

**MULTICHANNEL EEG MONITORING SYSTEM
WITH ARTIFACT REMOVAL, QUALITY ASSESSMENT
AND BRAIN MAPPING PROGRAM**

The seal of Mahidol University is a large, circular emblem in the background. It features a central golden chakra (a multi-tiered umbrella) surrounded by a blue ring. The outermost ring contains the university's name in Thai script: "มหาวิทยาลัยมหิดล" (Mahavithayalai Mahidol) at the top and "วิทยาเขตพุทธ" (Witayalai Phutth) at the bottom.

SQN. LDR. PINYO KHUMKAEW

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF ENGINEERING
(BIOMEDICAL ENGINEERING)
FACULTY OF GRADUATE STUDIES
MAHIDOL UNIVERSITY
2010**

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Thesis
entitled

**MULTICHANNEL EEG MONITORING SYSTEM
WITH ARTIFACT REMOVAL, QUALITY ASSESSMENT
AND BRAIN MAPPING PROGRAM**



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was submitted to the Faculty of Graduate Studies, Mahidol University
for the degree of Master of Engineering (Biomedical Engineering)

on
April 9, 2010



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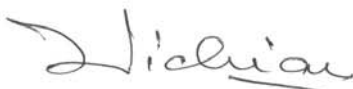
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ACKNOWLEDGEMENTS

I would like to thank my supervisor Lect. Dr. Yodchanan Wongsawat for constantly motivating and encouraging me, and also for his supporting and invaluable advice during the course of my master studies. I am highly grateful to my co-adviser Asst. Prof. Dr. Warakorn Charoensuk for providing me useful guidance on my research. I would like to thank my co-adviser Lect. Dr. Zeng Lertmanorat for his comments and suggestions for the development of Bio-Amplifier for my thesis. I wish to thank my co-advisors Lect. Dr. Wichian Sittiprapaporn for his interests in my research and for taking time advice me in EEG knowledge, in practice and application.

I would like to extend my appreciation to the chair of oral thesis defence committee Lect. Dr. Yuttapong Jiraraksopakun, King Mongkut's University of Technology Thonburi, for his interests in my research and for taking time suggest me for the improvement.

Furthermore, I appreciate all my professors, my friends and all staff in Department of Biomedical Engineering for their contribution during my coursework and through all my academic years. My special thanks go to my BCI labmates for their helpful comments and supporting on my research. Many thanks go to Navy Admiral Dr. Pibul Nacaskul for suggestion on my paper writing.

I would like to thank Dr. Kianoush Nazarpour and Dr. Saeid Sanei, the school of engineering, Prof. Edward Wilding, the school psychology, Cardiff University, for providing the dataset for the artifact removal experiment.

I would also like to acknowledge Khumklao Foundation scholarship, Bhumibol Adulyadej Hospital, Directorate of Medical Services, Royal Thai Air Force for great opportunity in education and research supports. Moreover, I would like to give a very worm thank to my boss and my friends in the Department of Hospital Engineering, Bhumibol Adulyadej Hospital who are working hard during my master studies.

Finally, my deep gratitude goes to my family for inspiring and supporting me toward my master degree.

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MULTICHANNEL EEG MONITORING SYSTEM WITH ARTIFACT REMOVAL, QUALITY ASSESSMENT AND BRAIN MAPPING PROGRAM

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ABSTRACT

The electroencephalogram (EEG) monitoring system has been widely applied to assist many researches and clinical applications. However, EEG monitoring systems are still very expensive. This issue results in developing countries, e.g. Thailand, seeking locally made devices that employ the local resources and achieve acceptable performance. In this work, a prototype of multichannel EEG monitoring hardware and software that can be used in conjunction with real time monitoring and can perform some EEG analyses are proposed. The prototype system provides a 19-channel EEG amplifier and can monitor EEG signals according to the 10-20 system. The options provided for the proposed system are real time signal waveform monitoring, signal filtering, signal quality assessment in terms of signal to noise ratio, power spectral density, and topographic brain mapping. The acquired dataset can be saved in ASCII format. Furthermore, a method used to enhance the performance of the implementation of robust minimum variance beamforming (RMVB)-based eyeblink artifacts removal from the multichannel EEG is also proposed as additional offline software. The system is suitable for measuring scalp EEG which has a frequency range between 0.5 to 45 Hz with amplification gain of 10,000. The system is also designed to meet the medical standards for electrical hazards protection. The provided software is helpful for EEG analyses and flexible for further development with respect to some specific problems, e.g. montage setup, 3-D brain mapping, more pattern recognition and source localization. Moreover, this inexpensive system could also be used for other multichannel bio-signals monitoring systems, intraoperative monitoring research and brain-computer interface (BCI) systems.

KEY WORDS: ELECTROENCEPHALOGRAPH / MONITORING SYSTEM / ARTIFACT REMOVAL / SIGNAL QUALITY ASSESSMENT / BRAIN MAPPING

77 pages

ระบบวัดสัญญาณไฟฟ้าจากสมองแบบหลายช่องสัญญาณ และโปรแกรมการกำจัดสัญญาณรบกวน การประเมินคุณภาพสัญญาณ และการทำแผนที่จากสัญญาณสมอง

