

**DEVELOPMENT OF SOFTWARE TECHNIQUE TO DENOISE
BACKGROUND FROM EVENT-RELATED POTENTIAL**



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FACULTY OF GRADUATE STUDIES
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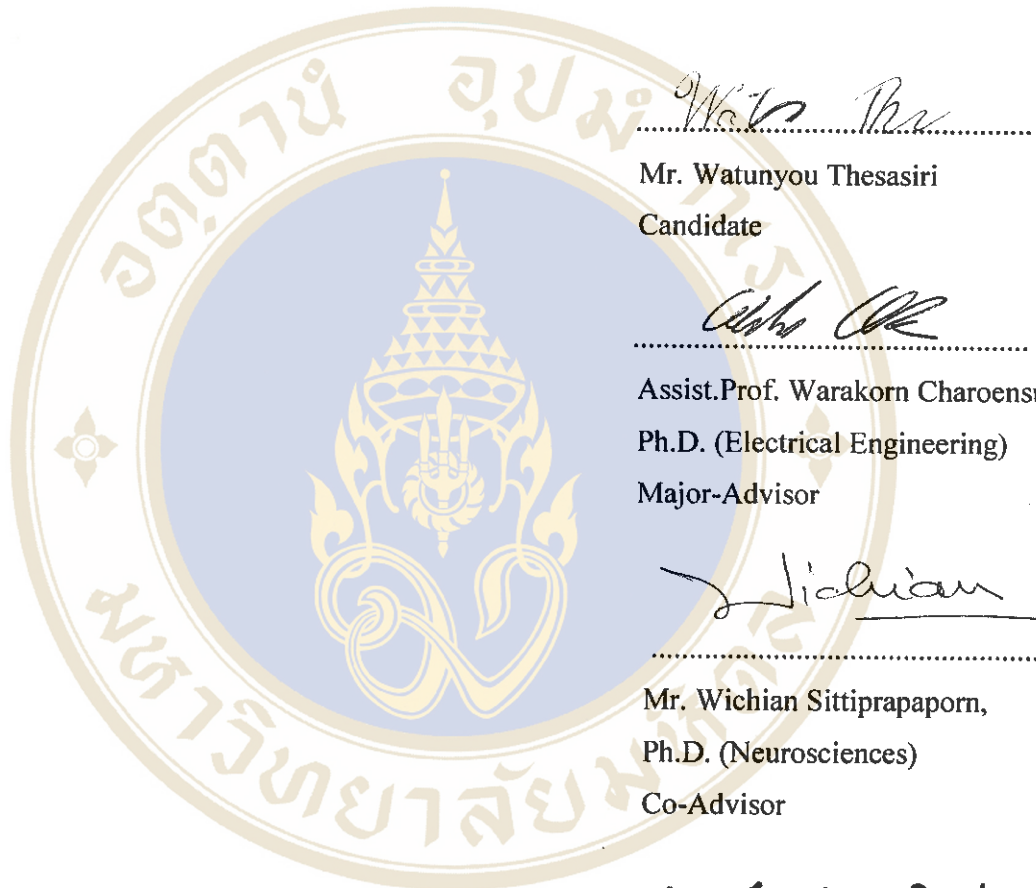
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Thesis
Entitled

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DEVELOPMENT OF SOFTWARE TECHNIQUE TO DENOISE BACKGROUND FROM EVENT-RELATED POTENTIAL

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ABSTRACT

Electroencephalography (EEG) is the neurophysiologic measurement of electrical activity from the brain. Recording of this activity can be done by placing electrodes on the scalp. For EEG analysis, some artifacts must first be removed before measurement from the raw signals. Many commercial programs have been developed for rejecting these artifacts. Finite Impulse Response (FIR) digital filters are widely used for implementation in the software for analyzing EEG data, either ongoing activity or event-related potentials (ERP).

Generally these data require the extraction of the signal from a noisy background. The study shows that the signals filtered by FIR filter were good enough and ready for ERP analysis. The ERP signals that researchers are interested in are of good quality for analysis and researchers are able to denoise the signal ahead. However, the problem with broadband noise is still existed. The reduction of noise by wavelet denoising technique was applied to these signals to remove this kind of artifact. The wavelets technique gives a better result over the linear FIR technique. So, the design of wavelet filter was developed in order to decrease broadband noise from waveforms. In conclusion, the study shows a good result when the wavelet denoising technique and FIR filter are combined and used to enhance the detection of the ERP signal.

KEY WORDS: EVENT-RELATED POTENTIALS (ERP) /
FINITE IMPULSE RESPONSE (FIR) / WAVELET DENOISING

58 pp.

การพัฒนาเทคนิคทางซอฟต์แวร์เพื่อขจัดคลื่นรบกวนจากคลื่นสมองที่สัมพันธ์กับเหตุการณ์
(DEVELOPMENT OF SOFTWARE TECHNIQUE TO DENOISE BACKGROUND
FROM EVENT-RELATED POTENTIAL)

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บทคัดย่อ

คลื่นไฟฟ้าสมองได้จากการวัดทางประสาทสรีรระเป็นการวัด ที่เป็นการวัดการทำงานของกระแสไฟฟ้าในสมอง โดยวิธีการบันทึกข้อมูลจากแผ่นอิเล็กโทรดที่ติดกับศีรษะ โดยสัญญาณของสมองนี้เรียกว่าคลื่นไฟฟ้าสมองในการวิเคราะห์สัญญาณคลื่นไฟฟ้าสมองนั้นมีความจำเป็นอย่างยิ่งในการลดสัญญาณรบกวนออกจากสัญญาณคลื่นไฟฟ้าสมอง ดังนั้นการพัฒนาซอฟต์แวร์เพื่อใช้ลดสัญญาณรบกวนประเภท Finite Impulse Response filter (FIR) จึงถูกนำมาประยุกต์ใช้อย่างกว้างขวางเพื่อพัฒนาซอฟต์แวร์ ในการวิเคราะห์สัญญาณคลื่นไฟฟ้าสมอง

การศึกษาเกี่ยวกับการแยกสัญญาณคลื่นไฟฟ้าสมองออกจากสัญญาณรบกวนนั้น จะเป็นการศึกษาความแตกต่างระหว่างสัญญาณก่อนและหลังการกรองสัญญาณด้วย FIR โดยสัญญาณคลื่นไฟฟ้าสมองที่ถูกกรองด้วย FIR filter นั้น จัดว่าเป็นสัญญาณที่มีคุณภาพดี ซึ่งเป็นประโยชน์ในการวินิจฉัยเกี่ยวกับพยาธิสภาพของสมอง นอกจากนี้การลดสัญญาณรบกวนโดยตัวกรองสัญญาณชนิด non-linear โดยทั่วไปแล้วมักจะให้ผลของการกรองสัญญาณที่ดีกว่าการกรองสัญญาณด้วยวิธีเชิงเส้น (linear technique) ดังนั้นการพัฒนาและออกแบบตัวกรองสัญญาณชนิด wavelet ซึ่งเป็นวิธีแบบ non-linear จึงได้ถูกนำมาประยุกต์ใช้ในการลดสัญญาณรบกวนออกจากสัญญาณคลื่นไฟฟ้าสมอง โดยผลจากงานการใช้ตัวกรองสัญญาณชนิด wavelet แสดงให้เห็นว่าเทคนิค wavelet transform สามารถนำมาใช้ควบคู่ไปกับ FIR filter เพื่อเป็นเป็นตัวกรองคลื่นไฟฟ้าสมองที่ทำให้สัญญาณที่มีคุณภาพมากยิ่งขึ้น

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CHAPTER I

INTRODUCTION

1.1 Introduction

An event-related potential (ERP) is any stereotyped electrophysiological response to an internal or external stimulus. More simply, it is any measured brain response that is directly the result of a thought or perception. ERPs can be reliably measured using electroencephalography (EEG), a procedure that measures electrical activity of the brain through the skull and scalp. As the EEG reflects thousands of simultaneously ongoing brain processes, the brain responses to a certain stimulus or event of interest is usually not visible in the EEG. One of the most straightforward features of the ERP response is a response to unpredictable stimuli. This response known as the P300 (or simply "P3") manifests as a positive deflection in voltage approximately 300 milliseconds after the stimulus is presented. The ERP study used to analyse the P3 (P300) component must rely on an embedded program of the EEG instruments. At the present time an EEG machine has a high price so it has restricted the approach of program development. The program development will be beneficial to assessment of cognitive functions with neurological and psychiatric malfunctions; therefore the purpose of this study is to develop software for ERP to compare our program (our hypothesis) with the embedded program and compare with the commercial software which has limitations on noisy signal analysis.

1.2 Objectives

This thesis proposes the program development for event related potential (ERP) detection which are written by C#.net program. The objectives are as follows.

Objective 1

To Develop Mahidol Brain Atlas Viewer program which is used in EEP Spike Detection with Wavelet Analysis [1].

Objective 2

To detect P3 component in ERP. Although the EEG signal is most strongly acquired around the parietal electrodes, interactions involving the frontal and temporal regions as well as several deep brain loci have been suggested.

1.3 Scope of Work

The scopes of the study are focused on:

- Study of Auditory Event-Related Potential (ERP) based on P3.
- Study and implement Wavelet Transform for denoising ERP signals into an application.
- Study ERP data and design algorithm.

CHAPTER II

LITERATURE REVIEW

2.1 Electroencephalography (EEG)

Electroencephalography is a method in recording the electric currents generated in the brain, by applying electrodes to the scalp, the surface of the brain, or placed within the brain. Electroencephalogram is a recording of the potentials on the scalp generated by currents emanating from the nerve cells in the brain. These are visible records of the amplified electrical current generated by the nerve cells of the brain. By placing electrodes on the scalp and amplifying the electrical activity that can see as rising and falling electrical potentials called “brain waves”. Research on the EEG can be traced back to 1929, Han Berger discovered in the ongoing EEG in human; a pair of electrodes were placed on the front and back of the head and connected to a sensitive recording device that displays the potential differences between two points. The display unit showed this potential difference to occur in two dimensions: time and amplitude. He realized that the amplitude and frequency of the EEG waveforms were affected by the alertness or the state of consciousness of the subjects. Berger continued to use the method for viewing what was a measure of global cortical activity. It was discovered by others that EEG activity varied in different locations on the head. Present EEG method is one of the most widely used for neuro-and psycho physiological studies.

2.1.1 Source of EEG Activity and Principal Mechanism

The EEG recorded at any region of the scalp approximately quantifies the summed activity of pyramidal neurons in a certain volume of tissue under the electrode. Pyramidal neurons are the major projection neurons in the cortical cortex.

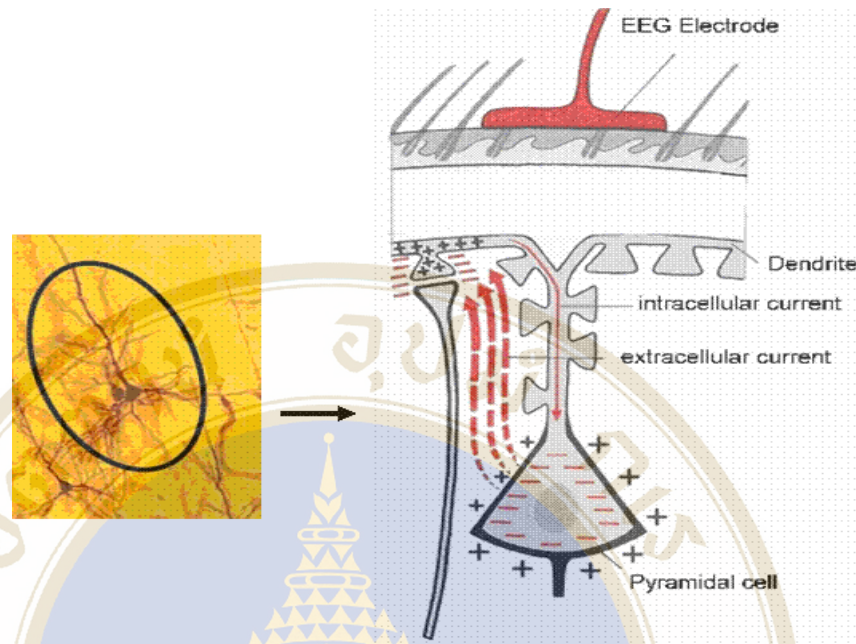


Figure 2.1 The diagram illustrates a pyramidal cell which is the major source of electrical current which is found in EEG data.

Their apical dendrites are oriented perpendicular to the cell body and receive a variety of synapse inputs. The ion exchange in the pyramidal neurons is the principal source of EEG activity. Action (Sodium (Na^+) and potassium (K^+)) and anion (large intracellular ions e.g., Chloride (Cl^-), protein) relate to the generation of electrical brain activity. During resting state, the inside of the cell provides the membrane resting potential of $-65 \mu\text{v}$. Most K^+ is inside the cell and the Na^+ concentration outside the cell is higher than inside. When the neuron is excited to reach the threshold that causes a gate in the Na^+ channel to open. Since there is a high concentration of Na^+ outside, Na^+ diffuses into the neuron. The electrical potential changes to about $+40 \text{ mV}$. The membrane resting potential is reduced that leads to the depolarization at the cell membrane. The Na^+ channels become refractory and K^+ channels open. When they do open, K^+ rushes out of the cell, reversing the depolarization. Also at about this time, sodium channels start to close. This causes the action potential to go back toward -60 mV . This action is later followed by depolarization as K^+ flows into the cell and Na^+ is pushed outward. The membrane potential will return to the resting state again (figure 2.2)

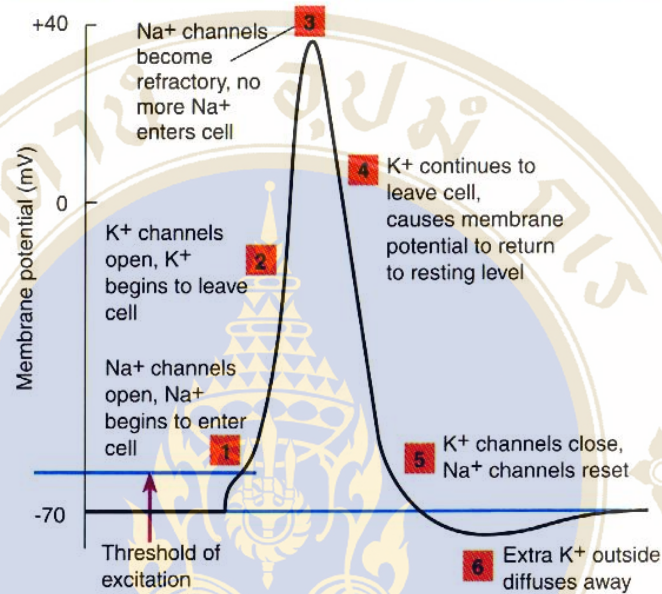
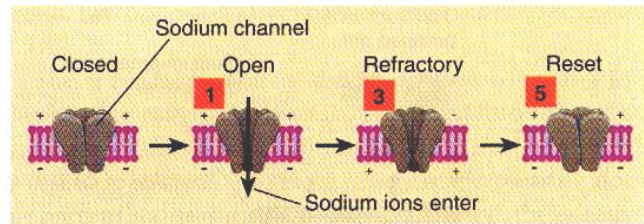


Figure 2.2 Step of action potential

Step of action potential are:

1. At rest, the outside of the membrane is more positive than the inside.
2. Na moves inside the cell causing an action potential, the influx of positive sodium ions makes the inside of the membrane more positive than the outside.
3. Potassium ions flow out of the cell, restoring the resting potential net charges.
4. Sodium ions are pumped out of the cell and potassium ions are pumped into the cell, restoring the original distribution of ions.

