in range of 4 to 8 Hz.

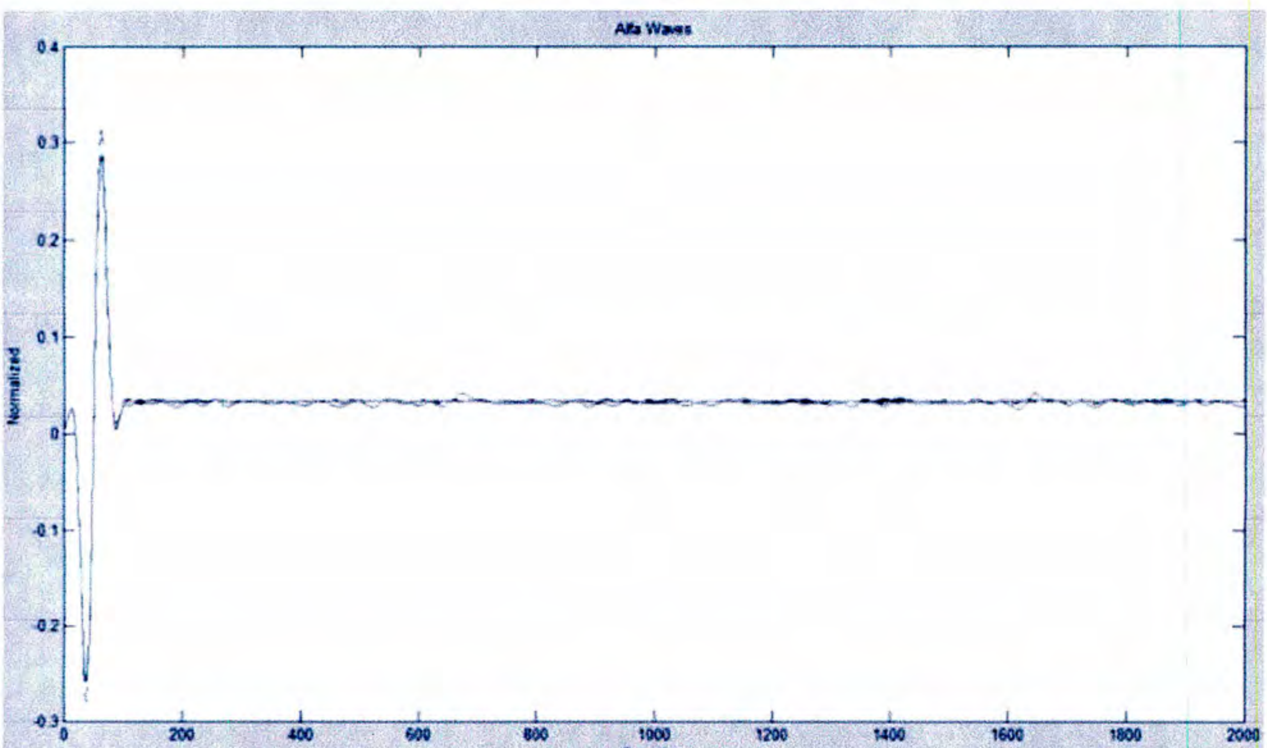

Figure 28. Alfa Waves. Passband filtered signal in range of 8 to 13 Hz.

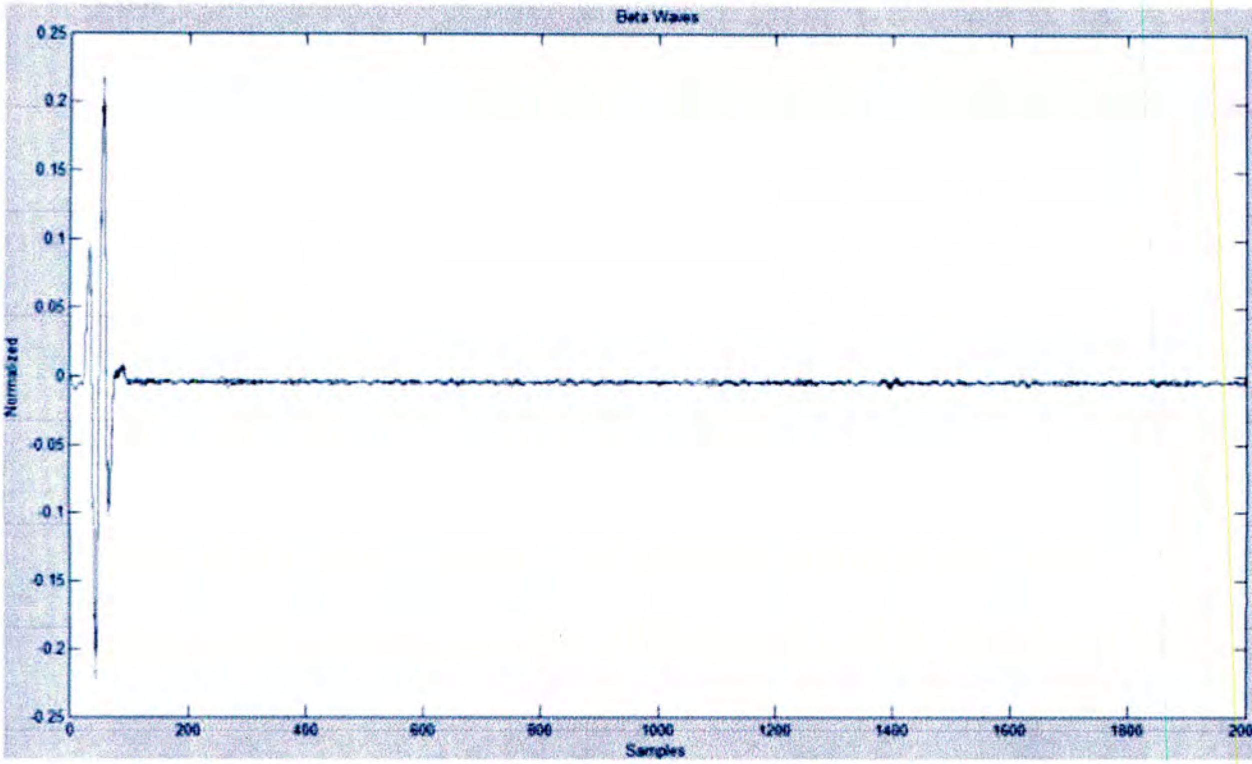

Figure 29. Beta Waves. Filter for 13 to 30 Hz.

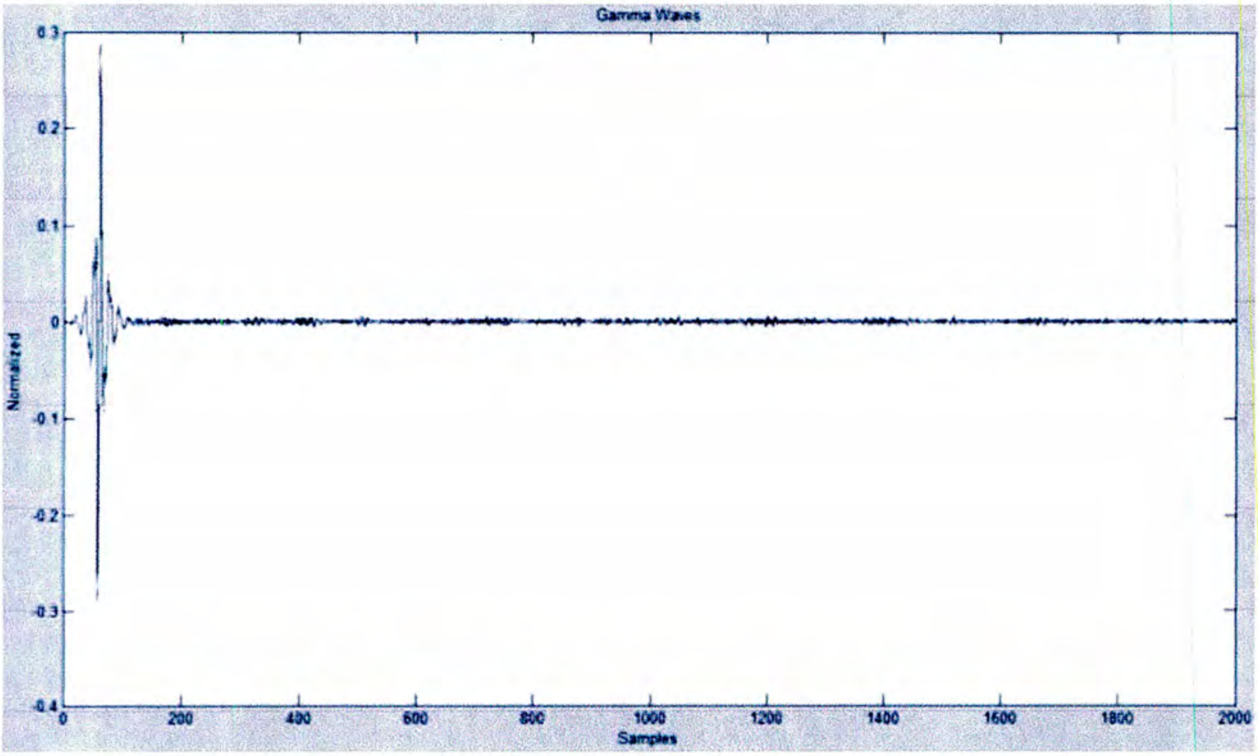

Figure 30. Gamma Waves. Filtered signals for signals among 30 to 100 Hz.

The hardware conditioning allows acquiring 128 samples per second; so on each graph is shown 15.625 seconds of recorded signal.

Chapter 3

Neural Networks and back-propagation training

Neural networks are wide used in the field of pattern recognition, even more with hard-mapping data or non-linear systems. Due its quality at results deliverance on patterns classification and the capacity for supervised-training networks for modeling almost any continuous signal, the model of a neural network with back-propagation training was used so the use of statistics based on tests performed in different times was enhanced with the purpose of establishing a pattern for each letter. These patterns will set the outputs for the final supervised Neural Network programmed in C++ and will classify in a deterministic time the fourteen signals.

3. 1 Back-propagation Training

Due the capacity for single perceptron for only solving linear problems, Frank Rosenblatt and the algorithm of Least Means Square (LMS) are not enough for training the purposed Neural Network. Although the awareness for this disadvantage, Rosenblant was not able to generalize the algorithm to train multilayer networks. However, until the mid-1980s was presented the base for what is currently the most widely used method for training a neural network. In order to specify the capabilities of these multilayer perceptron there is illustrated (Figure 9) the structure and how it helps to map no-linear systems. It is a good analogy to view networks as function aproximators. For the bio-signals presented in this thesis, the transfer functions between the four layers are sigmoidal. The reason is due the soft-continuity that it offers at the change between positive and negative values generated when the function is evaluated and because its oscillation between zero and one; this property helps for establishing a binary catalogue for twenty eight different possibilities classified between each other and from noise on each channel.

The set for nominal values of the weights and biases for the network will be as proposed:

$$w_{1,1}^1 = 10,\ w_{2,1}^1 = 10, b_1^1 = -10, b_2^1 = 10,\ w_{1,1}^2 = 1, w_{1,2}^2 = 1, b_1^2 = 0$$

The network response for these parameters is shown in Figure 9 where it can be appreciated the network output a^2 as the p is varied over the range [-2, 2].

$$\left\{p_1 = \begin{bmatrix}0\\0\end{bmatrix}\right\} \quad \left\{p_2 = \begin{bmatrix}0\\1\end{bmatrix}\right\} \quad \left\{p_3 = \begin{bmatrix}1\\0\end{bmatrix}\right\} \quad \left\{p_4 = \begin{bmatrix}1\\1\end{bmatrix}\right\}$$

It can be appreciated that response is drawn in two steps one for each logistic function applied at the end of the sum for each perceptron at the first layer. If there is any change at the network parameters it can change the shape and location of each step.

The centers for each step occur where the net input to a neuron in the first layer is zero (*Eq 1. and Eq. 2)*:

$$n_1^1 = w_{1,1}^1 p + b_1^1 = 0 \Rightarrow p = -\frac{b_1^1}{w_{1,1}^1} = -\frac{-10}{10} = 1, \qquad Eq.\ (\ 1\ )$$

$$n_2^1 = w_{2,1}^1 p + b_2^1 = 0 \Rightarrow p = -\frac{b_2^1}{w_{2,1}^1} = -\frac{10}{10} = -1, \qquad Eq.\ (\ 2\ )$$

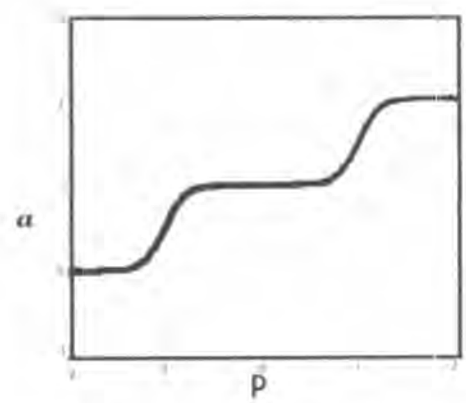

Figure 31. Nominal Response for the network.

To illustrate the behavior for a two layered network, consider the two-layer, 1-2-1 network shown in Figure 10. The transfer function or evaluation function for the first layer is sigmoid, in the second layer is proposed a linear (Eq. 3) function, although at final implementation it was used a sigmoidal (Eq. 4) functions that retains the possibility of values in a range from 0 to 5.

$$f^1(n) = \frac{1}{1+e^{-n}} \quad Eq.3 \qquad\qquad f^2(n) \quad Eq.4$$

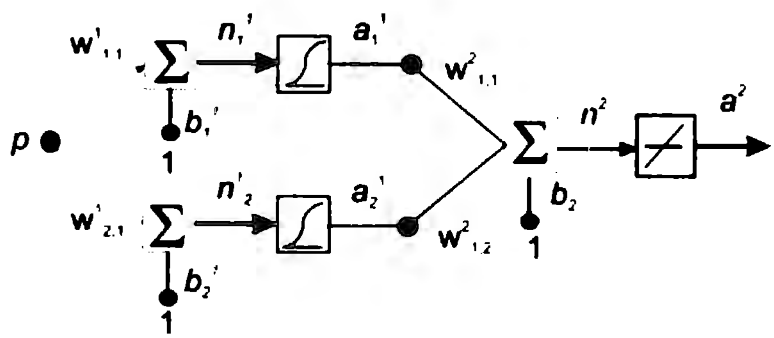

Figure 32. Representation for an Approximated Network.

In Figure 10 it may be appreciated the effects of parameters changes on the network response. The different curves correspond to the network response when one parameter at a time is varied over the ranges:

$$-1 \le w^2_{1,1} \le 1, -1 \le w^2_{1,2} \le 1, 0 \le b^1_2 \le 20, -1 \le b^2 \le 1$$

In Figure 11(a) is shown the influence of network biases in the first hidden layer and can be used to locate the position on each step. By other hand Figure 11 (b) illustrates how the weights influence at the slope of the steps and finally the constant bias are capable of manipulating the entire network response up or down on Figure 11 (d).

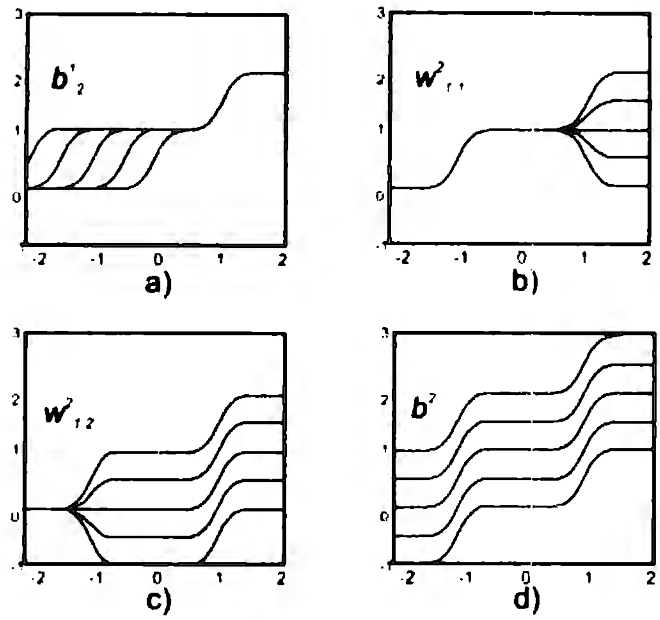

Figure 33. Representation for variations on the Neural Network.

The representation and data mapping for the shape is really flexible as more layers get involved at the hidden layer until the fact that it may be mapped almost any signal so almost any function could be approximated.

Since this brief introduction for the structure, it is established that multilayer networks at the output will become the input for the following layer. This equation will be represented by Eq. 4:

$$a^{m+1} = f^{m+1}(W^{m+1}a^{m} + b^{m+1}) \quad for \quad m = 0,1,\ldots,M-1 \qquad Eq.4$$

where *M* is the number of layers in the network. The neurons in the first layer receive external inputs:

$$a^0 = p$$

At the entrance for the Neural Network a^0 will be the input and the outputs in the last layer will be considered as:

$$a = a^M$$

3.1.1 Performance index

The Least Means Squares (LMS) algorithm is an example of supervised training, where the learning rules are provided with a set of examples of proper network behavior.

$$[p_1, t_1], [p_2, 2], \dots, [p_Q, t_Q],$$

where p_q is an input to the network and t_q is the corresponding target output. The LMS algorithm will adjust the weights and biases in the neural network in order to minimize the mean square error, where the error is the difference between the target output and the network output.

The algorithm used for multilayer networks is a generalization of the LMS algorithm in both cases the *mean square error* is used as performance index. As each input is applied to the network, the network output is compared to the target. The algorithm should adjust the network parameters in order to minimize the mean square error *(Eq. 5)*.

$$F(x) = E[e^2] = E[(t-a)^2] \qquad Eq.5$$

Where x is the vector of the network weights and biases. If the network has multiple outputs this generalizes to:

$$F(x) = E[e^T e] = E[(t-a)^T(t-a)] \qquad Eq.6$$

The mean square error can be approximated by

$$\hat{F}(x) = \left(t(k) - a(k)\right)^T \left(t(k) - a(k)\right) = e^T(k)e(k) \quad Eq.7$$

At this case the expectation of the squared error has been replaced by the squared error at iteration *k*. The steepest descent algorithm for the approximate mean square error is

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \propto \frac{\delta F}{\partial w_{i,j}^m}, \qquad Eq.8$$

$$b_j^m(k+1) = b_j^m(k) - \propto \frac{\delta \hat{F}}{\delta b_i^m}, \qquad Eq.9$$

where α is the learning rate.

For the multilayer network the *error* is not an explicit function of the weights in the hidden layers, it is more complicated to compute the weights.

Because the error is an indirect function of the weights in the hidden layers, the chain rule will be used to calculate the derivatives. If we have a function *f* that is an explicit function only of the variable w. The chain rule is then:

$$\frac{df(n(w))}{dw} = \frac{df(n)}{dn} \times \frac{dn(w)}{dw} \qquad Eq.10$$

Given the following function:

$$f(n) = e^n \ and \ n = 2w, so\ that\ f\big(n(w)\big) = e^{2w}$$

Then

$$\frac{df(n(w))}{dw} = \frac{df(n)}{dn} \times \frac{d\,n(w)}{dw} = (e^n)(2)$$

The concept to find the derivatives as it was shown in *Eq. 8*:

$$\frac{\partial \hat{F}}{\partial w_{i,j}^m} = \frac{\delta \hat{F}}{\partial n_i^m} \times \frac{\partial n_j^m}{\partial w_{i,j}^m} \qquad Eq.11$$

$$\frac{\partial \hat{F}}{\partial b_j^m} = \frac{\partial \hat{F}}{\partial n_i^m} \times \frac{\partial n_i^m}{\partial b_i^m} \qquad Eq.12$$

The second term in each of these equations can be easily computed, since the net input to layer *m* is an explicit function of the weights and bias in that layer:

$$n_i^m = \sum_{j=1}^{S^{m-1}} w_{i,j}^m a_j^{m-1} + b_i^m \qquad Eq.13$$

For this case

$$\frac{\partial n_i^m}{\partial w_{i,j}^m} = a_j^{m-1}, \qquad \frac{\partial n_i^m}{\partial b_i^m} = 1$$

For this case

$$s_i^m = \frac{\partial \hat{F}}{\partial n_i^m}$$

The sensitivity of $\hat{F}$ to changes in the *ith* element of the net input at each layer. It can be simplified to:

$$\frac{\partial \hat{F}}{\partial w_{i,j}^m} = s_i^n a_j^{m-1} \qquad Eq.14$$

$$\frac{\partial \hat{F}}{\partial b_i^m} = s_i^m \qquad Eq.15$$

The steepest descent algorithm can be expressed as following:

$$w_{i,j}^{m}(k+1) = W^{m}(k) - \propto s^{m}(\propto^{m-1})^{T} \qquad Eq.16$$

$$b^{m}(k+1) = b^{m}(k) - \propto s^{m} \qquad Eq.17$$

$$s^{m} = \frac{\partial \hat{F}}{\partial n^{m}} = \begin{bmatrix} \frac{\partial \hat{F}}{\partial n_1^m} \\ \frac{\partial \hat{F}}{\partial n_2^m} \\ \vdots \\ \frac{\partial \hat{F}}{\partial n_{S^m}^m} \end{bmatrix} \qquad Eq.18$$

For training, the neural network was programmed on LabVIEW, the algorithm throws the weights for the desired inputs on a *.txt* file that will be used on the *.exe* file.

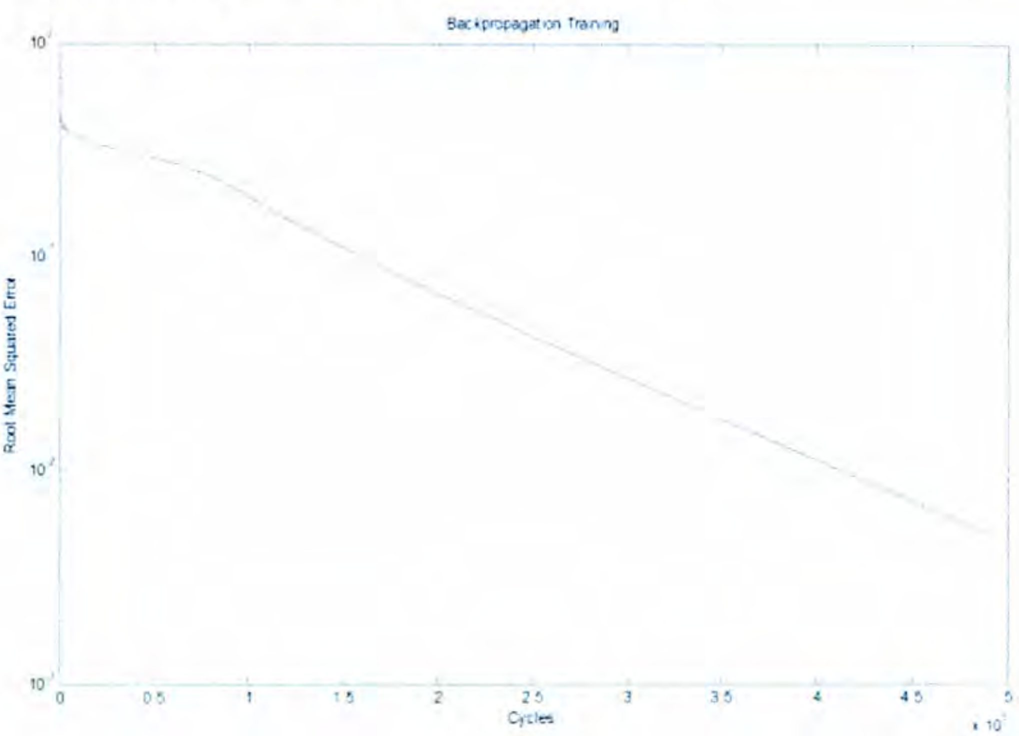

Figure 34. Neural Network training. Minimum Error: 0.005 Step: 0.0000000000000000001 Iterations: 500000

Although there exist convergence in the training, a better performance is possible to be reached if the number of neurons is incremented in the hidden layer and in fewer amount of iterations it is possible to reach the minimum error established for the system. However, the user must remain in a position while working with the system, therefore no distance conditions should vary in order to preserve training conditions. This situation could be uncomfortable for some users and really difficult for being reached.

Regarding classification, if there is set coordinate axes with origin at central point in the keyboard and classification data are keyboard letters dispersed in the four quadrants; it is possible to say that classification between data in different quadrants is easier than data in the same quadrant. Therefore, although there is created a separation between each letter, it will always be easier for the Artificial Neural Network to recognize, as less as possible letters, that are in different quadrants.

4 Eye tracker

Once an eye movement has been generated between two already known points, voltage perturbations get delayed over the skull. Not only voltage perturbations by the skin are the main source for these signals, there are also voltages generated at cerebral cortex which are really tenuous. The intensity of this kind of sources depends on which area is activated and are related with the activity that the person is developing in that moment, however, it was observed that skin perturbations may reach bigger amplitudes so cerebral cortex signals will be detected but overlaid by eye's voltage propagation over the skull.

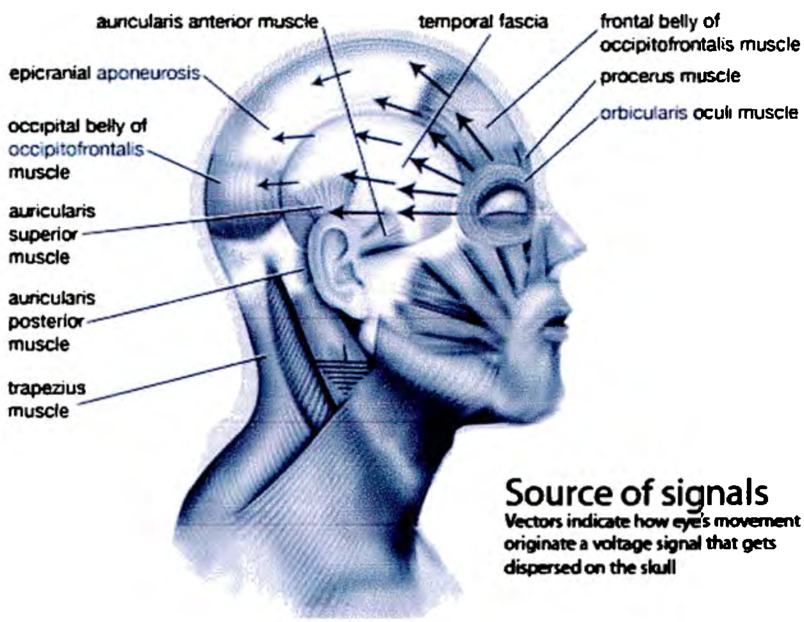

Figure 35. Voltage source and how it gets delayed over the skull.

By setting the analogy that facial muscles are like elastic layers stretched in a mesh over the cranium, facial bones, the openings they form and the cartilage, fat and other tissues of the head. They may act in single movements or together, for this thesis both will be analyzed, indeed, for each electrode it is possible to sense more than one muscle in movement.

Figure 35 shows how it is possible to generate a signal that will be propagated through the skull and being classified in different parts of the head. Of course all the signals or voltage differences must have a ground or a reference (Figure 35) which will be set at the back part of the ears where is the most protruding region of bone close to this region.

MUSCLE	ORIGIN	INSERTION	ACTION
Frontalis	Galea Aponeurotica	Skin of eyebrows and nose	Raise eyebrows, wrinkles forehead skin
Orbicularis oculi	Frontal and Maxillary bone	Skin of eyelid	Blinking, squinting, forceful closing of eyelids
Orbicularis oris	Fibers of other mouth muscles	Muscles and skin at angle of the mouth	Closes and protrudes lips
Platysma	Pectoralis and deltoid fascia	Lower border of the mandible, mouth skin and muscle	Depresses mandible, draws angle of mouth downward, tightens skin of the neck

Table 6. Signals's source.

Since Table 3 indicates which muscles is moved at certain gesticulation it is possible to know where will occur a bigger perturbation. So it was proposed for this thesis an eye tracker that is able to indicate where the person is looking at. By using a modified *qwerty* keyboard and by placing a set-point which will be the reference from it will be possible to track where the person looked at and by using National Instruments devices it is possible to use the keyboard to write without touching it.

For setting how the patterns must be repeated the following conditions must be found on each set in order to find the patterns.

1. A minimum distance must be set by the user but there must be considered the facts that:
    a. As far (distance between the set point and the final target) as the letter is, the eye movement will be greater and for the generated signal this means bigger amplitude so it will be easier for the tracker to identify the signal.
    b. The distance between the orbicularis oculi muscle and the modified keyboard must be comfortable for the person and should not be greater than 50 cm. This is because the spin of the eye when looking for a target is not enough to generate a voltage difference.

4.1 Noise filtering

The incoming data from fourteen electrodes is represented on Figure 36. The signal is obtained at 128 samples per second per channel. The signals where taken when the subject was looking for letter *A*, from sample 118 to sample 143 it can be appreciated a significant perturbation in the sampled signal and that perturbation its repeated from input 352-377 and from 685-710.

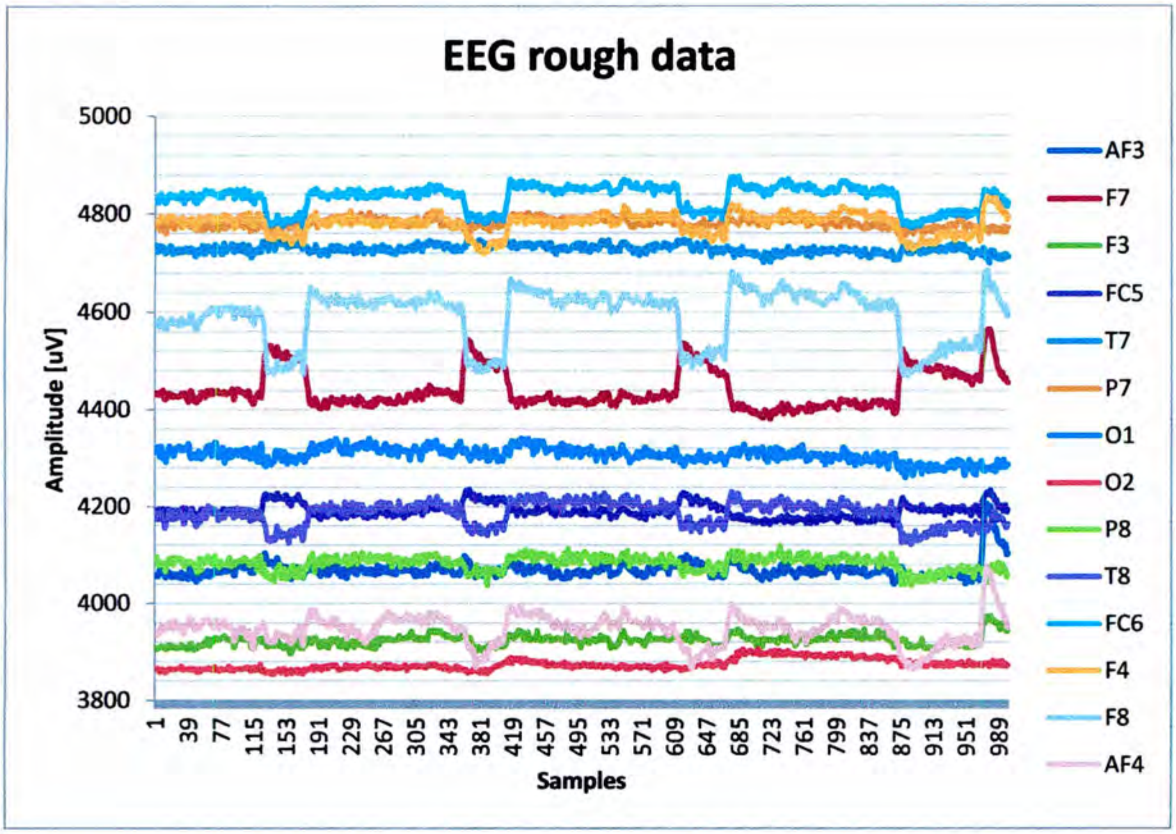

Figure 36. Incoming data for letter A.