MULTICHANNEL EEG MONITORING SYSTEM WITH ARTIFACT REMOVAL, QUALITY ASSESSMENT AND BRAIN MAPPING PROGRAM

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บทคัดย่อ

ระบบวัดและเฝ้าระวังสัญญาณไฟฟ้าจากสมองมีการใช้งานแพร่หลายมากขึ้นทั้งในงานวิจัยและทางคลินิก เนื่องจาก ระบบ ดังกล่าวมีราคาสูงมาก จึงมีความเหมาะสมที่จะพัฒนาระบบดังกล่าวขึ้นใช้งานโดยใช้ทรัพยากรภายในประเทศ โดยต้องมีประสิทธิภาพในระดับที่ยอมรับได้ จุดประสงค์ของการวิจัยนี้ เพื่อพัฒนาและสร้างต้นแบบของระบบวัดและเฝ้าระวังสัญญาณไฟฟ้าจากสมองแบบหลายช่องสัญญาณ ที่สามารถแสดงผลตามเวลาจริง (Real Time) รวมทั้งสามารถประเมินและวิเคราะห์สัญญาณด้วยเครื่องมือบางชนิดได้ ระบบต้นแบบที่พัฒนาขึ้นประกอบด้วยช่องขยายสัญญาณจำนวน 19 ช่อง ซึ่งใช้สำหรับวัดสัญญาณไฟฟ้าสมองตามระบบ 10-20 (10-20 system) โปรแกรมต้นแบบที่พัฒนาขึ้นสามารถแสดงรูปแบบของสัญญาณตามเวลาจริง รวมทั้งสามารถเลือกกรองความถี่ในช่วงที่ต้องการได้ ในส่วนของการประเมินและวิเคราะห์สัญญาณ ระบบได้ออกแบบให้สามารถประเมินคุณภาพของสัญญาณโดยการแสดงอัตราส่วนของสัญญาณกับสัญญาณรบกวน (Signal to Noise Ratio) แสดงค่าการกระจายของพลังงานของสัญญาณในโดเมนของความถี่ (Power Spectrum Density) ของแต่ละช่องสัญญาณ แสดงการทำแผนที่ด้วยสัญญาณสมอง (Topographic Brain Mapping) รวมทั้งสามารถบันทึกข้อมูลไว้ในรูปแบบแอสกี (ASCII format) นอกจากนี้ยังได้พัฒนาวิธีการเพิ่มประสิทธิภาพของการตัดสัญญาณการกระพริบตาออกจากสัญญาณสมองโดยใช้หลักการ Robust Minimum Variance Beamforming (RMVB) ในรูปแบบของออฟไลน์ (Offline) ซอฟต์แวร์ ระบบที่พัฒนาขึ้น นี้มีความเหมาะสมสำหรับวัดสัญญาณไฟฟ้าสมองที่มีช่วงความถี่ระหว่าง 0.5-45 รอบต่อวินาที (Hz) โดยมีอัตราการขยายประมาณ 10,000 เท่า รวมทั้งใช้อุปกรณ์ที่มีความปลอดภัยทางไฟฟ้าตามมาตรฐานเครื่องมือแพทย์ โปรแกรมที่พัฒนาขึ้นมีประโยชน์ในการประเมินและวิเคราะห์สัญญาณเบื้องต้นและมีความยืดหยุ่นในการพัฒนาให้ตรงกับความต้องการของผู้ใช้ได้ง่าย ระบบดังกล่าวมีต้นทุนที่ไม่สูงและยังสามารถนำไปประยุกต์ใช้กับการวัดสัญญาณชีพอื่นๆ ระบบเฝ้าระวังระหว่างการผ่าตัด และระบบการเชื่อมต่อสัญญาณสมองกับคอมพิวเตอร์ (Brain-Computer Interface, BCI) ได้

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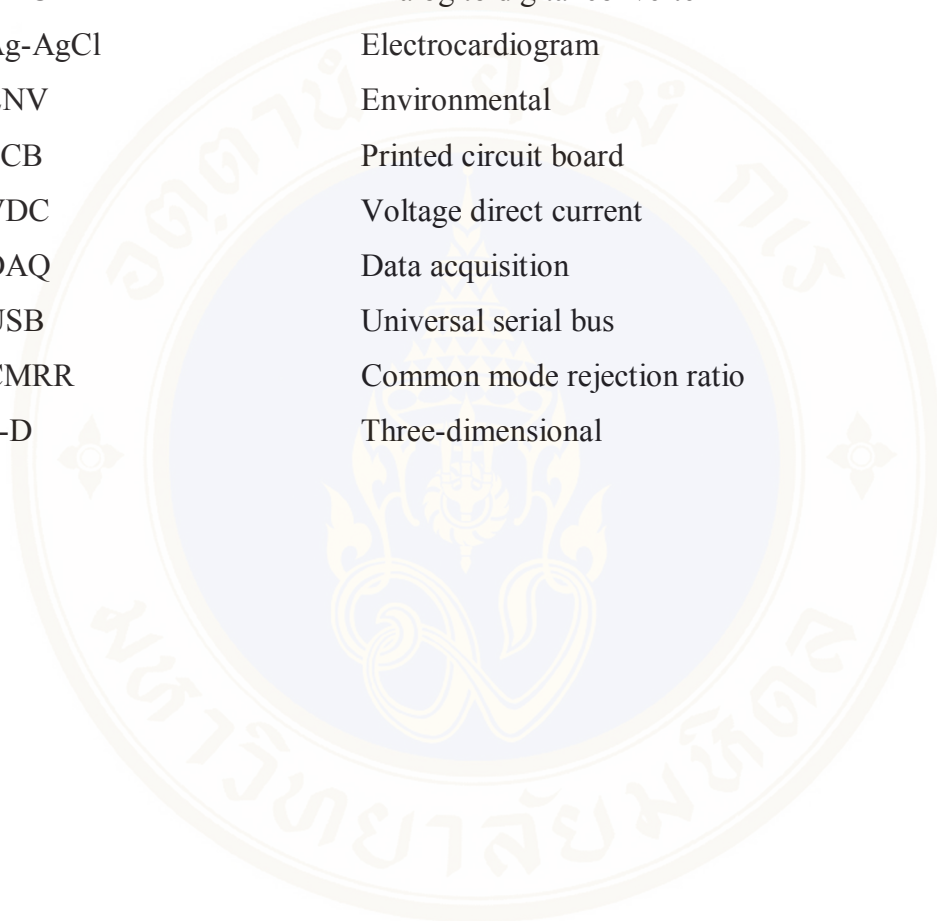
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LIST OF ABBREVIATIONS