The propagation of the action potential reaches to the postsynaptic membrane and leads to the depolarization of the postsynaptic cell, it is called excitatory postsynaptic potential (EPSP). If that signal leads to the hyper polarization of the postsynaptic cell, it is called inhibitory postsynaptic potential (IPSP). Both types of synapses make contact with a neuron. The summation of potential at postsynaptic site

will be either depolarization or hyper polarization. If the depolarization reaches a threshold level, an action potential will be launched. The EEG signal probably comes from postsynaptic cells.

The electrical activity of the EEG requires thousands of neurons to be synchronously activated to generate a signal large enough to be measured by EEG. However, not all cells contribute equally to the EEG because, some cells predominantly reflect the activity of cortical neurons close to the surface of the skull but the deep structures (e.g., hippocampus, thalamus, brain stem) do not contribute directly to the surface.

2.1.2 General Basic of the EEG Signal

The EEG signal comes from the large neural population in the cerebral cortex synchronized together to summate at the scalp surface. However, recordable voltage at the scalp surface is reduced by the meninges, cerebro-spinal fluid, skull and scalp tissue, so it is measured in microvolt (μV). The signal describes voltage differences between electrodes and a reference electrode on the skull over a certain time range. The neuroelectrical signal will be transformed from an analogue to a digital signal to display the biological signal in the computer. However, the neuro-electrical signal is very small. This signal needs to be amplified. The signal gets further adjusted to get clear, by means of gain, sensitivity and filtering. The EEG signal is described in its frequency (Hz, cycles per second) and amplitude (μV , microvolt).

The amplitude of the EEG signals changes depending on spatial (position) and temporal (time) parameters (Figure 2.3). The EEG amplitudes of the scalp EEG lie between 10-100 μV , and about 1-2 mV (millivolt) when measured on the surface of the brain. Moreover, the size of amplitude depends on how synchronous is the activity of neurons under that brain area. The more neurons are excited simultaneously, the greater the increase in amplitude. While EEG provides a rather poor spatial resolution (because of the limited number of electrodes and the distortion of the signal after passing through the volume conductor such as bone and brain tissue), it gives very high temporal resolution (in milliseconds). It thus is greatly sensitive to even minor change of brain activity. The following EEG-related-terms, which are usually referred to, are shortly described:

Frequency: It refers to the temporal dimension of EEG activity (Hertz; Hz).

Voltage (volt): It refers to the potential difference between two locations.

Morphology: It refers to the shape of the waveform. The shape of a wave or an EEG pattern is determined by the frequencies that combine to make up the waveform and by their phase and voltage relationships.

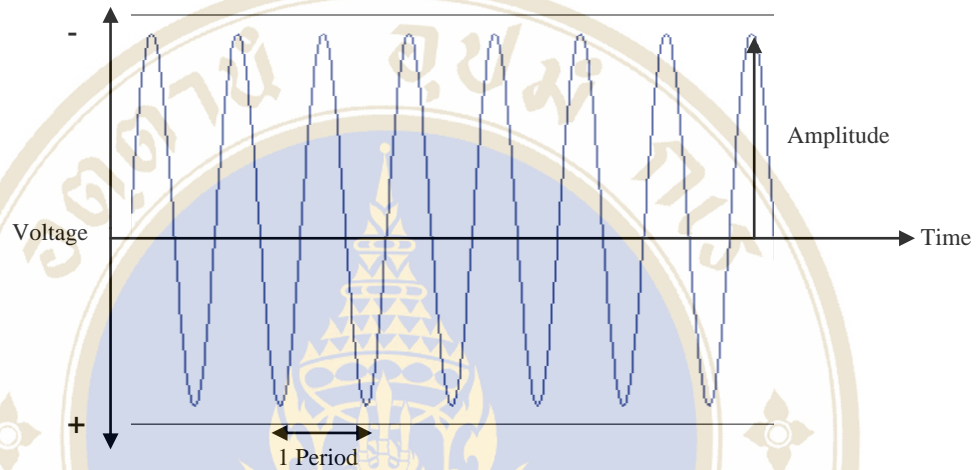


Figure 2.3 The EEG amplitude and frequency [2]

2.1.3 EEG rhythms

Spontaneous activation of neural assemblies will generate oscillations in the EEG record. These oscillations are characterized by their frequency bands and their amplitude usually decreases with increasing frequency. These oscillatory patterns and their temporal fluctuations are associated with cognitive processes [3]. The frequency range of EEG lies between 0.3 Hz and 70 Hz [4]. The EEG frequency ranges differentiate into the following bands:

- Delta (δ); frequency below 3.5 Hz
- Theta (θ); frequency between 4-7.5 Hz
- Alpha (α); frequency between 8-13 Hz
- Beta (β); frequency between 14-30 Hz
- Gamma (γ); frequency above 30 Hz

2.1.3.1 Alpha Rhythm

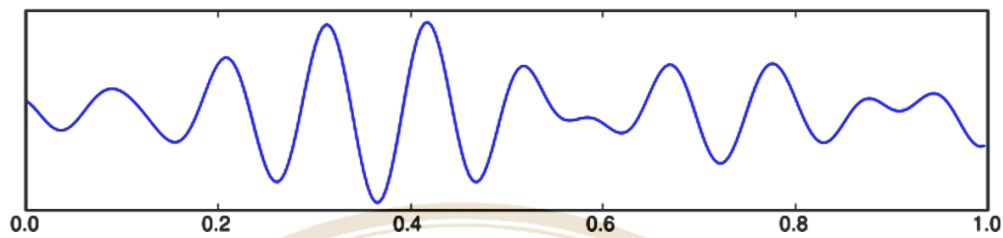


Figure 2.4 An EEG 1 second sample. The signal is filtered to present only the alpha waves. The signal was acquired in the Oz position [2].

Rhythm at 8-13 Hz occurs during wakefulness over the posterior regions of the head, generally with higher voltage over the occipital areas. Amplitude is variable but is mostly below 50 μV in adults. It is best seen with eyes closed and under conditions of physical relaxation and relative mental inactivity. It is blocked or attenuated by attention, especially visual, and mental effort (IFSECN, 1974). Research has shown that alpha frequency varies to a large extent as a function of age, neurological diseases, brain volume and task demands. Alpha reactivity is used to describe the change in alpha amplitude induced by sensory stimulation, or by mental or motor processes. Alpha is the correlate for a state of relaxed wakefulness best obtained with the eyes closed. A degree of higher alertness can block the alpha rhythm, which becomes low voltage and fast activity [4].

Many studies have confirmed that alpha wave can be attenuated or blocked by mental activity. It is usually concluded that the resulting alpha topography matches the relevant cortical functional topography. Diminution of alpha power over the left hemisphere was found during mental arithmetic. Creutzfeldt et al., in 1969, used eight tasks designed to involve different degrees of attention, including mental arithmetic and Yingling found that alpha power was enhanced during mental arithmetic and during reading in each case when compared to resting eyes in open condition. Diminution of the alpha power over the right hemisphere could be observed during spatial imagery and music processing.

Previous studies found two narrow alpha frequencies band; upper (10-12 Hz) and lower (8-10 Hz) most probably reflect different neuronal events associated with different cognitive processes. The responses of the upper alpha frequency band have

been reflecting “higher-level processes” such as memory functions and language processing. The responses of the lower alpha frequency band are associated with attention and for stimulus-orientation processes, which would be most prominent during initial stages of auditory information processing. It assumed that lower alpha activity could serve as some kind of mechanism responsible for initiating attention capacity in specific cortical regions by selective gating information to the cerebral region of interest [5, 6].

2.1.3.2 Beta Rhythm

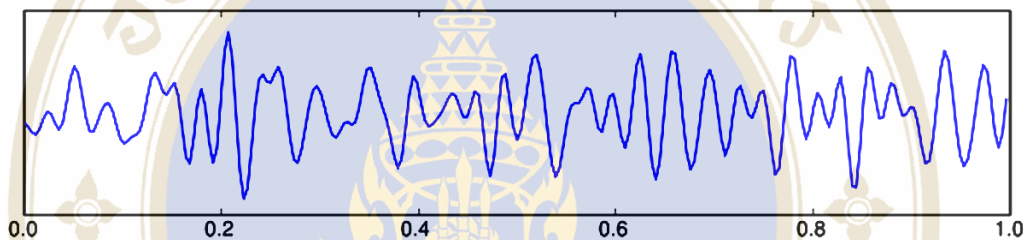


Figure 2.5 An EEG 1 second samples. The signal is filtered to present only the beta waves. The signal was acquired in the Oz position [2].

It is a fast activity and reflects desynchronized neuronal activation. The rhythm is above 13 Hz [4]. It is usually seen on both sides in symmetrical distribution and is most apparent in the frontal and central region of the brain. It may be reduced in areas of cortical damage. It is generally regarded as a normal rhythm and is associated with several cognitive processing such as listening to music and linguistic tasks. Beta rhythm (14–30 Hz) is a measure of cortical integrity because it attenuates in the cortical injury person and loss of its activity [7].

2.1.3.3 Theta Rhythm

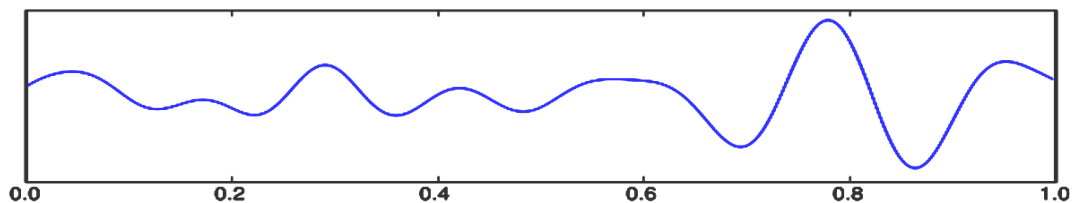


Figure 2.6 An EEG 1 second sample. The signal is filtered to present only the theta waves. The signal was acquired in the Oz position [2].

According to the international nomenclature the theta rhythm is the frequency of 4 to 8 Hz. It is classified as slow activity. Theta waves are strong during internal focus, meditation and praying. It reflects the state between wakefulness and sleep and relates to subconscious states of the mind. Its distribution is usually regional, more prominent on the left side than the right side. It may appear in small amounts in the central, temporal and parietal areas, but the rhythm rarely occurs. It has shown to be more dominant on the left side than the right side in all age groups. During sleep, this wave is usually more prominent in the temporal areas of the brain. Theta also occurs in anxiety, behavioural activation and inhibition. Addition theta oscillations appeared while participants learned to navigate virtual T-junction mazes, and their presence covaried with maze difficulty, suggesting that theta oscillations play a role in spatial learning and related with task difficulty. Bland and Oddie proposed the sensorimotor integration hypothesis; theta oscillations act to coordinate activity in various brain regions to update motor plans on the basis of sensory input. The recording intracranial electroencephalogram (iEEG) from human epileptic patients, found theta oscillations during both exploratory search and goal-seeking behaviour and, in particular, during virtual movement when compared with periods of self-initiated stillness. Theta oscillations had different topographic and spectral characteristics during searching than during goal-seeking, suggesting that human cortical theta oscillations act to coordinate sensory and motor brain activity in various brain regions to facilitate exploratory learning and navigational planning.

2.1.3.4 Delta Rhythm

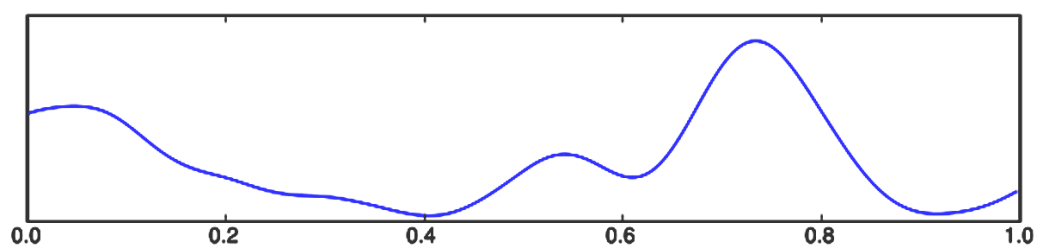


Figure 2.7 An EEG 1 second sample. The signal is filtered to present only the delta waves. The signal was acquired in the Oz position [2].

It is a frequency less than 4 Hz which is rare and often considered pathological when observed in the normal waking adult. It occurs during deep sleep, dreamless sleep, non-REM sleep and trance, unconsciousness and in brain-damaged subjects. It reflects the unconscious mind, not moving, not attentive and low-level of arousal. Few studies relating EEG and mental activity have analyzed the delta band, because of several artifacts may be present in this band such as eye movements. However, a delta increase has been reported in different types of mental tasks. The study, relating EEG narrow band changing during performance of complex arithmetic task, found increasing of power in the EEG frequencies from 1.56 to 5.46 Hz during mental tasks that require attention to internal processing than similar physical characteristic to arithmetic symbols. This study suggested increase in delta activity may be related to attention to internal processing [8].

2.1.3.5 Gamma Rhythm

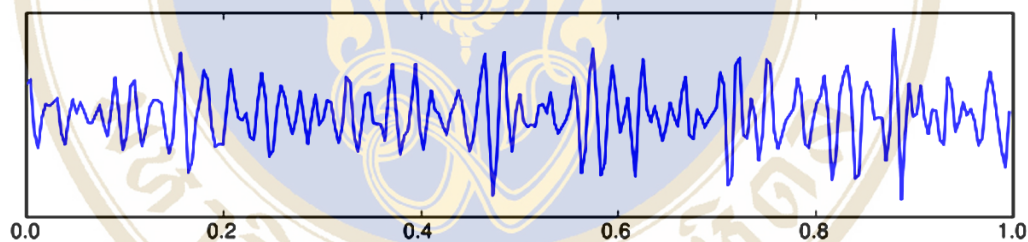


Figure 2.8 An EEG 1 second sample. The signal is filtered to present only the gamma waves. The signal was acquired in the Oz position [2].

Rhythms in the gamma range (>30 Hz) are thought to be strongly correlated with cognitive tasks. Berger's hypothesis proposes that high frequency oscillations may indicate "mental processes". Gamma rhythm can be observed in association with visual, auditory and motor task and may relate in a number of brain structure that is different in function or behavioural correlation. The EEG and MEG experiments demonstrate that spectral responses in the 30 Hz range were specifically elicited by meaningful word processing, but not by meaningless non-word [4]. It has also been emphasized that the gamma band activity serves as a mechanism for binding mechanism. The gamma frequencies serve for temporal binding of information from

various sensory modalities; neuronal activity is expressed separate in several areas of cortex, which require linking processes for separate nodes of activity allowing identification of meaningful concepts [9]. The study of synchrony analysis of music listening in musicians and non-musicians found degree of the gamma band synchrony were significantly higher in musicians. Additionally the several electrodes location is found to be highly significant for musicians, especially right midfrontal (F4) and frontobasal cortical regions (F8) [10,11].