Graphically the whole package of signals is noisy and the patterns for each channel are really fuzzy in order to be classified. By using C++ code there was designed a two order (FIR) Butterworth filter that allows obtaining a better representation. The re-building of the signal in order to be analyzed does not need the whole incoming data, indeed part of the noise is deleted by implementing a digital sampling. The low pass filter was configured with cutoff frequency of sixteen Hertz that was determined by sampling the behavior of the rough data in different days for one subject in order to look for a repeatable signal. The implemented function works with the sample rate, the cutoff frequency and two parameters related to the FIFO structure designed for filtering data in a period of five samples per channel.

The Low-pass filter was configured to receive voltage signals in a FIFO structure but for each iteration, it holds the data from the previous one so the filter does not need to oscillate in order to be re-adjusted.

As previously stated, the signal was filtered with a low-pass filter and normalized by using a statistical peak identified on tests appended at the end of this document. Also, using statistics on the appended signals, the perturbations on each channel can be re-drawn in twenty samples. But for a margin security there was considered a delay in the amount of data not in the data frequency that could occur in any channel. Figure 37 plots the reference or pattern for a letter 'A' without filtering it, this pattern was the reference for the Neural Network. Due the scale, there is not a wide variation or oscillation that might be graphically represented on this graphic. However, in order to perceive this perturbation, the signal from electrode T8 was isolated in Figure 39. By working with float precision it was possible to estimate the variation for the patterns on each channel per letter. Just as observed on Figure 39 the variation range is wider and it can be easily differentiated from other letter at the same channel.

For pattern recognition, it is necessary to set generalization on each letter so it is possible to achieve common signals for more users. For this thesis, there were gathered signals from four different users so it can be achieved a common pattern. However, for each person, patterns may reach huge variations since the simple placing of the headset is not possible to be repeated.

Figure 38 shows the filtered signal and is the pattern for being trained in the Neural Network. As shown in Figure 39, it is necessary to use float precision in order to reach patterns classification but also important for setting triggers in order to reach a classification for any letter. T

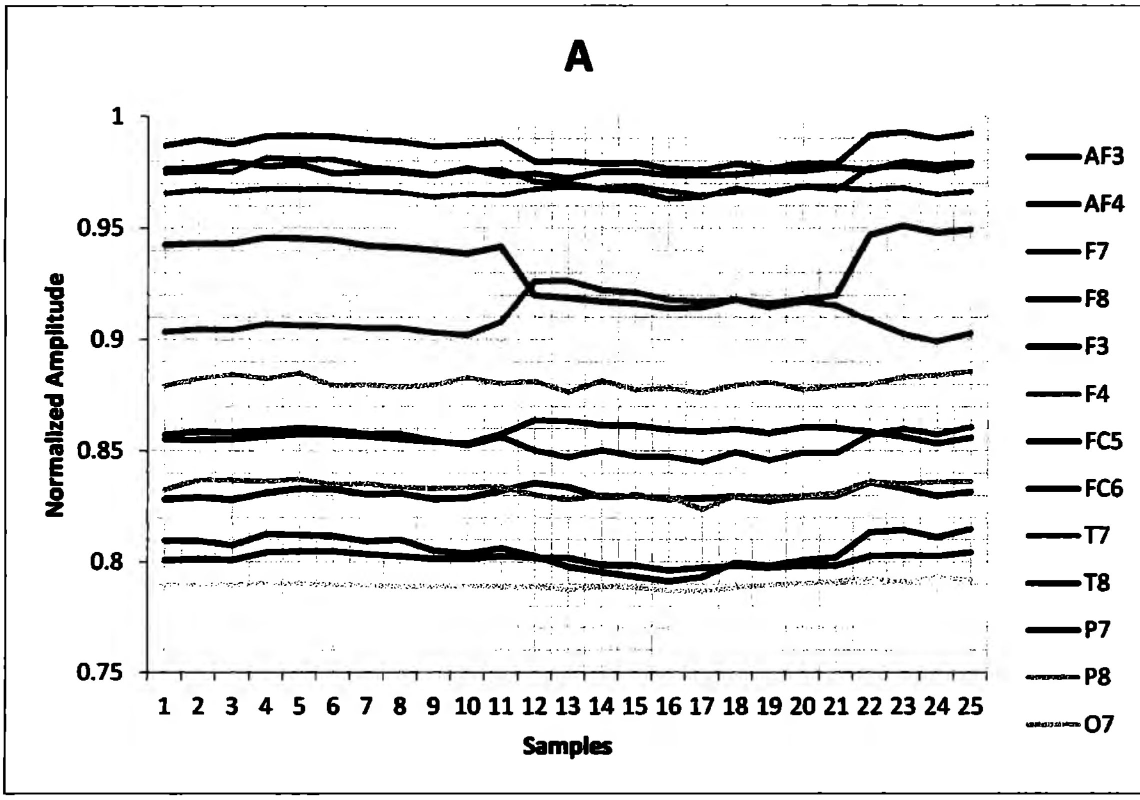

Figure 37. Non-filtered signals for letter A.

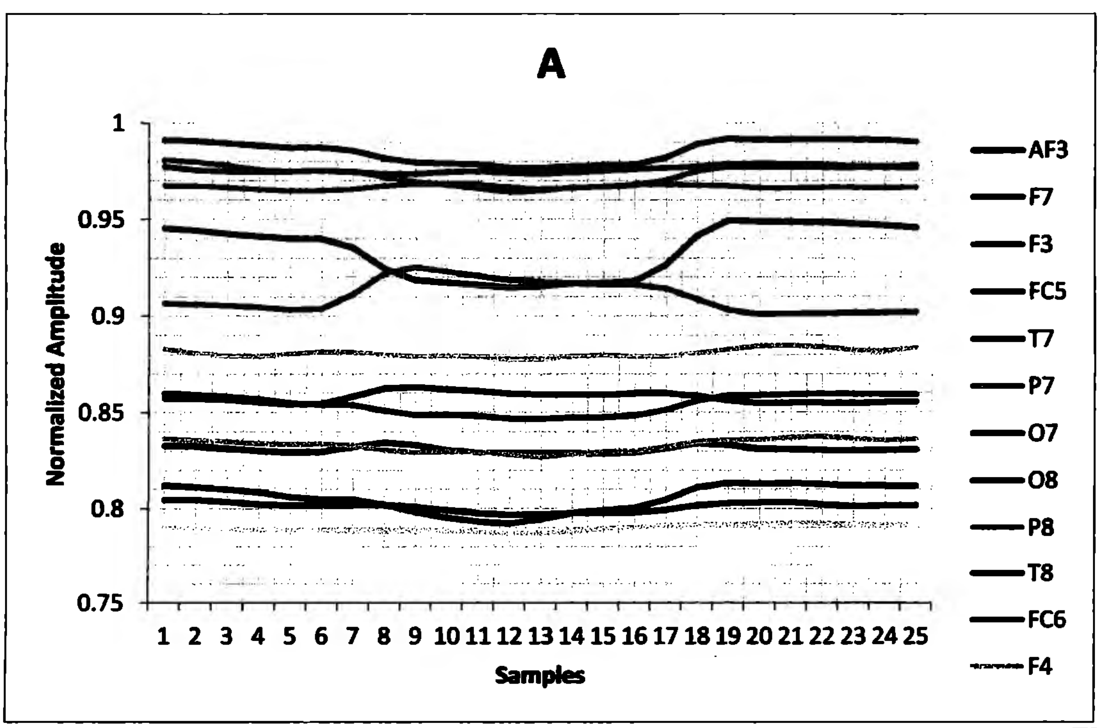

Figure 38. Applied filter

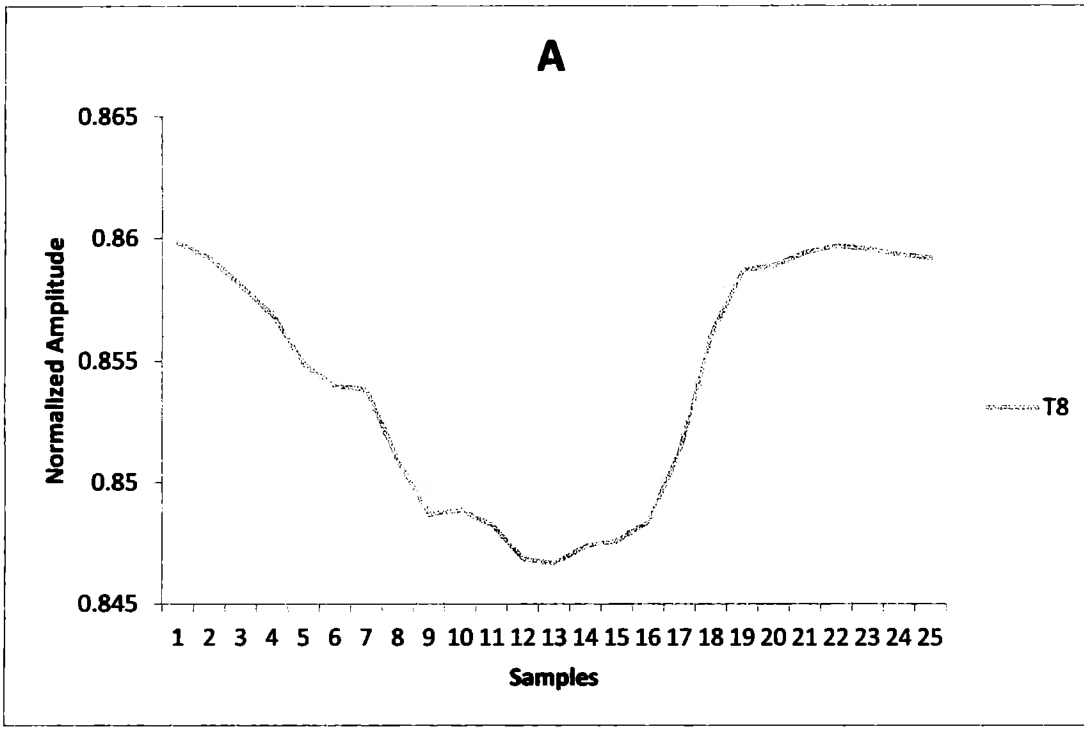

Figure 39. T8 Electrode signal with more resolution.

It is a remarkable fact that T8 is placed at the posterior part of the head and the source for all the signals is at approximately 180° at the semi-sphere drawn by the skull. The perception of this signal aids to the neural network so it may have more basis for differentiate the whole letters.

5 Wheelchair controller

The wheelchair that was used in order to mount controllers was a commercial Quickie wheelchair (David Gregory Monnard, 2009). The wheelchair on its system includes drivers for controlling motor's direction and speed by PWM signals. The transmission supports heavy loads and there will not be controlled the wheelchair's speed.

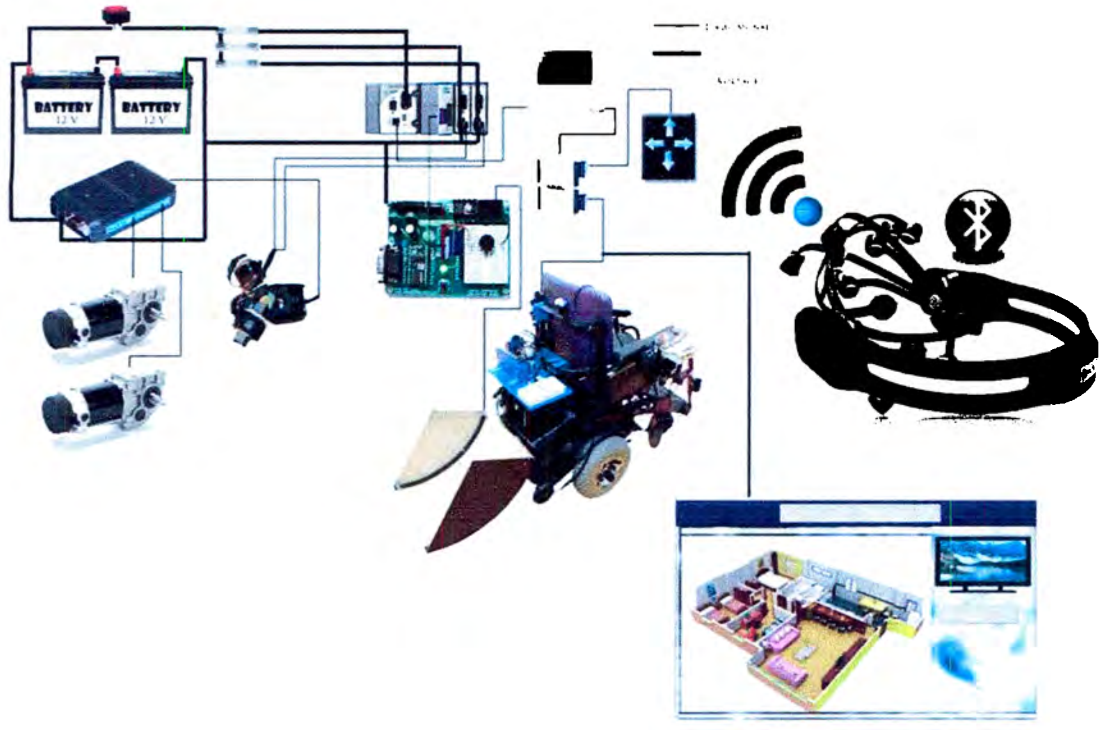

Figure 40. Diagram for controlling the system

A *gyroscope* is a device for measuring orientation, based on the principles of conservation of angular momentum. In this case the electronic gyroscope indicates disturbances regarding the spin of the head.

As previously mentioned, the headset includes a gyroscope system that enables two channels for data deliverance. Both channels may be altered at the same time by executing a spin over *z* axis (Figure 44) and independently over *x* and *y* axis.

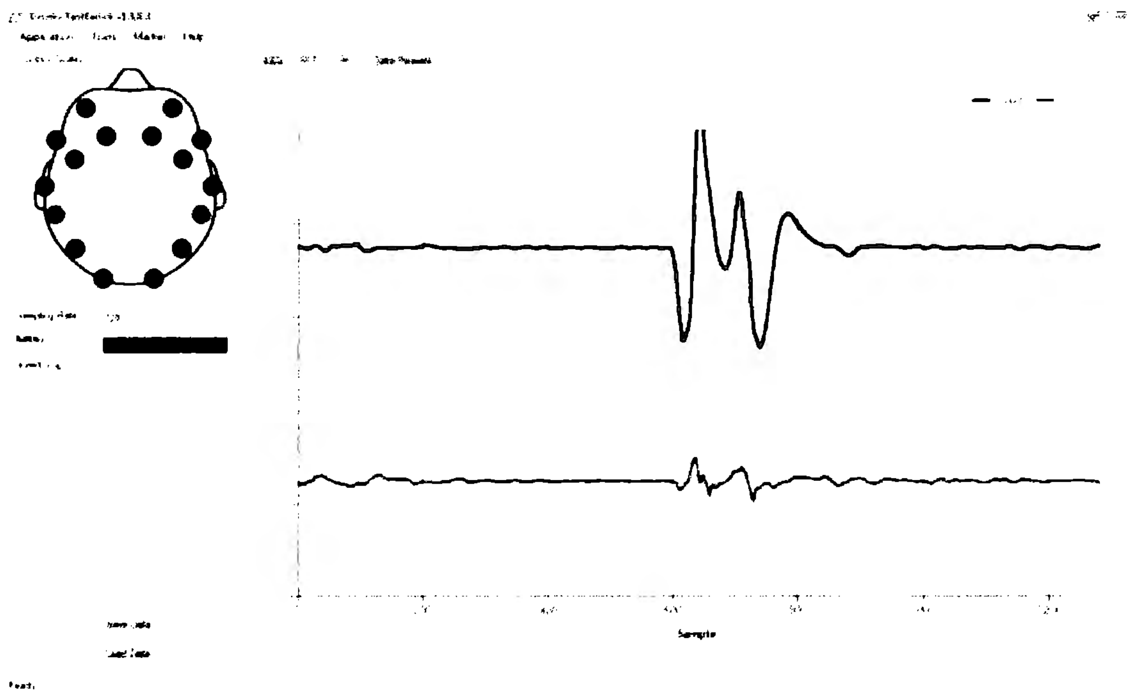

Figure 41. Gyroscope signals.

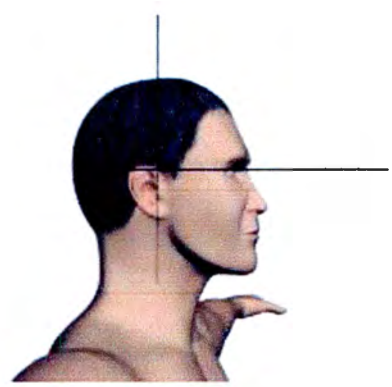

Figure 42. Tight point fairly in front of the subject.

By using this zero point configuration, there can be applied a neural network depending on the direction and position of the subject the wheelchair or any system can be manipulated depending on the inclination:

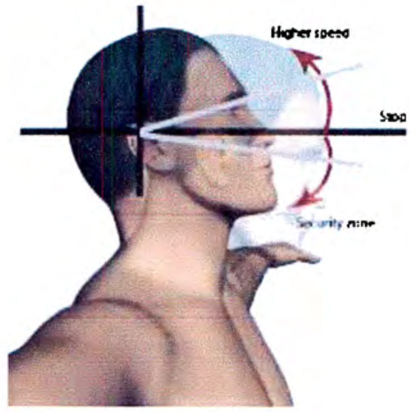

Figure 43. Head movement for speed and control direction.

In the case of the direction, it is just necessary to turn the head in such direction.

Thinking about control of directions, it is possible to configure a quite speed-direction control. It can be programmed by using the gyroscope which is included in the EPOC system. It can be achieved by centering at the beginning of the navigation, a tight point, which will be placed just in front of the subject (Figure 42). For this case the gyroscope will only indicate the spin over three axes:

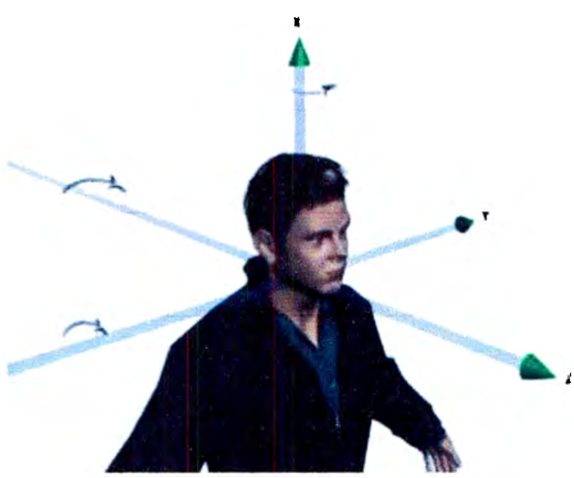

Figure 44. Possible spin axes.

In the case of these movementes on x and generated over theses axes, the signals can be identified dependig on the first valley originated in the signal. The amplitud will depend on the speed of change for all three degrees of freedom.

The gyroscope is enabled for sensing movements generated by the head in any direction, however the perturbations gets reflected in two channels as it is was already explained. The amplitud on each channel depends on the acceleration on that axis, it is remarkable to mention that it does not matter the amount of angle spinned by the head. By this means, if there is a slow spin for 30° the signal will not suffer any alteration.

The required information for establishing the different patterns is really simple due the data for being recognized is binary, indeed it is really difficult to justify the use of a Neural Networks. For both channels the analysis is done apart, there were trained two different networks and both channels must differentiate just bewtween two paterns that are exatly the opposite. However, the hidden layer was trained by only using ten perceptrons, so the matrix multiplication will imply less time per analysis. The main reason is due the possible noise introduced by the user whenever there is a natural or non-direction-control movement that the user introduces so the clasification trigger will not be fired. Figure 40 show continuous signals that do not show high frequencies rates, so it ispossible to work without signal filtering.

Figure 45. Rough input signals from Gyroscope.

For the trajectory shown in Figure 46 it was completed in 1 minute and 33 seconds. The headset was used by a person who has not ever used the system. His training included indications about how the head should be tossed for about 1 minute. Due wheelchair's motors the trajectory was set in a semi-circle pattern in order to help the wheelchair to late less time in spins to left direction.

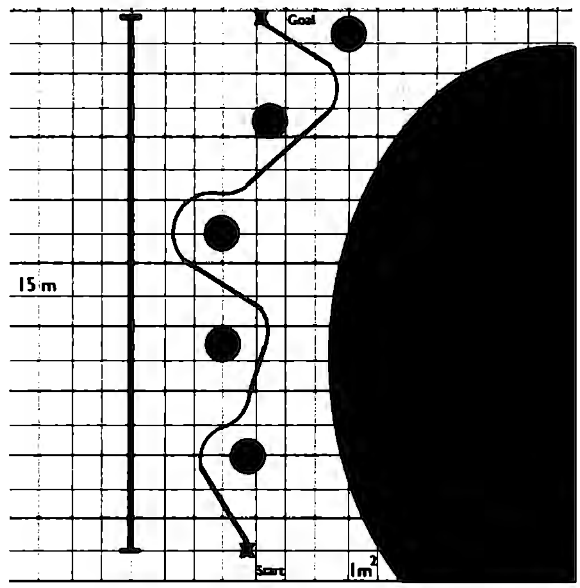

Figure 46. Trajectory for testing the headset response.

As a remarkable fact, 3 more different subjects tested the system with the same training and they were able for controlling the system in different terrains and with different slopes in the terrain.

The system is suitable for being driven by a person that is not seat at wheelchair, so it is possible to have control of the wheelchair at the distance allowed by the Bluetooth connection (about five meters if the headset is not interfered by any obstacle).

More tests were performed in order to set the behavior of the wheelchair inside buildings and outside them; they can be watched in the CD attached to this document.

Figure 47. Validation with different users.

Performance developed for each one of these users can be visualized on the videos attached to this document.

5. Controlling a virtual Scenario

Thinking about more controllers for people with any disability, it was programmed a virtual scenario that in further applications was thought for being linked to preprogramed actions that manipulate real devices. The scenario was designed on LabVIEW and actions may be pre-programmed depending on user's needs. It contains two images displays and two text indicators. The user may select which room must go, so a path planning algorithm must be designed in order to drive the wheelchair from one place to another. Once the user reaches that room, it is possible to control devices that use digital controls (ON/OFF) in order to turn them on or off.

The software was thought for being controlled as easy as possible; in order to activate the system the user only needs to assent with the head so the different rooms will be highlighted and on the text display will be available different devices that might be activated. All the devices will be displayed in sequence and will change on intervals of two seconds so the users just needs to assent in order to select that action.

Figure 48. Virtual Scenario for being manipulated with head movements.

6. Software structure

All the programs that linked the headset with the computer were realized on Visual Studio 2010 Premium by using dll's and header files from EMOTIV Epoc and National Instruments. At Neural Network training LabVIEW Code was used. For Wheelchair's controller, signals were trained by one user and outputs (Weights) just remained constants for all users.

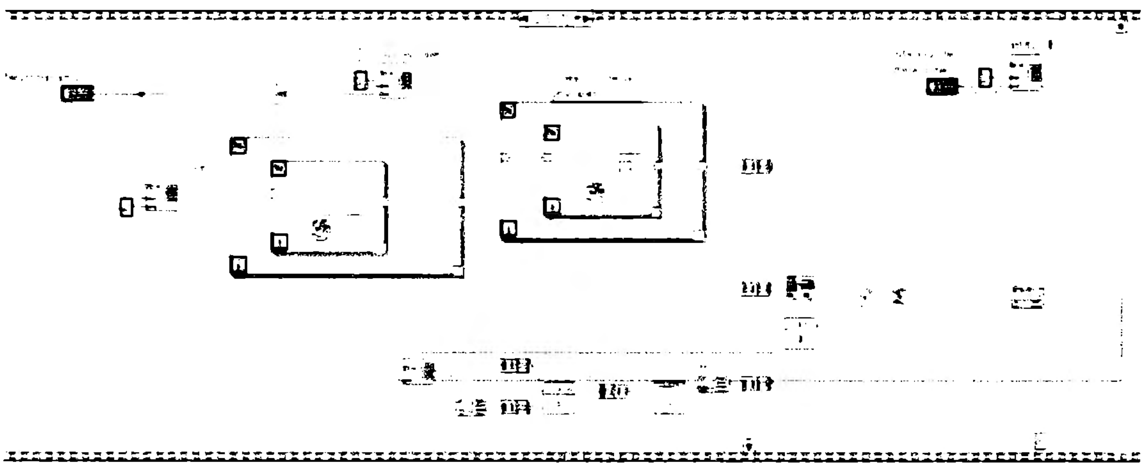

Figure 49. Weight's initialization by using random function.

In order to obtain weights so they are capable to rebuild head movements, since both channels are trained apart, the initial part of the trainer receives a 25 x 2 matrix per channel. Channel 1 is for left and right. Channel 2 is for up and down. In both cases just two cases must be recognized; this is the reason for the 2 rows and the 25 columns come from how many samples need to be used for rebuilding the pattern signal. Since algorithm will approximate the answer by using Means Square Error on each iteration, there will be a comparison with a target minimum error and training will stop until this minimum is reached or until limit for iterations is reached. The sigmoidal function is used as evaluation function for each perceptron.

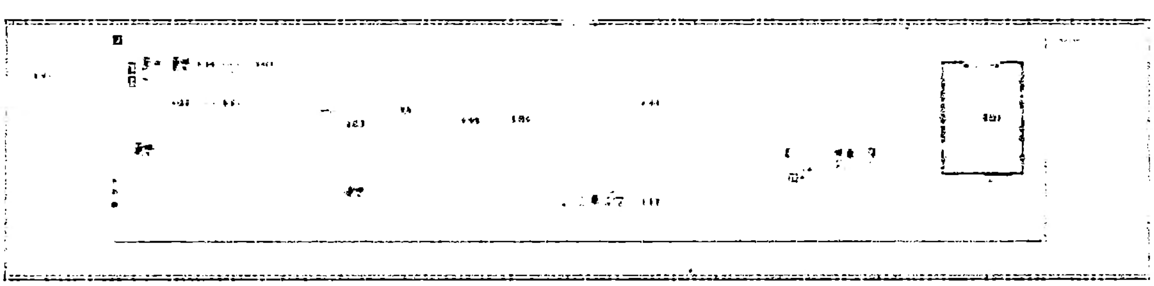

Figure 50. Cycle for Neural Network training.

Finally the trained weights are tested and the answer is graphed. In order to recognize whether for each channel is one direction or the other, a target pattern is associated with each movement. Due there are just two possibilities per channel, 0 and 1 represent one direction each one and restricted by sigmoidal function, the possible obtained values will be between 0 and 1. A trigger value was set in order to reach classification for each direction and for each channel.

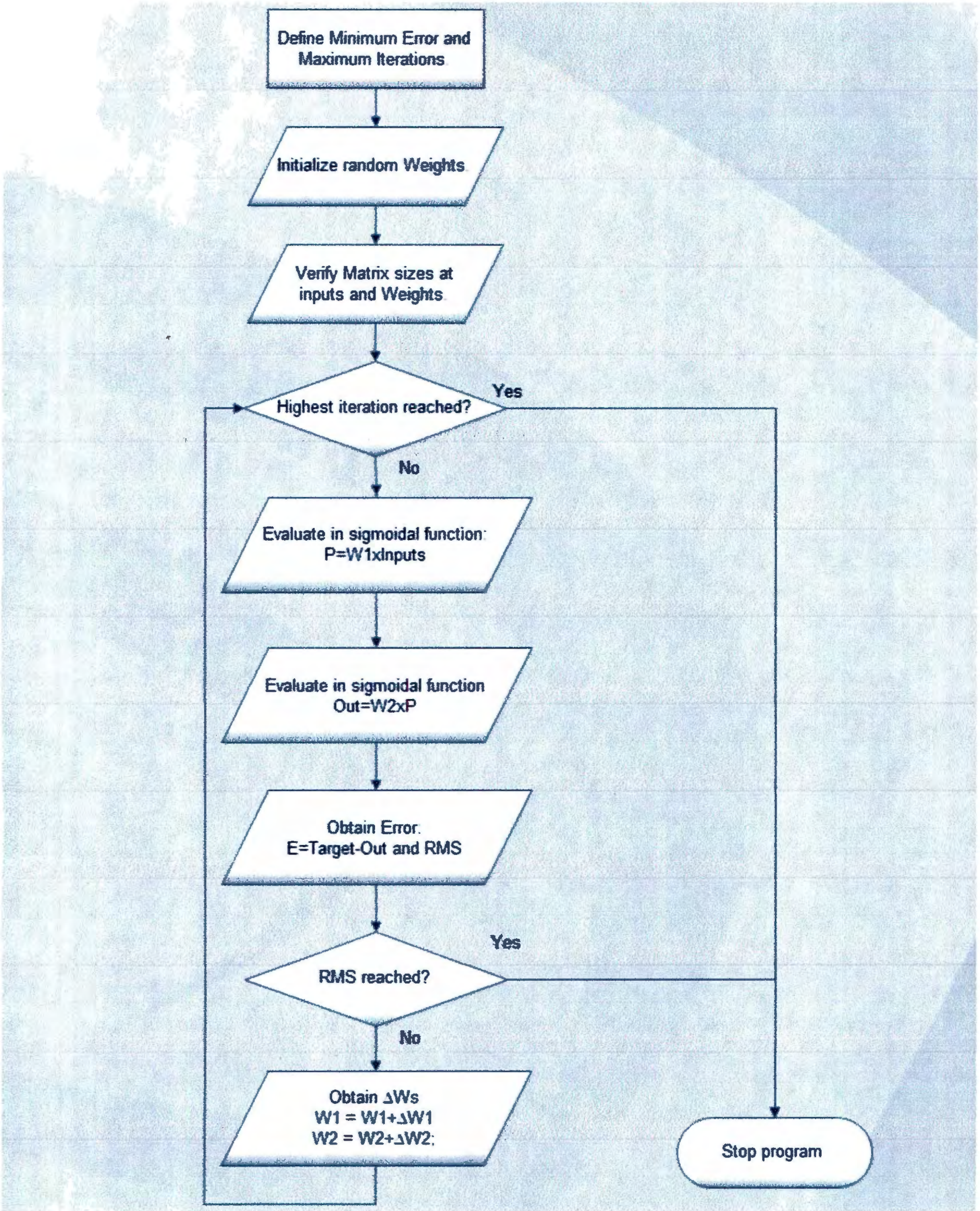

Figure 51. Flow diagram for Obtaining weights.

Figure 45 indicates the algorithms in order to obtain final weights for pattern recognition. It is the final stage reaching as minimum error as possible. Notice that number of iterations and minimum RMS is possible to be configured.