EEG	Electroencephalography
BCI	Brain computer interface
EB	Eye-blink
RMVB	Robust minimum variance beamforming
2-D	Two dimensional
PSD	Power spectral density
QEEG	Quantitative electroencephalography
ERPs	Event-related potentials
BIS	Bispectral index
EEGo	Nonlinear EEG monitor
EOG	Electrooculogram
EMG	Electromyogram
BSS	Blind source separation
PCA	Principle component analysis
SDA	Source dipole analysis
ICA	Independent component analysis
SVM	Support vector machine
STF	Space-time-frequency
SSBE	Semi-blind signal extraction
PARAFAC	Parallel factor analysis
STF-TS	Space-time-frequency-time/segment
SNR	Signal to noise power ratio
FFT	Fast furrier transform
ADH	Attention deficit hyperactivity disorder
EPs	Evoked Potentials
FIR	Finite impulse response
ASCII	American Standard Code for Information Interchange

LIST OF ABBREVIATIONS (cont.)

MSE	Mean square error
ADC	Analog to digital converter
Ag-AgCl	Electrocardiogram
ENV	Environmental
PCB	Printed circuit board
VDC	Voltage direct current
DAQ	Data acquisition
USB	Universal serial bus
CMRR	Common mode rejection ratio
3-D	Three-dimensional

CHAPTER I

INTRODUCTION

1.1 Problem Statement

Traditionally, the electroencephalogram (EEG) monitoring system has been widely applied to assist many researches and clinical applications, such as to monitor alertness, coma, brain death, cognitive engagement, human and animal brain development [1]. Recently, EEG system has been used for neurofeedback training, monitoring the depth of sedation in patients under intensive care, or monitoring the effects of anesthetics and sedatives. However, EEG monitoring systems are still very expensive. For example, the EEG monitoring system produced by Nihon Kohden cost more than 2 million baht. The issue makes the developing countries, e.g. Thailand, seeking for the local made devices that employ the local resources together with the acceptable performance.

Not only the instruments themselves that consume very high cost, but also the software that can interface with the instrument. Moreover, some commercial softwares are still lack of the flexibility to adjust the function. Hence, development of local made software with respect to some specific problems is also needed.

Another issue needs to be concerned on designing the monitoring system is that the system need to be able to use in field and real-time analysis with the acceptable signal quality, e.g. in brain-computer interface (BCI). This means that the system also needs to be able to handle the artifact problems. Furthermore, the qualities of signals (multichannel EEGs) need to be quantitatively assessed.

In this work, 19-channel EEG monitoring device will be developed. It provides 19 channels for EEG signals. The signal wave form, signal quality, power spectral density and brain mapping will be displayed on the monitor of computer for monitoring in online mode. The acquired dataset can also be saved and used to analyze in offline mode. In the offline mode, the methods of eye blink (EB) artifacts removal are focused. In this study, we propose the method used to enhance the

performance of the robust minimum variance beamforming (RMVB)-based EB artifact removal from the EEGs by employing a simple digital filter. Subsequently, ideas about the evaluation methods for validating that artifact removal algorithm are presented.

1.2 Objectives

The objectives of the study are as follows:

1.2.1 To develop the prototype both hardware and software of the 19-channel EEG monitoring device that employs the local resources.

1.2.2 To develop the practical algorithm that can efficiently assess the quality of the multichannel EEG signals.

1.2.3 To develop and validate the method used for enhancing the quality of the EB artifacts removed EEG signals.

1.3 Expected Results

The expected results of this thesis are

1.3.1 The prototype of 19-channel EEG monitoring hardware and software that can perform some EEG analyses, e.g. filtering, 2 dimension (2-D) brain mapping and power spectral density (PSD).

1.3.2 The EEG assessment modality that can be used in conjunction with real time monitoring.

1.3.3 The method for reducing EB artifacts from the EEG signals which is well-suited to quantitative electroencephalography (QEEG) analysis and brain computer interface (BCI) applications.

CHAPTER II

LITERATURE REVIEWS

In this chapter, a brief introduction to EEG and related knowledge are presented. The previous research and the methodology that has been proposed to develop EEG monitoring system are also discussed.

2.1 Electroencephalography (EEG)

Human brain generates electrical signal which is called EEG. Groups of neurons in our body generate potentials which refer to the mixture of extracellular currents [1, 2]. EEG is the summation of these potentials [3]. We can measure EEG directly from the cortical surface using a technique called electrocortigram. In other technique, called electrogram, EEG can measure by using depth probes. The technique measures EEG from the scalp surface can be applied repeatedly to the subjects without risk and completely non-invasive manner.

2.1.1 EEG Rhythms

EEG rhythms are usually classified based on ranges of their frequencies as delta, theta, alpha, beta, and gamma [2]. Normal brain rhythms are presented in Figure 2.1.

a) The delta rhythm (2 to 4 Hz) emerges when the subject/patient is sleeping, unconscious (e.g. anesthesia), in meditative states and conscious focus of attention without sensory stimuli.