2.2 Event Related Potentials

Event Related Potentials (ERP) are different from Evoked Potentials (EP) in the sense that they from essentially a kind of “follow up” or “follow through” on the prior sensory EP input, reflecting specifically longer-latency sensory-related cognitive information processing by the central nervous system, in addition to the earlier sensory EP signal. In Eps are centered on primary sensory cortex but in ERPs are mainly focused on associative cortical and sub cortical areas, and therefore appear to arise from a larger area of brain. This information is present in the raw, ongoing EEG all the time there is such task related information processing going on, but while generally higher voltage than EPs. It is still usually too small to be seen, and still tends to get swallowed up by mass of other information processing going on in the brain at the same time. For recording ERP is a method for use to turn in to one specific part of the evaluation and decision making processes that go on in the brain most of the time, in order to try to get an indication of how the brain’s overall “thinking system” works. Recording ERP mainly involves, beyond the standard EP recording technology, the use of a longer recording window or epoch following the stimulus, in order to record the subsequent cognitive activities. Additionally, as most ERPs require a task performance involving either some sort of discrimination between two randomly alternating sensory inputs, or a conditional evaluation on a second stimulus, based on its information content, compared with a prior stimulus, provision must be made for the delivery of two stimuli, as well as either the separate or sequential recording of the brain’s responses to each.

2.3 P300

The P300 (P3) was discovered over 40 years ago and has provided much fundamental information on the neural underpinnings of cognition [12]. The P300 wave is an event related potential (ERP) which can be recorded via electroencephalography (EEG) as a positive deflection in voltage at a latency of roughly 300 ms in the EEG. The signal is typically measured most strongly by the electrodes covering the parietal lobe. The presence, magnitude, topography and time of this signal are often used as metrics of cognitive function in decision making processes. While the neural substrates of this ERP still remain unclear, the reproducibility of this signal makes it a common choice for psychological tests in both the clinic and the laboratory. Despite many studies, the usefulness of P300 as a practical assessment tool has been limited because its neural generators are still unclear. However, recent advances on the underlying processing mechanisms of the P3a and P3b subcomponents have suggested a plausible approach.

2.3.1 P300 theory

The major interpretation of P300 amplitude is that it indexes brain actions when the mental representation of the stimulus environment is updated. This theory has its roots in Sokolov's model of the orienting response that was derived from habituation and dishabituation effects [12], which also have been found to affect P300. After initial sensory processing, the current stimulus is compared to the previous oddball stimulus in working memory. If no stimulus attribute change is detected, the old stimulus "schema" is maintained, with sensory evoked potentials recorded. If a new stimulus is processed, attention mechanisms are engaged that cascade an "update" of the memory representation for the stimulus context to elicit the P300 [13]. These events are thought to be associated with long-term storage, as larger P300 amplitudes occur for remembered previous stimuli [14, 15].

2.3.2 P3A and P3B

An infrequent tone presented with physically different frequent tones in the absence of a task can produce a positive waveform having a central/parietal maximum

amplitude distribution and relatively short peak latency. This component has been dubbed the “P3a” to distinguish it from the task-relevant target “P3b” potential [16].

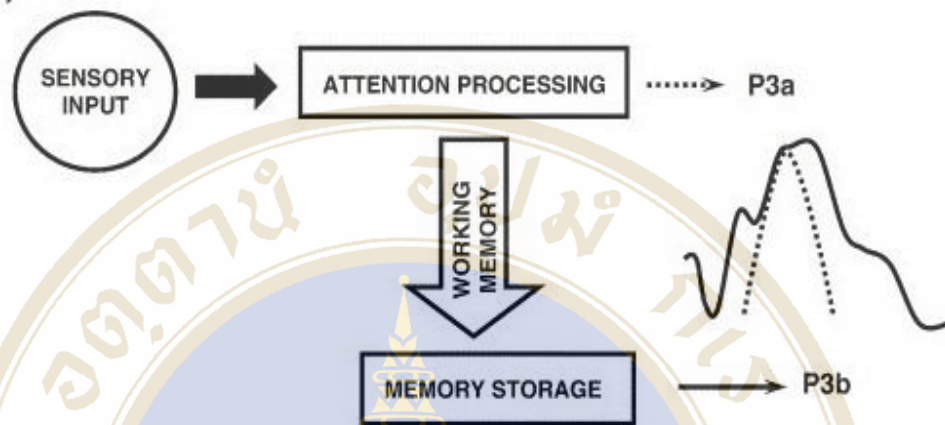


Figure 2.9 Model of the cognitive events associated with P300 [16]

As the model suggests, the neuroelectric events that underlie P300 generation stem from the interaction between frontal lobe and hippocampal/temporal–parietal function. ERP and fMRI studies using oddball tasks have obtained patterns consistent with this frontal to temporal and parietal lobe activation pattern. In Fig. 2.9, Sensory input elicits attention processing that facilitates maintenance of the stimulus representation in working memory. The P3a can be elicited if the distracting nature of the stimulus automatically demands focal attention. Working memory engages storage operations that produce a P3b if the subject discriminates the target from other stimuli. The overall P300 from a traditional oddball task appears to involve P3a and P3b activities that overlap in time.

2.4 Wavelet Transform

Wavelet Transform or Wavelet analysis is the representation of a function by wavelets. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-stationary signals. Wavelet transforms are divided into three classes: continuous wavelet transforms (CWTs), discrete wavelet transforms (DWTs) and multiresolution-based [17].

2.4.1 Continuous wavelet transforms

In continuous wavelet transforms, a given signal of finite energy is projected on a continuous family of frequency bands (or similar subspaces of the L^P function space $L^2(\mathbb{R})$). For instance the signal may be represented on every frequency band of the form $[f, 2f]$ for all positive frequencies $f > 0$. Then, the original signal can be reconstructed by suitable integration over all the resulting frequency components. The frequency bands or subspaces are scaled versions of a subspace at scale 1 . This subspace in turn is in most situations generated by the shifts of one generating function $\psi \in L^2(\mathbb{R})$, the *mother wavelet*. For the example of the scale one frequency band, this function is

$$\psi(t) = 2 \sin c(2t) - \sin c(t) = \frac{\sin(2\pi t) - \sin(\pi t)}{\pi t}$$

The subspace of scale a or frequency band $[1/a, 2/a]$ is generated by the functions (sometimes called *child wavelets*)

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$$

where a is positive and defines the scale and b is any real number and defines the shift. The pair (a, b) defines a point in the upper half plane $\mathbb{R}_+ \times \mathbb{R}$. The projection of a function x onto the subspace of scale a then has the form

$$\chi_a(t) = \int_{\mathbb{R}} WT_{\psi}\{x\}(a,b) \cdot \psi_{a,b}(t) db$$

with *wavelet coefficients*

$$WT_{\psi}\{x\}(a,b) = \langle x, \psi_{a,b} \rangle = \int_{\mathbb{R}} x(t) \overline{\psi_{a,b}(t)} dt$$

2.4.2 Discrete wavelet transforms

It is computationally impossible to analyze a signal using all wavelet coefficients, so one may wonder if it is sufficient to pick a discrete subset of the upper half plane to be able to reconstruct a signal from the corresponding wavelet coefficients. One such system is the affine system for some real parameters $a > 1, b > 0$. The corresponding discrete subset of the half plane consists of all the points $(a^m, na^m b)$ with integers $m, n \in \mathbb{Z}$. The corresponding *baby wavelets* are now given as

$$\psi_{m,n}(t) = a^{-m/2} \psi(a^{-m}t - nb)$$

A sufficient condition for the reconstruction of any signal x of finite energy by the formula

$$x(t) = \sum_{m \in \mathbb{Z}} \sum_{n \in \mathbb{Z}} \langle x, \psi_{m,n} \rangle \cdot \psi_{m,n}(t)$$

is that the functions $\{\psi_{m,n} : m, n \in \mathbb{Z}\}$ form a tight frame of $L^2(\mathbb{R})$

2.4.3 Multiresolution-based discrete wavelet transforms

In any discretised wavelet transform, there are only a finite number of wavelet coefficients for each bounded rectangular region in the upper half plane. Still, each coefficient requires the evaluation of an integral. To avoid this numerical complexity, one needs one auxiliary function, the father wavelet $\phi \in L^2(\mathbb{R})$. Further, one has to restrict a to be an integer. A typical choice is $a=2$ and $b=1$. The most famous pair of father and mother wavelets is the Daubechies 4 tap wavelet. From the mother and father wavelets one constructs the subspaces

$$V_m = \text{span}(\phi_{m,n} : n \in \mathbb{Z}) \text{ where } \phi_{m,n}(t) = 2^{-m/2} \phi(2^{-m}t - n)$$

and

$$W_m = \text{span}(\psi_{m,n} : n \in \mathbb{Z}) \text{ where } \psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m}t - n)$$

From these one requires that the sequence

$$\{0\} \subset \dots \subset V_1 \subset V_0 \subset V_{-1} \subset \dots \subset L^2(\mathbb{R})$$

forms a multiresolution analysis of $L^2(\mathbb{R})$ and that the subspaces $\dots, W_1, W_0, W_{-1}, \dots$ are the orthogonal "differences" of the above sequence, that is, W_m is the orthogonal complement of V_m inside the subspace V_{m-1} . In analogy to the sampling theorem one may conclude that the space V_m with sampling distance 2^m more or less covers the frequency baseband from 0 to 2^{-m-1} . As orthogonal complement, W_m roughly covers the band $[2^{-m-1}, 2^{-m}]$. From those inclusions and orthogonality relations follow the existence of sequences $h = \{h_n\}_{n \in \mathbb{Z}}$ and $g = \{g_n\}_{n \in \mathbb{Z}}$ that satisfy the identities $h_n = \langle \phi_{0,0}, \phi_{1,n} \rangle$ and

$$\phi(t) = \sqrt{2} \sum_{n \in \mathbb{Z}} h_n \phi(2t - n)$$

$$g_n = \langle \phi_{0,0}, \phi_{1,n} \rangle \text{ and } \psi(t) = \sqrt{2} \sum_{n \in \mathbb{Z}} g_n \phi(2t - n)$$

2.5 Wavelet-based denoising

The noise corrupting the signal, more often than not, it must be removed in order to recover the signal and proceed with further data analysis. From the advantages of wavelet transform we can throughoutly proceed by this method .

The general wavelet denoising procedure is as follows

- Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish the PD occurrence.
- Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises.
- Inverse wavelet transforms of the thresholded wavelet coefficients to obtain a denoised signal.

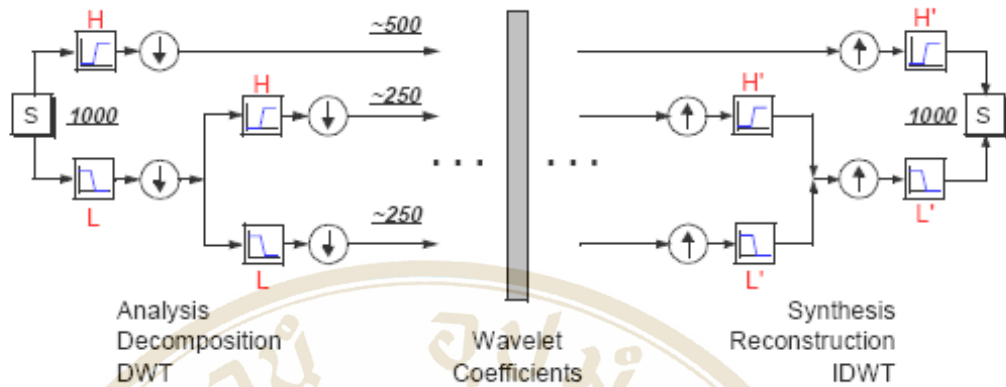


Figure 2.10 Wavelet denoising diagram

From wavelet denoising study, Petr Klapetek adds some noises in original signal. Then he uses wavelet transform to denoise signal (Fig.2.12) and compare with original signal.

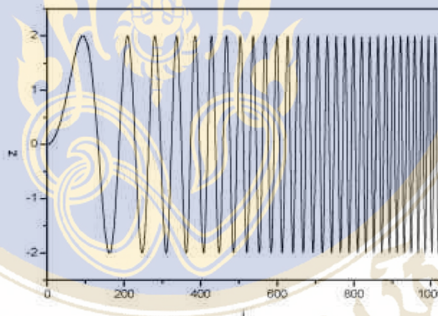


Figure 2.11 original signals [18]

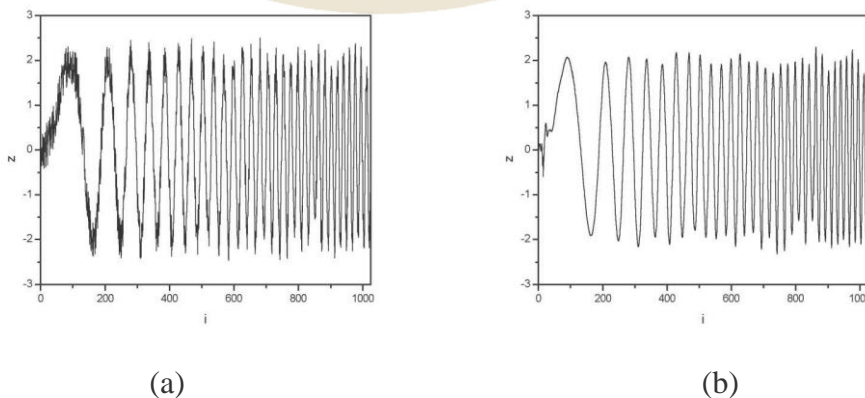


Figure 2.12 The uniform noise was added to the 1024 points long signal [18].

(a) Signal with uniform noise (noise range (-0.5; 0.5))

(b) Signal denoised by means of DWT

There are many researches about wavelet transform to denoise EEG signal such as wavelet transform in the analysis of the frequency composition of evoked potentials [19], in this study the results show examples of the better performance of the wavelet decomposition in comparison with Fourier transformation methods, R. Quian Quiroga , H. Garciab study single-trial event-related potentials with wavelet denoising [20]; they perform in simulated data as well as in visual and auditory ERPs. The study gives a significantly better reconstruction of the single-trial event-related responses in comparison with the original data and also in comparison with a reconstruction based on conventional Wiener filtering. In addition, with wavelet denoising they obtain a significantly better estimation of the amplitudes and latencies of the simulated ERPs. A reconstruction based on conventional Wiener filtering; with wavelet denoising they obtain a significantly better estimation of the amplitudes and latencies of the simulated ERPs. The results inform about complementing the conventional analysis of ERPs. Haiyan Ding, Datian Ye perform non-stationary of Evoked Potential Tracked by ICA and WT [21] by Daubechies-5 wavelet. This research is helpful to study the uncertainty and singularity of evoked potential.

2.6 Spike detection

The signals after passing denoising step are smooth shapes, and one can detect spike easily. We can use easy technique, which uses 3 points line up. If second point is in a higher position than other points, we can summarize this point as spike.

CHAPTER III

MATERIALS AND METHODS

3.1 Research Planning

The researching steps are related with chapters in this thesis.

Firstly, the early scope of research is on “Developing Mahidol Brain Atlas Viewer program”. So, it is necessary to include some medical diagnosis function in part of ERP into the research. The new scope is “Developing program to detect P3 in ERP signal” which is carried out in this research.