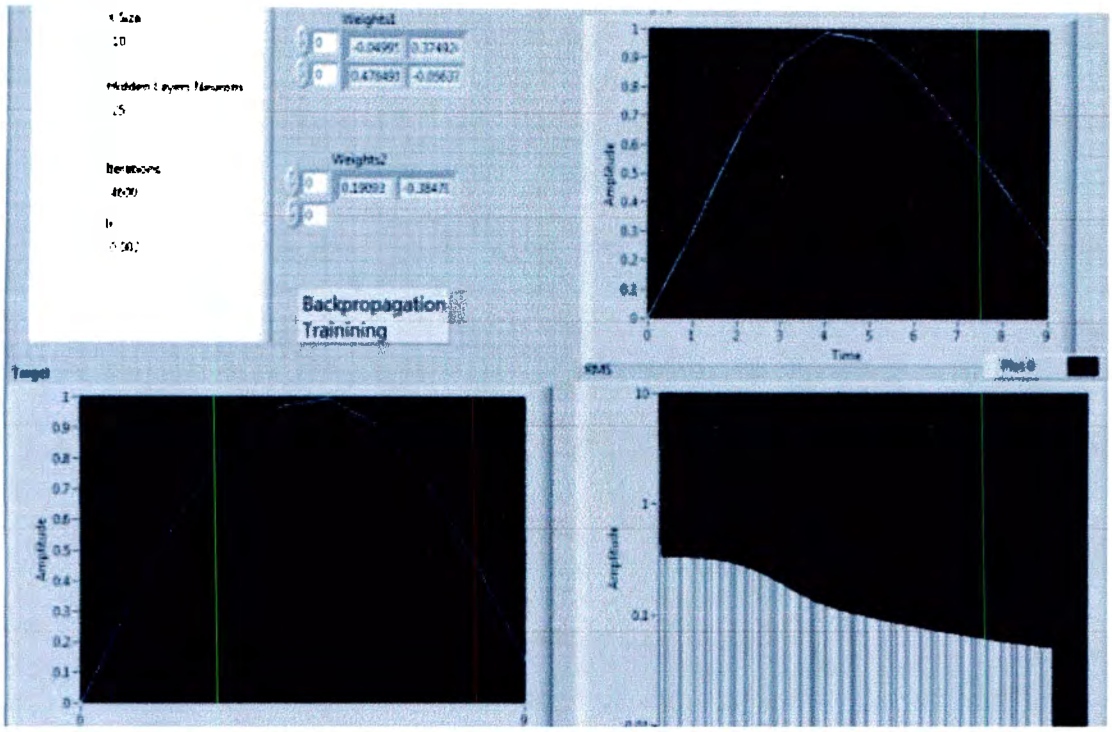

Figure 52. Backpropagation training GUI.

For graphical representation on final stage, pattern signal and test inputs with corresponding Weights are tested.

6.1 Wheelchair and virtual scenario controllers

The following code was configured in C++ and the structure is as following:

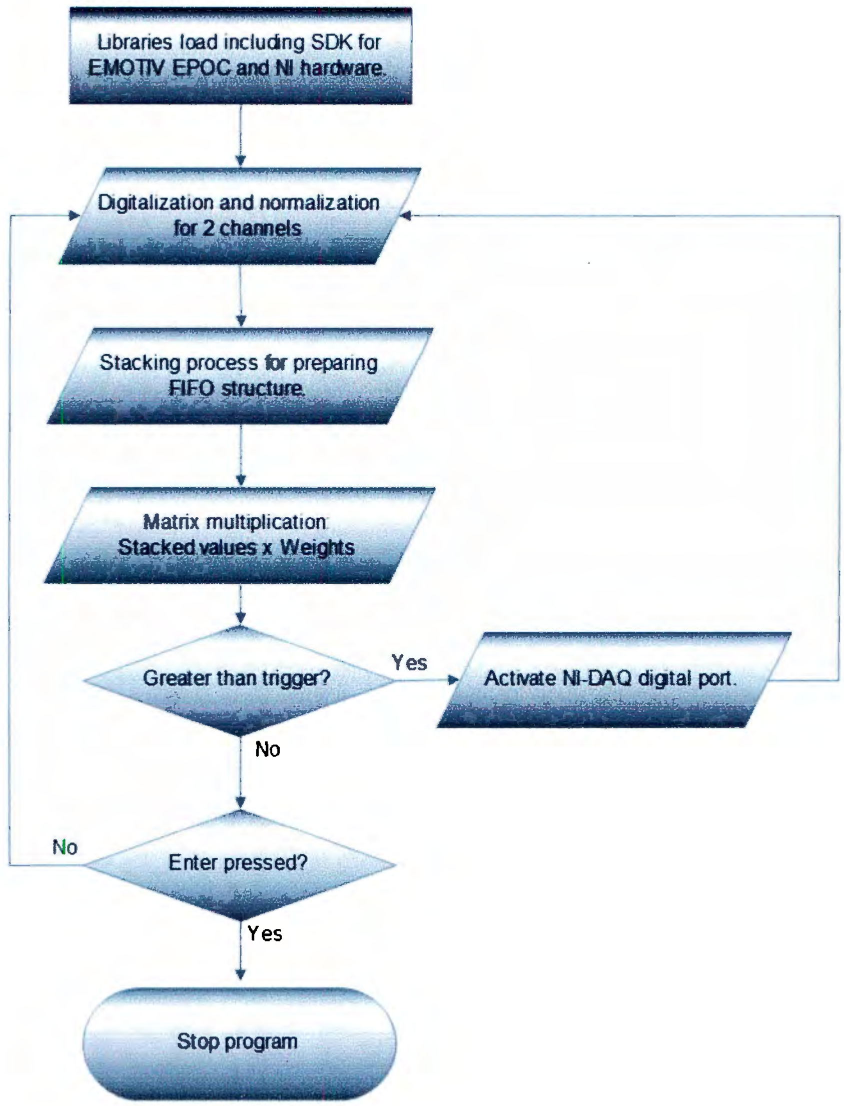

Figure 53. Flow diagram for Gyroscope signals classification.

At first stage and for performed tests, it was determined that analog signal was possible to be rebuilt in 25 samples from 125 analog data. Data can be obtained in approximately 1 second; it depends on more tasks developed by the processor. Data is normalized on each channel but no filter is applied since high frequencies cannot be continuously executed due it is annoying and tiring for the user. Once completed, FIFO stack is updated with five new samples. Vertical movements are associated with advance and stopping the wheelchair. Vertical movements are associated with advancing and stopping the wheelchair; horizontal movements for left and right.

At evaluation stage, input data is multiplied by weights, multiplications occur per channel so confusion between different channels is avoided. Finally, per channel, is obtained a value between 0 and 1, unless answer is 0.5 ±0.2 there will not be executed any action otherwise NI-DAQ will be activated.

If virtual Scenario is wished for being controlled, it is just necessary to run LabVIEW scenario and Classifier.exe files. Once activated, virtual scenario is configured for automatically pass by each available room at main menu and typing in a text field the actual room. Once selected by user, a smaller menu will automatically display possible commands that might be activated in the room.

6.2 Letters classification

As previously mentioned facial movements and movements generated by eye's movements are greater than ECGs signals. Depending on speed and amount of movement, variations in fourteen channels are capable for being sensed. In the case of eye's movements the amount of spin and the acceleration will affect the detected signal so it is possible to determine where the person is looking at. Indeed, what is possible to classify is the movement that eye's movement produces when it is moved from a tight point to a target letter.

Although it is common to think that just frontal electrodes will be used, T7 and T8 also reflect oscillations at eye's spin, just as previously shown. The usage of the whole set of electrodes aids the Artificial Neural Networks system in order to create redundancy in the outputs so a letter can be detected.

Normalization values were taken from previous tests performed with different users, highest pikes that did not represent noise that were repeatable patterns. There also was considered a security margin for the normalization value, it was established for each channel. Since analog signal is able for being rebuilt in 25 samples from 125 obtained, only these samples are filtered by using a lowpass Butterworth filter of second order.

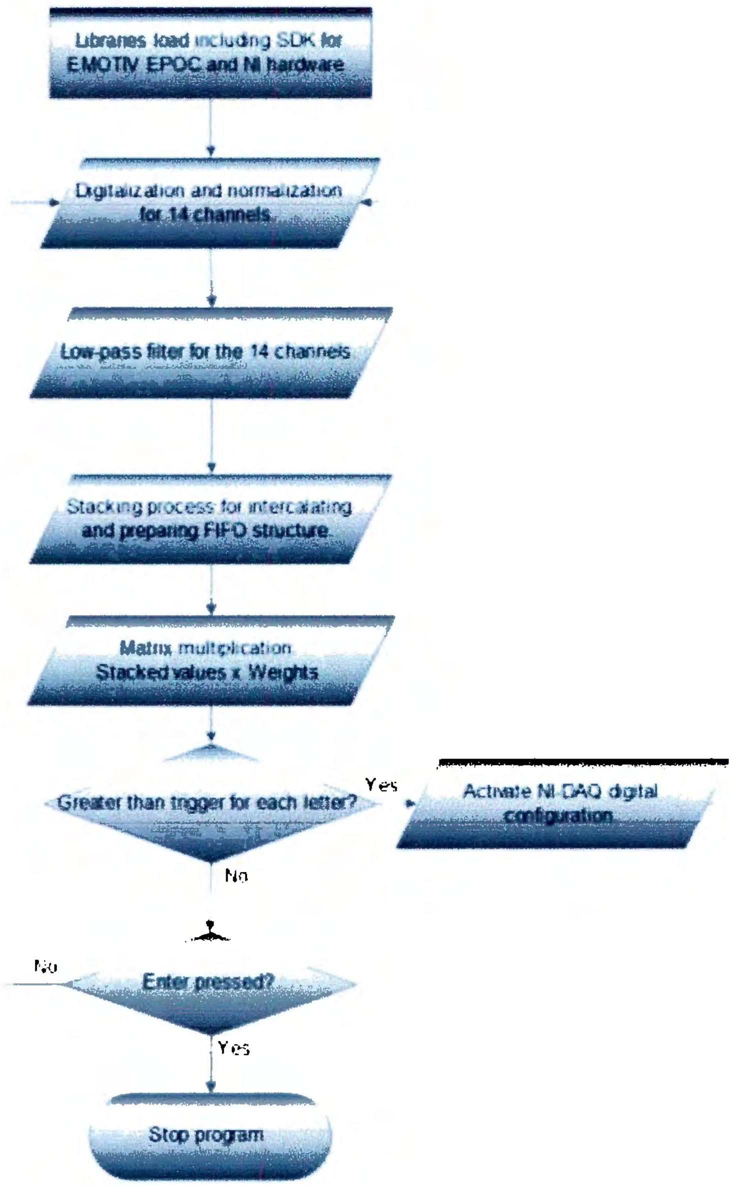

Figure 54. Flow diagram for letters c68lassification.

Once filter has been applied, data is stacked per channel and finally gathered in a 350 vector that will be the input for being evaluated by multiplying the weights corresponding to each hidden layer. Finally a binary number is delivered; the number will represent one letter. The amount of bits will depend on how many letters has just been trained in order to indicate which letter was detected. By comparing a trigger value for each bit with the delivered response, Ni-Daq channels are activated.

By other hand, qwerty keyboard was modified so Artificial Neural Networks may reach a better response since elements for each letter are far from the element of another letter. The keyword was separated so bigger amplitude might be reached and the user is proposed to be approximately 35 cm far from the tight point in height and approximately 10 cm far from tight point to lower part of the frontal bone.

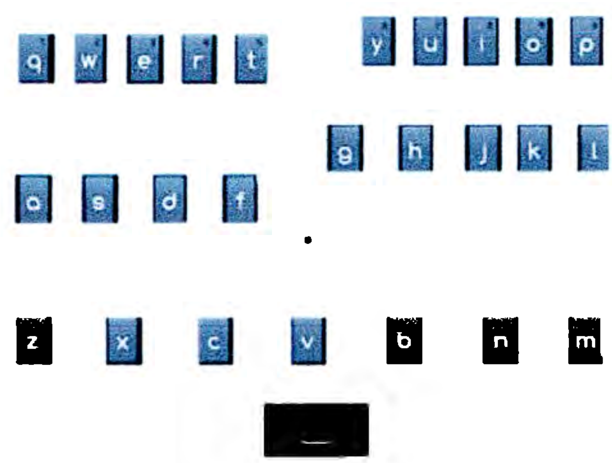

Figure 55. Modified qwerty keyboard. Qwerty order was preserved due it is commonly used.

Although redundancy might be set from using more electrodes in different parts of the body, an action must be executed by using determined part of the body, so in people with tetraplegia this action must be avoided.

EMOTIV Epoc code

EmoStateDLL.h, edk.h and edkErrorCode.h are the imported libraries for working with the headset. Variables are initialized, by creating an Event with *EE_EmoEngineEventCreate()* method, a variable that will handle the communication with the headset and the computer is set. Other variables are initialized so they will be used as flags in the program. Electrodes to be read are indicated in a target list, so when EmoEngine accesses the physical headset, it just reads these targets. The main functions ask for a file in order to save data acquired in the session. If no error connection is detected, then and object of type DataHandle (is an array)is created in order to save incoming data from headset. The initiation of this variable is until now because it must be previously ensured that connection was reached. In order to ensure Real Time, deliverance of samples was set to 1 second. Function *EE_EngineGetNextEvent(eEvent)* receives the previously created object that will set communication between Bluetooth port for incoming data handling.

While there is not any pressed key, and if no error occurs and deliverance has been completed, for cycle is executed and depending on the amount of received data, there will be read the amount of signals marked at channel list. For analysis, this data will be the delivered inputs for the Neural Networks.

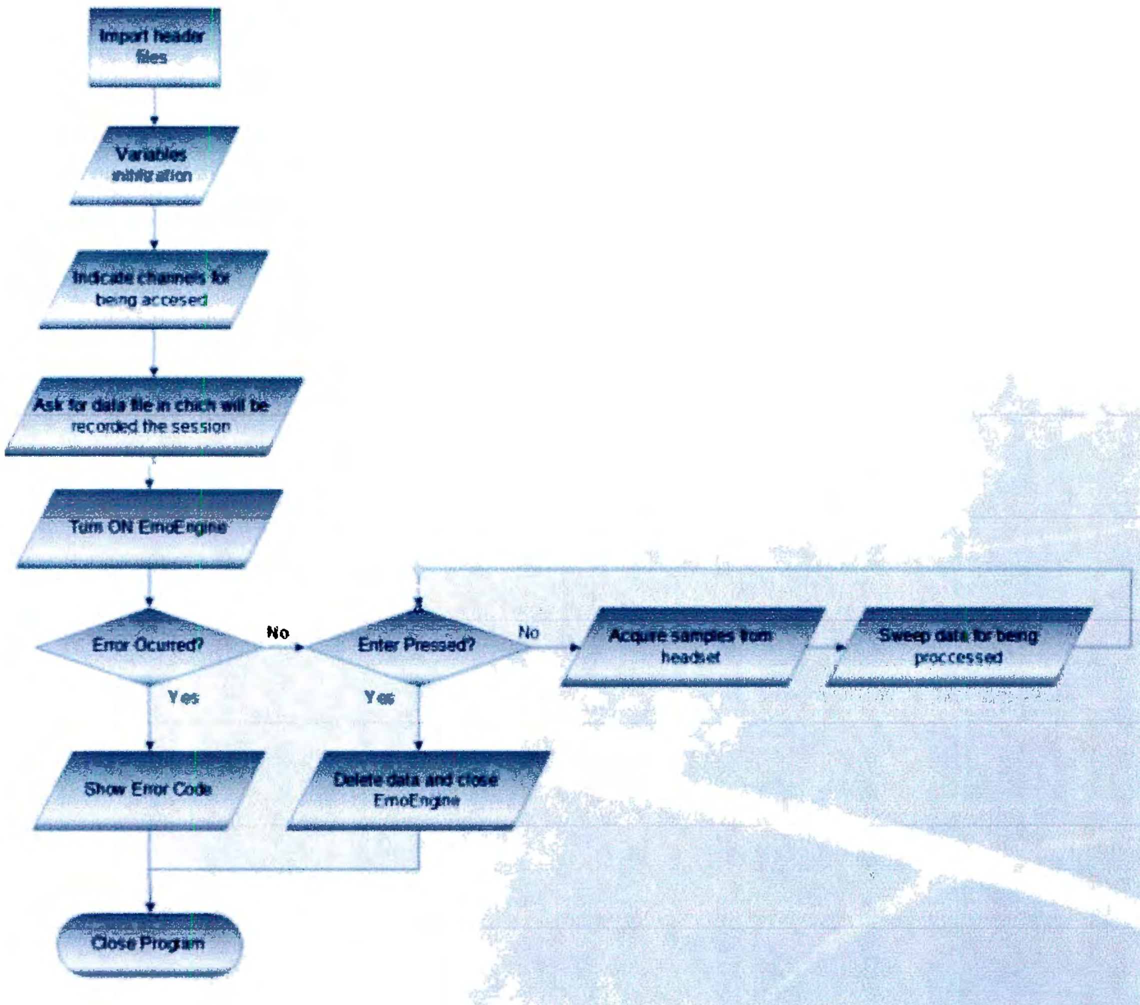

Figure 56. EMOTIV Epoc code for data handling.

I-DAQ code

Nidaqmx header includes different methods that allow the user to configure hardware: digit. data, connections between references for the sensed phenomenon, frequencies for reading and writing data, error checking, etc.

Once Error handler and data for being written is initialized, by using class *Task Handle,* each port can be accessed. This is executed by calling a constant array that is linked to a letter. this array will be received by Task Handle and writing the final port with the command `DAQmxWriteDigitalLine`. Following to this function time must be waited and finally error method is executed, if any is detected, error code is shown on Command prompt and program is terminated.

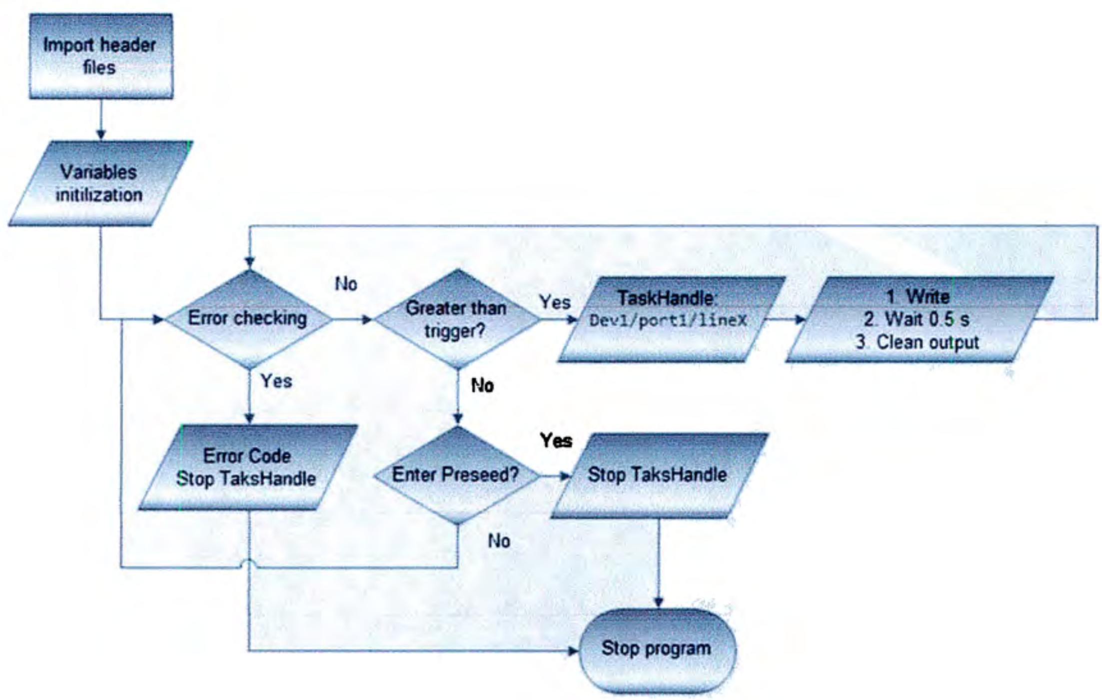

Figure 57. DAQ program for being accessed with C++.

6 Hardware control

6.1 NI-DAQ

In order to execute hardware manipulation, C++ code was programmed on Visual Studio. This program is focused on manipulating digital output for NI hardware, in this case digital NI-DAQ channels will be manipulated according to the classified signal.

A NI-DAQ system consists of sensors, DAQ measurement hardware, and a computer with programmable software. (National Instruments, 2012) National Instrument offers different models and depending on user's final needs, by software, it is possible to work with inputs and outputs. For this thesis a NI-DAQ 6211 and its main characteristics are the following:

- 16 analog inputs (16-bit, 250 kS/s)
- analog outputs (16-bit, 250 kS/s); 4 digital inputs; 4 digital outputs; 32-bit counters
- Bus-powered USB for high mobility; built-in signal connectivity
- NI signal streaming for sustained high-speed data streams over USB; OEM version available
- Compatible with LabVIEW, LabWindows™/CVI, and Measurement Studio for Visual Studio .NET
- NI-DAQmx driver software and NI LabVIEW SignalExpress LE interactive data-logging software

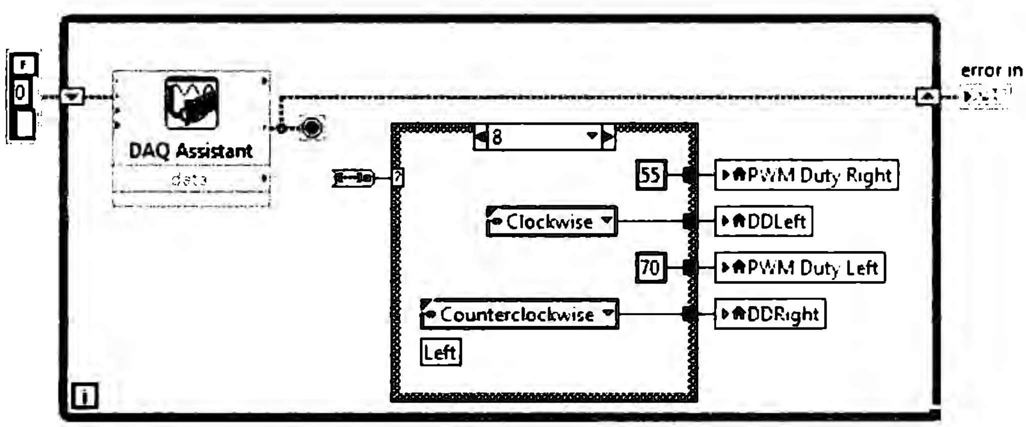

Figure 16. Data flow for local variables in order to control PWM.

The output binary data was configured on Reference single ended at DAQ device and the sampling was executed *On demand*. The incoming data was treated in an *Enum* structure for the four possibilities; each case contains a PWM duty and the direction for the current. The variables will be updated at CompactRIO through local variables with preset constant values. They manipulate PWM duty and current direction. More information about these variables is indicated aCompactRIO section.

6.2 NI-CompactRIO

Compact Reconfigurable Input/Output is an embedded control and acquisition system. This module supports interchangeable modules for I/O, a reconfigurable field-programmable gate array (FPGA) chassis and an embedded controller. It may be configured in NI-LabVIEW. System is enabled for working using Real Time and FPGA processes. Real time process can be updated to CompactRIO module but FPGA processes cannot. If access is needed from computer to FPGA, then RT software must be configured by using local or global variables since FPGA works at frequencies of 800 MHz and for several OS is not possible to work at this frequency updating data for LabVIEW.

The VI is run in a virtual instrument that works with Real Time and FPGA interfaces, both work over a CompactRIO 9103 device. Through manipulating the Real Time VI by using 2 variables per H bridge (9505) the FPGA updates the Duty cycle and the direction for each motor in order to lead a wheelchair (David Gregory Monnard, 2009).

1. The sign bit of the PWM Duty Cycle specifies drive direction. A positive number is clockwise, negative is counterclockwise.

2. A counter in conjunction with a single-cycle timed loop, assuming a 40 MHz FPGA clock, is used to generate a PWM frequency of 20 kHz (2000 ticks).

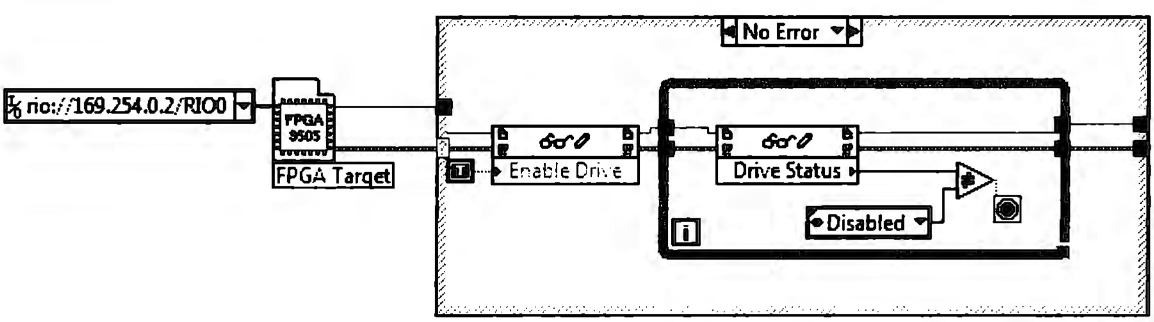

Figure 58. Code for writing on FPGA code. Part 1.

Figure 58 shows how on each attempt for writing on RIO modules it is verified if any error occurred, if true automatically the VI deny access to any port and for all the program, no code will executed until reach the part where the program must be terminated. If No error occurred, FPGA reference will be accessed through ip address, and whole system will be enabled. Figure 59 updates local variables with the configured values for each direction in the wheelchair.

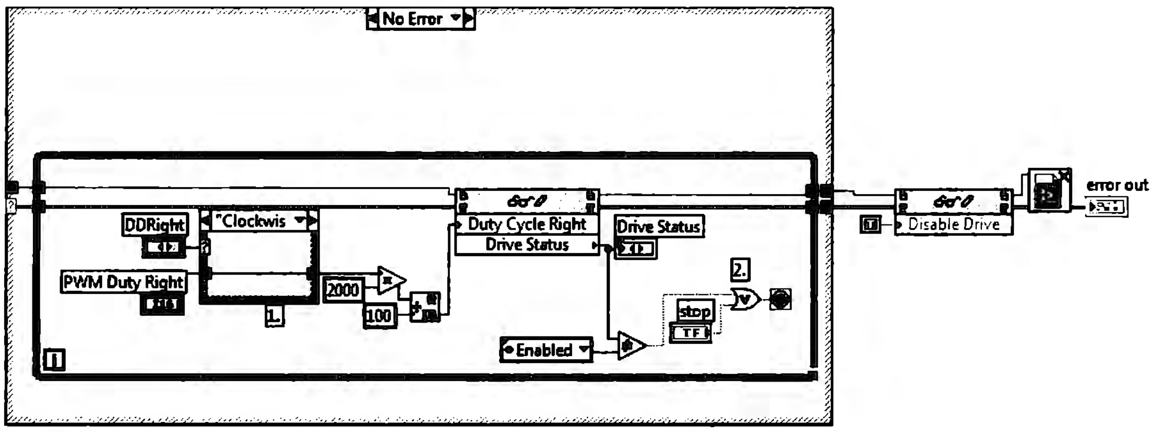

Figure 59. Code for writing on CompactRIO. Part 2.

7 Future Work

Since first proposal was to look for patterns in EEG, it is highly recommended for future work, using an invasive method in order to set patterns for different activities in the brain. Invasive method must also be applied in the system at final circumstances, so it is possible to detect different interferences realized by human being when it is using the whole system. In order to obtain more information from EEGs there could be implemented the wavelet transform. By other hand, in ocular tracker there must be set a digital compass, capable to indicate which one is the best position for the user. There must also be implemented a more robust system so it is capable for being adjusted with human movements after training each letter. Both suggestions may be useful in order to reach a better classification system. Regarding scenario, physical controls must be implemented in a real house. For wheelchair, it is suggested to implement motor controllers for each motor and remove coils, so less energy will be consumed and wheelchair directions ensured.

Conclusions

Regarding people with disabilities, there is still a huge work to do, since social education until technology devices that replace great part of the dependence between disabled people and other human beings. Although researches have been done regarding BMI's, most functional interfaces use invasive methods but its functionality remains just for research laboratories since big workstations are used for processing data. A big challenge is faced when there is a special need for any patient, this means *personalization*. Great amount of money are need for designing special devices and for underdeveloped countries this is not an option. Devices focused on aiding people with Tetraplegia are not plenty developed because for many industries they are not economically attractive.

Common Electroencephalograms may reflect different anomalies at cerebral cortex, indeed they must be realized at controlled environments by influencing in patient's relaxation states. Due final stage at this research was to control devices by working with human EEGs patterns, noisy conditions generated by non-relaxation states will always be present. So it is recommendable to look for patterns using invasive methods in order to be later applied for pattern recognition in non-invasive methods. EMOTIV Epoc headset is capable to deliver satisfactory EEGs, however due it sacrifices easiness in usage and comfort by decreasing price and accuracy, the headset cannot deliver deep electric activity generated at brain cortex. The main sensed voltage at skull was the one produced when any face or eye movement is executed and it is possible to indicate since this movement, which one was its source and how it was produced.

Regarding signals analysis for EEGs, wavelet transform might be a more powerful technique for being used. This technique is used for noise reduction and time-frequency analysis. On last investigations regarding Bio-Signals acquisition, there have been enhanced papers that deal whit continuous wavelet transform (CWT) for real time processing implemented on EEG (electrocardiograms). Although there is not bibliography regarding the pattern recognition of thoughts in the EPOC EMOTIV system, it is inferred that it uses this kind of processing.

On the other hand, pattern recognition using Neural Networks was satisfactory implemented and results were easily reached at gyroscope's signal classification. Furthermore, for eye tracking it was possible to improve classification since redundancy was created by using fourteen electrodes for sensing eye's movement. Using a set point, it was possible to produce different signals that vary in amplitude depending on the angle rotated by eye's spin.

National Instrument's hardware was the base for enabling communication between LabVIEW and EMOTIV Epoc system, communication between both systems has been a big challenge for the researches because DLL's do not allow working with rough incoming data from headset. However communication was reached in this research through using NI-Hardware.

It is for ease that pattern recognition from now on will deal with different areas activated on the brain, this is due the fact that thinking about word saying a word only activates a determined area of the brain which is more confusing for the system and makes not any sense to get into that problem whether there are more possible regions to activate.