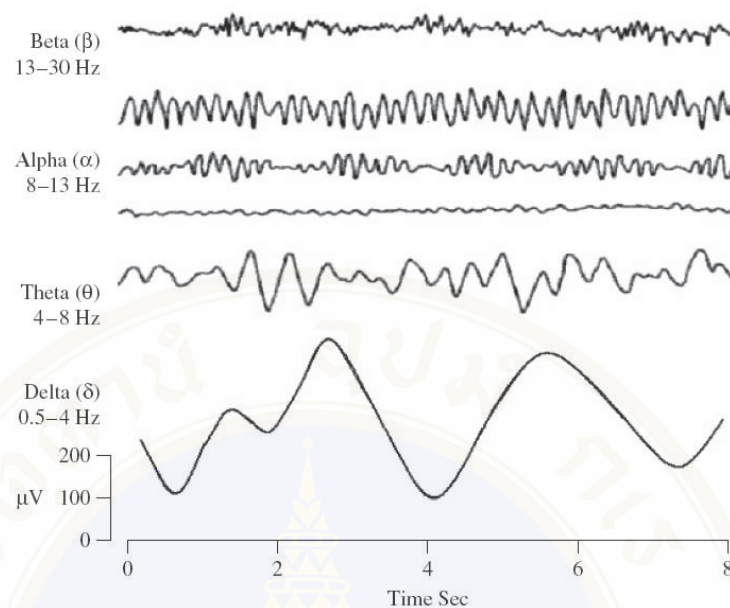


Figure 2.1 The samples of brain rhythms [2].

b) The theta rhythm (4 to 8 Hz) is the result of interaction between cortical and hippocampus neuronal groups. The rhythm happens when the subject is in periods of emotional stress and during rapid eye movements.

c) The alpha rhythm (8 to 13 Hz) happens when subject is resting and it disappears when he/she perceives a sensory signal or when he is making mental efforts. The rhythm originates from the interaction among cortical neuronal groups, some thalamic nuclei and cortical neurons.

d) The beta rhythm (13 to 30 Hz) derives from neuronal oscillators which located inside the cortex. The rhythm occurs when nervous system works intensely. It principally occurs in the parietal and frontal regions.

e) The gamma rhythm (higher than 30Hz) derives from the interneuronal feedback between neurons situated close to each other in the cortex. It happens during the period of attention, perception and cognition.

We can confirm some brain diseases by detecting these rhythms. The analysis of EEG rhythms and their interactions provide indices that are correlated with mental stages.

2.1.2 EEG Recording and Measurement

We precede the following steps [3] to acquire EEG signal, namely

a) Having the subject to sit comfortably in a chair in a dimly illuminated room.

b) Placing electrodes on the subject's head according to 10-20 system which the locations of electrode on the head are shown in Figure 2.2. In order to improve the conduction between subject's skin and electrode surfaces, we can use electrode gel or salt solutions. Even numbers show electrode locations on the right side of the head and odd numbers show electrode locations on the left side. Letters before these numbers indicate the general areas of the cortex which the electrode is located. A stands for auricular, C for central, Fp for frontal pole, F for frontal, P for parietal, O for occipital and T for temporal. The designation 10-20 as shown in the picture comes from the percentage ratio of inter-electrode distances with respect to the nasion-inion distance. Placing the electrode array on subject's scalp is done by having subject to wear a cap with the electrodes fixed on. The cap will provide the electrode placement with appropriate inter electrode distance automatically.

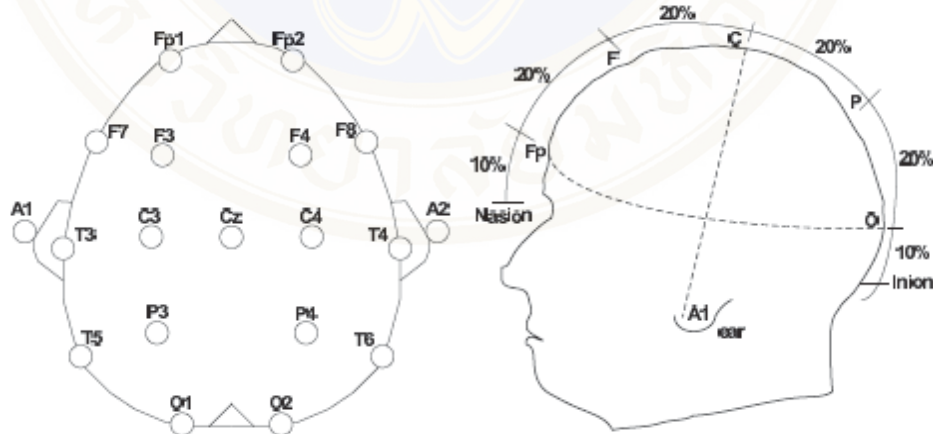


Figure 2.2 Electrodes location placement according to the 10-20 international system [3].

c) Choosing the reference electrode. It should be placed on a presumed “inactive” zone. We may record EEG with any scalp electrode as a reference and then compute the average reference as a mean of all electrodes.

d) Calibration the acquisition system.

e) Recording EEG. Normally, frequency content of interest of EEG signals is limited to 0.5 - 45 Hz band a minimum sampling rate of 200 samples/second is recommended to avoid aliasing.

2.1.3 Applications of EEG

Examples of some EEG applications are shown as below [1].

a) It is applied to monitor alertness, coma and brain death, cognitive engagement, human and animal brain development. In addition, it is also used to test epilepsy drug effects, afferent pathways and test drugs for convulsive effects.

b) It is used to identify the areas of damage after head injury, stroke and tumor.

c) It is used to investigate epilepsy, seizure origin, sleep disorder and physiology.

d) It is recently applied in biofeedback to study the evoked potentials or event-related potentials (ERPs). It allows person to alter brain waves, in other word, brain exercise or neurofeedback training.