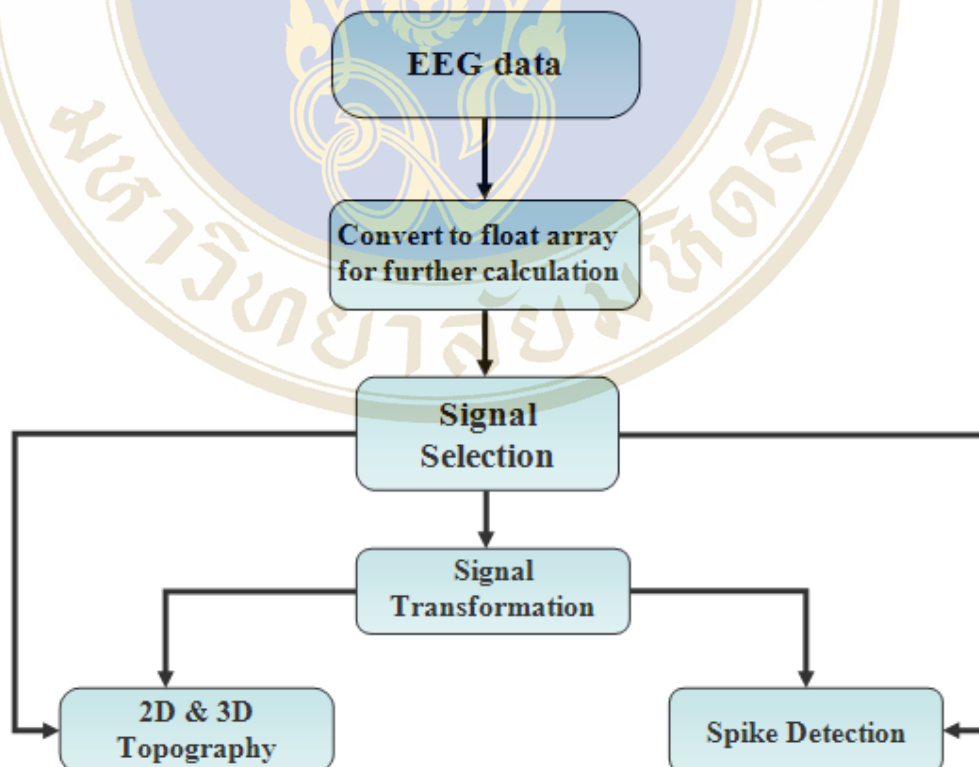


Figure 3.1 Flowchart of program flow

3.2 Software Design and Development

In the developing phase, parts of the software are developed separately. The purpose is to ensure that each process can work efficiently, without internal errors (or external errors). The first part in Mahidol Brain Atlas Viewer program, the clustering part is developed for comfort in any researches. This part can cut off some parts of noise in EEG signal before the researchers bring the signal to use in their works. The second part is software to translate EEG data to ERP data add detect peak position of the signal based on P3. In EEG analysis, signals are noisy and varied over time. Mathematical transformations are applied to those noisy signals to obtain further information that can hardly see from the raw signals (time-domain signals). Most of the signals in practice are TIME-DOMAIN signals in their raw format. That is, whatever that signal is measuring, it is a function of time. In other words, when we plot the signal, one of the axes is time (independent variable), and the other (dependent variable) is usually the amplitude. When we plot time-domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency SPECTRUM of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal. Recall that the FT gives the frequency information of the signal, which means that it tells us how much each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal is so-called stationary (signals whose frequency content do not change in time). We basically need some ultimate solution for non-stationary signals.

3.3 Filter Design

Filter design or signal processing design is carried out to search for the most efficient method to get the solution on non-stationary signals. In this study we choose the method on the basis of Linear filter and Non linear filter.

3.3.1 Linear filter

The finite impulse response (FIR) filter is a type of a digital filter, in which every sample of output is the weighted sum of past and current samples of input, using all past samples, but the weights of past samples are an inverse function of the sample age, approaching zero for old samples. A filtering process, in which an output signal is the response of a digital filter: the FIR filters are used in this process because they are simple and stable, due to the fact that all the poles are located at the origin and thus are located within the unit circle. They can easily be designed to be "linear phase". This is usually desired for phase-sensitive applications, in that the phase change is proportional to the frequency.

In Artifact removal from EEG signals adaptive filters are used in cascade [22]. They use a finite impulse response (FIR) filter. In all cases, line-frequency, ECG and EOG artifacts were attenuated. It is concluded that the proposed filter reduces the common artifacts present in EEG signals without removing significant information embedded in these records. In Digital filtering for EEG/ERP analysis, technical and empirical comparisons [23] FIR, digital filters have increasingly used sets of unequal weights.

3.3.2 Non-linear filter

In this part, the wavelet denoising technique is used for rejecting artifact and compared with FIR method. Wavelet Transform analysis is the representation of a function by wavelets. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-stationary signals. Wavelet transforms are divided into three classes: continuous wavelet transforms (CWTs), discrete wavelet transforms (DWTs) and multiresolution based which will be explained in the next subtopic.

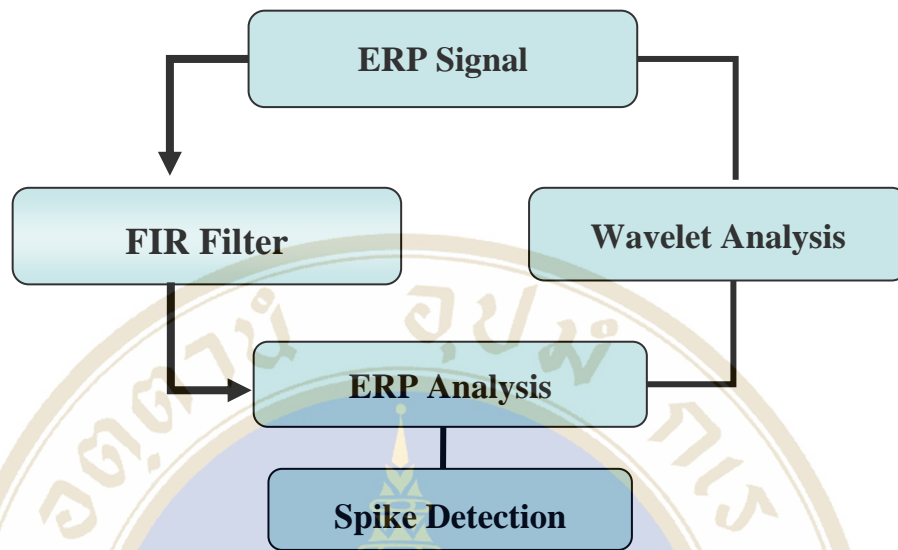


Figure 3.2 ERP signal processing method

3.4 Protocol of data collection

The method can be categorized in two steps: Material & Recording step and Signal processing step. In material and recording step, the participants are suggested to listen to the sound while recording the EEG signal. They should be comfortable during the recording step. Next, the electrode cap is connected to the electrode that is plugged into the EEG instrument. The EEG signal is recorded and then processed by the signal processing technique.

CHAPTER IV

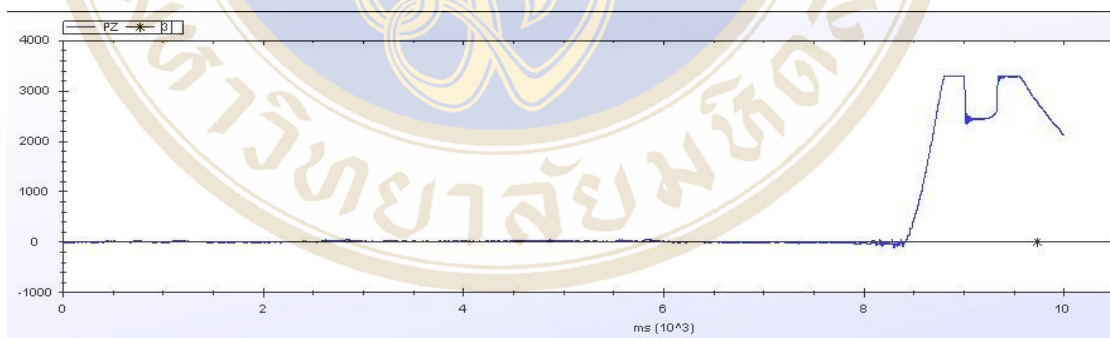
RESULTS

This section contains the results of the ERP signals, both passing through the filters (FIR and/or wavelet denoising) and not passing through any filter.

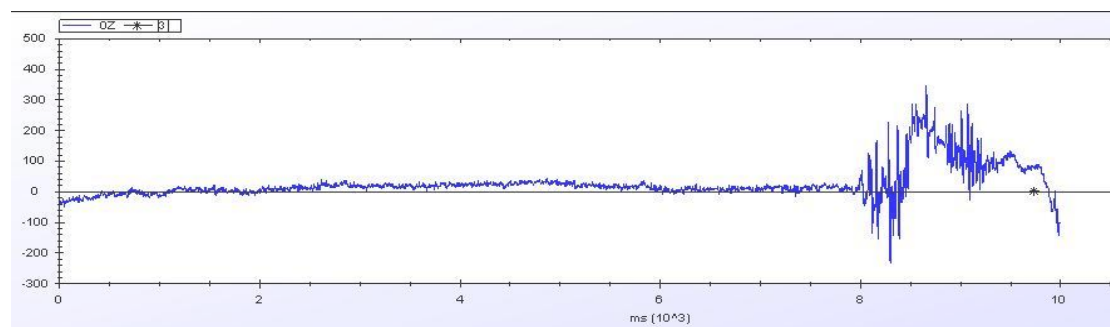
4.1 Linear filter

4.1.1 EEG signals with FIR filter

We use EEG signals to analyze ERP, by using Pz and Oz electrodes to compare the signals among real signals and filtered signals. Figure 4.1 shows the signals at Oz and Pz electrode before filtered compared with after filtered. Signals in Oz electrode have many artifacts than Pz electrode.



(a)



(b)

Figure 4.1 EEG Signals before filtered: (a) Pz electrode (b) Oz electrode

For this research, we use FIR filter to denoise EEG signals before applying ERP analysis. For EEG, we are normally interested in the signals which contain the frequencies between 0.1 Hz to 30 Hz, we will design FIR filter to have the cut off frequency range. After the signal is filtered, we can see clearly the shape of signals as in Figure 4.2.

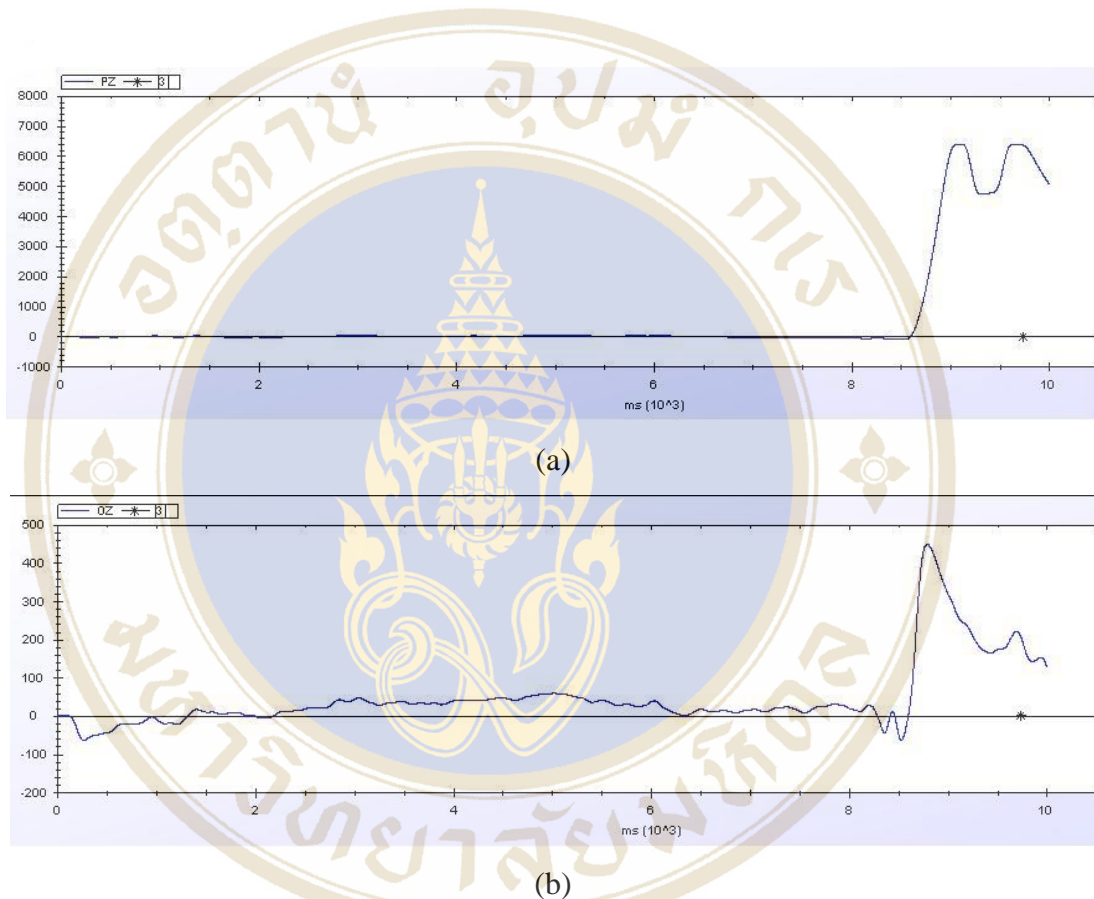


Figure 4.2 EEG signals after filtered

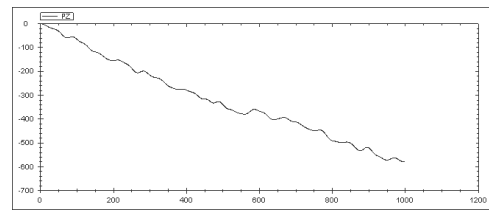
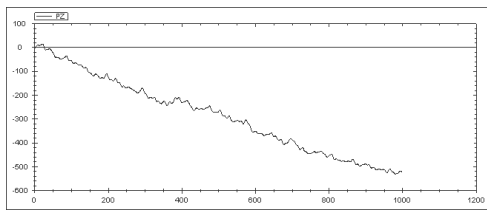
(a) Pz electrode (b) Oz electrode

4.1.2 ERP analysis with FIR filter

For ERP analysis, we use signals before filtered compared with after filtered, by using the same range of artifact rejection and use auto reject epoch. In Figures 4.3-4.4 show the epoch graphs of the non-filtered signals and epoch graph of the filtered signal. Furthermore, Figure 4.5 shows the average graph of non-filtered signals (a, c) and average graph of filtered signal (b, d).