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Attachment 1: DAQ connection using C++

```
#include <stdio.h>
#include <NIDAQmx.h>

#define DAQmxErrChk(functionCall) if( DAQmxFailed(error=(functionCall)) ) goto
Error; else

int main(void)
{
	int32       error=0;
	TaskHandle  taskHandle=0;
	uInt8       data[1]={0};
	char        errBuff[2048]={'\0'};

	/*********************************************/
	// DAQmx Configure Code
	/*********************************************/
	DAQmxErrChk (DAQmxCreateTask("",&taskHandle));
	DAQmxErrChk
(DAQmxCreateDOChan(taskHandle,"Dev1/port1/line0","",DAQmx_Val_ChanForAllLines));

	/*********************************************/
	// DAQmx Start Code
	/*********************************************/
	DAQmxErrChk (DAQmxStartTask(taskHandle));

	/*********************************************/
	// DAQmx Write Code
	/*********************************************/
	DAQmxErrChk
(DAQmxWriteDigitalLines(taskHandle,1,1,10.0,DAQmx_Val_GroupByChannel,data,NULL,NULL)
);
	system("Pause");

Error:
	if( DAQmxFailed(error) )
		DAQmxGetExtendedErrorInfo(errBuff,2048);
	if( taskHandle!=0 ) {
		/*********************************************/
		// DAQmx Stop Code
		/*********************************************/
		DAQmxStopTask(taskHandle);
		DAQmxClearTask(taskHandle);
	}
	if( DAQmxFailed(error) )
		printf("DAQmx Error: %s\n",errBuff);
	printf("Fin del programa, presione Enter para terminar la sesión.\n");
	getchar();
	return 0;
}
```

Attachment 2: Code for EPOC connection with C++

```
#include <iostream>
#include <fstream>
#include <conio.h>
#include <sstream>
#include <windows.h>
#include <map>

#include "EmoStateDLL.h"
#include "edk.h"
#include "edkErrorCode.h"

#pragma comment(lib, "../lib/edk.lib")

EE_DataChannel_t targetChannelList[] = {
		ED_COUNTER,
		ED_AF3, ED_F7, ED_F3, ED_FC5, ED_T7,
		ED_P7, ED_O1, ED_O2, ED_P8, ED_T8,
		ED_FC6, ED_F4, ED_F8, ED_AF4, ED_GYROX, ED_GYROY, ED_TIMESTAMP,
		ED_FUNC_ID, ED_FUNC_VALUE, ED_MARKER, ED_SYNC_SIGNAL
	};

const char header[] = "COUNTER,AF3,F7,F3, FC5, T7, P7, O1, O2,P8"
		      ", T8, FC6, F4,F8, AF4,GYROX, GYROY, TIMESTAMP, "
		      "FUNC_ID, FUNC_VALUE, MARKER, SYNC_SIGNAL,";

int main(int argc, char** argv) {

	EmoEngineEventHandle eEvent			= EE_EmoEngineEventCreate();
	EmoStateHandle eState				= EE_EmoStateCreate();
	unsigned int userID				= 0;
	const unsigned short composerPort = 1726;
	float secs					= 1;
	unsigned int datarate				= 0;
	bool readytocollect				= false;
	int option					= 0;
	int state					= 0;


	std::string input;

	try {

		if (argc != 2) {
			throw std::exception("Please supply the log file name.\nUsage:
EEGLogger [log_file_name].");
		}

		std::cout <<
"===================================================================" << std::endl;
		std::cout << "Example to show how to log EEG Data from
EmoEngine/EmoComposer."	<< std::endl;
```

```
            std::cout <<
"=================================================================" << std::endl;
            std::cout << "Press '1' to start and connect to the EmoEngine
" << std::endl;
            std::cout << "Press '2' to connect to the EmoComposer
" << std::endl;
            std::cout << ">> ";

            std::getline(std::cin, input, '\n');
            option = atoi(input.c_str());

            switch (option) {
                  case 1:
                  {
                        if (EE_EngineConnect() != EDK_OK) {
                              throw std::exception("Emotiv Engine start up
failed.");
                        }
                        break;
                  }
                  case 2:
                  {
                        std::cout << "Target IP of EmoComposer? [127.0.0.1] ";
                        std::getline(std::cin, input, '\n');

                        if (input.empty()) {
                              input = std::string("127.0.0.1");
                        }

                        if (EE_EngineRemoteConnect(input.c_str(), composerPort)
!= EDK_OK) {
                              std::string errMsg = "Cannot connect to
EmoComposer on [" + input + "]";
                              throw std::exception(errMsg.c_str());
                        }
                        break;
                  }
                  default:
                        throw std::exception("Invalid option...");
                        break;
            }


            std::cout << "Start receiving EEG Data! Press any key to stop
logging...\n" << std::endl;
      std::ofstream ofs(argv[1],std::ios::trunc);
            ofs << header << std::endl;

            DataHandle hData = EE_DataCreate();
            EE_DataSetBufferSizeInSec(secs);

            std::cout << "Buffer size in secs:" << secs << std::endl;

            while (!_kbhit()) {

                  state = EE_EngineGetNextEvent(eEvent);

                  if (state == EDK_OK) {
```

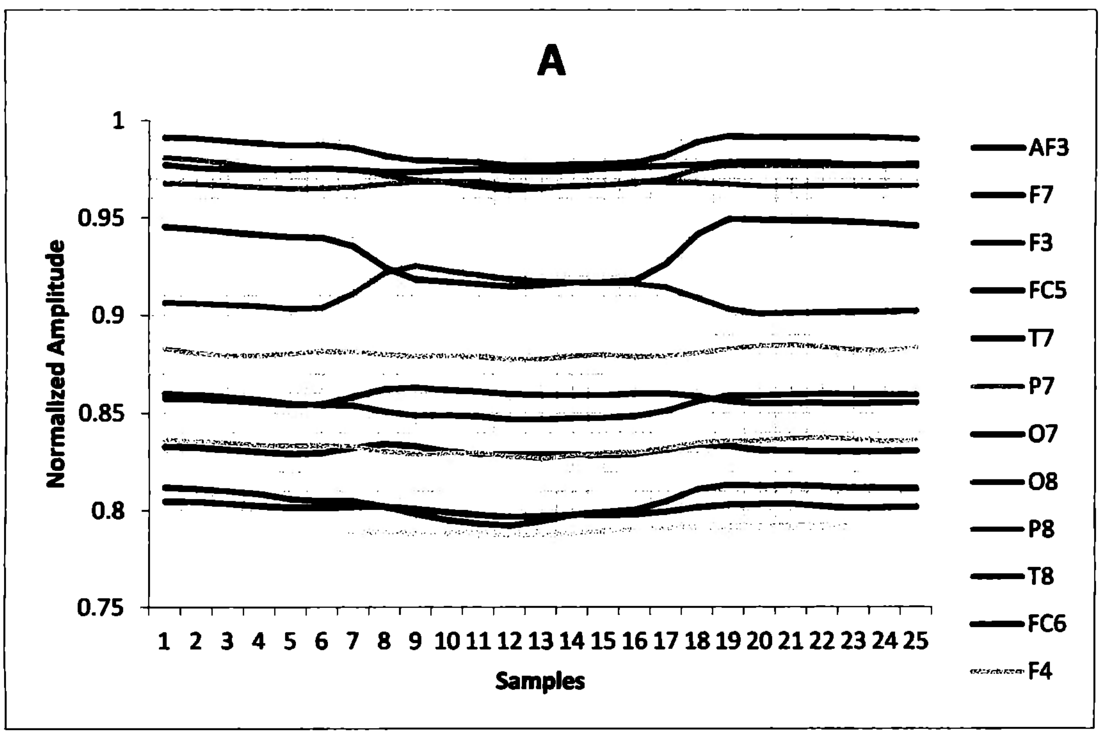
```
                        EE_Event_t eventType = EE_EmoEngineEventGetType(eEvent);
                        EE_EmoEngineEventGetUserId(eEvent, &userID);

                        // Log the EmoState if it has been updated
                        if (eventType == EE_UserAdded) {
                              std::cout << "User added";
                              EE_DataAcquisitionEnable(userID,true);
                              readytocollect = true;
                        }
                  }

                  if (readytocollect) {

                                    EE_DataUpdateHandle(0, hData);

                                    unsigned int nSamplesTaken=0;

      EE_DataGetNumberOfSample(hData,&nSamplesTaken);

                                    std::cout << "Updated " << nSamplesTaken <<
std::endl;

                                    if (nSamplesTaken != 0) {

                                          double* data = new
double[nSamplesTaken];
                                          for (int sampleIdx=0 ;
sampleIdx<(int)nSamplesTaken ; ++ sampleIdx) {
                                                for (int i = 0 ;
i<sizeof(targetChannelList)/sizeof(EE_DataChannel_t) ; i++) {

                                                      EE_DataGet(hData,
targetChannelList[i], data, nSamplesTaken);
                                                      ofs << data[sampleIdx]
<< ",";
                                                }
                                                ofs << std::endl;
                                          }
                                          delete[] data;
                                    }

                  }

                  Sleep(100);
            }

            ofs.close();
            EE_DataFree(hData);

      }
      catch (const std::exception& e) {
            std::cerr << e.what() << std::endl;
            std::cout << "Press any key to exit..." << std::endl;
            getchar();
      }

      EE_EngineDisconnect();
```

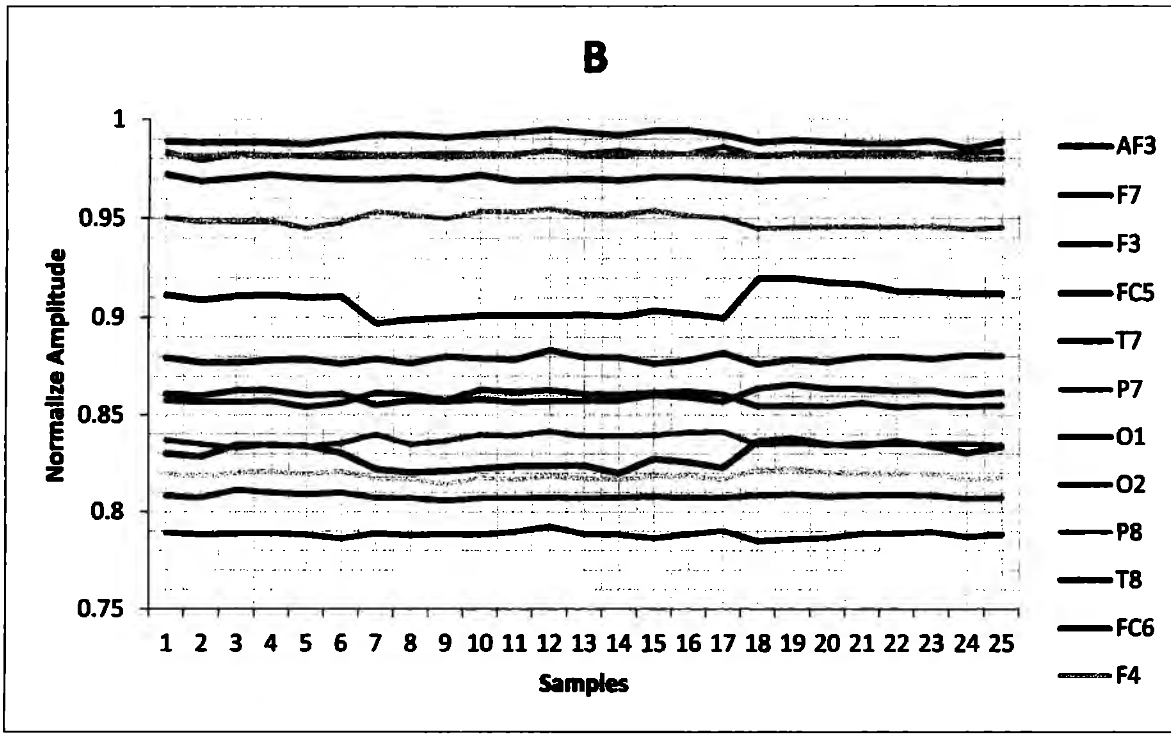
```
    EE_EmoStateFree(eState);
    EE_EmoEngineEventFree(eEvent);

    return 0;
}
```

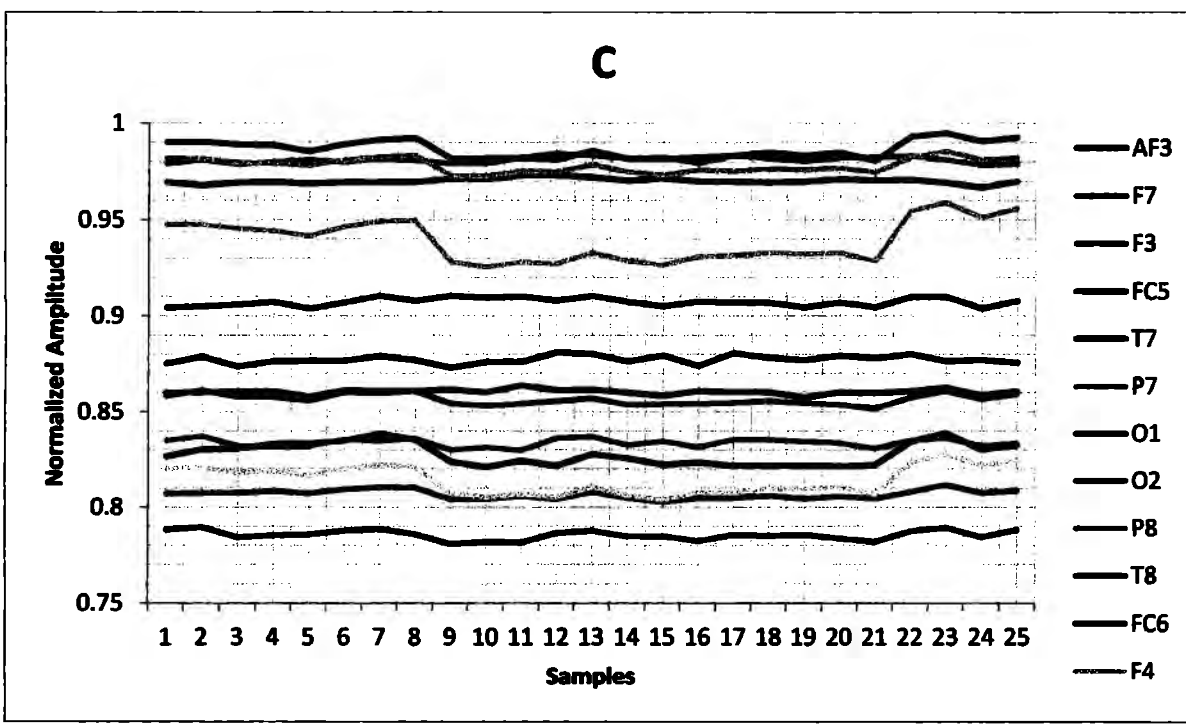
Attachment 4: Lowpass filter.

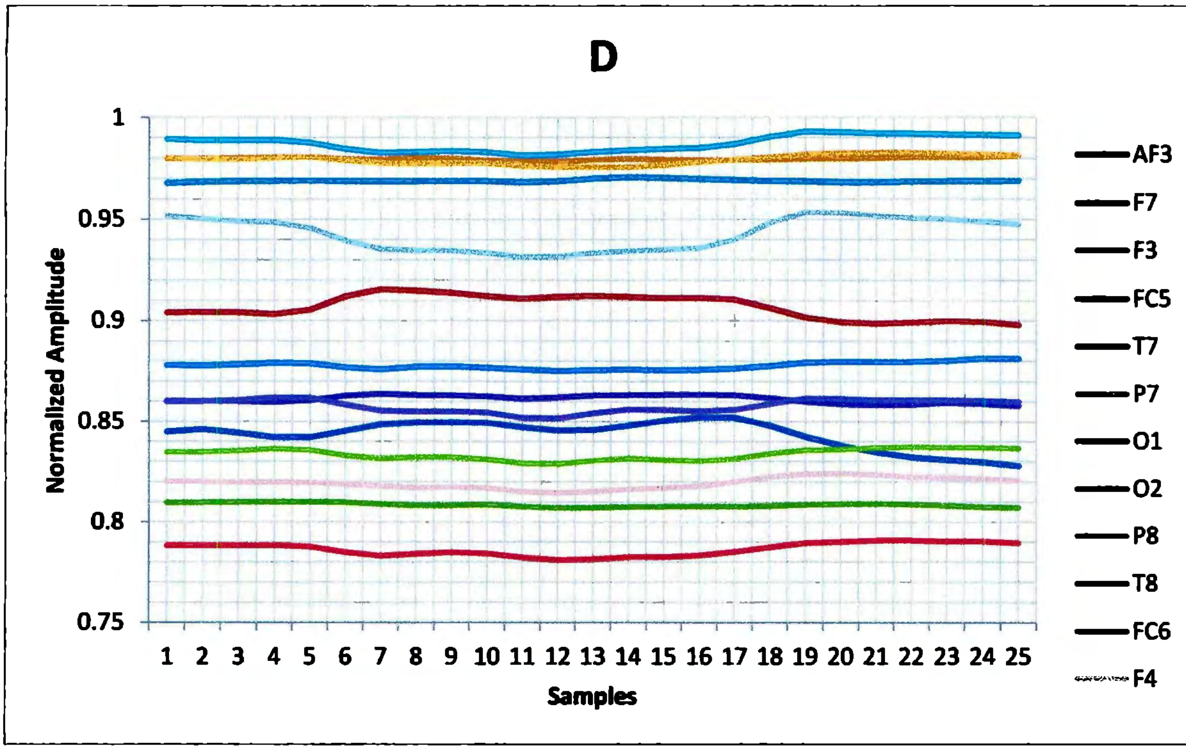
```
double QcRaw  = (2 * PI * cutoff) / samplerate;
double QcWarp = tan(QcRaw);
double gain = 1 / (1+sqrt2/QcWarp + 2/(QcWarp*QcWarp));
by[2] = (1 - sqrt2/QcWarp + 2/(QcWarp*QcWarp)) * gain;
by[1] = (2 - 2 * 2/(QcWarp*QcWarp)) * gain;
by[0] = 1;
```

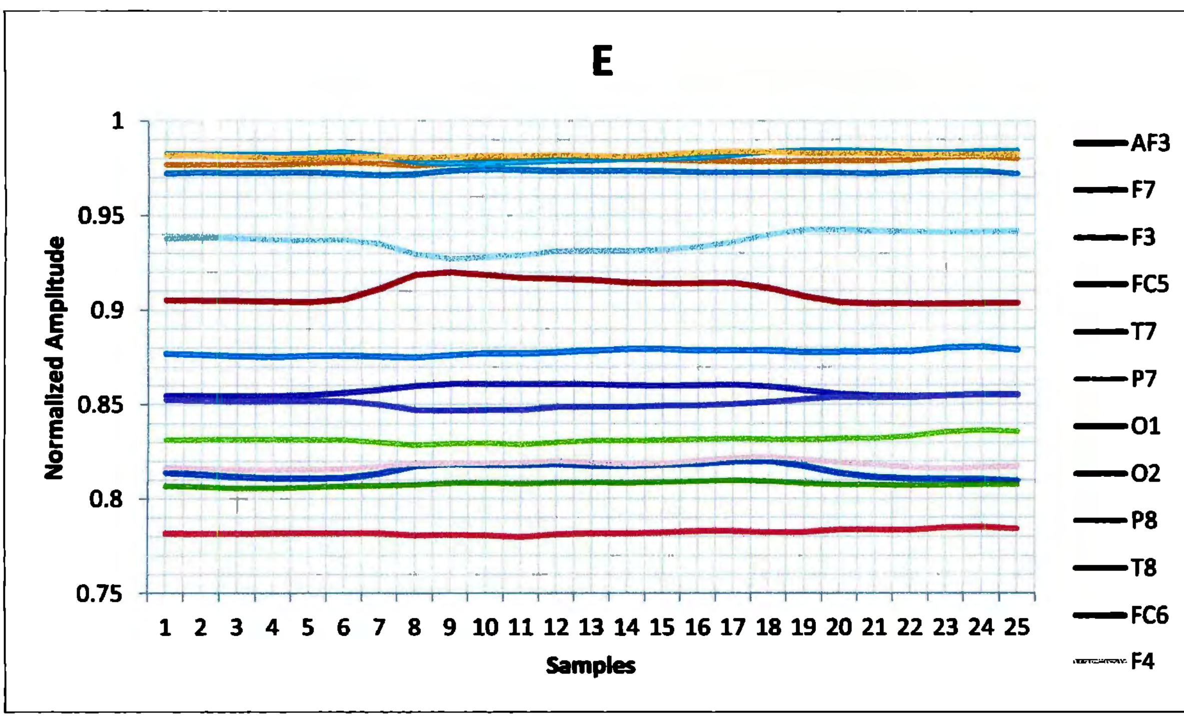
Attachment 5: Letters.

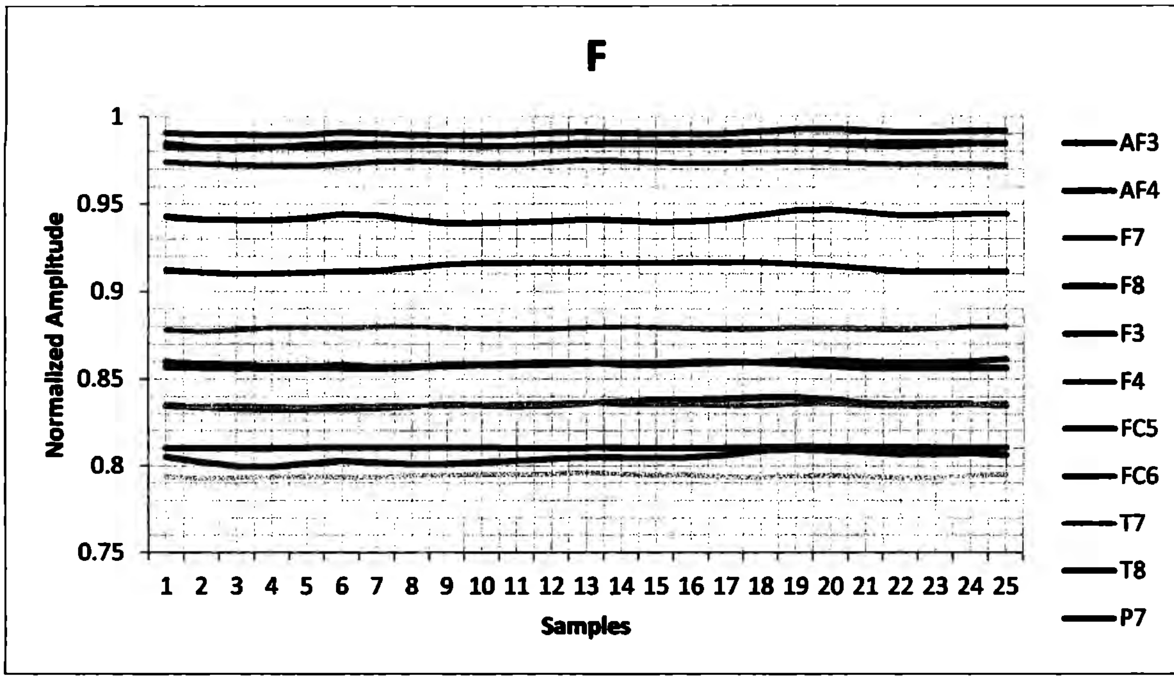


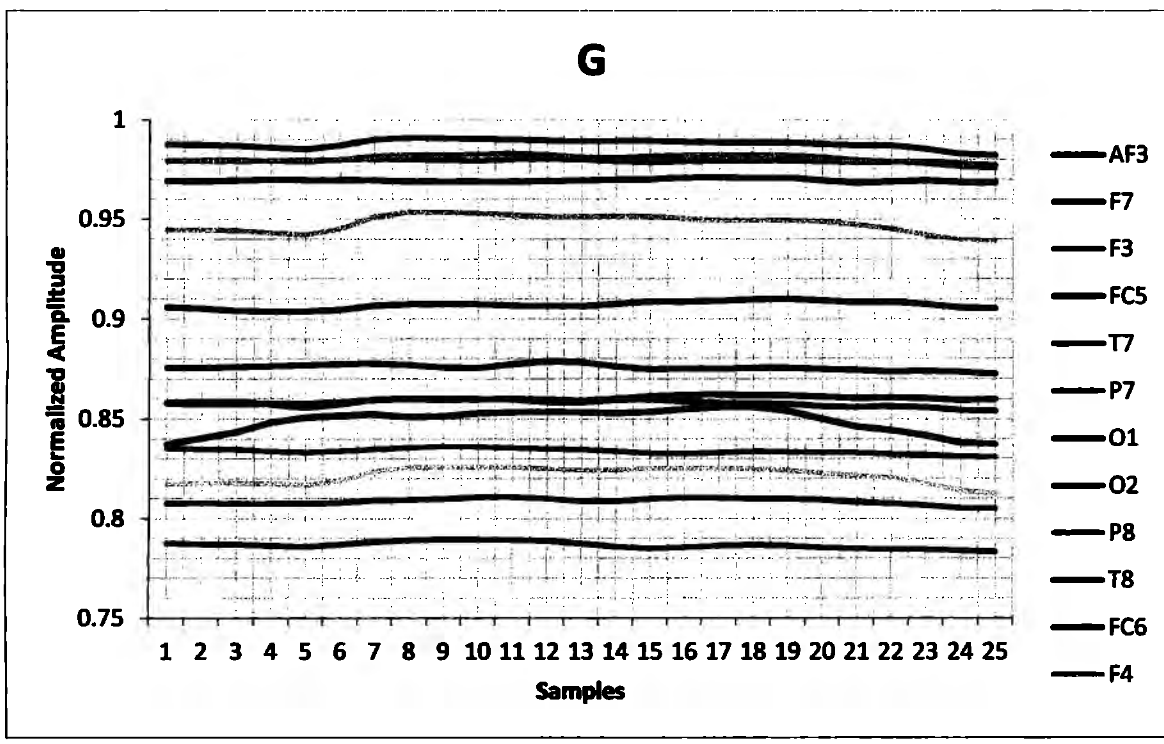

B
Normalize Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

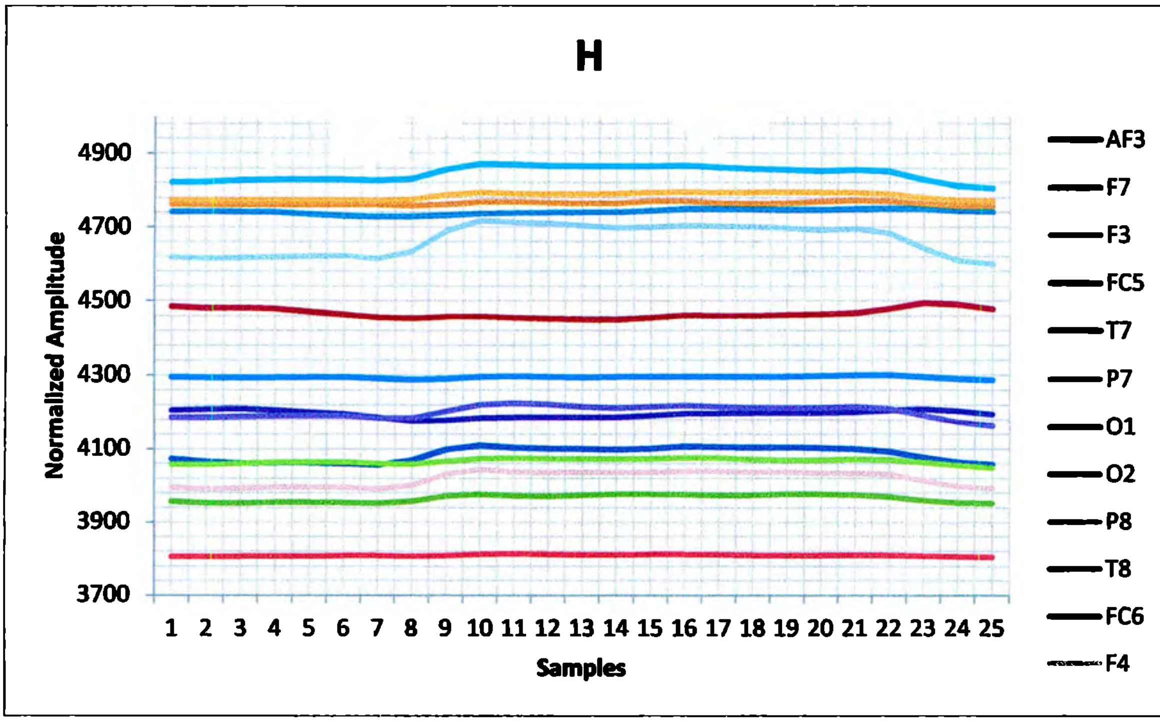

C
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

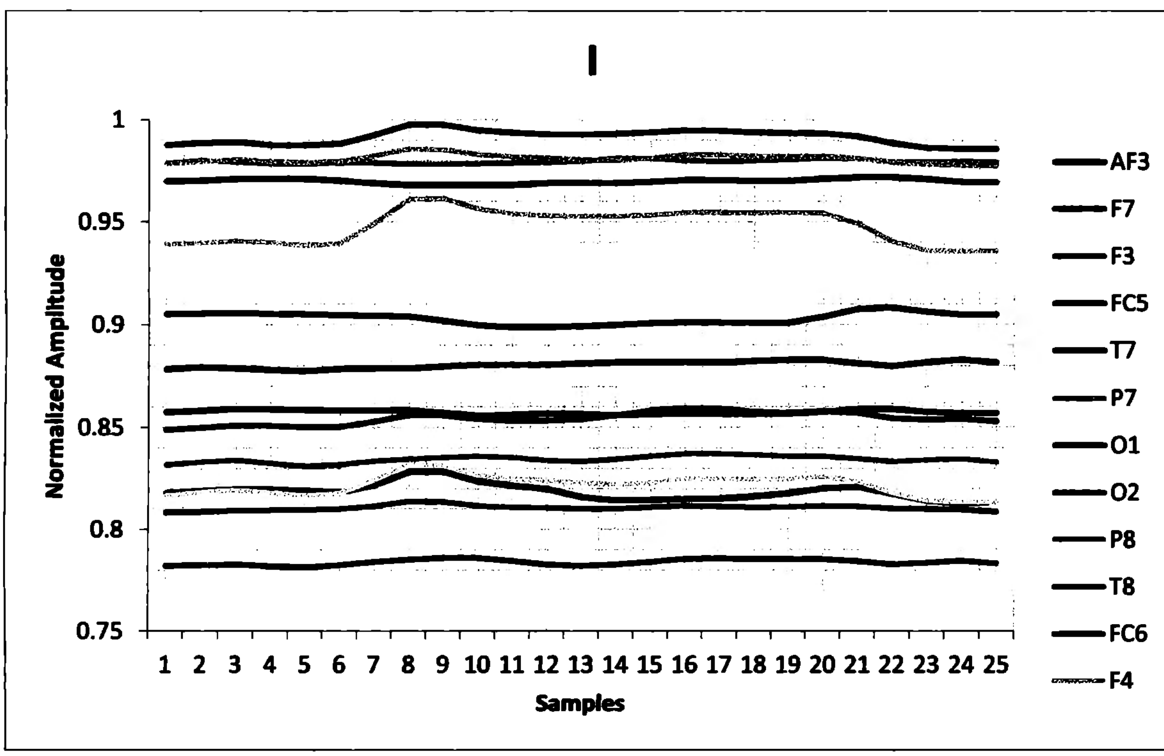

D
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

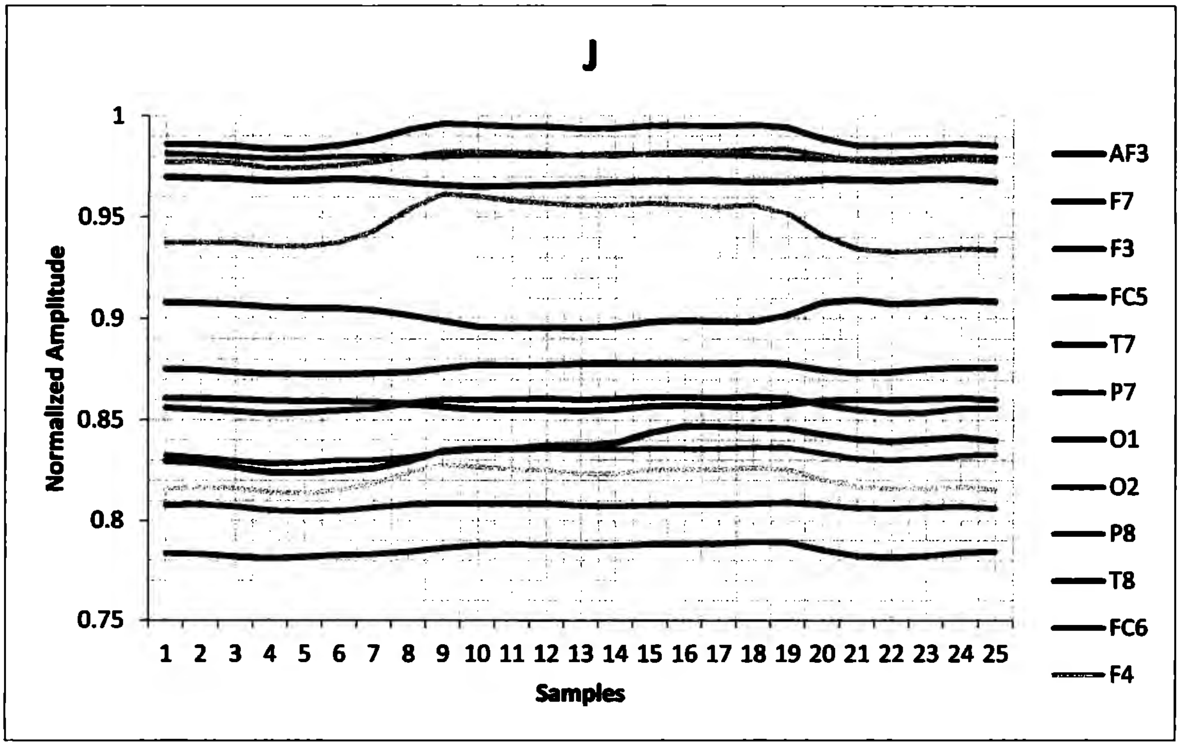

E
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

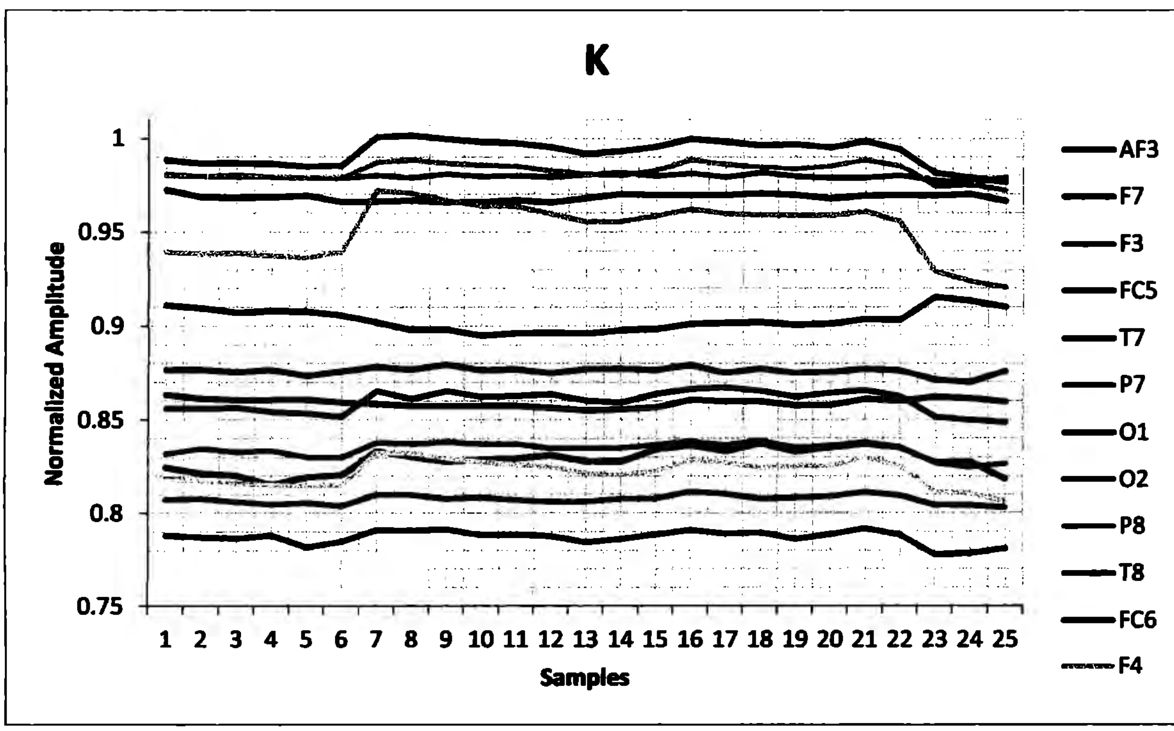

F
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
AF4
F7
F8
F3
F4
FC5
FC6
T7
T8
P7