EEG monitoring system has been used in operating room and intensive care unit for monitoring the effects of anesthetics and sedatives [4].

2.2 Electroencephalograph and EEG Monitoring Device

2.2.1 Electroencephalograph

We can study the image of the electrical activity of the brain with electroencephalograph [5], the example of electroencephalograph presented in Figure 2.3. The device allows for both medical diagnosis and neurobiological research. Major components of the device include electrodes, amplifiers, a computer control module and a display device. Although the device was useful, it did not achieve commercially because it was complex and expensive.



NeurofaxEEG-1100

Figure 2.3 192 channel digital EEG; developed by **Nihon Kohden** corporation, Japan.

2.2.2 EEG Monitoring Device

EEG monitoring device is the device used for monitoring the patient's symptom [4]. It records patient's neuronal signal and calculate a parameter representing a quantitative measure of patient's EEG signal.

2.2.3 Application of EEG Monitoring Device

In the past, the cost of this device was quite high. But nowadays, we have EEG bedside monitoring device with a lower price. Figures 2.5 and 2.6 show some of EEG monitoring devices and their applications. It has been used for long-term EEG monitoring to assess emergence from neuro-anesthesia, burst, suppression and seizure monitoring and ambulatory EEG both in clinics and researches [6,7].

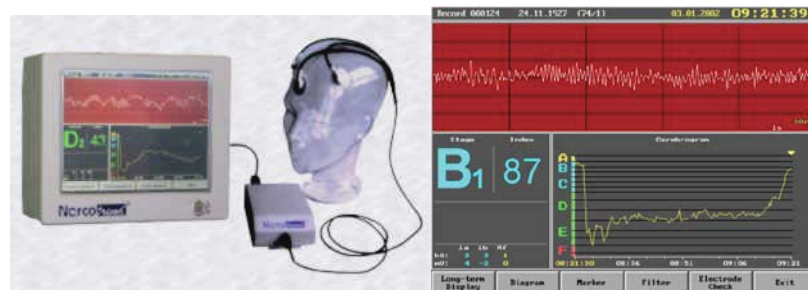


Figure 2.4 The EEG monitor for the operating room and the intensive care unit; developed by Dr. Arthur Schultz; GERMANY

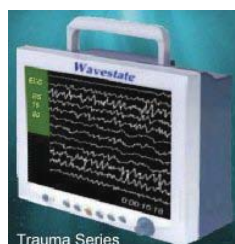
**Trauma Series Monitors****NeuroTablet**

Figure 2.5 Burst suppression and seizure monitoring, portable, battery-operated, 24 channel continuous display; developed by Wavestate Inc.

2.2.4 Commercial EEG Monitoring Devices

Nicolet Biomedical had developed electroencephalogram (EEG) monitoring device. It is used to indicate anesthetic depth [7]. Next, the researcher from University of Manitoba, Canada [8] had used bispectral index (BIS) as show in Figure 2.6 to assess emergence from neuroanesthesia and compared with the nonlinear EEG monitor (EEGo).



Figure 2.6 BIS monitoring system for display of processed data and real-time EEG waveforms; developed by Aspect Medical Systems.

It was found that BIS was better in term of time to awakening and time in the recovery room. These results can reduce the cost of anesthetic drugs and OR and Recovery Room. Meanwhile, EEGo is suitable for providing a visual output related to depth of anesthesia.

2.2.5 The Future EEG

In future [5], the devices will be improved. They will become smaller, more portable and less expensive. Individual consumers or applications might be able to use these devices more conveniently. Just recently, a similar device has been developed to screen for Alzheimer's disease. The innovation, called Brain Computer Interface (BCI) system, can use information from EEG electrodes to control. The user just wears a cap and controls cursor on the screen by using his thoughts. If the technology was fully developed, it could be a revolutionary development for paraplegics.

2.3 EEG Artifacts

The artifacts refer to signals generated by non-physiological or physiological sources such as power-line noise, changes in electrode impedances, electromagnetic interferences, potentials derived from body movements, eye movement, eye blinks, head muscular activity and so on. Figure 2.7 shows different format of perturbation by noise and artifacts and their corresponding power spectral densities (PSD).

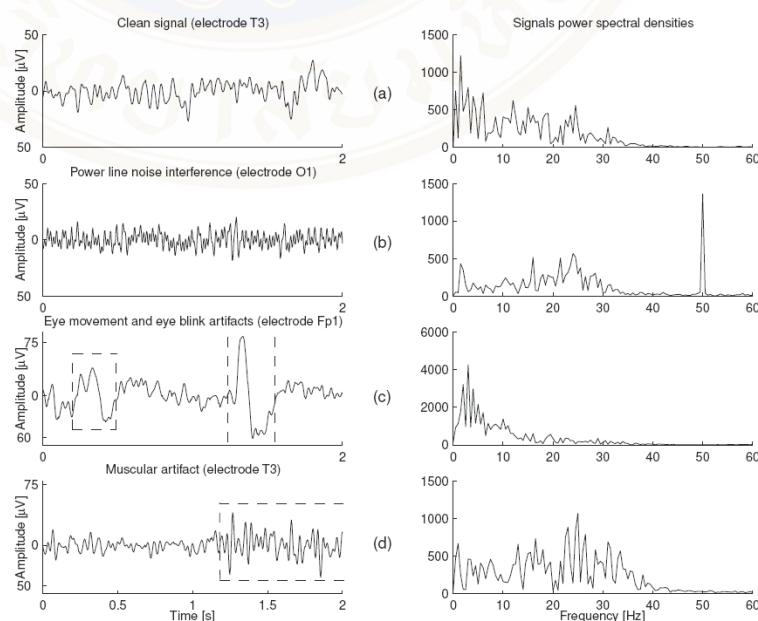


Figure 2.7 EEG signals contaminated by noise and artifacts and their corresponding PSD [3]

Most of artifacts in EEG are electromagnetic interferences and power-line noise. We can avoid these artifacts or at least attenuate them by controlling the environment of measurement.