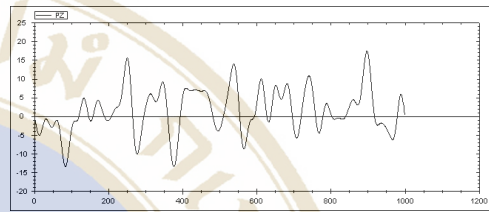
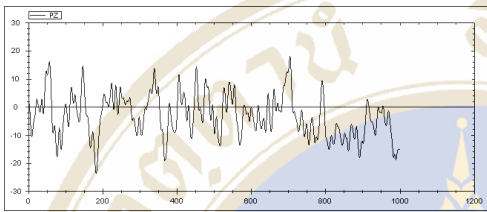
Non-filtered

Filtered



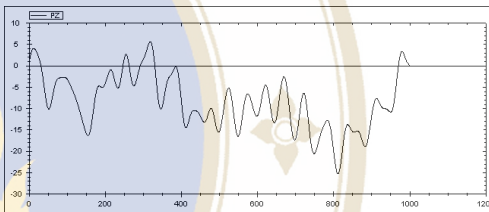
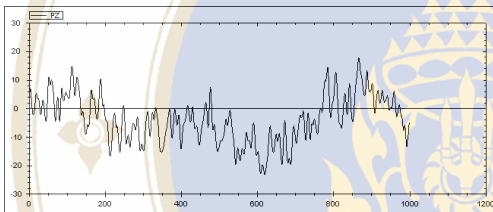
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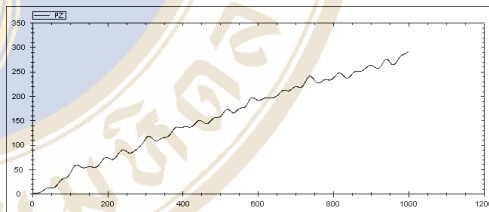
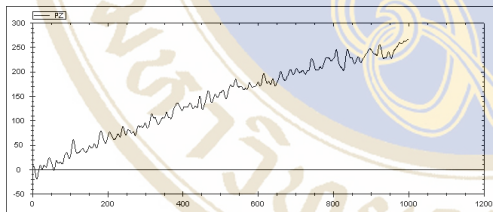
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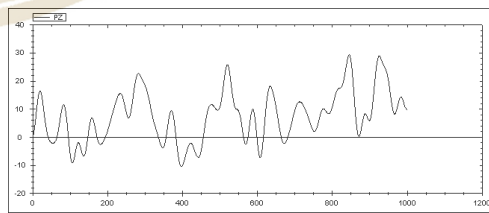
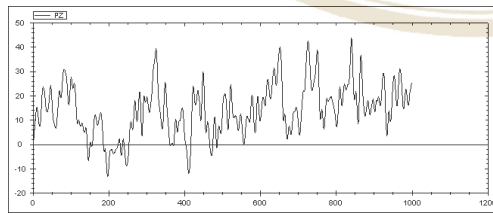
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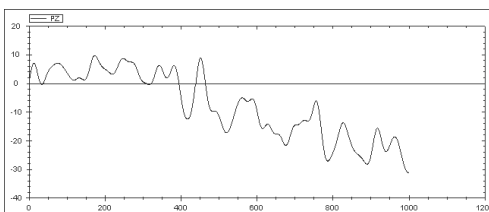
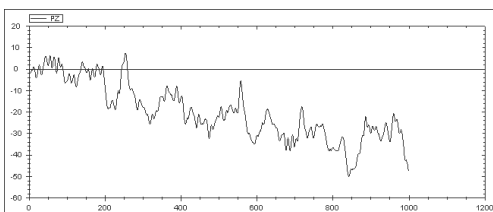
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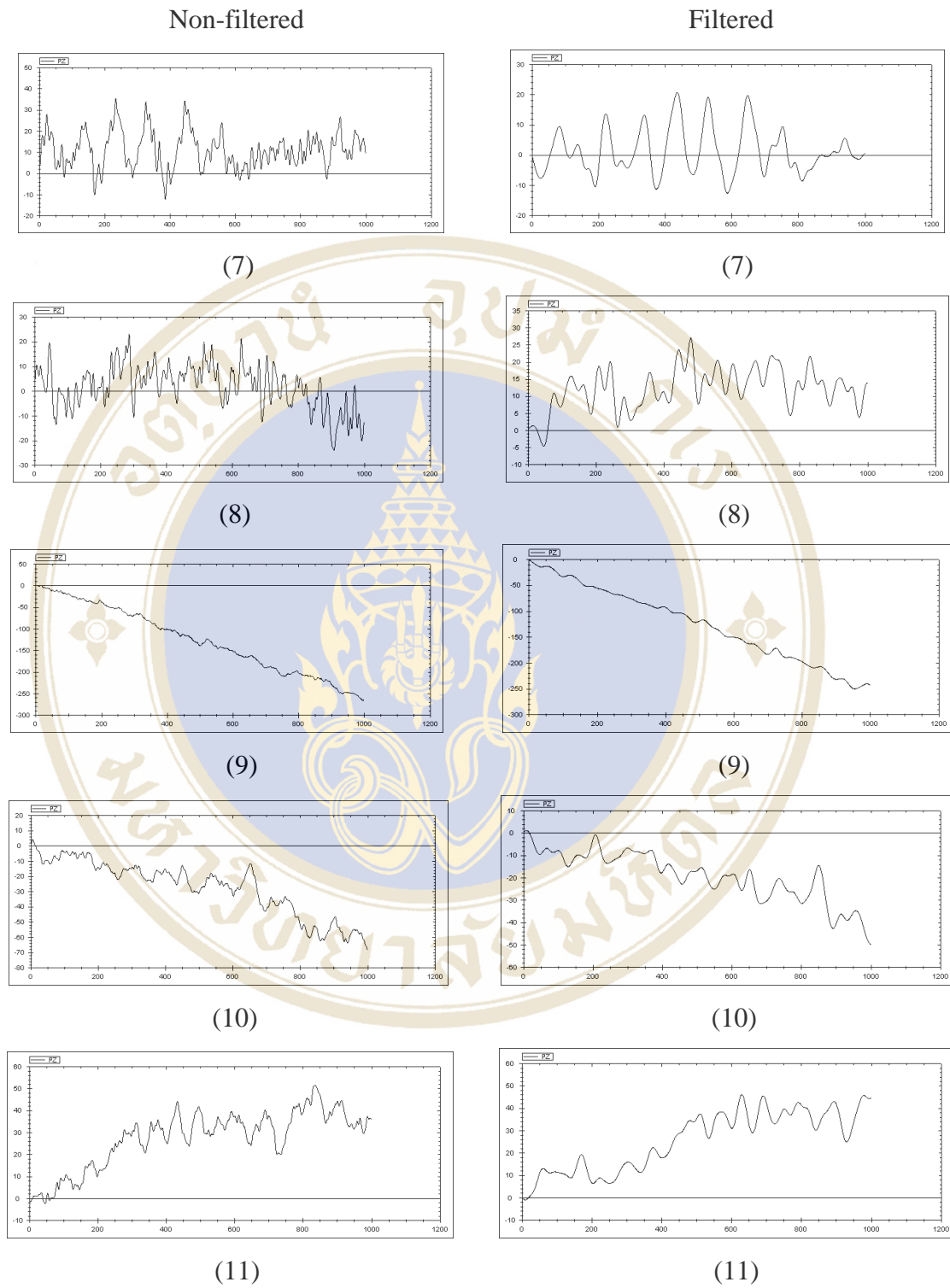
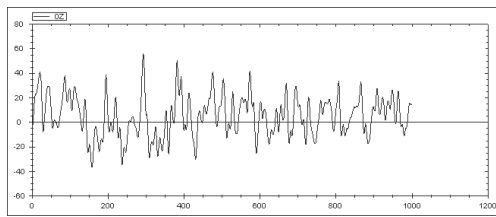


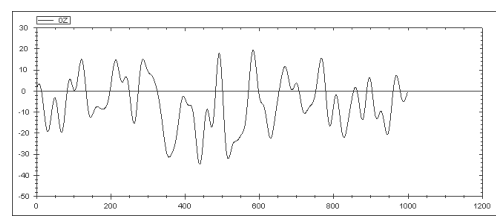
Figure 4.3 Epoch graph at Pz

Non-filtered

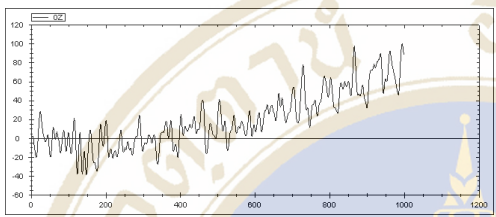
Filtered



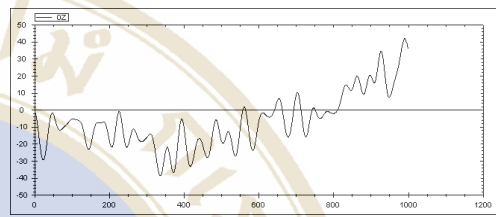
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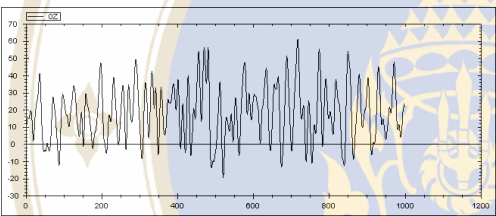
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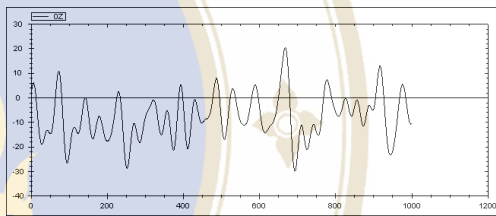
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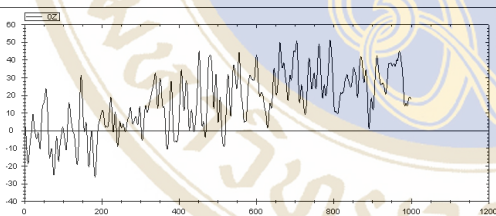
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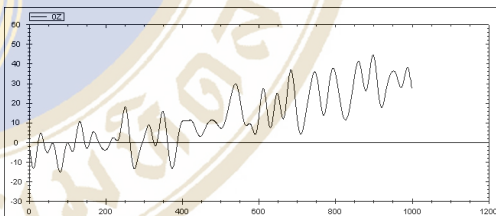
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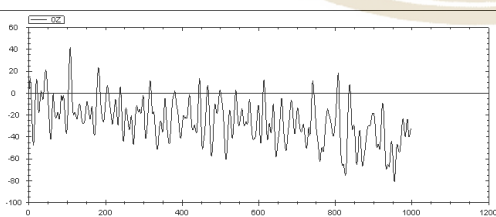
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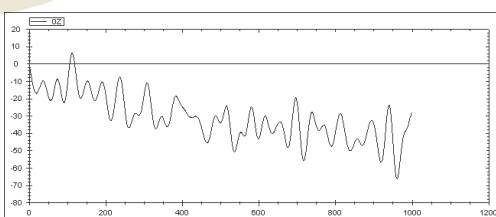
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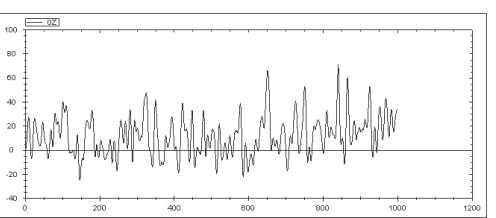
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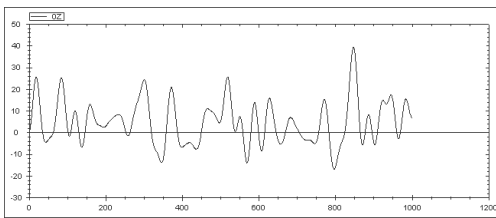
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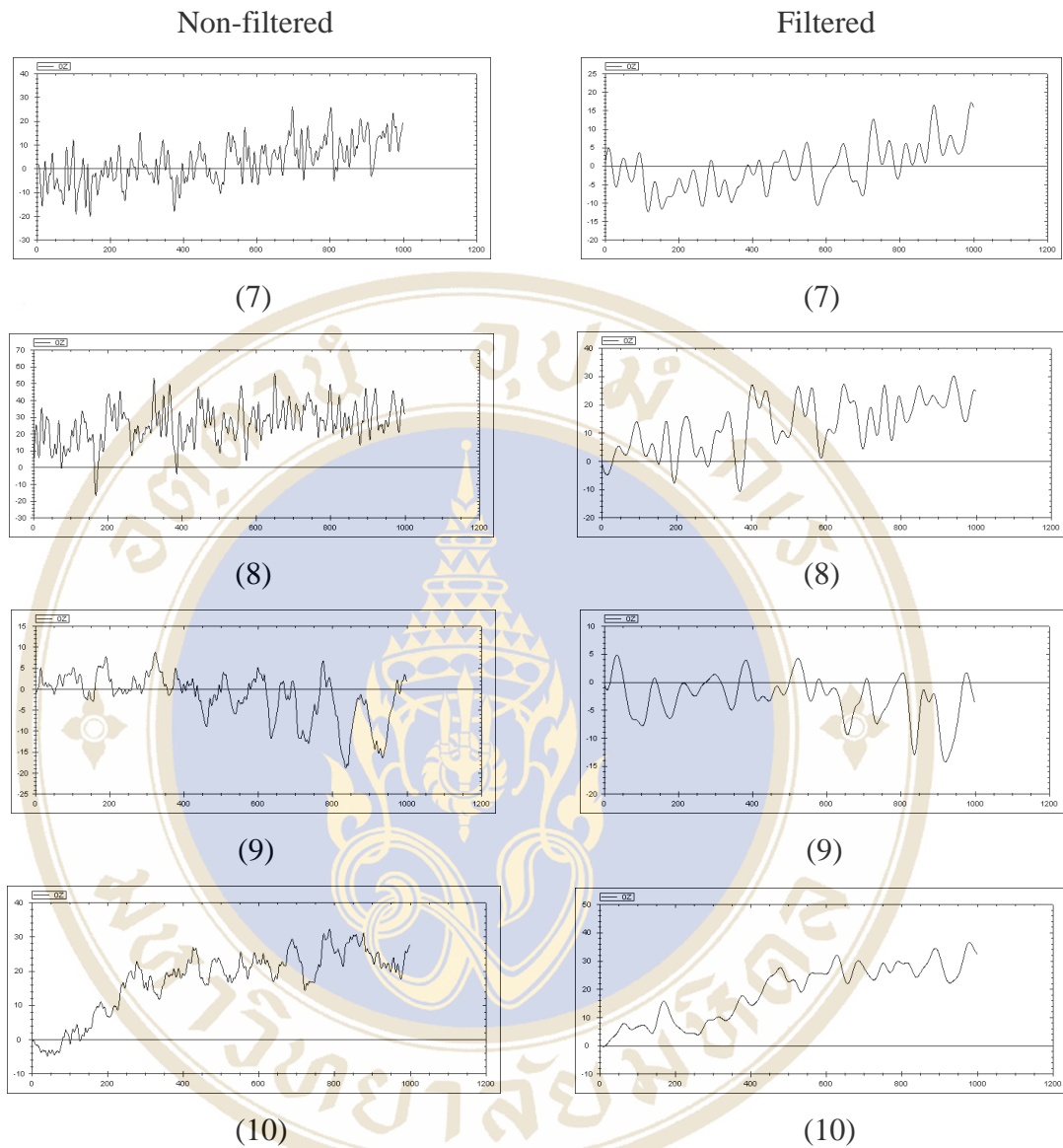
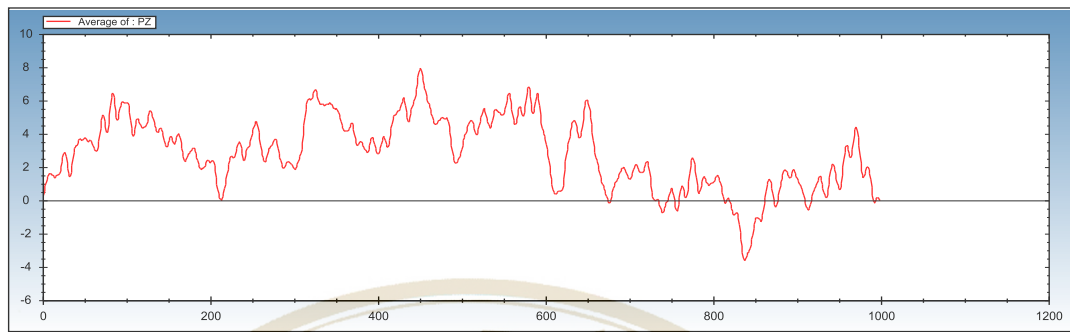
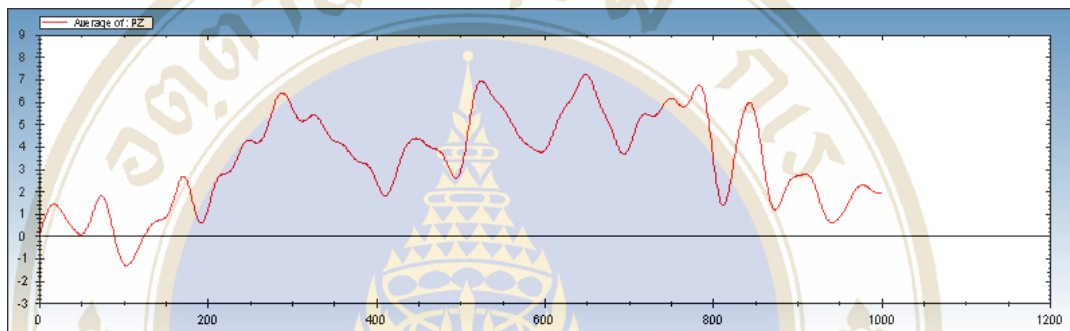