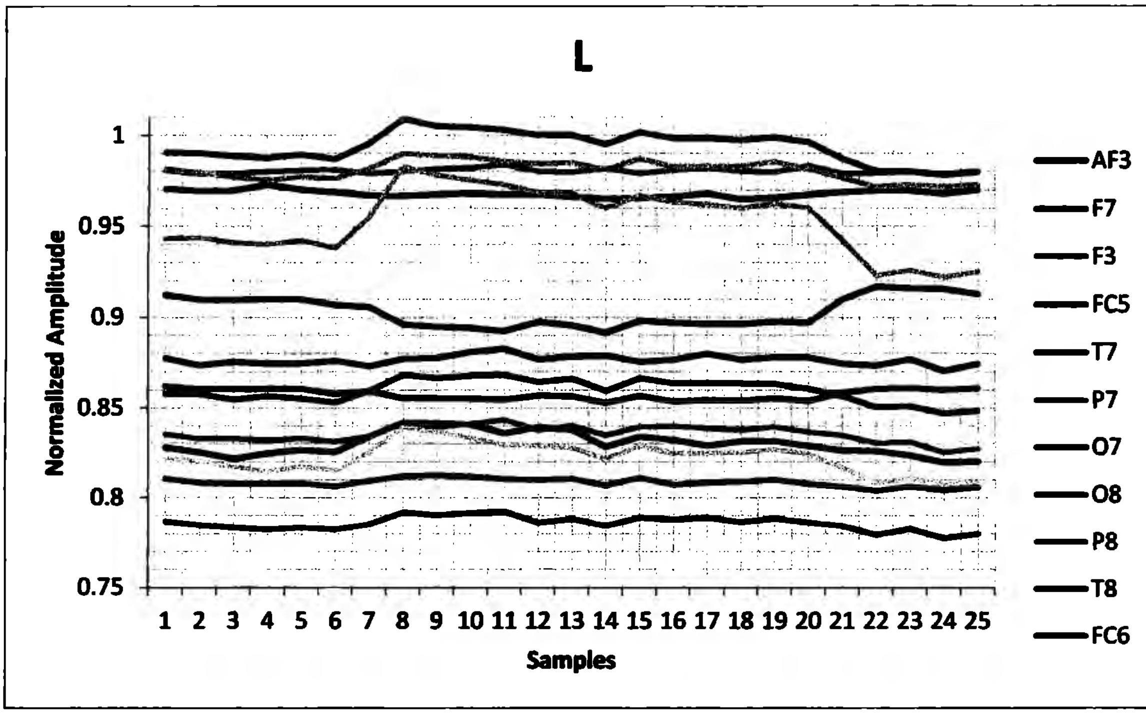

G
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

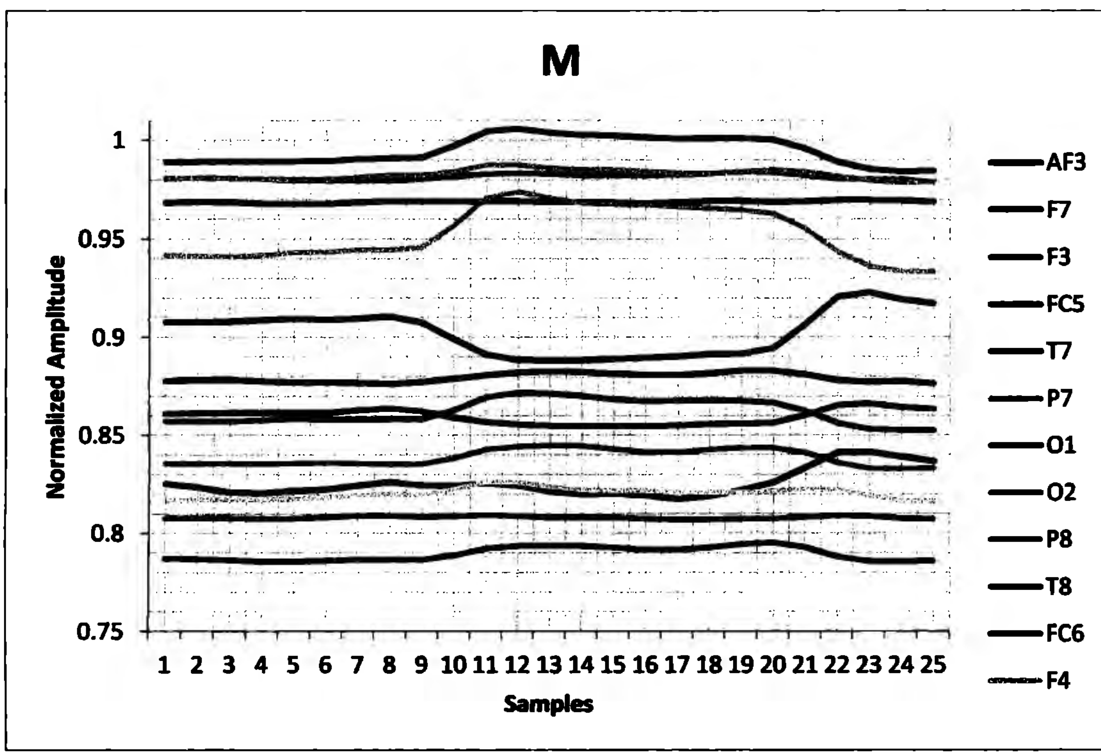

H
4900
4700
4500
4300
4100
3900
3700
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

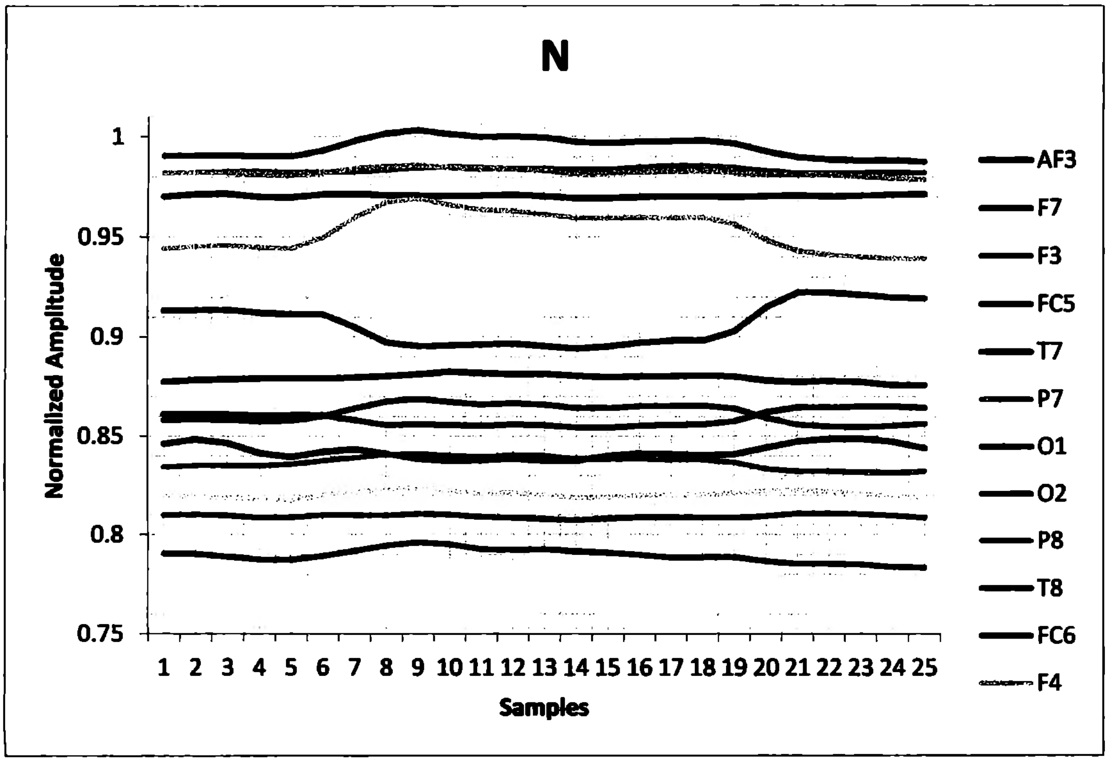

I
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

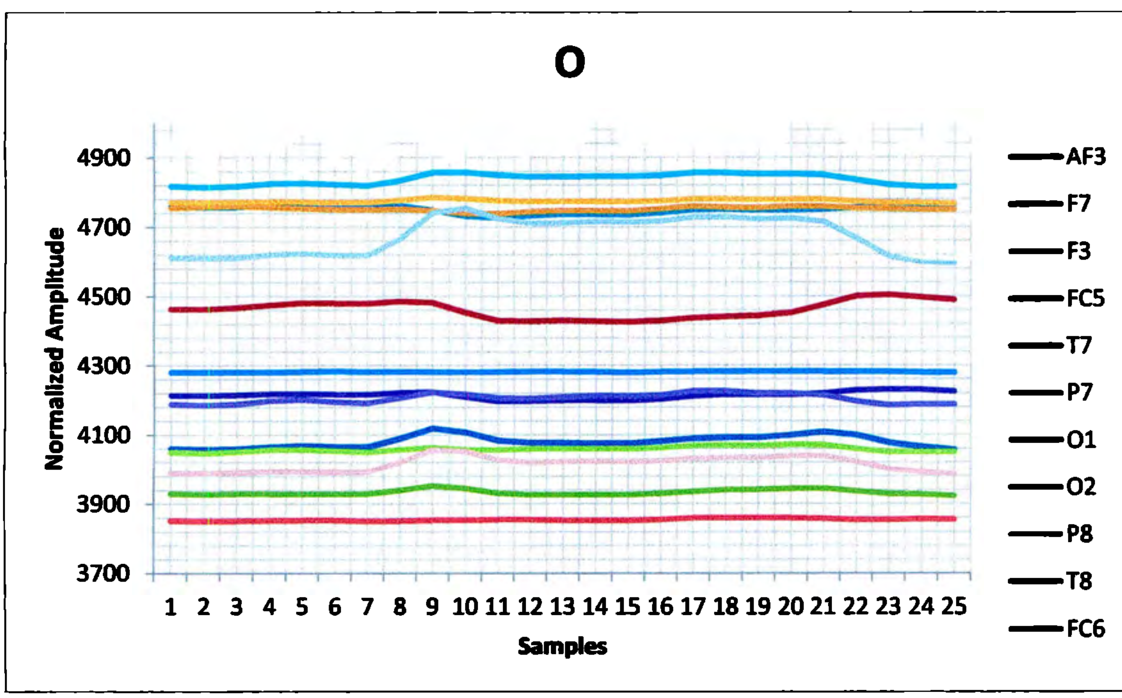

J
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4


K
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

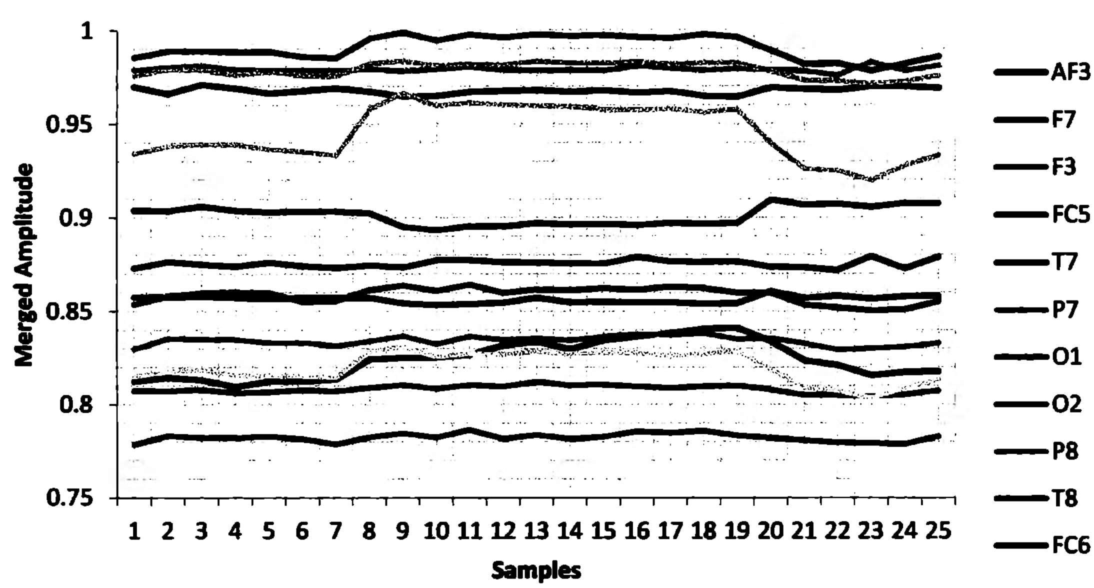

L
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O7
O8
P8
T8
FC6


M
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

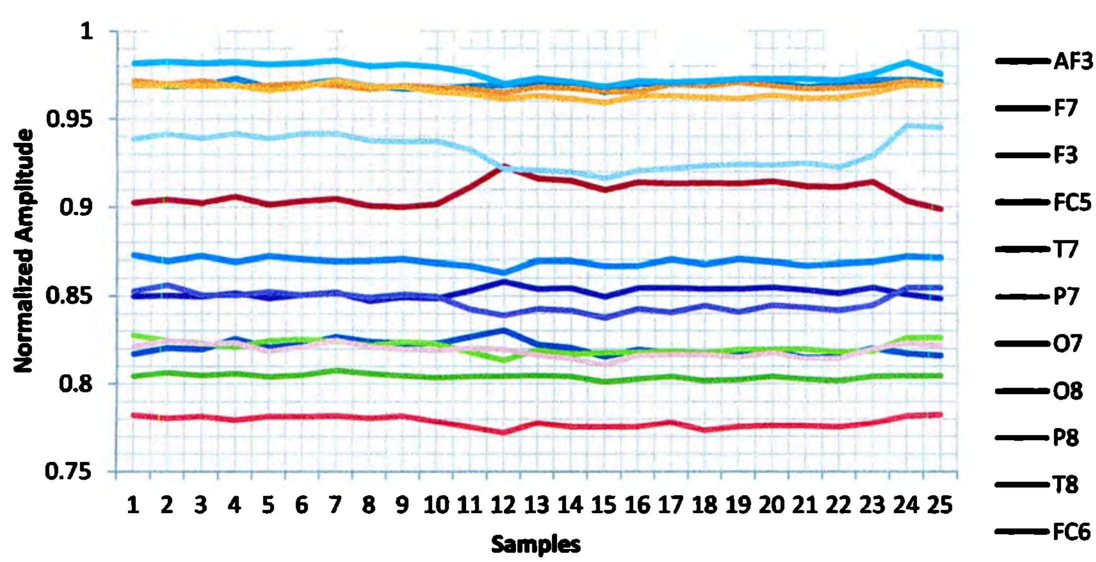

N
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

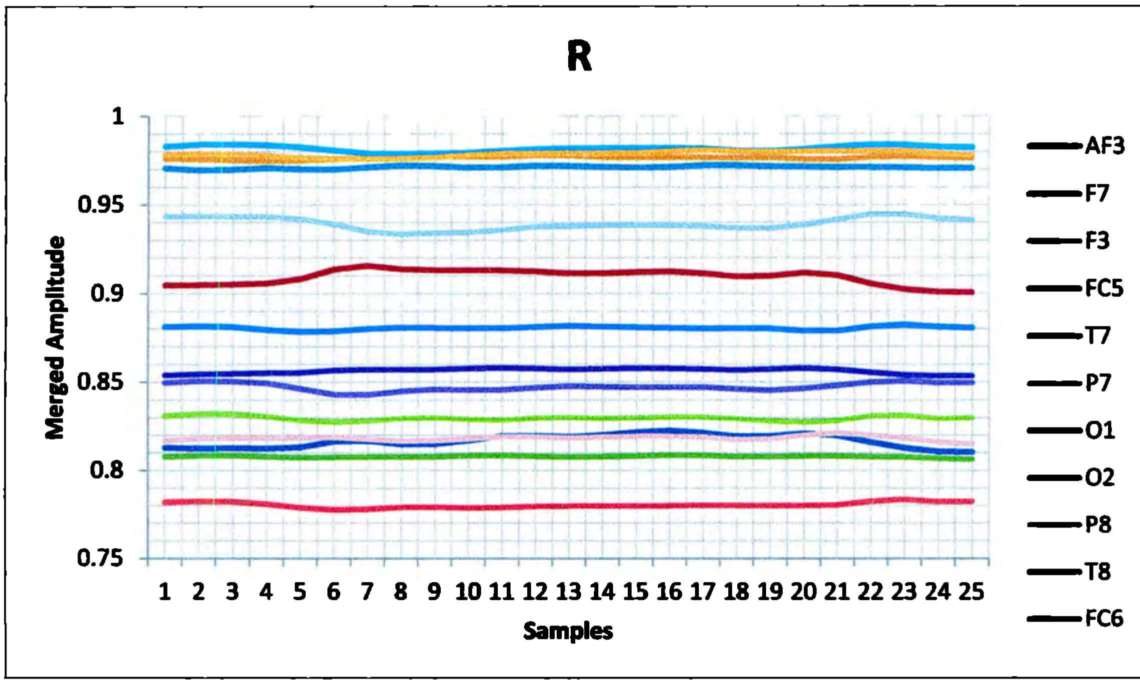

O
Normalized Amplitude
4900
4700
4500
4300
4100
3900
3700
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6

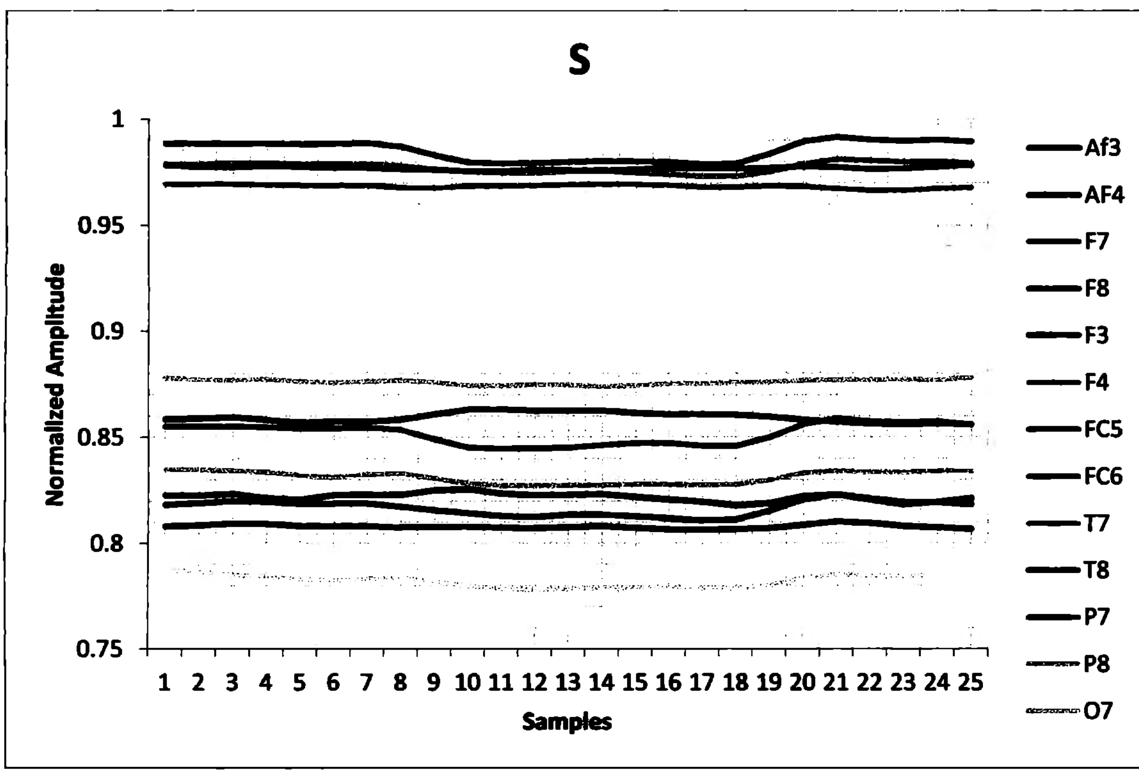
P

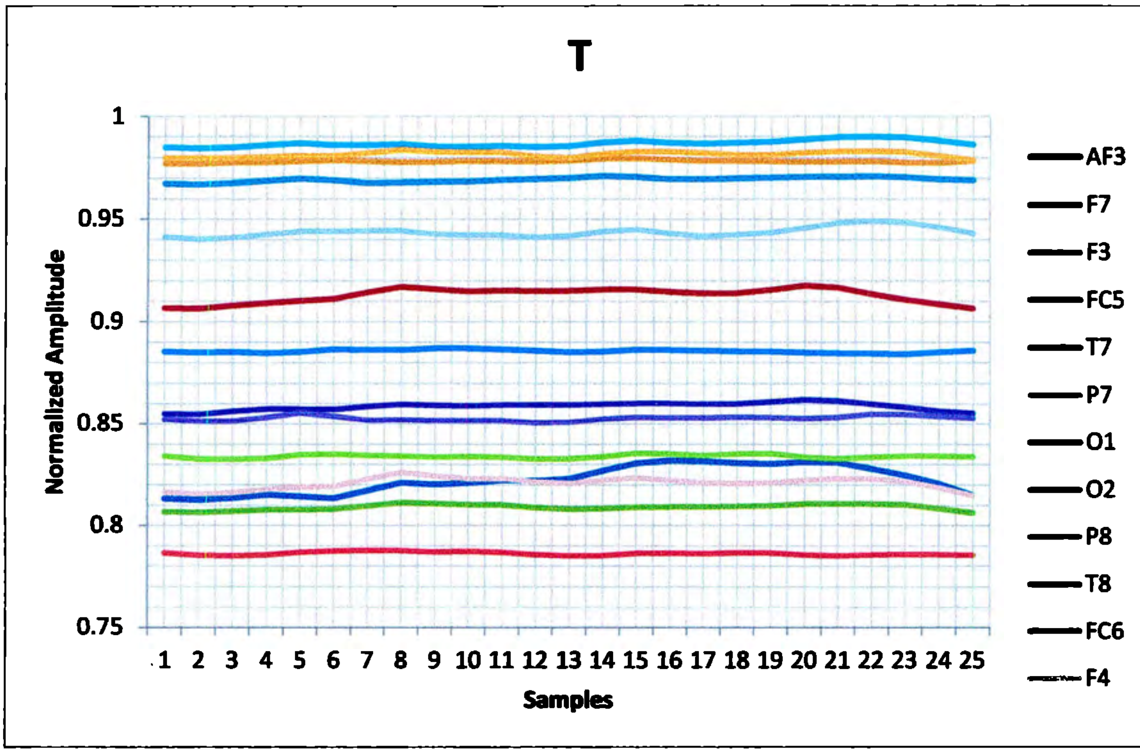

Merged Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6

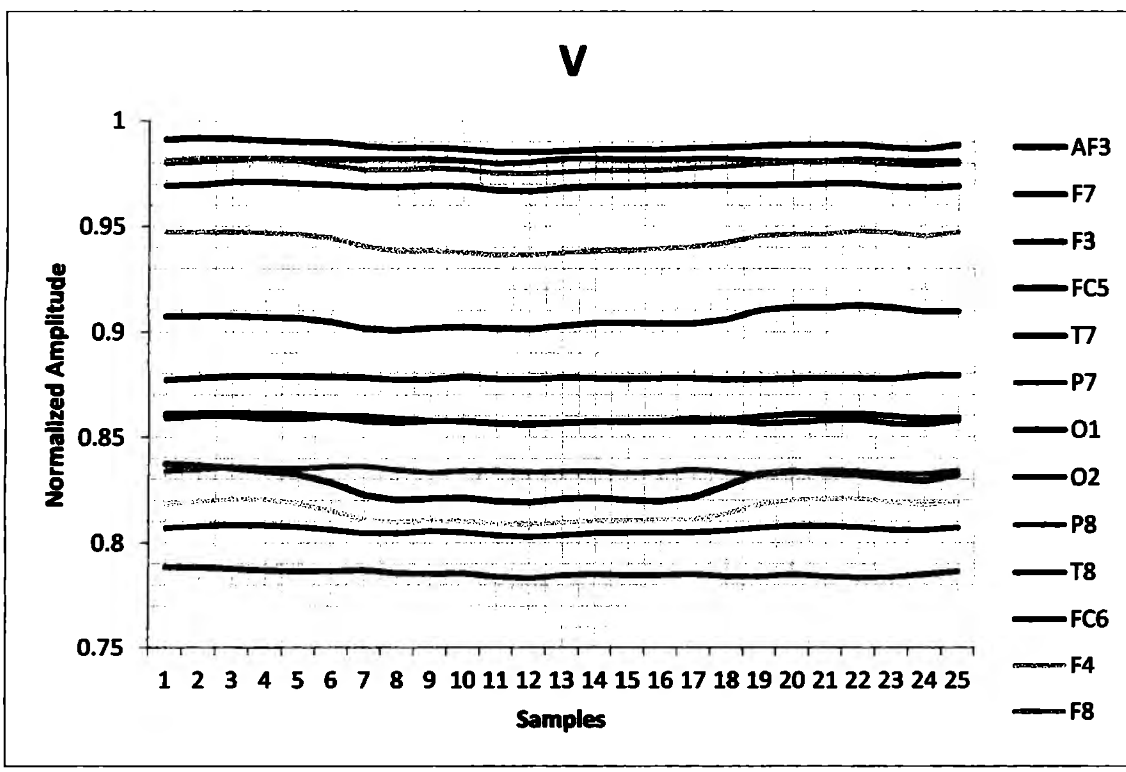
Q

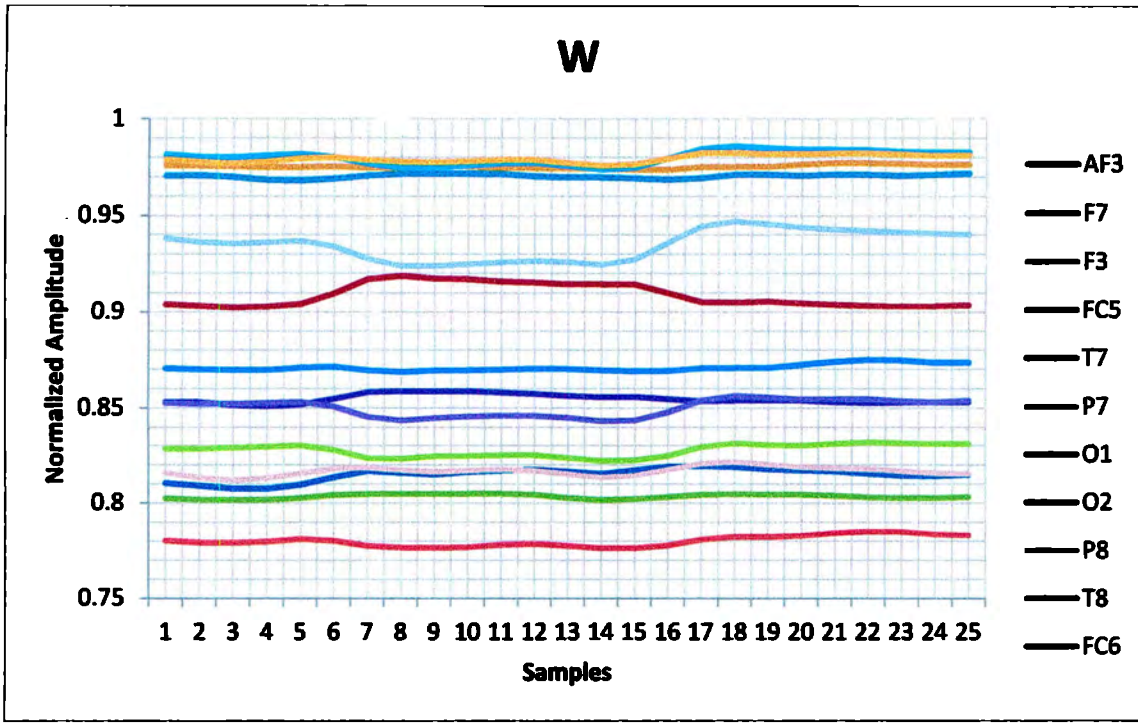

Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O7
O8
P8
T8
FC6

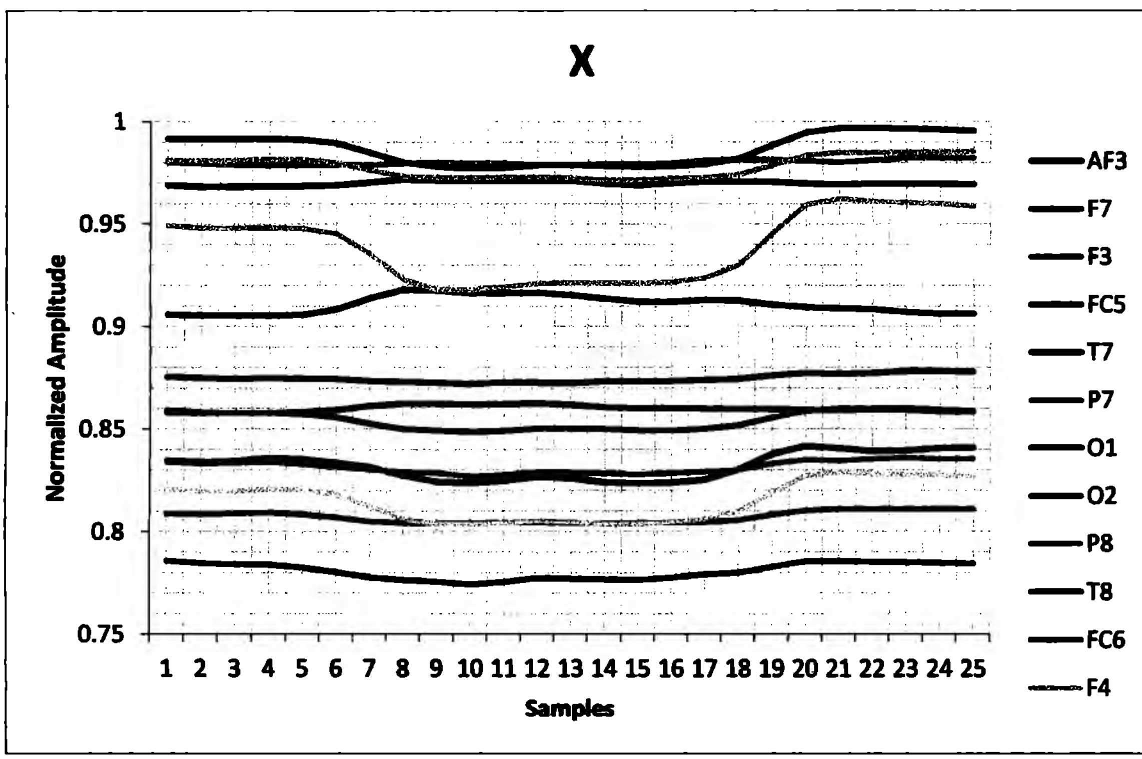

R
1
0.95
0.9
0.85
0.8
0.75
Merged Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6