Eye movement artifacts derive from reorientation of the retinocorneal dipole. We can recognize them by their quasi square shape and their amplitude in the range of that of regular EEG.

We find eye blinks artifacts commonly in EEG data. Their amplitudes are up to 100 micro volts which are usually higher than the range of regular EEG amplitude of -50 to 50 micro volts.

During the close interval, there are commonly eye movements and eye blink artifacts or ocular (EOG) artifacts. They can corrupt data on all electrodes.

The activity in different muscle groups can generate muscle movement artifacts or muscle (EMG) artifacts. We recognize their characteristics from their wide frequency content which mainly appear in temporal and parietal electrodes.

2.3.1 Methods of Handling Artifacts [9]

2.3.1.1 Artifact avoidance. This is the first step and most common and least computationally demanding method to avoid artifacts. For instance, instructing users to avoid blinking during the experiments. Anyway, we cannot avoid ocular activity during and online operation of any EEG monitoring system.

2.3.1.2 Artifact Rejection. Artifact rejection might be the simplest way to avoid artifacts by rejecting the trials affected by artifacts. Comparing to the first method, artifact rejection is easier for users to participate in the experiments and performs required tasks. It is simply done by visually inspect the EEG or the artifact signals or use an automatic detection method.

a) Manual Rejection. Manual rejection is done by having expert to check the trials with an assumption that a human expert can identify and remove artifact contaminated epochs from the analysis. Any artifacts contaminated trial will be removed from the analysis. It is also a non-computationally demanding. However, the method has some disadvantages namely. It is a human labor cost intensive method. Using human expert may cause selection bias and the artifact free

sample trials may not be representative of the entire population of the trials. It may lead to a substantial loss of data during offline analysis.

b) Automatic rejection. With automatic rejection method, artifact contaminated trials are discarded by the EEG monitoring systems automatically. The method is commonly used in offline investigations and it is less labor intensive than manual rejection method. It can be done in two different ways as below.

1) Rejection using EOG (EMG) information: EOG (EMG) signal in an epoch exceeds a pre-determined threshold is considered as artifact contaminated trial and it will be rejected automatically.

2) Rejection without using EOG (EMG) information: this method is similar to the above method. The method is useful if the EOG (EMG) signal is not recorded during data collection. However, it is possible to have sampling bias and loss some valuable data with this method.

Prior to choose the method, user must aware that 1. There are a lot of artifacts in EEG monitoring systems; we cannot reject all the artifact contaminated trials. 2. We cannot avoid artifacts in online applications. During some specific time, the EEG monitoring system is unreachable and loss some EEG component while it is rejecting artifact contaminated signal.

2.3.1.3 Artifact Removal. Artifact Removal refers to the process to identify and remove artifacts out of brain signals. The right method for doing this should be efficient to remove the artifacts and keep neurological phenomenon intact at the same time. There are many methods used in common as below.

a) Linear Filtering Method. It is good for remove some frequency bands that do not overlap with neurological phenomena of interest. It is a simple method which is successful in BCI system that use features extracted from high-frequency components of the EEG but fails to remove artifacts when neurological phenomenon of interest and the EMG or EOG artifacts overlap or lie in the same frequency band. In addition, since EOG artifacts consist of low frequency components, using a high-pass filter will remove most of the artifacts.

b) Linear Combination and Regression. Linear Combination Method uses a linear combination of EOG-contaminated EEG signal and the EOG signal. It is commonly used to remove ocular artifacts from EEG signals. The combination is based on the following formula.

$$EEG'_{nc}(t) = EEG'_{ac}(t) - K \cdot EOG(t) \quad (1)$$

EEG_{ac} stands for the EOG-contaminated EEG signal of channel i

EEG_{nc} stands for the non-contaminated EEG signal of channel i

EOG(t) stands for the EOG signal

k stands for unknown constant

A fraction of the EOG signal(s) will be subtracted from EEG_{ac} to generate EEG_{nc}. We can estimate K value by using linear regression using least square criterion.

Although it is commonly used, the problem was the EOG signal to be subtracted from the EEG signal is also contaminated with the EEG signal. Subtracting the EOG signal may also remove part of the EEG signal.

c) Blind Source Separation (BSS). In this technique category, the EEG signals are separated into components that build them. They will identify the components that are contributed to artifacts and reconstruct the EEG signal without these components [10]. The most widely used technique in this category is Independent Component Analysis or ICA. It blindly separates mixtures of independent source signals and forces independent components. It can remove ocular artifacts from EEG signals effectively. That is why it is widely used along with its useful for removing artifacts from EEG signals. The advantage of this method is they do not rely on the availability of reference artifacts for separating the artifacts from the EOG signals. Anyway, they need visual inspection to identify artifact components.

d) Principle Component Analysis (PCA). In this technique, eigenvectors of the covariance matrix of the signal is used to transform the data to a new coordinate system and find the projection of the input data with greater variances. The method can remove ocular artifacts from EEG signal effectively but the method requires that artifacts are uncorrelated with the EEG signal. In addition, eye

movement artifacts cannot completely separated from the EEG signal with this method, especially when they have comparable amplitudes.

e) Other methods. The remaining methods includes wavelet transform, nonlinear adaptive filtering and source dipole analysis (SDA) are also proposed.