Figure 4.4 Epoch graph at Oz

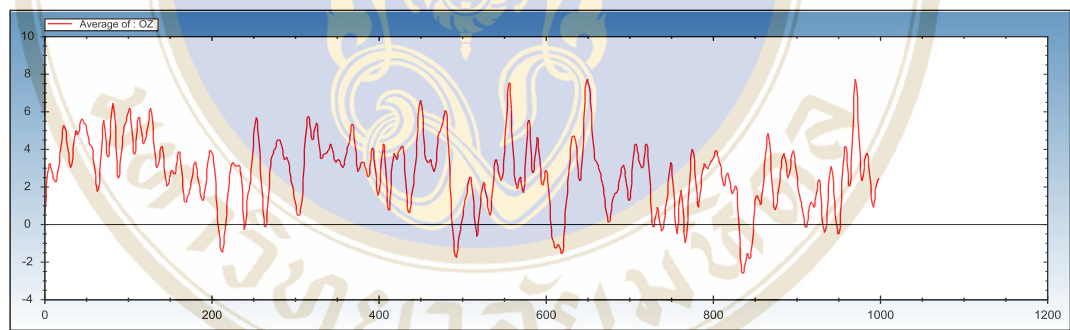
From Figures 4.3-4.4, these signals in left side were shown the signals, non-filtered, and the right side were shown filtered signals with FIR. These signals appeared in the process of ERP analysis before averaging signals. In Figure 4.5, they showed an average signal in the process of ERP analysis.



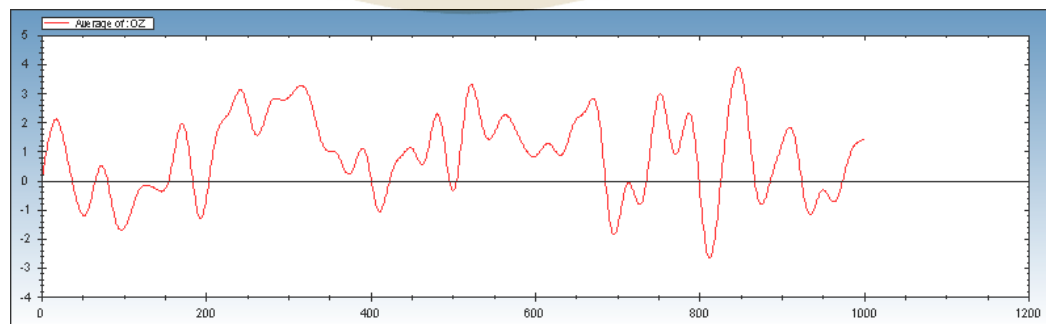
(a)



(b)



(c)



(d)

Figure 4.5 ERP signal

(a) Pz electrode (non-filtered) (b) Pz electrode (filtered)

(c) Oz electrode (non-filtered) (d) Oz electrode (filtered)

4.2 Non-linear filter

The wavelet technique is applied to our research. In this application, the EEG is filtered by the wavelet function. This filtered EEG is shown in Figure 4.6. As the result, the wavelet method is able to reduce noise from EEG signals. In this study we apply three types of wavelet which can denoise the signals for ERP analysis. We use the signals before and after filtered with FIR and also in comparison with wavelet transform for instance by Daubechies-6, by Symlets-7 and by Haar with fifth level of decomposition.

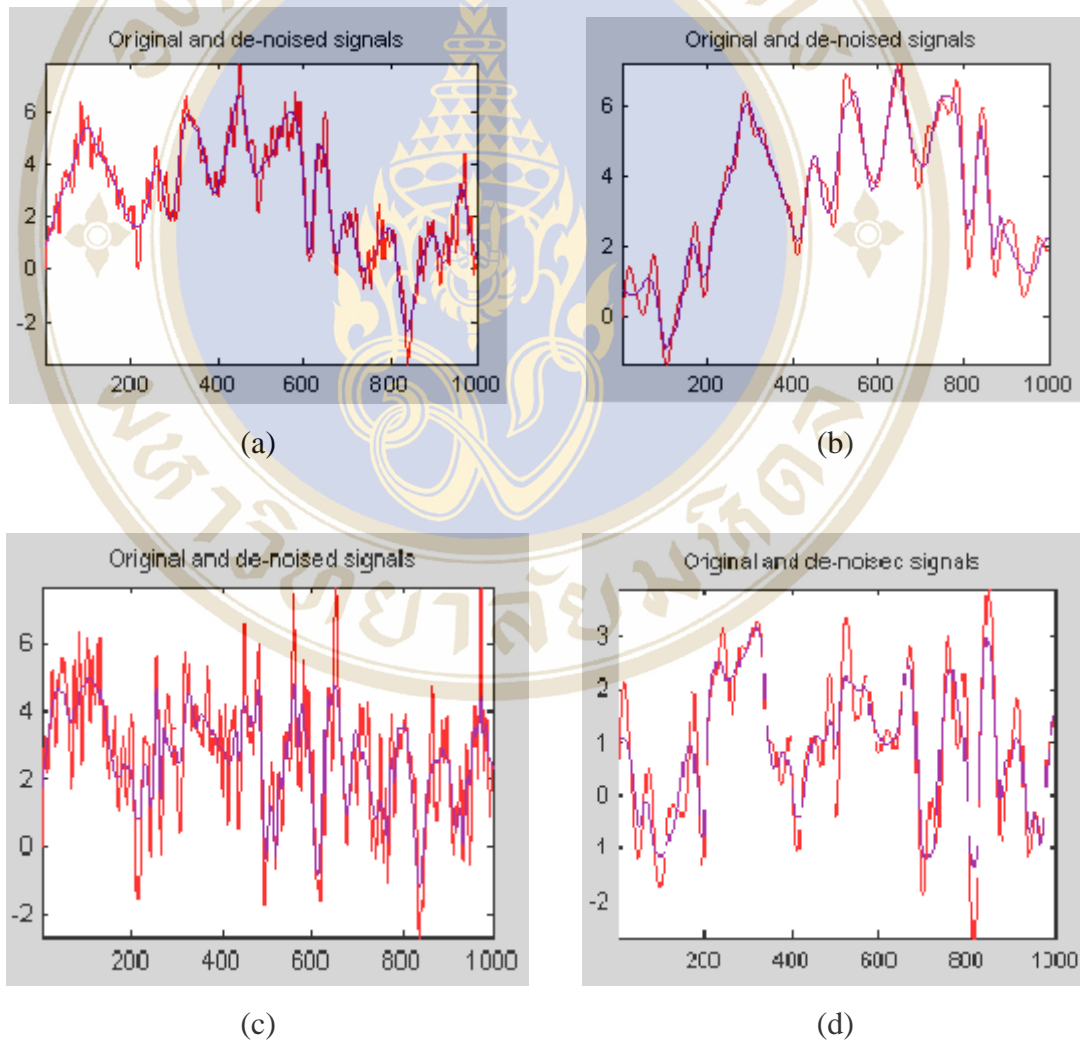


Figure 4.6 Filters by Daubechies-6

- (a) Average signal in Pz (non-filtered) (b) Average signal in Pz (filtered)
- (c) Average signal in Oz (non-filtered) (d) Average signal in Oz (filtered)

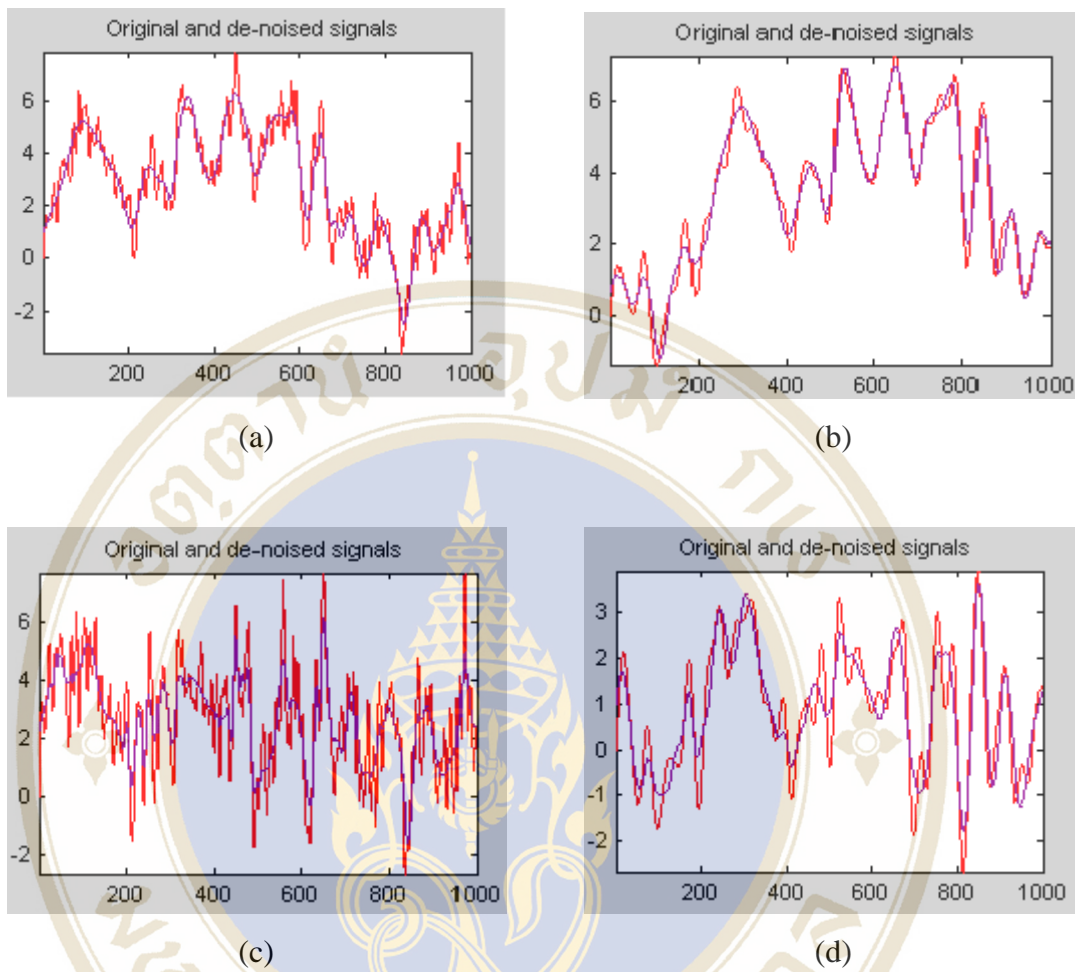


Figure 4.7 Filters by Symlets-7

- (a) Average signal in Pz (non-filtered)
- (b) Average signal in Pz (filtered)
- (c) Average signal in Oz (non-filtered)
- (d) Average signal in Oz (filtered)

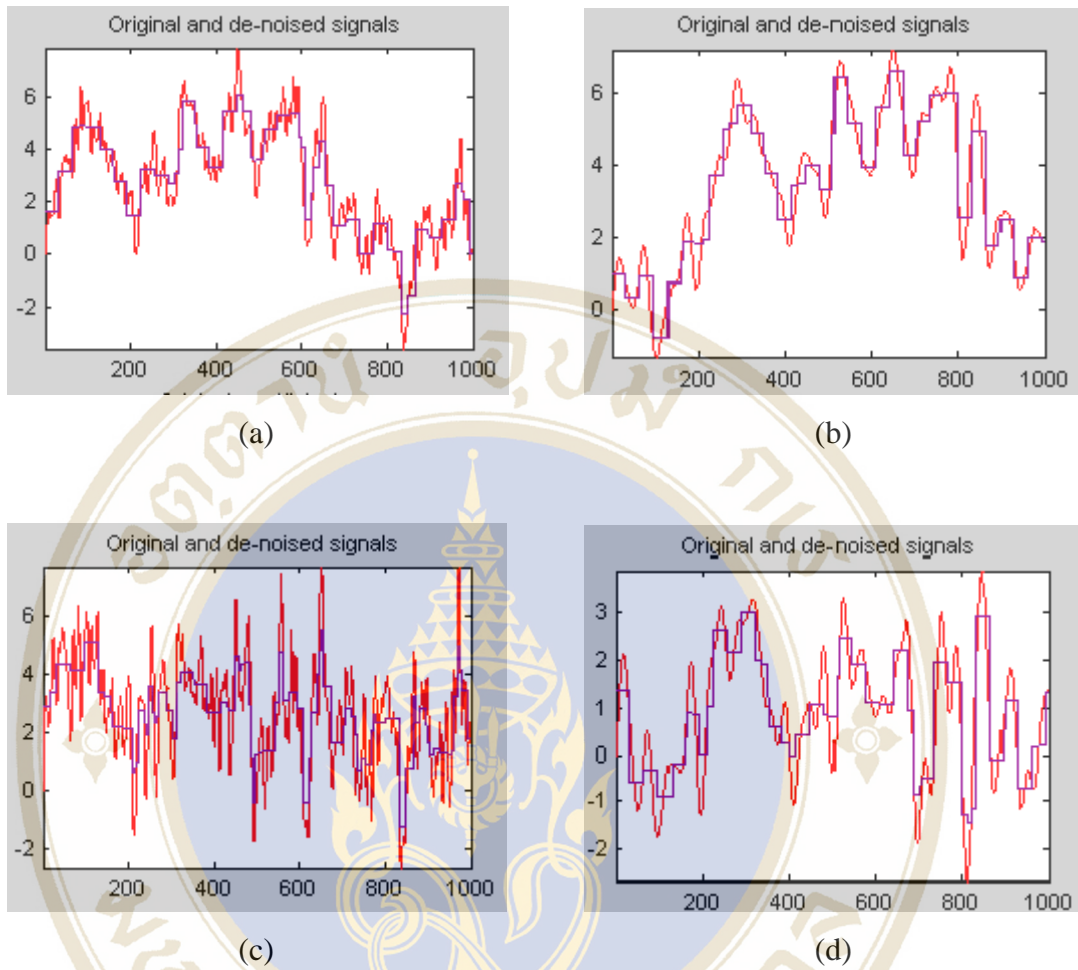


Figure 4.8 Filter by Haar

- (a) Average signal in Pz (non-filtered) (b) Average signal in Pz (filtered)
- (c) Average signal in Oz (non-filtered) (d) Average signal in Oz (filtered)

Figures 4.6-4.8 show that kinds of wavelet selection can highly act on ERP signal denoising: Daubechies-6 and Symlets-7 wavelet can improve greatly the signal but Haar wavelet cannot give significantly denoise as a result of Haar’s characteristic is stepping graph which is not suitable for ERP signal denoising.