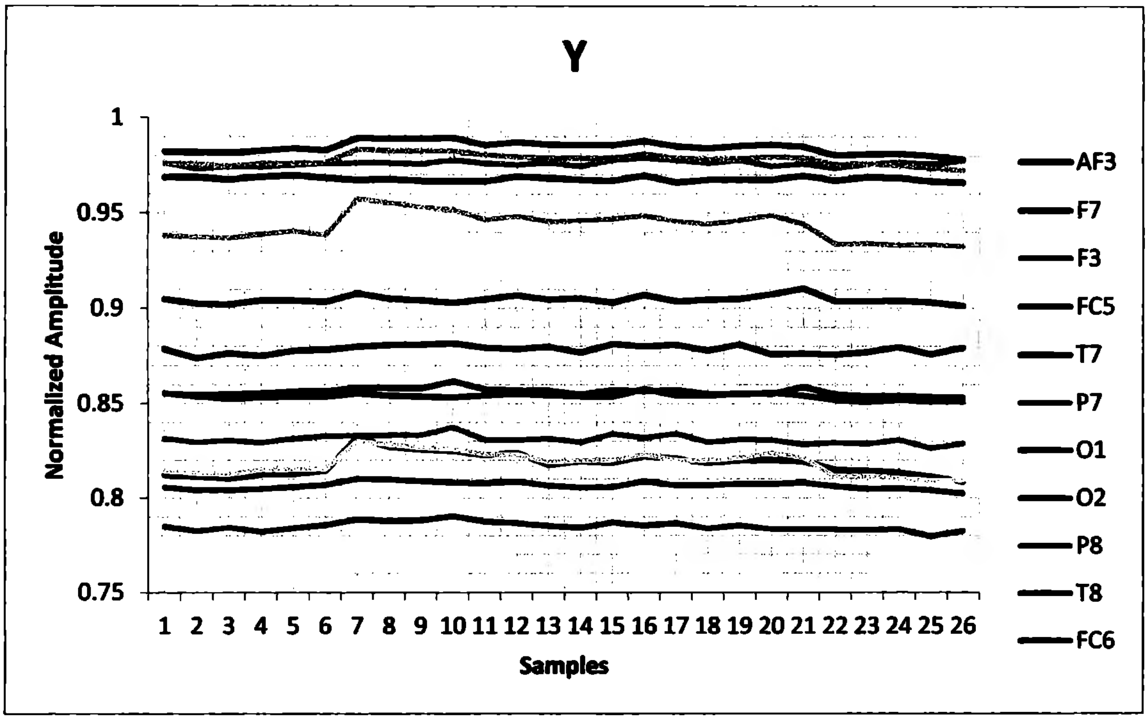

S
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
Af3
AF4
F7
F8
F3
F4
FC5
FC6
T7
T8
P7
P8
O7

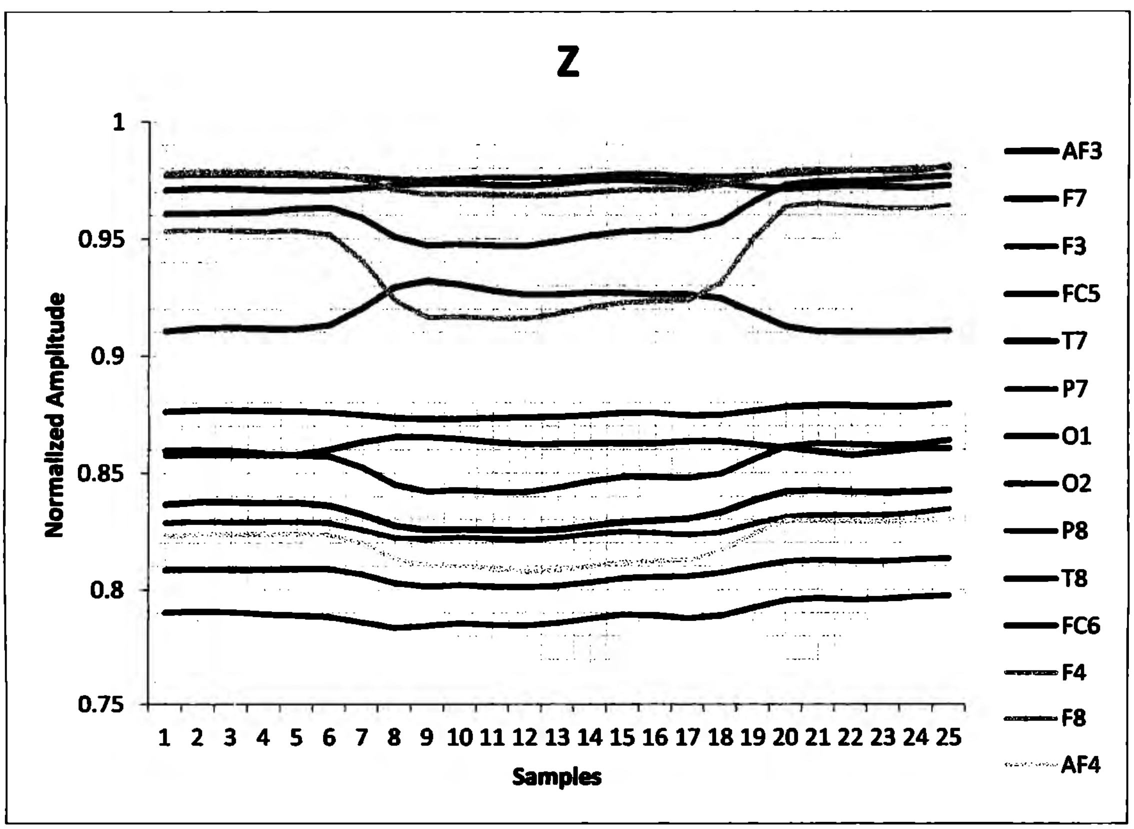

T
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4


V
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4
F8


W
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6

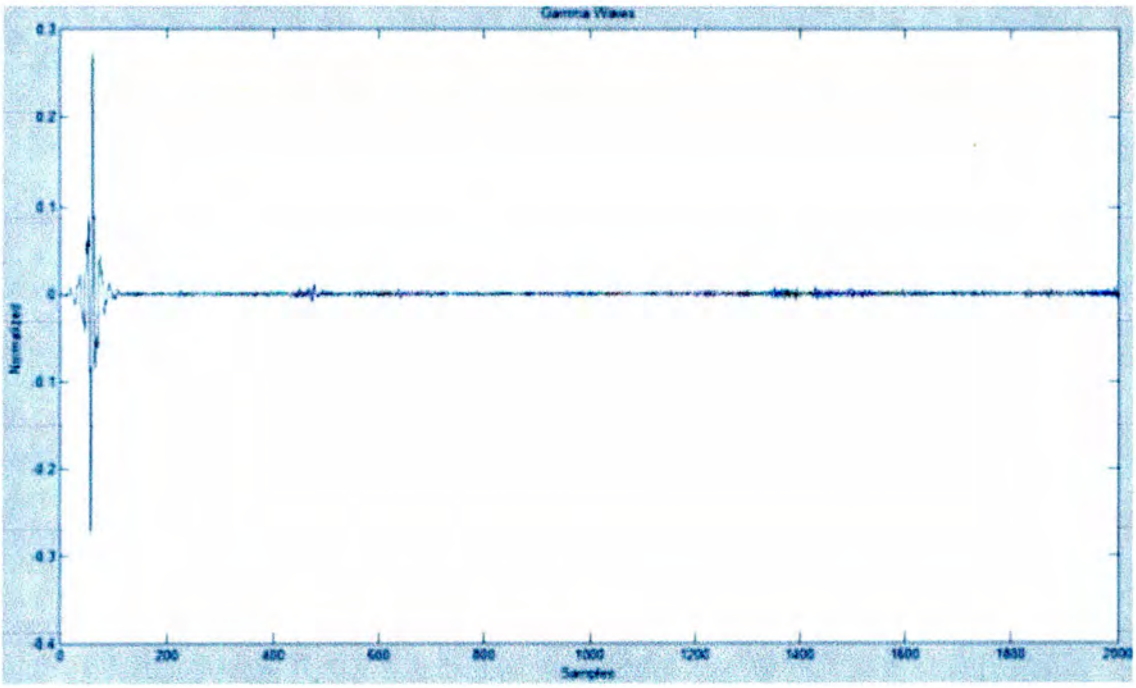

X
1
0.95
0.9
0.85
0.8
0.75
Normalized Amplitude
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4

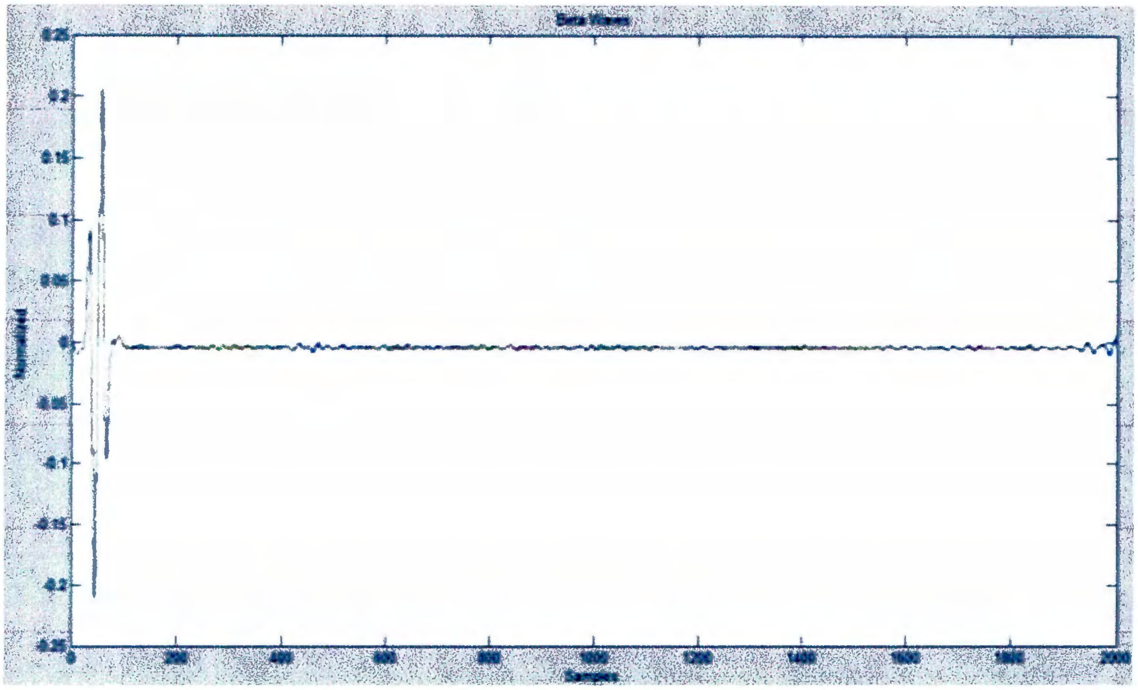

Y
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6

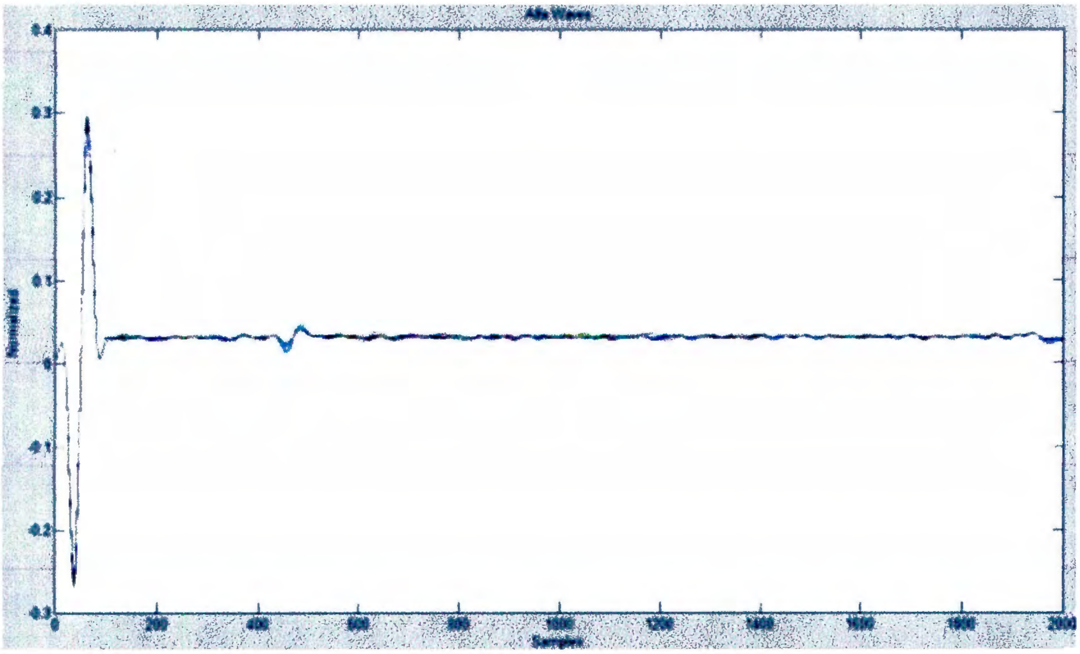

Z
Normalized Amplitude
1
0.95
0.9
0.85
0.8
0.75
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Samples
AF3
F7
F3
FC5
T7
P7
O1
O2
P8
T8
FC6
F4
F8
AF4