2.3.2 Approaches for the Removal of Eye-Blink Artifact from EEGs.

Reliable and fast methods for removal eye blink artifacts without distorting the underlying brain activity are essential for Brain Computer Interfacing (BCI) system and ambulatory EEG setting. Besides, there are several methods for removal eye-blink artifacts from EEGs have been documents, that are mainly based on independent component analysis (ICA) [2, Chapter 2], including trail rejection, eye fixation, EOG subtraction, principal component analysis (PCA) [9], blind source separation (BSS) [12-14] and robust beamforming [15], hybrid BSS-SVM method [13,14] and methods based on H^∞ adaptive [16] and spatial filters [17]. It has been shown that the regression [11] and BSS-based methods [12, 13–15, 17, 18] are most reliable.

In 2007, Nazarpour et al. [19], has presented Semi-Blind Signal Extraction (SSBE) technique. This method is based on blind source extraction [20] and investigates STF signatures of extracted factor. Advantages of this method are below.

a) BSS- and CBSS-based methods [12, 14, 21–25] can identify correct number of sources. They use the spatial prior information to guarantee that the first extracted source is one of eye blink source, so it reduces the computational requirements. However, the simplicity of their method [19] is due to using the spatial prior information to guarantee that the first extracted source is the one of interest, that is, the eye-blink source. Therefore, there is no need to extract other sources which significantly reduces the computational requirements. EEGs are then reconstructed in a batch deflation procedure.

b) It is unlike methods presented in [12, 13], computing objective criteria for distinguishing eye-blink and spurious peaks in the ongoing EEG is not needed.

c) It is unlike the regression-based methods [26], It does not need to separate the dataset into training and testing subsets.

d) There is no need to separate the dataset into training and testing subsets as in [15].

In addition, they have introduced a new technique [27] based on RMVB[28], where the spatial a priori knowledge of the mixing process obtained by parallel factor analysis (PARAFAC) [29] to estimate the steering vector corresponding to the EB source. This method does not need reference EOG channel recording or objective criterion for distinguishing between EB and spurious peaks in the ongoing EEGs. Therefore the computational complexity can be reduced. With PARAFAC model, time domain is subdivided into a number of segments and a four way array. Next, it is set to estimate the space-time-frequency-time/segment (STF-TS) model of the data using four way PARAFAC. Consequently, the STF-TS model can provide lower computational cost significantly. This method does not require dataset separation into training and testing subsets to tune the parameters. The artifact can be removed from EEGs with this method.

2.4 Signal Quality Assessment

In order to assess signal quality in scalp EEG, we must minimize artifacts derived from power-line interference, variation in electrode-skin contact or motion artifacts. This can be done by carefully preparing, washing, peeling and shaving the skin. The user needs to base the signal quality assessment on the acquired EEG signals directly and over short periods of time.

Visual inspection or visual assessment can determine low-quality signals in EEG signal quality assessment. Users must be careful in case of multichannel EEG because the electrodes size is small, inter-electrode distances are short and contact paste is not always convenient which will cause more low-quality signals.

At the present time, there is not the best method to validate artifact removal algorithms and EEG signal quality [9]. The most common used method is visual inspection.

Technical quality evaluation of EEG recording is essential for improving the accuracy of EEG interpretation. The evaluation of EEG recording refers to detection of technical artifacts and physiological status. The evaluation record displays updated

EEG records and instant evaluation results to the user. In [30] they develop the system used for the evaluation of EEG recording comprises the detection of technical artifacts and physiological status, which indicates the recording status objectively. In addition, the caution signals to users are generated in the system according to the undesired status detected. Implementation of the evaluation record is useful for improve the results of visual and automatic EEG interpretation.

The measurement of signal to noise power ratio (SNR) is fundamental important in electrical engineering. In [31] they proposed two algorithms to estimate the signal to noise ration of a noisy sine wave from discrete-time data. The first one is based on estimating four parameters of the underline sine wave. The second one, the spectrum average method, is based on estimating the average noise power by averaging the squared magnitude of the FFT bins. They had found that both methods show excellent performance. Advantage of the second method is that it shows robustness over a very wide range of normalized frequencies and SNRs. It is regarded as a very useful method for various applications.

Automatic detection of artifacts is an important factor to determine the quality of intraoperative EEG monitoring. Since undetected artifacts can lead to misinterpretation of the EEG. Determination of the quality of artifacts or artifact level with computer assisted methods [32] can reduce misclassification of highly artifact contaminated epochs in the awoken patient without anesthesia relevant changes.

The major artifacts such as eye blink and eye movement are absent in both invasive and non-invasive EEG recordings. it had found that blink causes pronounced artifacts with non-invasive EEG recording both above prefrontal and motor cortical regions. On the other hand, invasive recording detects blink caused artifacts in prefrontal region. When comparing artifact amplitude, it finds that signal quality of invasive EEG is 20 to above 100 times better than non-invasive EEG. It was found that invasive EEG emphasizes much better signal quality than non-invasive EEG. It is suggested that users should consider blink especially when analyzing potentials in fronto-anterior brain regions. It is highly recommended to use techniques for reducing ocular artifacts to further optimize the signal quality of both invasive and non-invasive EEG recordings.

Scalp electrode impedance influences EEG signal amplitude and power line noise, in [33] they evaluate the effect of electrode-scalp impedance on EEG data quality. Results showed that there was no significant amplitude change in any EEG frequency bands as scalp-electrode impedance increased from less than 10 kilo-Omega to 40 kilo-Omega. It was concluded that we can record high quality EEG with high input-impedance amplifiers and accurate digital filters for power line noise without brain invasion.