CHAPTER V

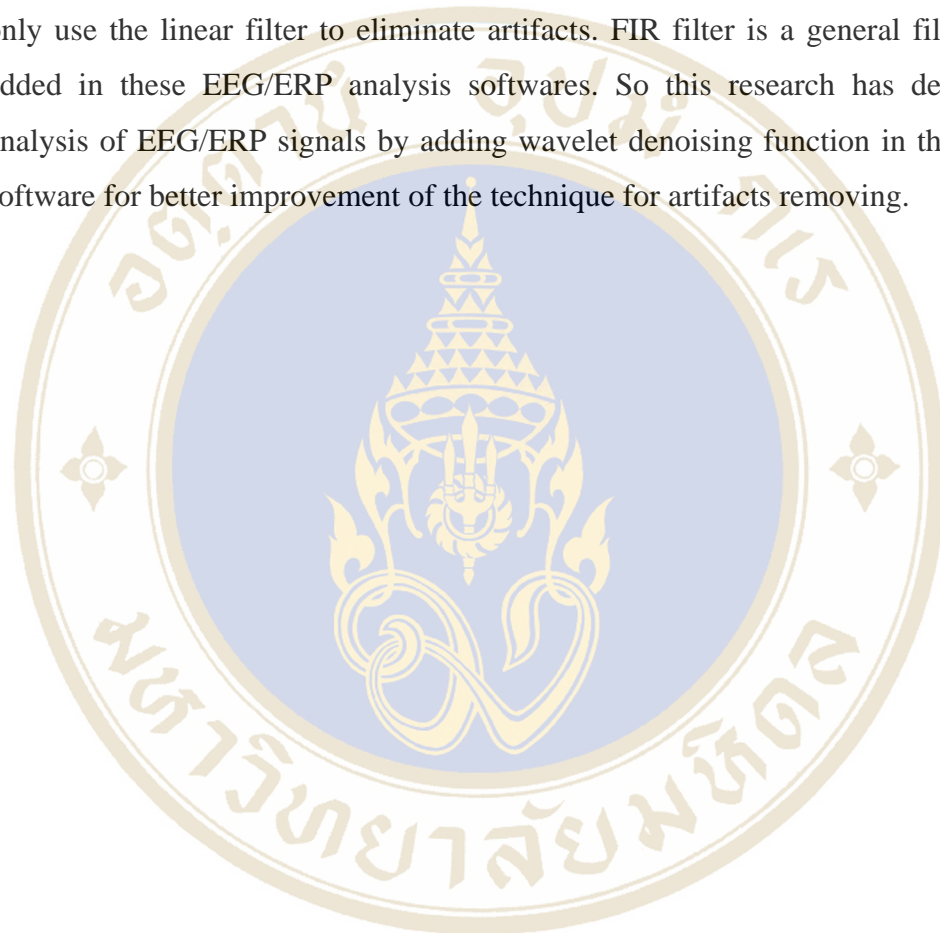
DISCUSSION

To compare the EEG/ERP signals from audio stimulus before and after filtering by FIR filter, Figure 4.1 - Figure 4.4 show that the FIR filter works well in the range of the interesting signals (0.1-30 Hz) and unwanted noises were removed from signals. We can see the P300 from the result in Figure 4.4 to Figure 4.5. These findings can reduce the burden of the analyst in diagnosing the graph. But we still have problems with the characteristics of the broadband noise so a better way to eliminate the noises from EEG signal should use wavelet transform which is a non-linear filter. Figures 4.6 and 4.7 show that Daubechies-6 and Symlets-7 wavelet denoising at the fifth level of decomposition can highly improve the signal-to-noise (EEG/ERP) enough to evaluate quantitatively, especially when it is combined with the FIR filter. It has a great performance. However, Figure 4.8 shows the signals which were filtered by Haar wavelet denoising at same level of decomposition. The signals cannot significantly be denoised as a result of the characteristics of Haar which is not suitable for ERP signal denoising. These wavelet functions use threshold selection by Donoho's technique [24]. So in the process of wavelet denoising, we need to know about signal processing well and to carefully choose wavelet function for wavelet denoising.

From R. Quian Quiroga [19, 20] and Haiyan Ding researches, they denoised the average EEG/ERP signal by using wavelet transform technique. The result is shown that wavelet transform has good performance to denoise EEG signals. The disadvantages in their methods are in the real research which sometimes we are interested in the certain range of frequency. In their researches they use wavelet denoise average signal. It may lead to the loss in some detail of signal that may be imperative to diagnostic signal. To improve this technique, we applied the FIR filter to the EEG signals and then applied the wavelet de-noising technique to EEG/ERP

signal. We can denoise the background noise and use the wavelet in order to enhance EEG signal. The result from these processes shows the good qualitative signal that help to gain benefit in diagnosis of the diseases from brain.

In comparison with EEG/ERP analysis softwares, the original commercial program is “Neuroscan” and some programs such as “EEGLAB” and “Eptor,” which only use the linear filter to eliminate artifacts. FIR filter is a general filter which is added in these EEG/ERP analysis softwares. So this research has developed the analysis of EEG/ERP signals by adding wavelet denoising function in the developed software for better improvement of the technique for artifacts removing.



CHAPTER VI

CONCLUSION

This study shows the difference between the signals before and after filtering by FIR filter. FIR filter works well for EEG/ERP analysis. The FIR filter can eliminate the artifacts from the EEG signal and help the analyst to diagnose the signal ahead. At present, the linear filter is widely used in commercial software which is built on EEG equipment. However, the reduction of additive noise by wavelet denoising technique is better than the linear technique. The properties of wavelets are appropriate to decrease broadband noise such as white noise. In this research the wavelet method performs well to reduce noise. However, some wavelet functions, such as Haar wavelet, do not work well in wavelet denoising process. Because the characteristic of Haar wavelet function is not suitable for EEG/ERP signals. So the researchers should select the suitable wavelets for each application. In this research, Daubechies-6 and Symlets-7 wavelets have good performances in the EEG/ERP signals de-noising process. Finally, the wavelet transform combined with the FIR filter was applied to remove the EEG artifacts. This technique works very well and is thus suitable for EEG/ERP analysis in aid of diagnoses.

Future Works

Furthermore, the other wavelet functions may be applied in this developed software. Additionally, the other functions may be used in the process of ERP analysis, such as comparison of 2 stimules.

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APPENDIX A

C# Program

FIR Highpass Filter

```

using System;
using System.Collections.Generic;
using System.Text;
using ZedGraph;

namespace Core
{
    public class HPFillter
    {
        //fc = ผู้ใช้กรอก
        //fs = Sampling Rate (อ่านมาจากไฟล์)
        public Double [] GetCoefficient(Int32 N, Double fc, Double fs)
        {
            Double [] H = new Double[N];
            Int32 n = (N - 1) / 2;
            Double F = fc / fs;
            Double wc = 2 * Math.PI * F;

            int k;
            Double wk;
            Double [] hd = new Double[n];
            for (k = 1; k <= n; k++)
            {
                wk = 0.5+0.5*Math.Cos((2*Math.PI*k)/N);
                hd[k-1] = -((Math.Sin(wc * k)) / (k * Math.PI)) * wk;
            }

            int n1 = 0;
            for (k = n-1; k > 0; k--)
            {
                H[n1] = hd[k];
                n1++;
                H[n1] = hd[k];
            }

            H[n1] = 1 - wc / Math.PI;

            for (k = 0; k < n; k++)
            {
                n1++;
                H[n1] = hd[k];
            }

            return H;
        }

        public PointPairList ApplyHP(PointPairList originalData, int
N, Double fc)
        {

```

```
//int N = 201;
Double fs = 1000;
//Double fc = 0.1;

PointPairList pplResult = new PointPairList();
Double[] cofs = GetCoefficient(N, fc, fs);

int n = 0;
foreach (PointPair pp in originalData)
{
    Double sum = 0;
    for (int k = 0; k < N; k++)
    {
        if (n - k >= 0)
        {
            sum += cofs[k] * originalData[n - k].Y;
        }
        else
        {
            sum += 0;
        }
    }
    PointPair ppResult = new PointPair(n, sum);
    pplResult.Add(ppResult);
    n++;
}
return pplResult;
}
}
```

FIR Lowpass Filter

```

using System;
using System.Collections.Generic;
using System.Text;
using ZedGraph;

namespace Core
{
    public class LPFillter
    {
        public Double[] GetCoefficient(Int32 N, Double fc, Double fs)
        {
            Double[] H = new Double[N];
            Int32 n = (N - 1) / 2;
            Double F = fc / fs;
            Double wc = 2 * Math.PI * F;

            int k;
            Double wk;
            Double[] hd = new Double[n];
            for (k = 1; k <= n; k++)
            {
                wk = 0.5 + 0.5 * Math.Cos((2 * Math.PI * k) / N);
                hd[k - 1] = ((Math.Sin(wc * k)) / (k * Math.PI)) *
                wk;
            }

            int n1 = 0;
            for (k = n - 1; k > 0; k--)
            {
                H[n1] = hd[k];
                n1++;
                H[n1] = hd[k];
            }

            H[n1] = wc / Math.PI;

            for (k = 0; k < n; k++)
            {
                n1++;
                H[n1] = hd[k];
            }

            return H;
        }

        public PointPairList ApplyLP(PointPairList originalData, int
N, Double fc)
        {
            //int N = 201;
            Double fs = 1000;
            //Double fc = 30;

            PointPairList pplResult = new PointPairList();
            Double[] cofs = GetCoefficient(N, fc, fs);

```

```
int n = 0;
foreach (PointPair pp in originalData)
{
    Double sum = 0;
    for (int k = 0; k < N; k++)
    {
        if (n - k >= 0)
        {
            sum += cofs[k] * originalData[n - k].Y;
        }
        else
        {
            sum += 0;
        }
    }
    PointPair ppResult = new PointPair(n, sum);
    pplResult.Add(ppResult);
    n++;
}
return pplResult;
}
}
```

Wavelet Denoising

```

using System;
using System.Collections.Generic;
using System.Text;
using ZedGraph;

namespace Core.Wavelet
{
    public abstract class AbstractWavelet
    {
        private Double[] _Lo_D;

        public Double[] Lo_D
        {
            get { return _Lo_D; }
            set { _Lo_D = value; }
        }
        private Double[] _Hi_D;

        public Double[] Hi_D
        {
            get { return _Hi_D; }
            set { _Hi_D = value; }
        }
        private Double[] _Lo_R;

        public Double[] Lo_R
        {
            get { return _Lo_R; }
            set { _Lo_R = value; }
        }
        private Double[] _Hi_R;

        public Double[] Hi_R
        {
            get { return _Hi_R; }
            set { _Hi_R = value; }
        }

        public WaveletResult Apply(PointPairList originalData, int
level, bool isDenoise, bool isSoft)
        {
            WaveletResult result = new WaveletResult();
            ResultNode root = new ResultNode();
            result.ResultRoot = root;
            result.Level = level;
            for (int i = 0; i < level; i++)
            {
                ResultNode node = null;
                if (i == 0)
                    node = root;
                else
                {
                    node = new ResultNode();
                    result.LastChild.Child = node;
                }
                PointPairList pplA = this.GetA(originalData);

```

```

        PointPairList pplD = this.GetD(originalData);
        if (isDenoise)
        {
            ApplyDenoise(pplD, isSoft);
        }
        node.A = pplA;
        node.D = pplD;
        originalData = result.LastChild.A;
    }
    result.S = GetS(result);
    return result;
}

protected PointPairList GetA(PointPairList original)
{
    PointPairList pplResult = new PointPairList();
    for (int n = 0; n < original.Count; n++)
    {
        //if (n > 5000)
        //    break;
        Double sum = 0;
        for (int k = 0; k < this.Lo_D.Length; k++)
        {
            if (n - k >= 0)
            {
                sum += this.Lo_D[k] * original[n - k].Y;
            }
            else
            {
                sum += 0;
            }
        }

        PointPair ppResult = new PointPair(original[n].X,
sum);
        pplResult.Add(ppResult);
    }
    DownData(pplResult);
    return pplResult;
}

protected PointPairList GetAr(PointPairList original)
{
    PointPairList pplResult = new PointPairList();

    for (int n = 0; n < original.Count; n++)
    {
        //if (n > 5000)
        //    break;
        Double sum = 0;
        for (int k = 0; k < this.Lo_R.Length; k++)
        {
            if (n - k >= 0)
            {

```

```

        sum += this.Lo_R[k] * original[n - k].Y;
    }
    else
    {
        sum += 0;
    }
}

PointPair ppResult = new PointPair(original[n].X,
sum);
pplResult.Add(ppResult);
}
return pplResult;
}

//protected PointPairList[] GetDs(PointPairList original,int
level)
//{
//    PointPairList[] pplResult = new PointPairList[level];
//    for (int count = 0; count < level; count++)
//    {
//        PointPairList ppl = new PointPairList();
//        for (int n = 0; n < original.Count; n++)
//        {
//            //if (n > 5000)
//            //    break;
//            Double sum = 0;
//            //Console.WriteLine("GetDs : pp = {0},{1}",
pp.X, pp.Y);
//            for (int k = 0; k < this.Hi_D.Length; k++)
//            {
//                if (n - k >= 0)
//                {
//                    sum += this.Hi_D[k] * original[n -
k].Y;
//                }
//                else
//                {
//                    sum += 0;
//                }
//            }
//            //Console.WriteLine("Sum : {0}", sum);
//            Console.WriteLine("{0}%", ((Double)n /
(Double)original.Count) * 100);
//            PointPair ppResult = new
PointPair(original[n].X, sum);
//            ppl.Add(ppResult);
//        }
//        DownData(ppl);
//        pplResult[count] = ppl;
//        original = pplResult[count];

```

```

//    }
//    return pplResult;
//}

private PointPairList GetS(WaveletResult waveResult)
{
    PointPairList pplSum = null;
    for (int i = waveResult.Level-1; i >=0 ; i--)
    {
        PointPairList d = UpData(waveResult.D[i]);
        PointPairList a = null;
        if (i == waveResult.Level-1)
        {
            a = UpData(waveResult.A[i]);
        }
        else
        {
            a = UpData(pplSum);
        }

        pplSum = Sum(GetAr(a), GetDr(d));
    }
    return pplSum;
}

private PointPairList Sum(PointPairList a, PointPairList d)
{
    PointPairList pplSum = new PointPairList();
    foreach (PointPair ppd in d)
    {
        //bool isMax = false;
        foreach (PointPair ppa in a)
        {
            if ((int)ppd.X == (int)ppa.X)
            {
                pplSum.Add(ppd.X, ppd.Y + ppa.Y);
                break;
            }
            else if ((int)ppa.X > (int)ppd.X)
            {
                break;
            }
        }
    }
    return pplSum;
}

protected PointPairList GetD(PointPairList original)
{
    PointPairList ppl = new PointPairList();
    for (int n = 0; n < original.Count; n++)
    {
        Double sum = 0;
        for (int k = 0; k < this.Hi_D.Length; k++)
        {
            if (n - k >= 0)