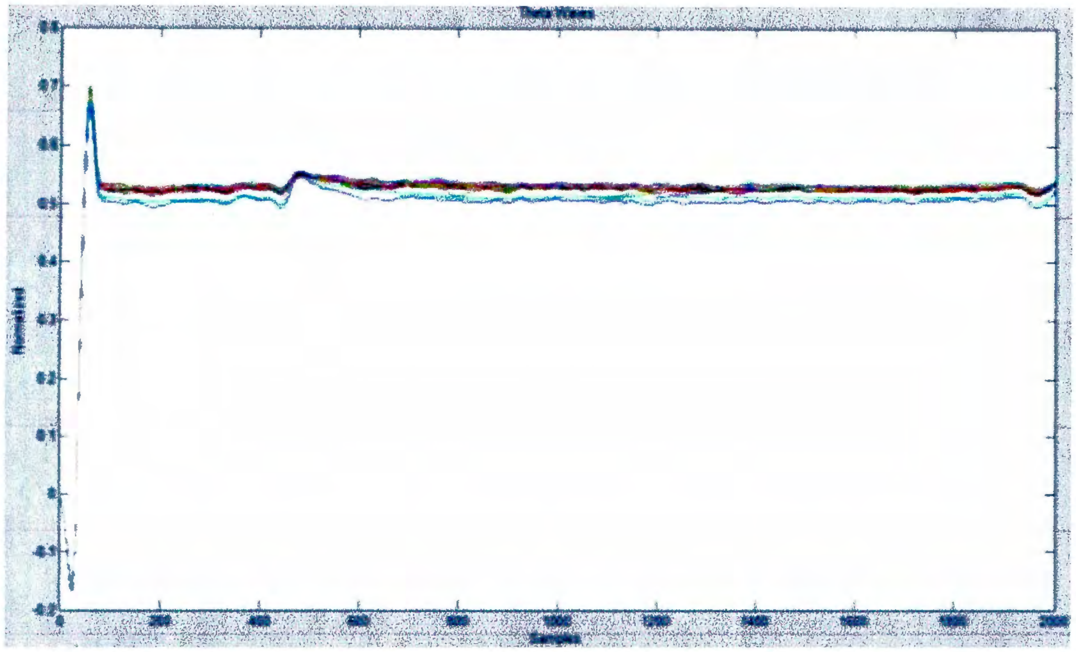
EEG for thoughts

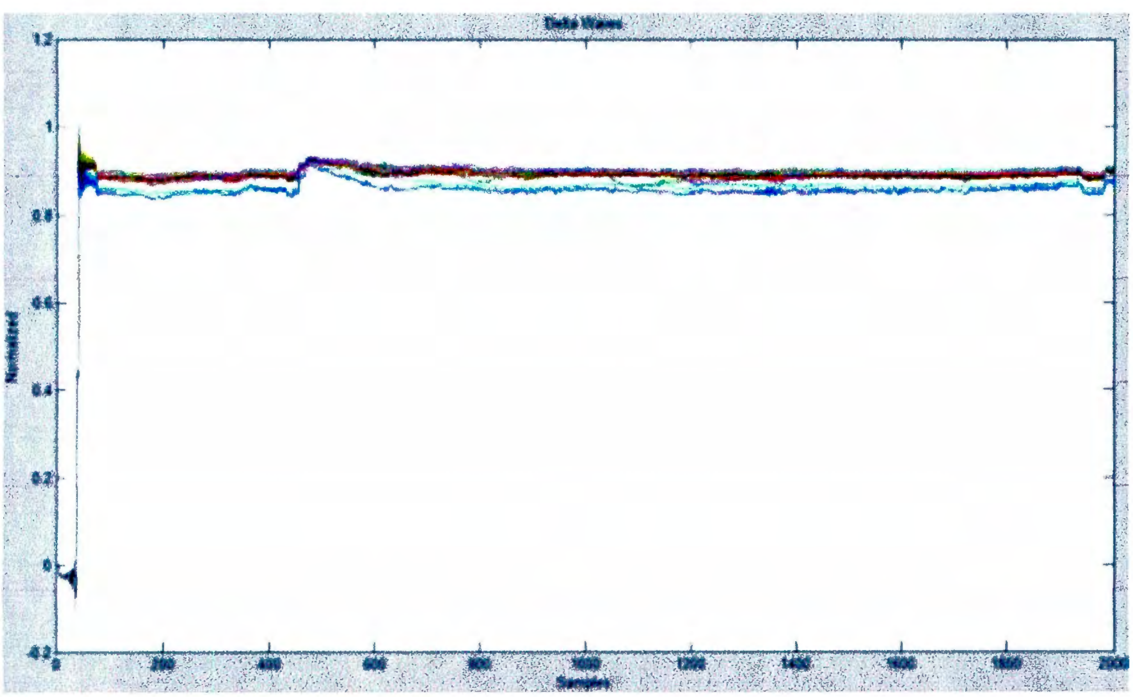
Subject 2: Right



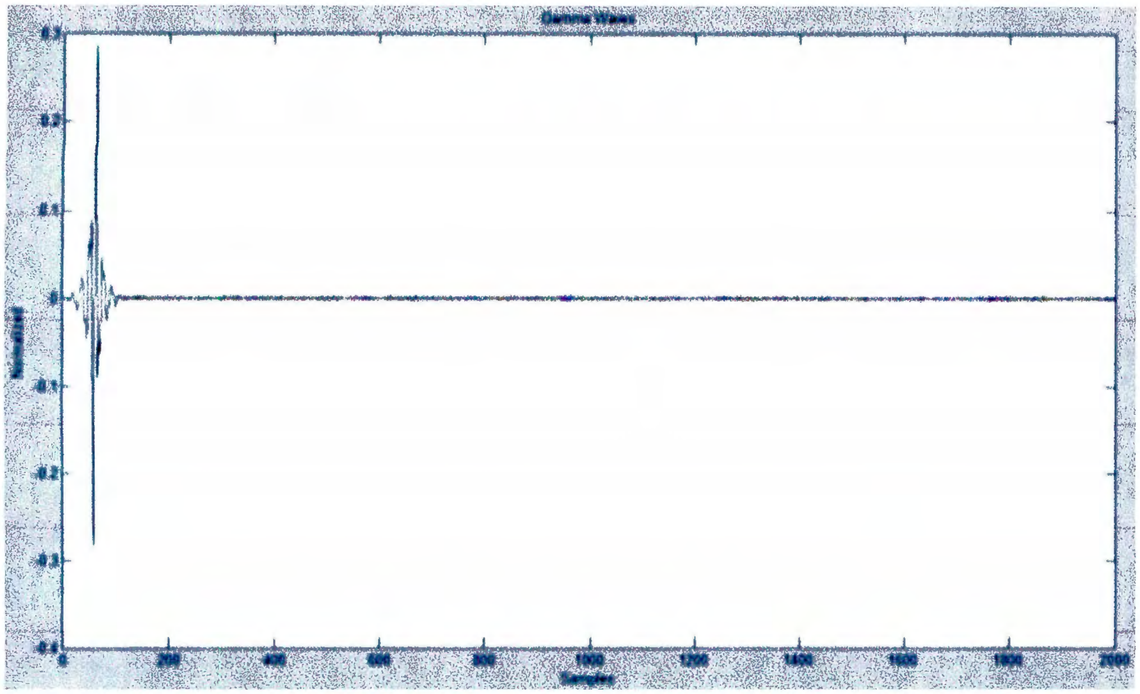

Beta Waves
Normalized
Samples

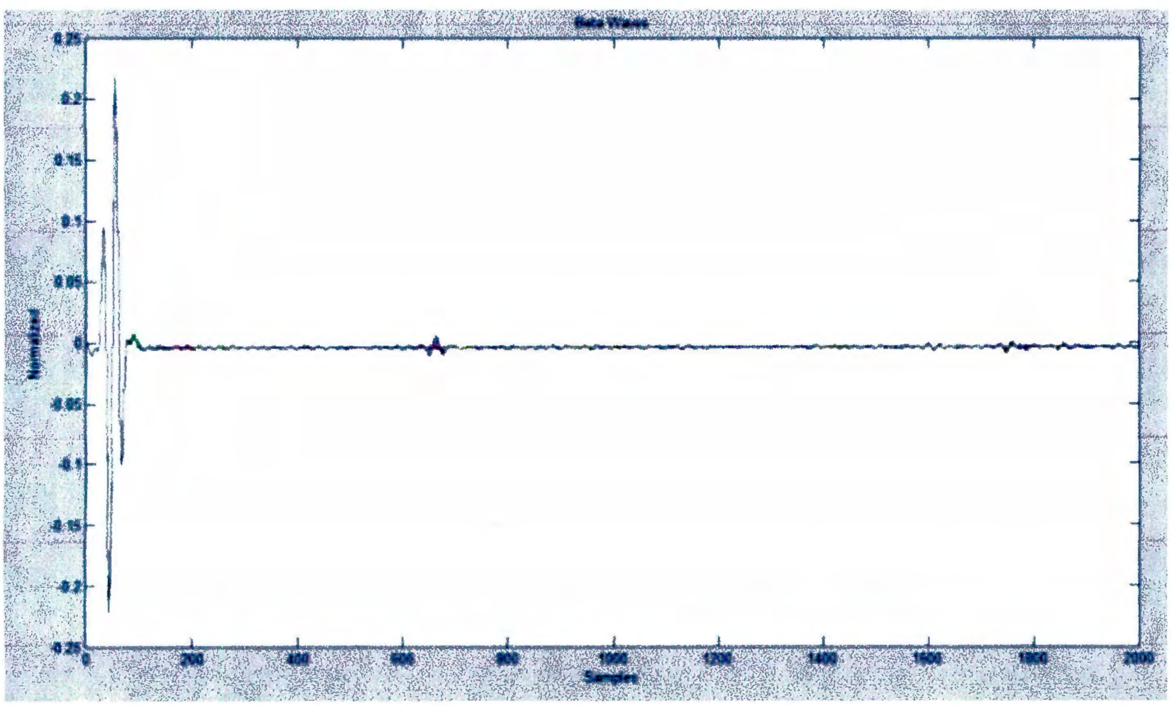

Alfa Waves
Normalized
Samples

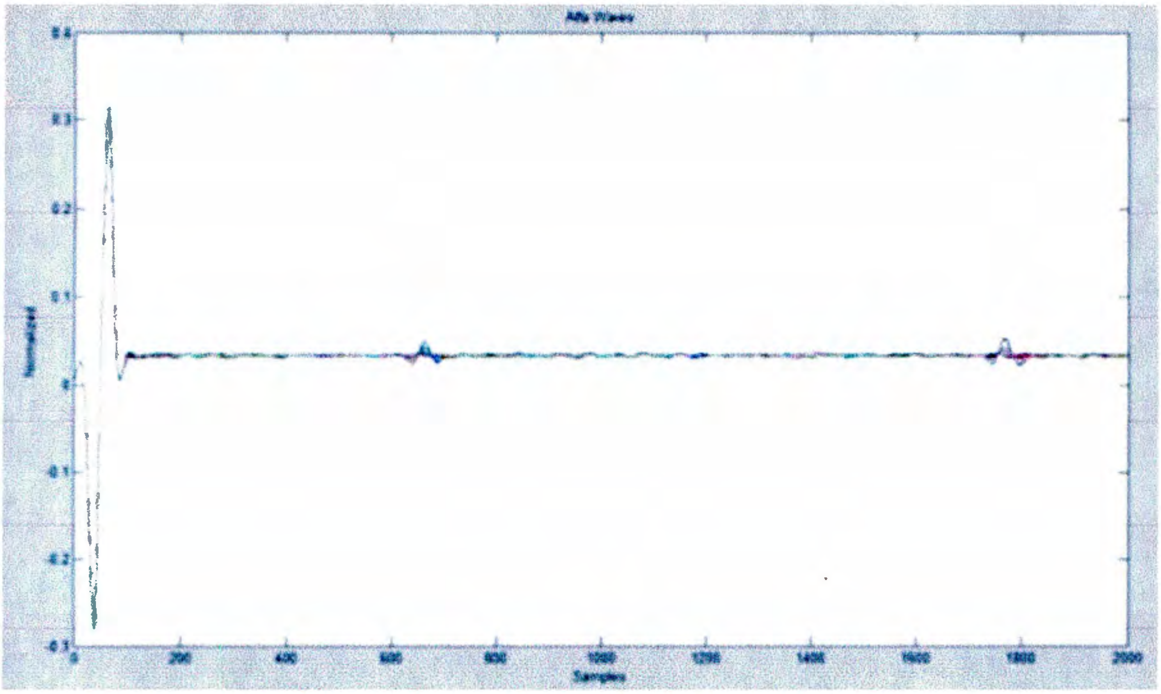


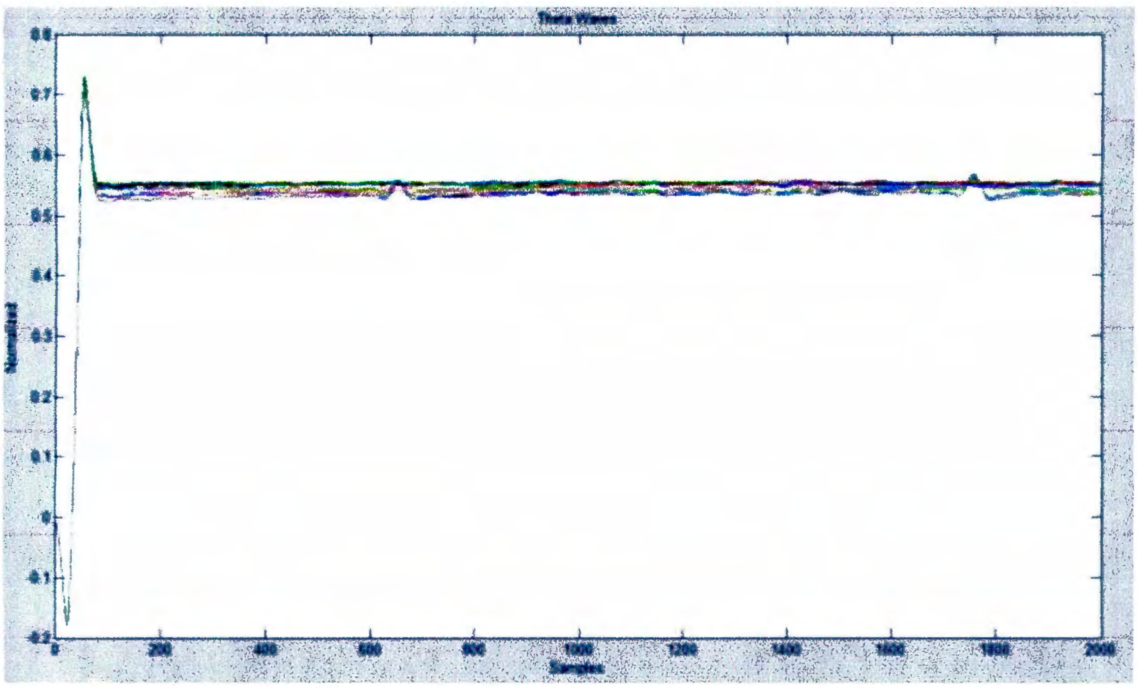


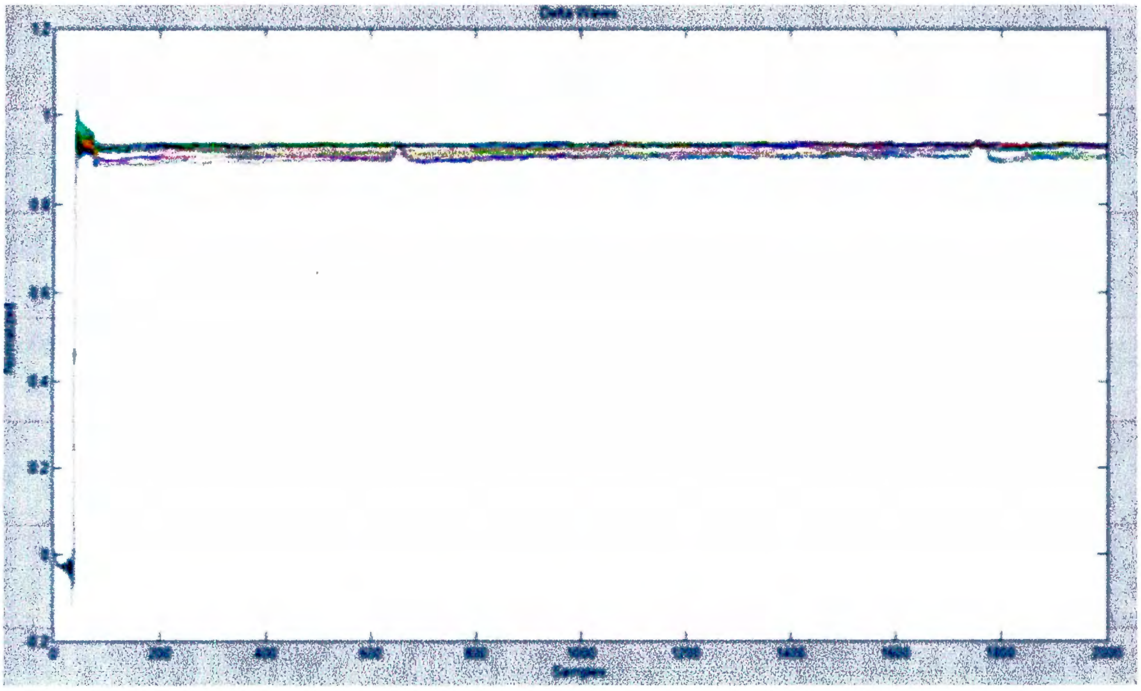
Subject 3: Right



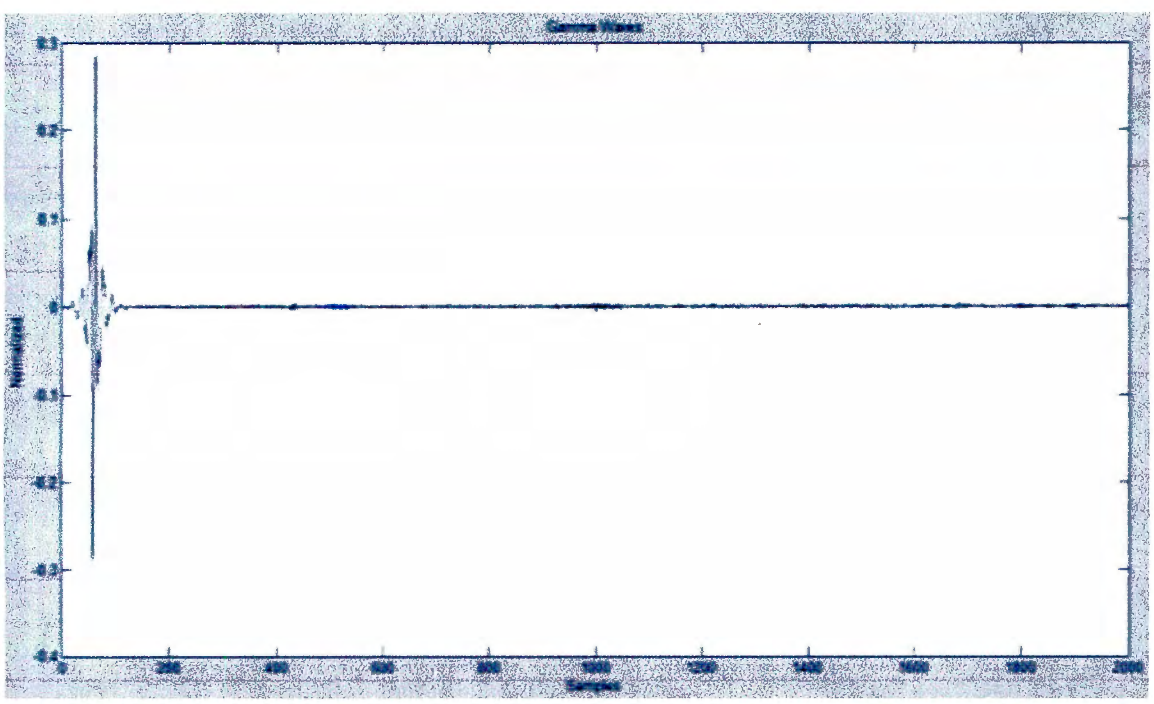


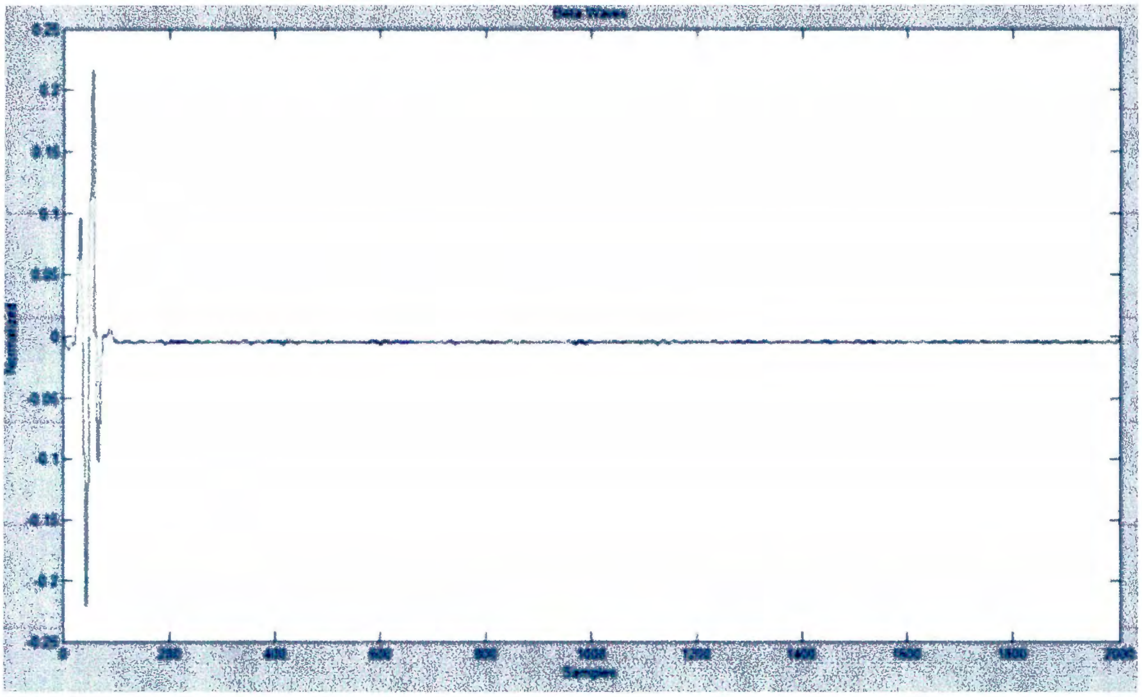


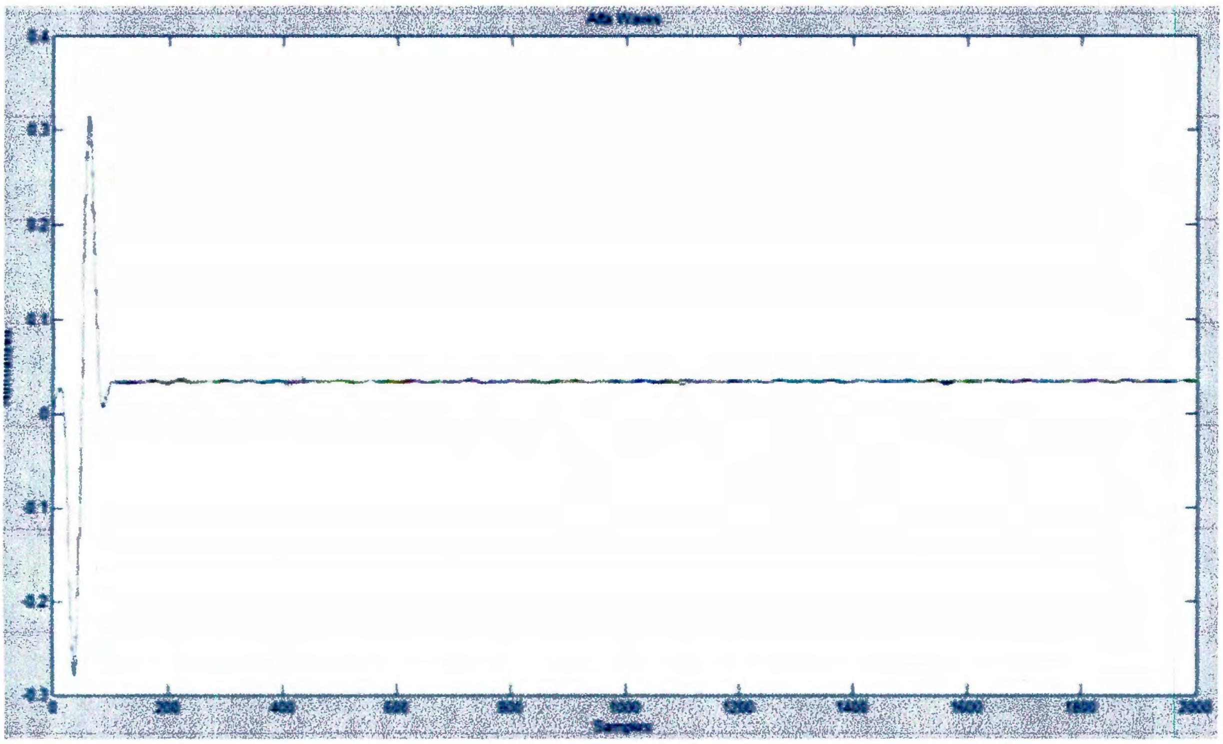


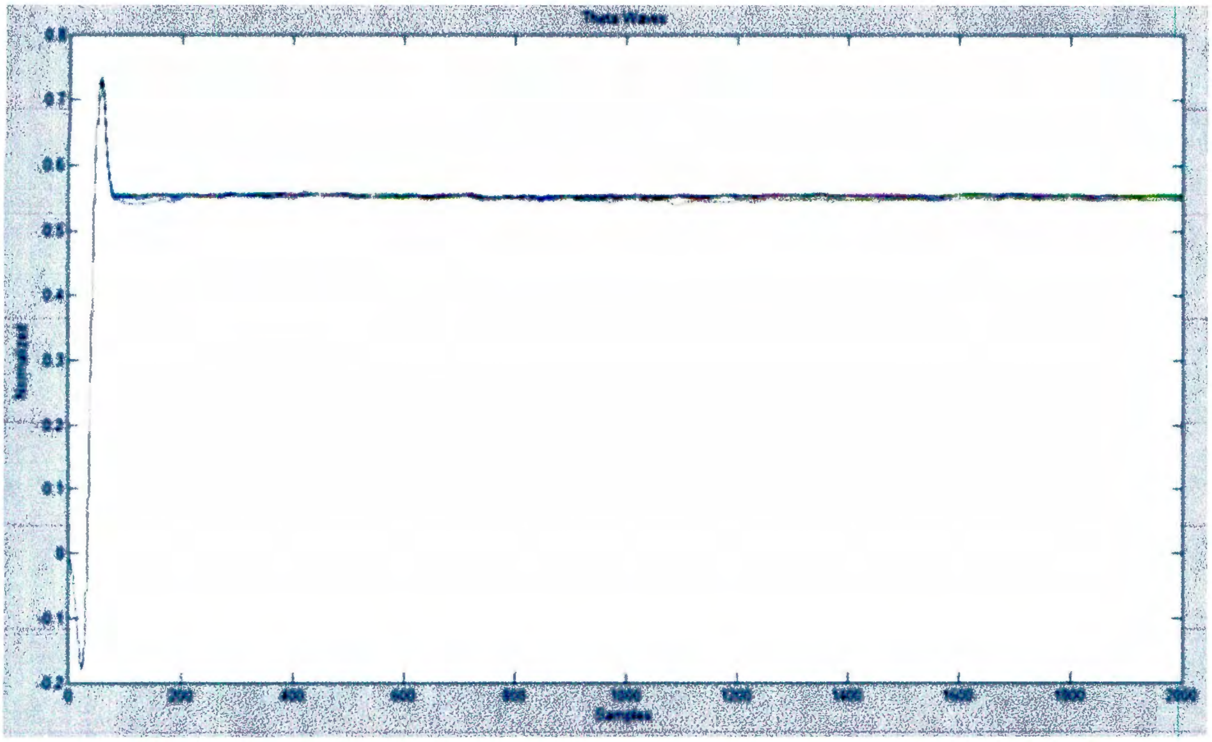


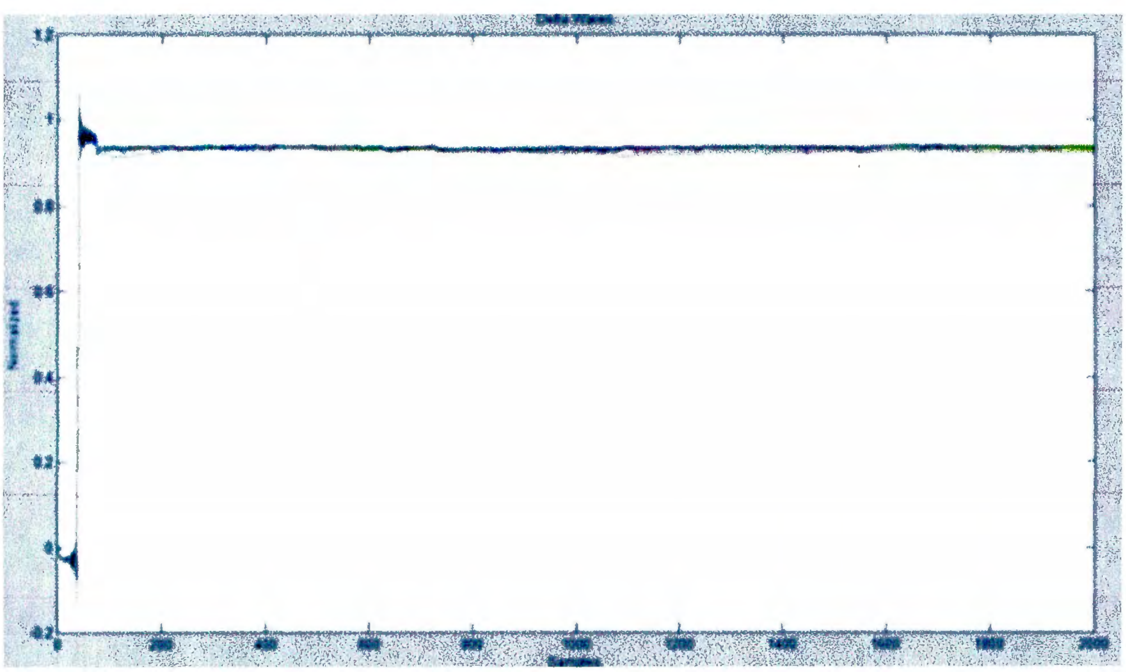
Subject 4: Right



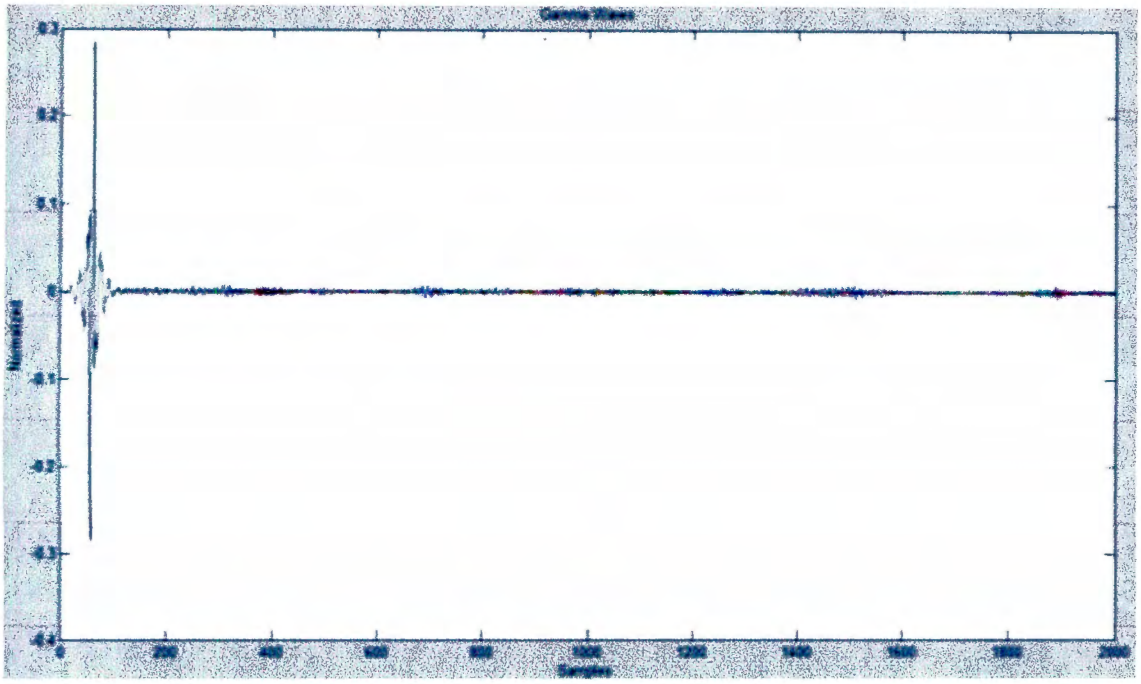


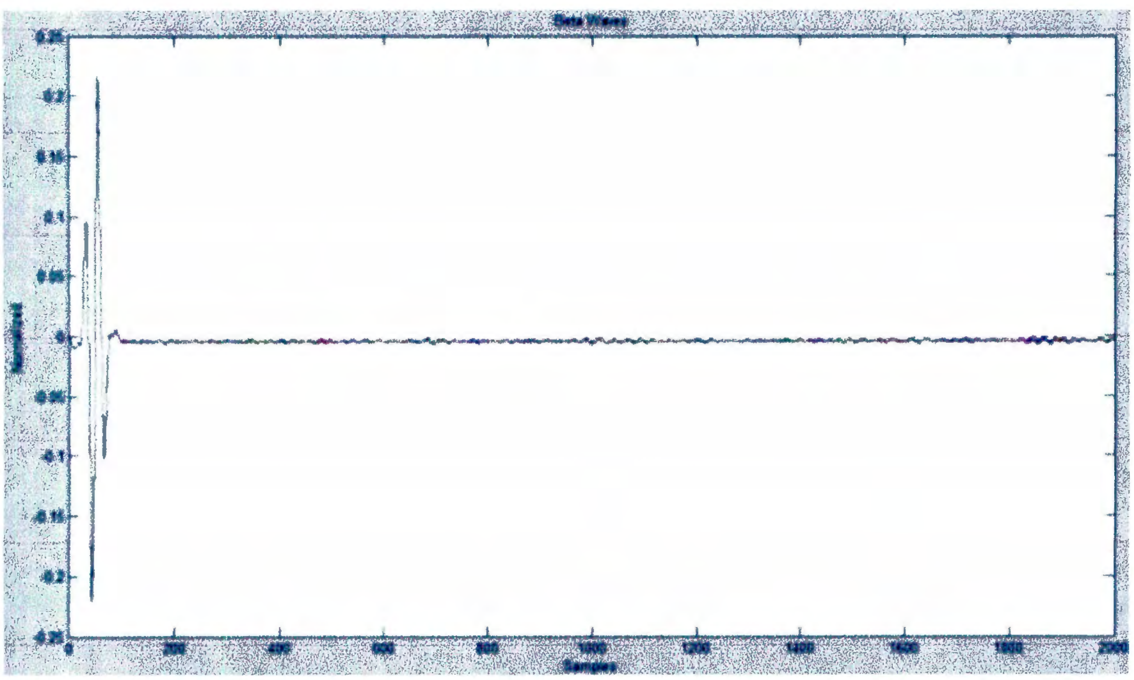


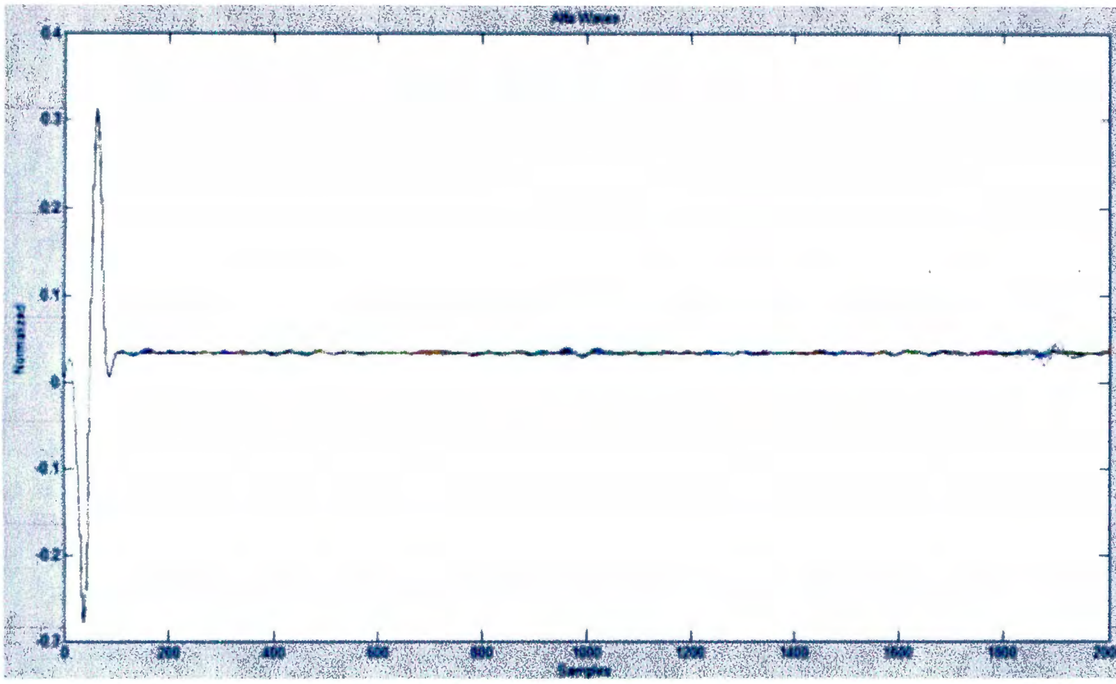


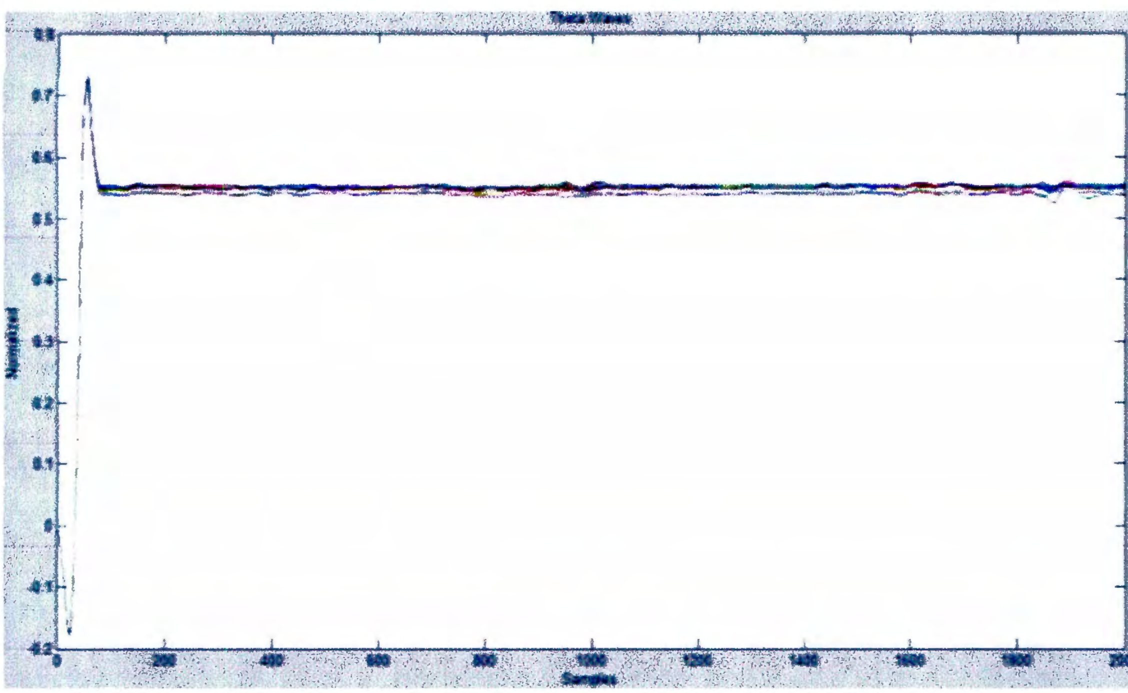


Subject 2: Left






0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Samples


0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
0
200
400
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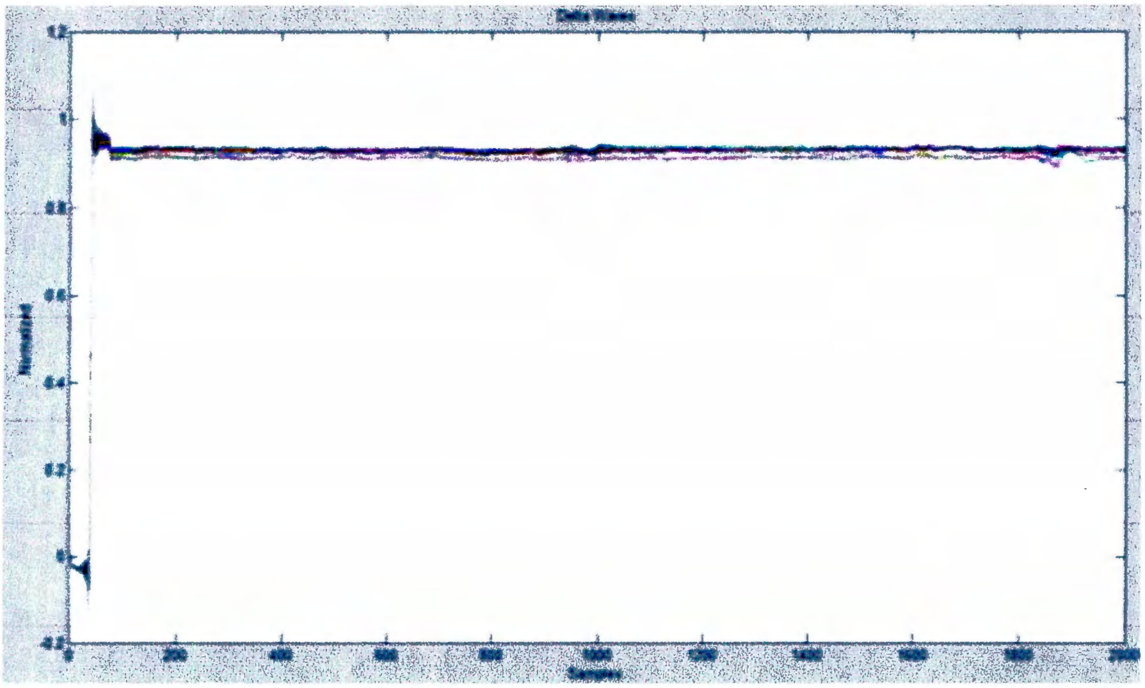
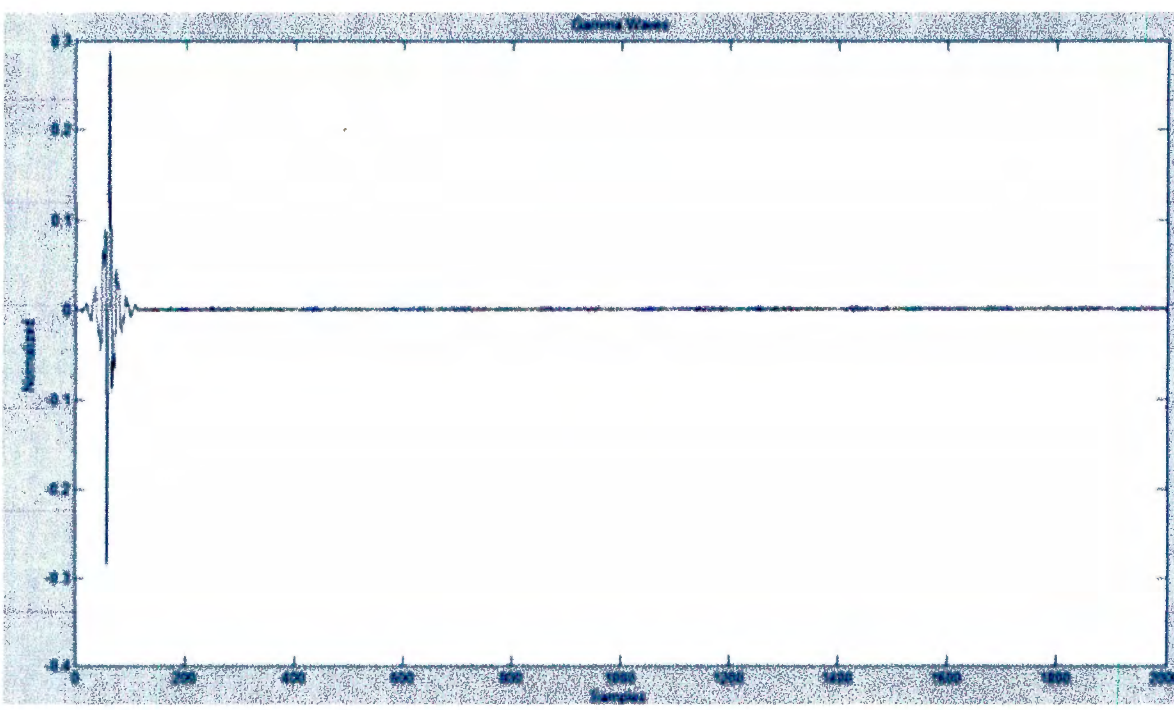
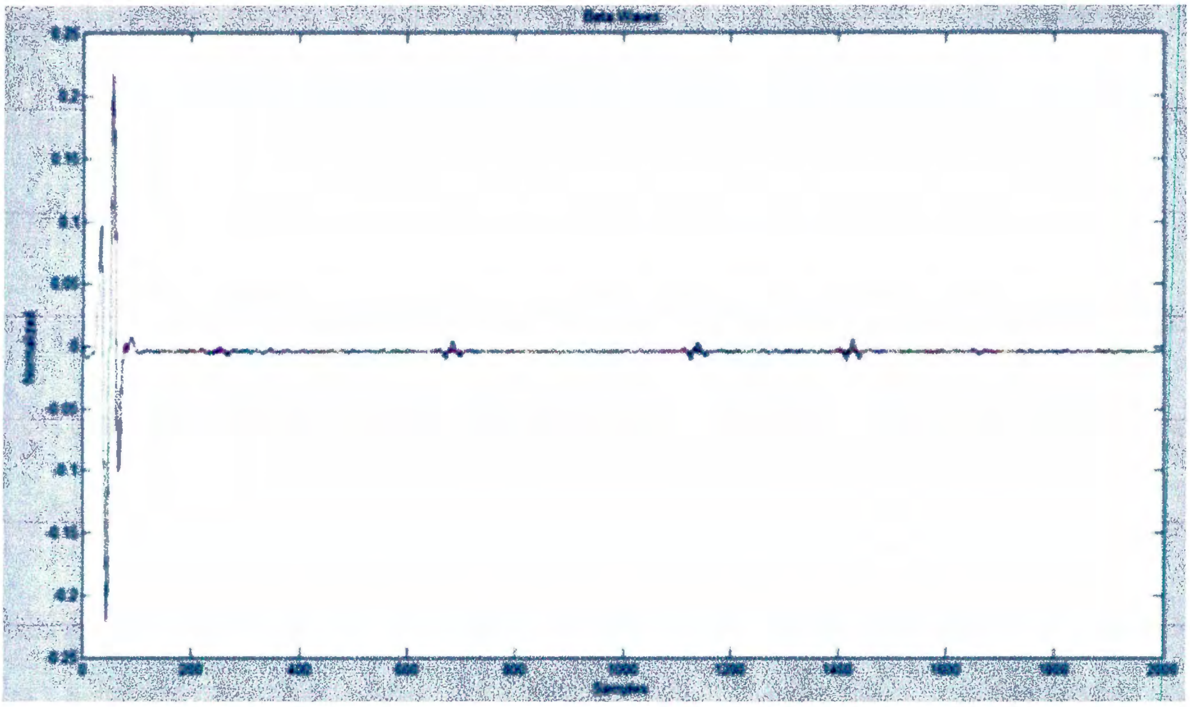
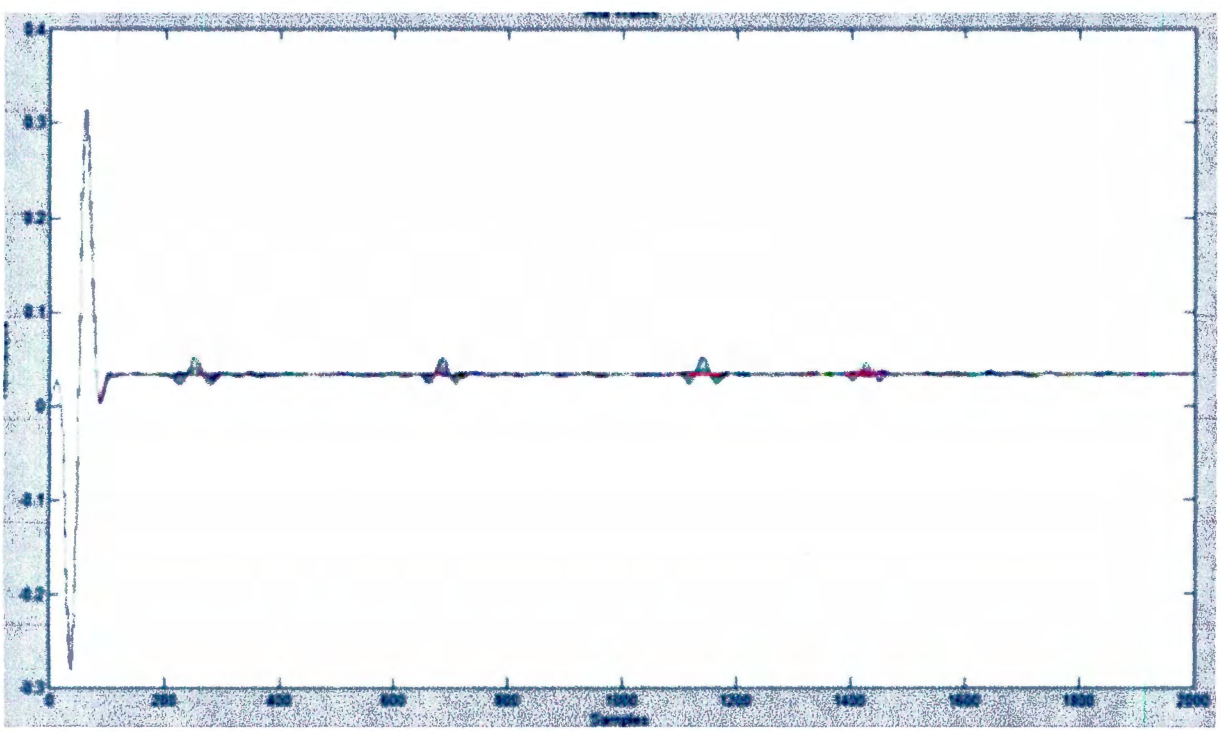
1000
1200
1400
1600
1800
2000
Samples

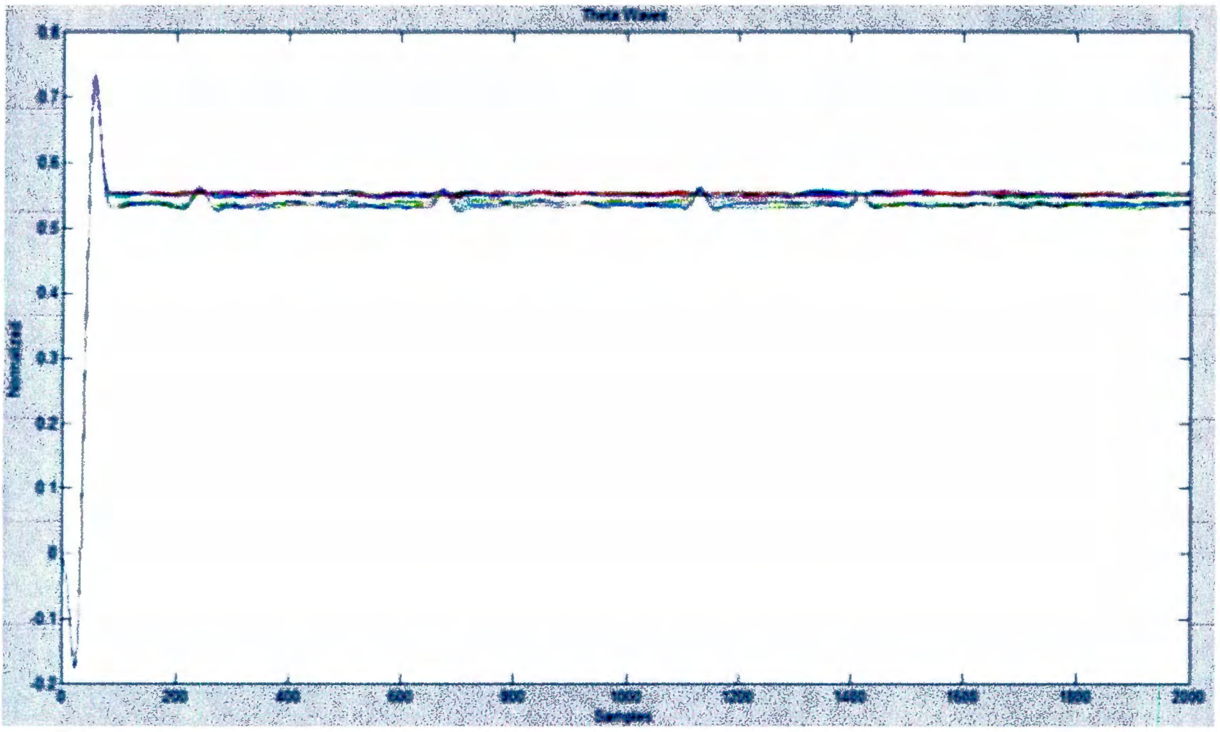


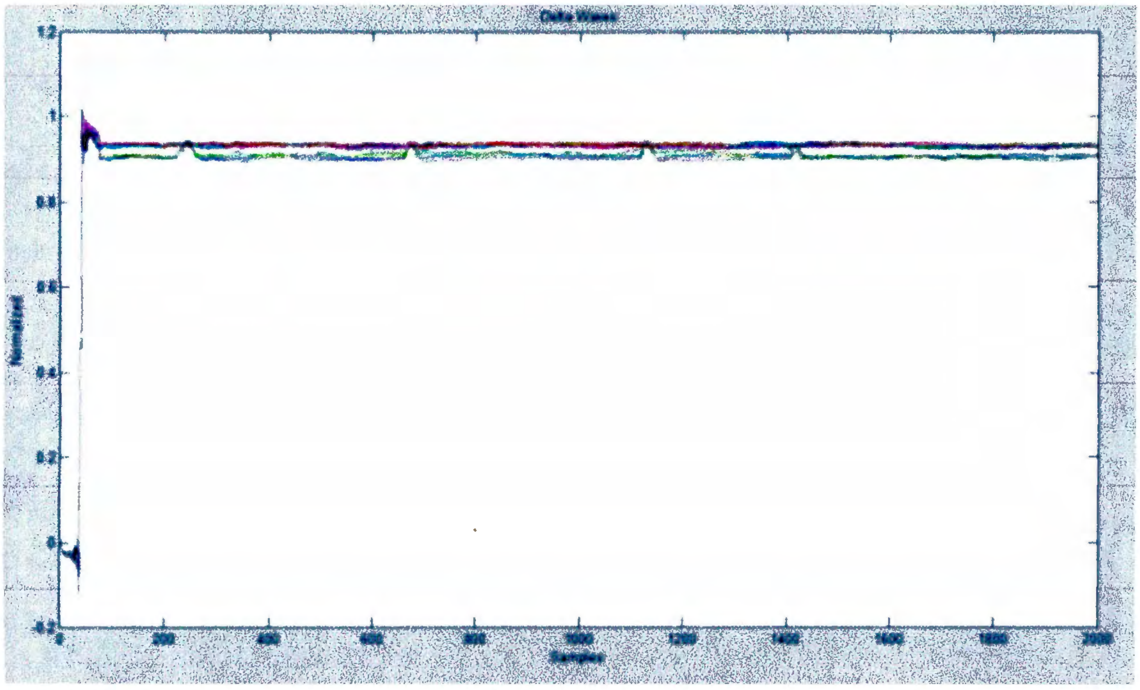
Subject 3: Left



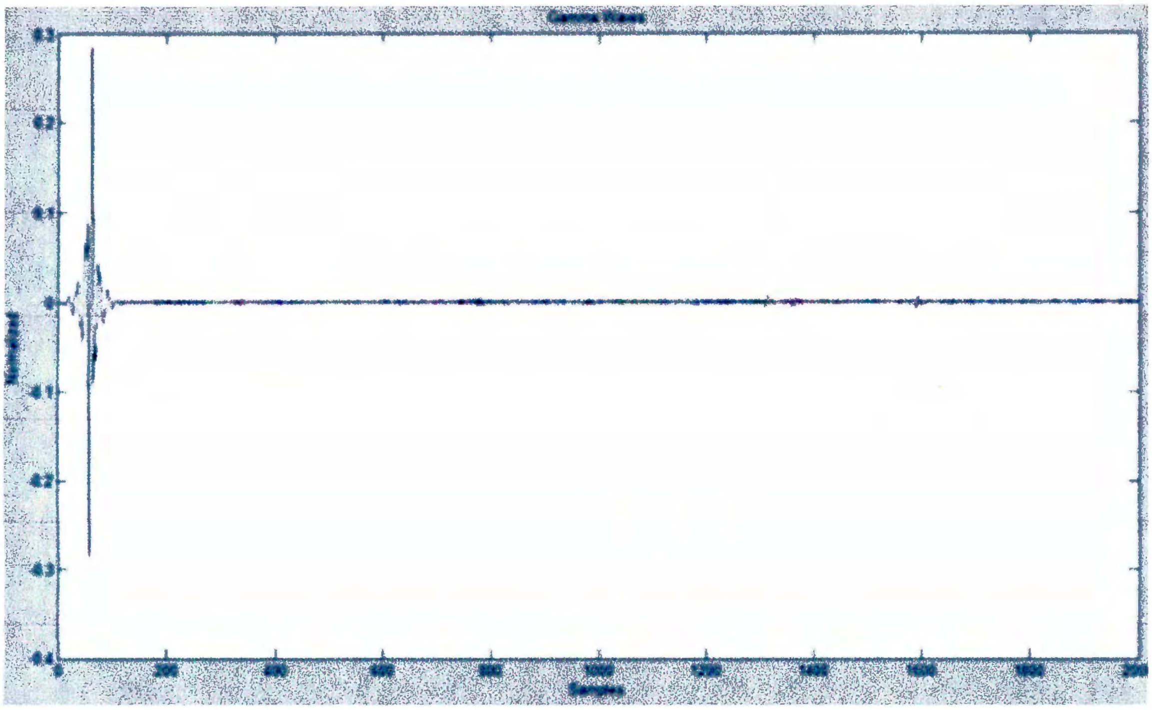

Beta Waves
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Samples

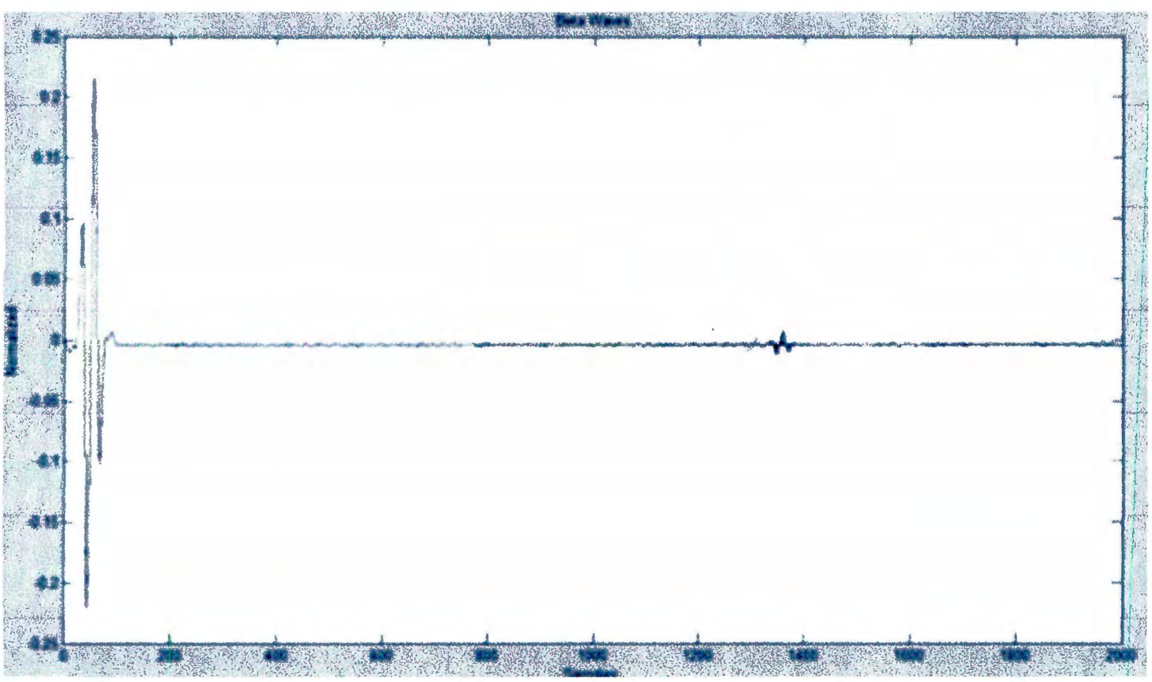

0.3
0.2
0.1
0
-0.1
-0.2
-0.3
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Samples

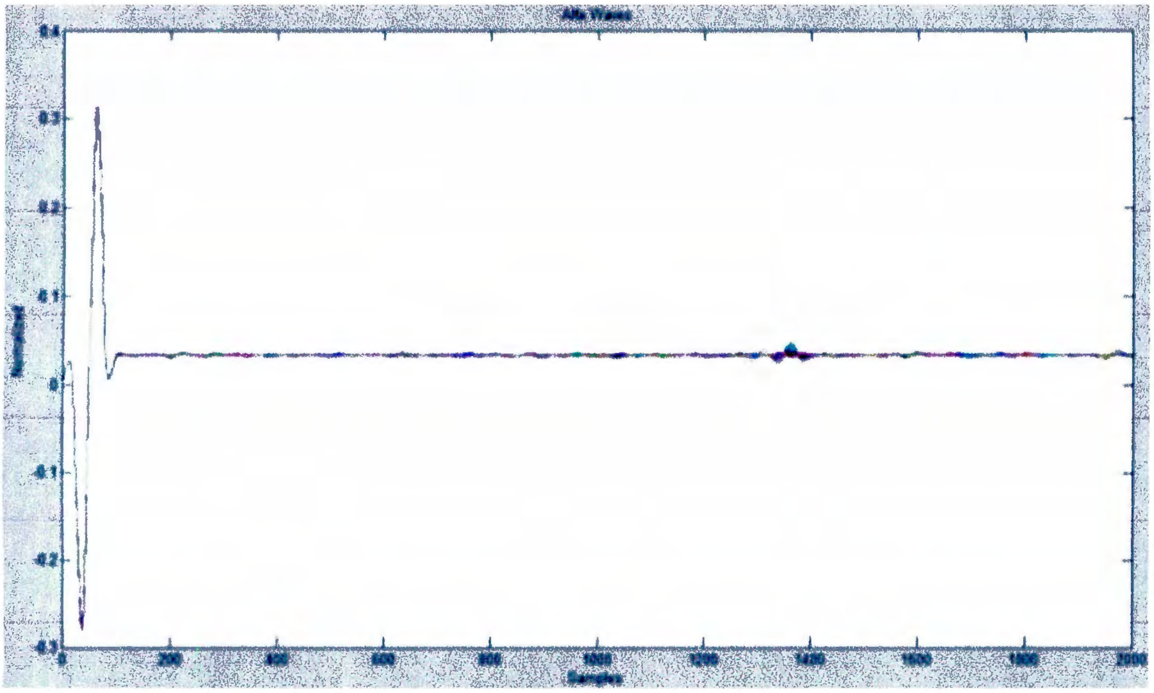


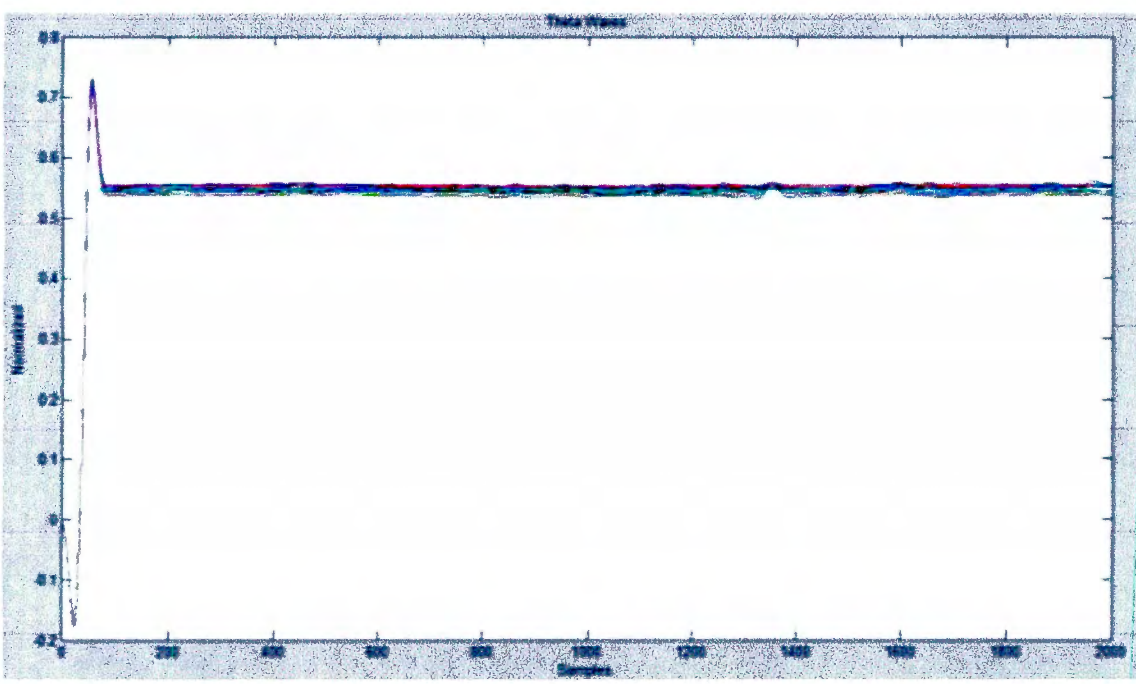


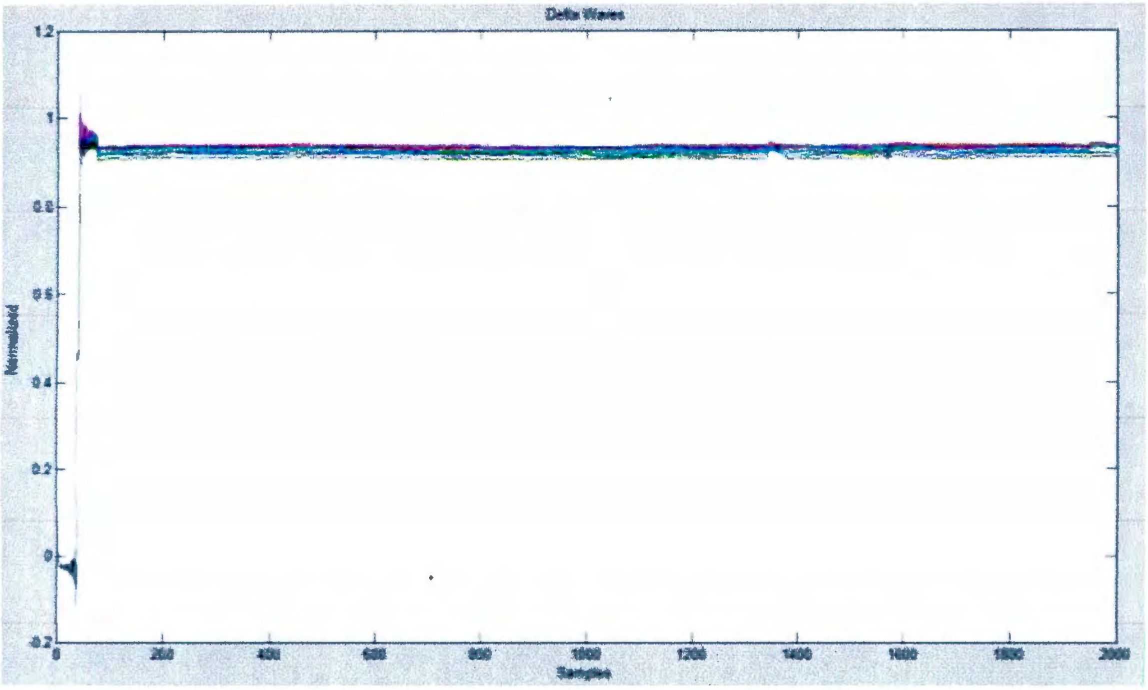
Subject 4: Left





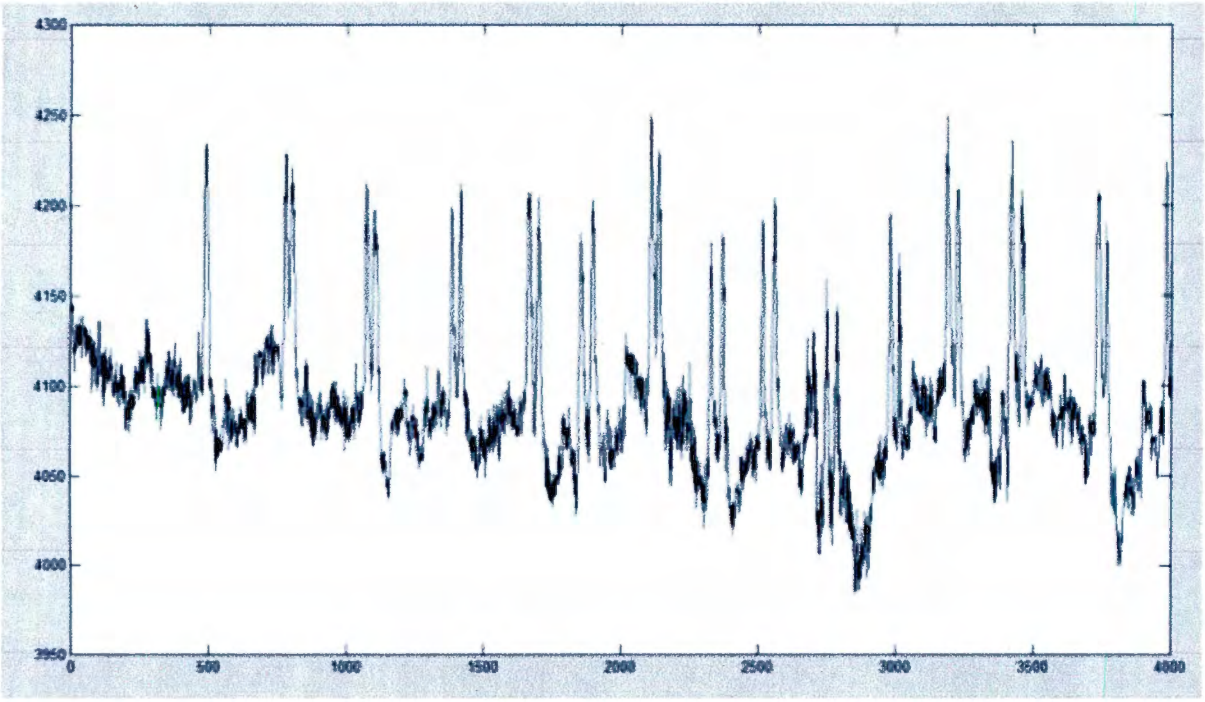




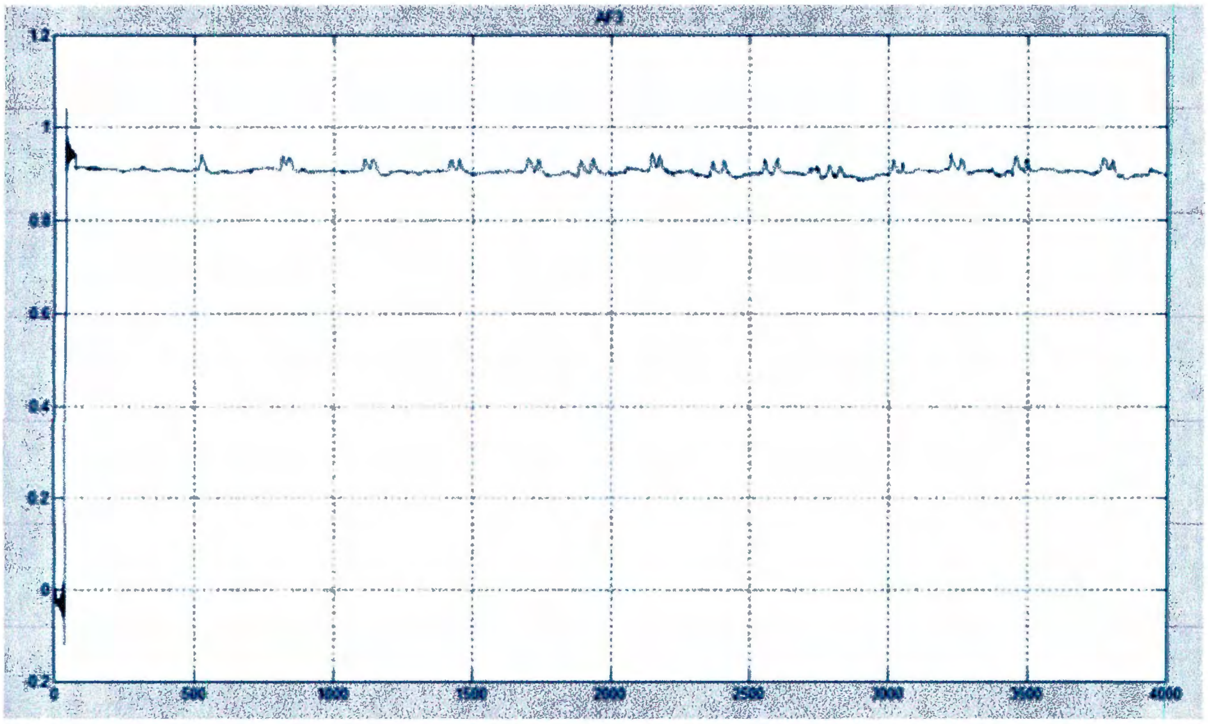


Possible Facial movements for more controls

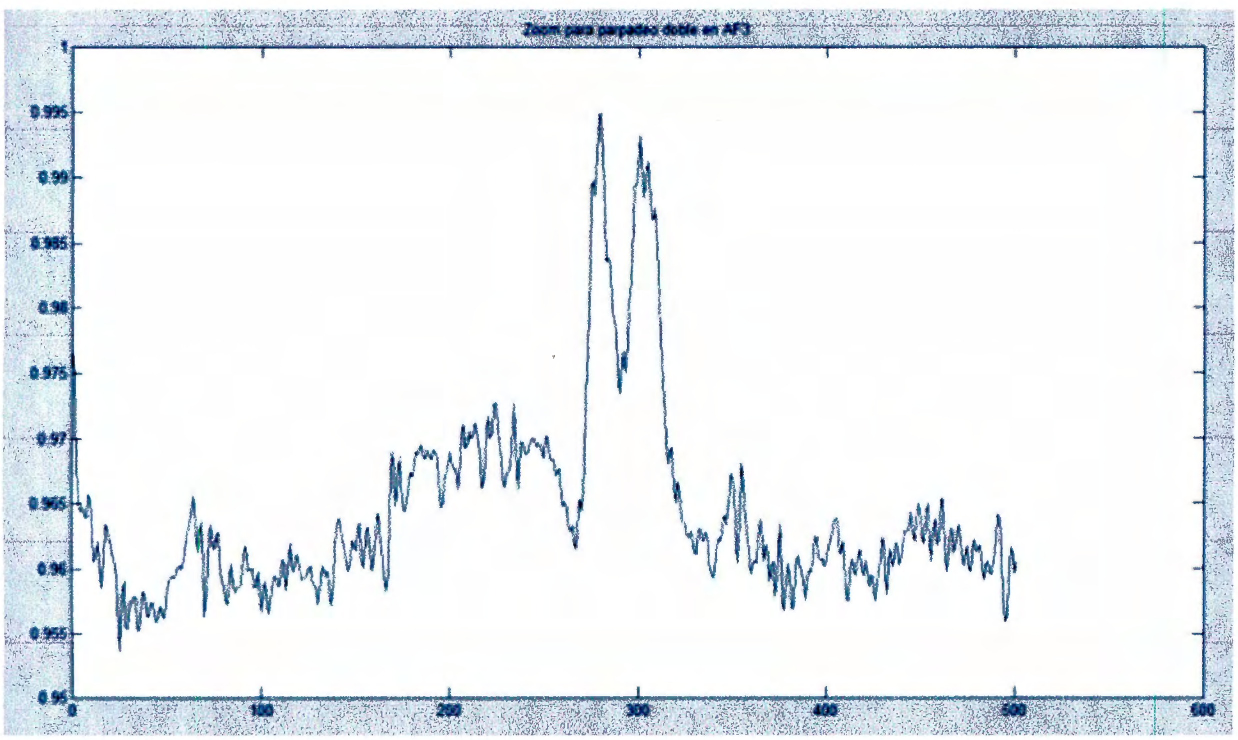
Double nlinking



In this screen It can be appreciated the double blinking. This signal has not any filter



Incoming filtered signal. Lowpass filter.



Zoom for double blinking.