```

```

        {
            sum += this.Hi_D[k] * original[n - k].Y;
        }
        else
        {
            sum += 0;
        }
    }
    PointPair ppResult = new PointPair(original[n].X,
sum);
    ppl.Add(ppResult);
}
DownData(ppl);
return ppl;
}

protected PointPairList GetDr(PointPairList original)
{
    PointPairList ppl = new PointPairList();
    for (int n = 0; n < original.Count; n++)
    {
        //if (n > 5000)
        //    break;
        Double sum = 0;
        //Console.WriteLine("GetDs : pp = {0},{1}", pp.X,
pp.Y);
        for (int k = 0; k < this.Hi_R.Length; k++)
        {
            if (n - k >= 0)
            {
                sum += this.Hi_R[k] * original[n - k].Y;
            }
            else
            {
                sum += 0;
            }
        }
        PointPair ppResult = new PointPair(original[n].X,
sum);
        ppl.Add(ppResult);
    }
    return ppl;
}

private void DownData(PointPairList ppl)
{
    int count = ppl.Count;
    PointPair next;
    PointPair ppToMove = ppl[1];
    for (int i = 1; i <= (count/2)-1; i++)
    {
        next = ppl[ppl.IndexOf(ppToMove)+1];
        ppl.Remove(ppToMove);
    }
}

```

```

        ppToMove = ppl[ppl.IndexOf(next) + 1];
    }
}

private PointPairList UpData(PointPairList pplOri)
{
    PointPairList ppl = pplOri.Clone();
    int count = ppl.Count;

    PointPair pre = ppl[0];

    //PointPair pp = new PointPair((int)(0 + pre.X) / 2, 0);
    //ppl.Insert(0, pp);

    //pre = pp;
    PointPair next = ppl[1];

    for (int i = 1; i <= count-1; i++)
    {
        PointPair pp = new
PointPair((int)(next.X+pre.X)/2,0);
        ppl.Insert(ppl.IndexOf(next), pp);
        pre = next;
        if(i!=count-1)
            next = ppl[ppl.IndexOf(next) + 1];
    }
    return ppl;
}

private void ApplyDenoise(PointPairList ppl, Boolean isSoft)
{
    double o = GetMedean(ppl) / 0.6745;
    foreach (PointPair pp in ppl)
    {
        Double t = o * Math.Sqrt(2*Math.Log(pp.X+1,Math.E));
        if (isSoft)
        {
            double temp = Math.Abs(pp.Y)-t;
            temp = (temp + Math.Abs(temp)) / 2;
            pp.Y = Math.Sign(pp.Y) * temp;
        }
        else
        {
            if (pp.Y < t)
            {
                pp.Y = 0;
            }
        }
    }
}

private Double GetMedean(PointPairList ppl)
{
    PointPairList pplClone = ppl.Clone();
    foreach (PointPair pp in pplClone)
    {

```

```
        pp.Y = Math.Abs(pp.Y);  
    }  
  
    pplClone.Sort(SortType.YValues);  
    return pplClone[pplClone.Count/2].Y;  
} }  
}
```

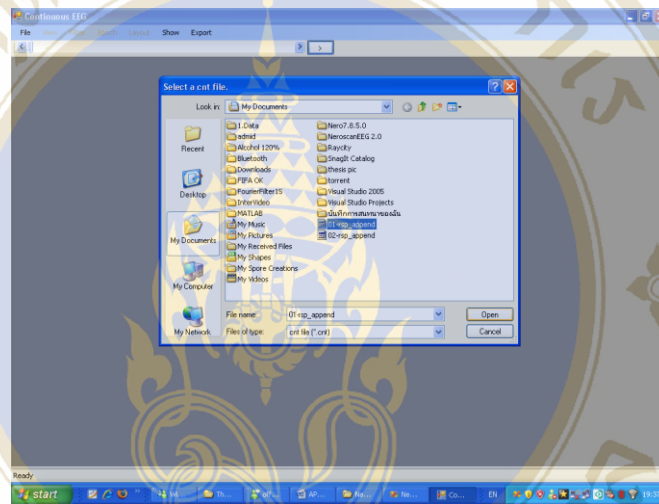


APPENDIX B

User guide

1. Open file

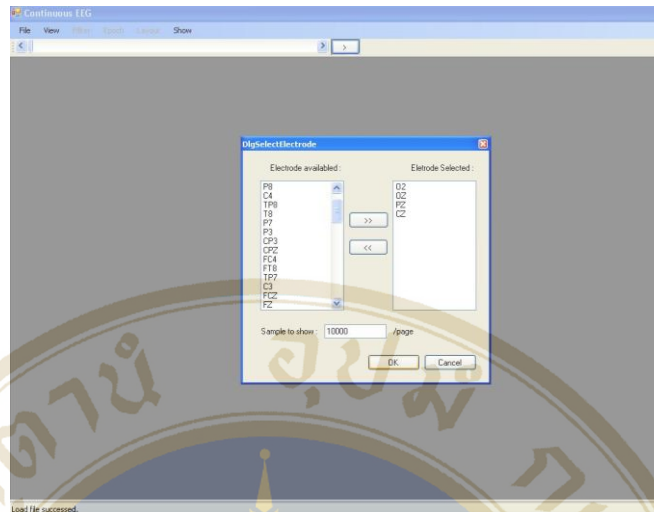
File → Open → choose *.cnt (EEG files which are recorded by neuroscan machine)



2. Select electrodes (according to following the number of recorded file)

Double click to select the interesting electrode at left side.

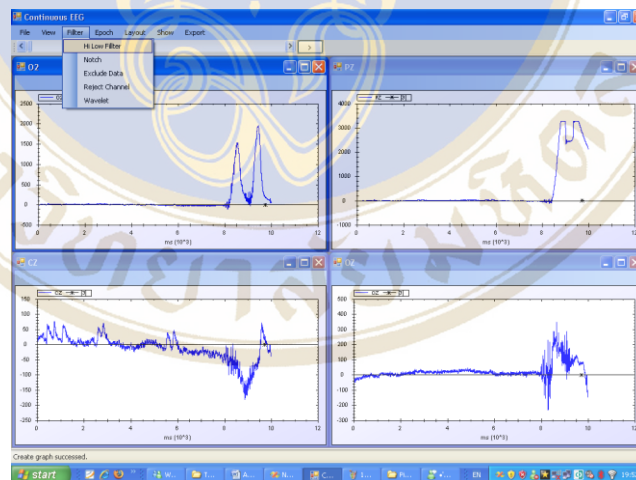
Key number of points for showing in each window.



3. The graph will appear as selected electrode

In case of Filter → Hi Low Filter is the Filter by mean of FIR filter.

And Filter → Wavelet is the Filter by using wavelet denoising technique.



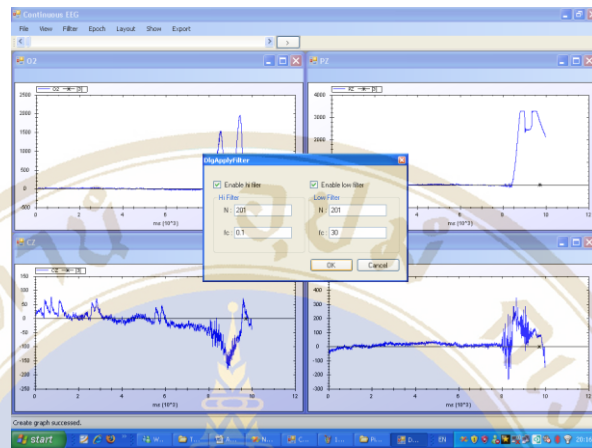
4. FIR filter

There are optional functions.

high pass filter (low frequency cut off) select at left side then fill a interesting frequency at fc channel.

low pass filter (high frequency cut off) select at right side then fill a interesting frequency at fc channel.

band pass filter (outside the scope of frequency cut off) select the both side then fill a interesting frequency at fc channel.

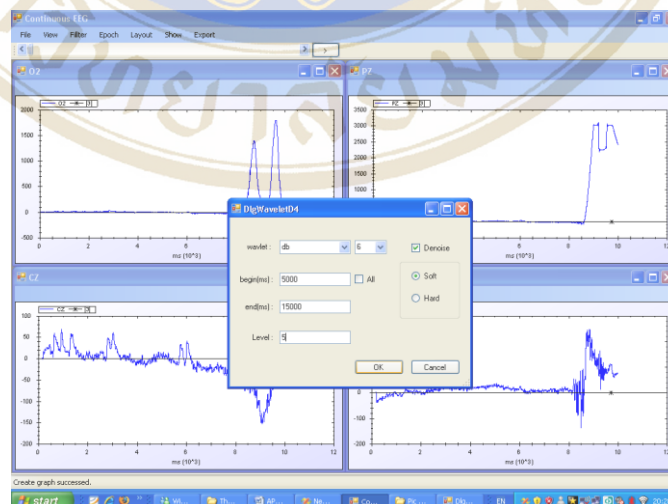


5. Wavelet denoising technique

Wavelet channel is selecting a type of wavelet function.

First, select interesting signal interval at the beginning point at begin (ms) channel: and end up at end (ms): channel

Then select a type of threshold at Denoise, either soft thresholding or hard thresholding.



6. Epoch selection

Select menu Epoch → Epoch Selection

Select the type of stimuli then choose signal interval

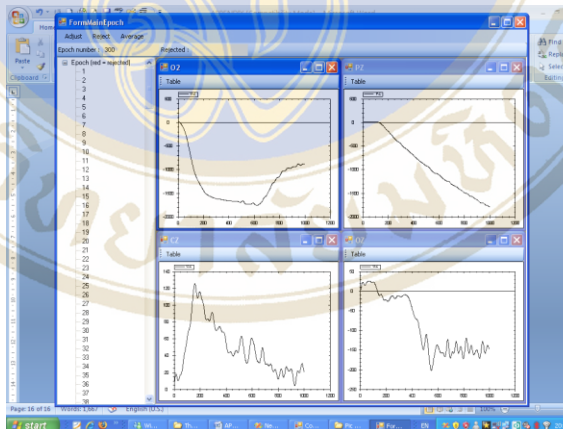
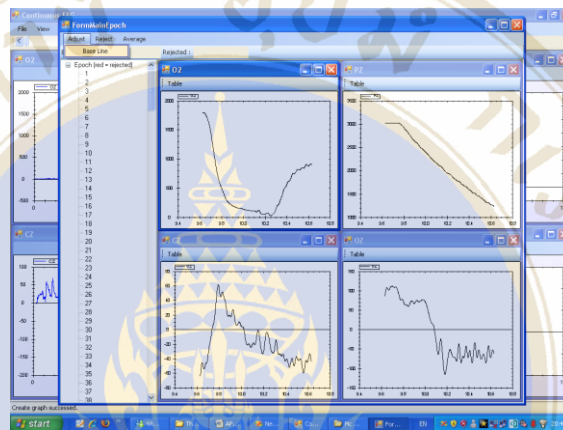
Before the starting time point before the stimuli start (milliseconds)

After the starting time point after the stimuli start (milliseconds)

7. Base line collection

Base line collection is for shift of the graph to the origin of the graph.

Select at menu Adjust → Base line

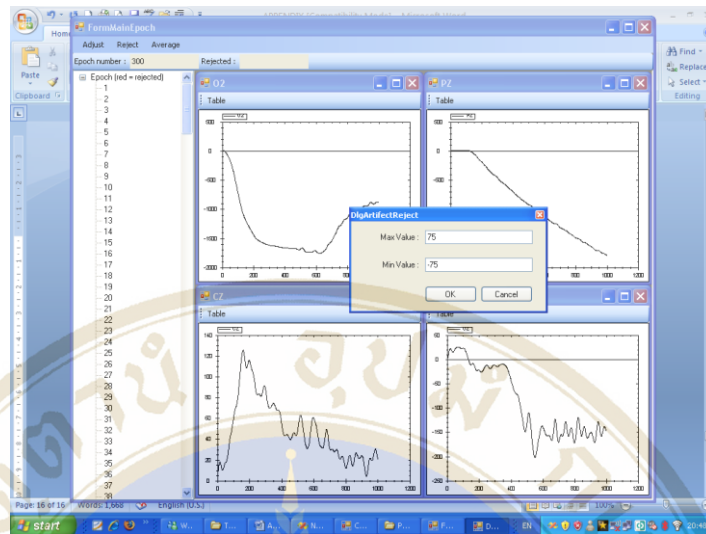


8. Artifact Rejection

Artifact Rejection is for eliminating the epoch which have amplitude which exceed the scope of the interest.

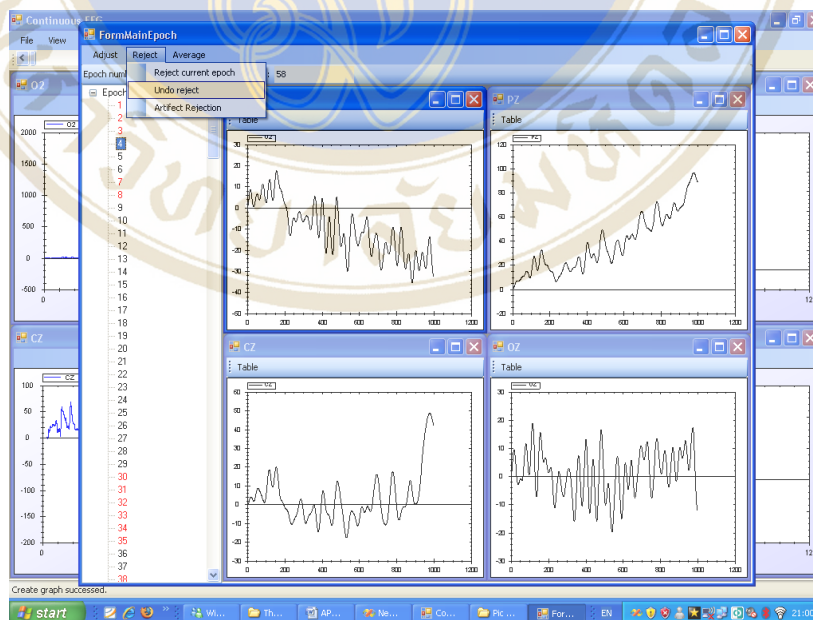
Select menu Reject → Artifact Rejection

Then set a value of the interesting amplitude in focus range (the highest and the lowest value amplitude)



After that we can select in each epoch either has epoch or not

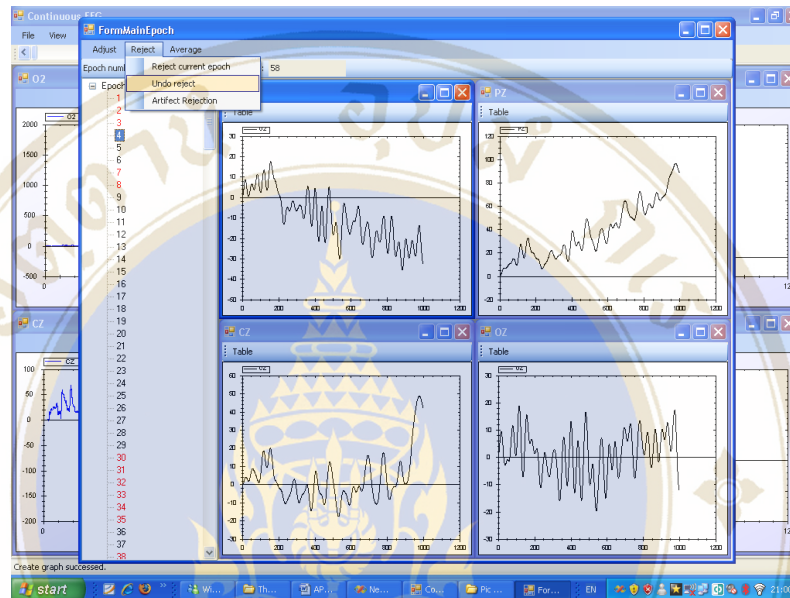
Select menu Reject → Reject Current Epoch and Undo Reject




9. Average Signal

After selecting the epoch then takes the selected graph to average

Select menu Average → Show average



BIOGRAPHY



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