On-line signal quality assessment proposed in [34], the quality of multichannel surface electromyograms signals was estimated by their outlier probabilities. This method has high accuracy comparing to visual assessment. It is suitable for multichannel monitoring system implementation.

2.5 Quantitative EEG

The highly used statistical analysis method in brain research, neurophysiology laboratories, and medical schools in USA is Quantitative EEG (QEEG). It is a useful method to diagnose abnormal brainwave patterns associated with ADHD, mild traumatic brain injury, learning disabilities, stroke, epilepsy and many other disorders.

2.5.1 The History of QEEG Testing

It has been developed since 1980's [35]. Anyway, it is not widely used nowadays because it required trained users. Psychiatrists, pediatricians and psychologists are not aware of support researches for the advantage of topometric quantitative electroencephalographic analysis (QEEG) as a diagnostic tool for differentiating between organic and functional brain disorders including learning difficulties, ADHD, schizophrenia, epilepsy, and cerebral atrophy associated with alcohol abuse, depression and anxiety.

Daniel Amen, has recently proved that QEEG analysis is a powerful adjunct to psychometric assessment of six subtypes of ADHD. It uses digital technology to measure electrical patterns at the surface of the scalp which reflect cortical activity or brainwaves and converted into numbers. Clinician compares this

number to a database and is able to determine if patient's brain is functioning abnormally and to what degree. It is non-invasive method and fast.

Jacques Duff et al., has studied the method and found that it can reveal underlying neurophysiology associated with the symptoms of attention deficit hyperactivity disorder (ADHD) and learning disorder and help differentiate these disorders from other co-morbidities. QEEG can perform various functions namely

- a) To determine focal presence or generalize cerebral dysfunction following a closed head injury, stroke, heart attack or pulmonary dysfunction following hypoxia
- b) To identify seizure disorder or tumors
- c) To inspect cerebral dysfunction related to substance abuse, pathological alteration in vigilance (narcolepsy, confusion or coma)
- d) To observe acute nervous system process (acute headaches, vomiting, aphasia)
- e) To investigate cerebrovascular disorders

2.5.2 Information from the QEEG

QEEG provides information on brain functioning and its impact on cognition and learning [36]. The information is summarized into topographic maps, spectral plots, topometric distributions, covariation maps and tables. Physician compares provided information with age related norms of QEEG database to diagnose patient's disorder and its degree.

2.6 Brain Mapping

Brain mapping is a tool to evaluate differences in brain functioning and compare to a norm database [37]. In brain mapping, it presents brain electrical activity and colder deficits, in which they mean abnormal and mood disorders. QEEG based treatment formulation relies on brain pattern associated with abnormal behaviors rather than on questionnaires. Brain mapping reports parameters as following [37];

- a) *Absolute power* – Neurologist can determine if whether enough brain power within a frequency range at each record site.
- b) *Relative power* – It provides data whether a particular frequency is overpowering other vital brain frequencies.
- c) *Mean frequency* – The average frequency tells us whether there is any bandwidth operating within normal ranges.
- d) *Ratios* – Various brain frequencies are compared to individuals with normal brain functioning. Lower or higher ratio means a sign of inefficiency.
- e) *Asymmetry* – Asymmetry scores tell the neurologist whether the brain waves in various part of the brain are balanced.
- f) *Coherence* – Coherence is the indicator represented brain functioning efficiency. We can identify if the brain is working to connects and disconnects different parts of itself to do particular task successfully. Excessive coherence indicates two or more areas of the brain are not processing and executing information efficiently. Deficient coherence is the sign shown inefficient connect cortical areas to perform some tasks. Abnormal coherence shows serious traumatic brain injury and learning disabilities.
- g) *Phase* – It means the energy from one part of the brain that arrived at another area at the right moment to perform some tasks. Excessive phase means the signals arrival too early and deficient phase means too late arrival. In both cases, the brain cannot perform some job with peak efficiency.

2.7 Topographic Brain Mapping

Topographic Brain Mapping [38] is a computerized technique that utilizes the digitized data from either EEG or Evoked Potentials (EPs), as recorded from each of the standard 19 electrodes (plus Oz) in the 10-20 System. The voltages are laid-out on a 'grid' diagram that simulates the original 10-20 scalp electrode array, and intervening 'spaces' between the electrode positions are filled-in with 'interpolated' voltage values, as if they had actually been recorded. Colors are then arbitrarily assigned to each of several voltage levels, and the results are 'mapped-out' on a head diagram, displaying the voltage field gradients of the activities.

With this method, neurologist can identify abnormal electrical activity in the brain areas around a tumor, diagnose some mental diseases and study the brain function.

2.7.1 Medical Applications

EEG brain topography is mainly used to determine tumors and focal disease of the brain including epilepsy, arteriovenous mal-formations and stroke, disturbance in consciousness and narcolepsy [39]. In addition, EEG brain topography is also used to monitor the effects of withdrawal of psychoactive drugs, infectious diseases of the brain such as meningitis and follow up brain operation patients. In psychiatry, the method is used to identify disorder of biological origin such as schizophrenia, dementias, hyperactivity and depression, brain atrophy and attention disorders in children.

2.7.2 Related Research in Topographic Brain Mapping

Recently, there are many EEG brain topography systems based on Windows or Macintosh based computer platforms.

P. Walerjan and R. Tarnecki [40] had designed brain electrical activity mapping technique. The technique uses PC to analyze EEG data and provide interpolation algorithm mapping. This technique is proved successfully used in clinical test of epilepsy and Parkinson disease in laboratories.

T.M. Itil et al. [41], had developed Dynamic Brain Mapping System and named it Field blending interpolation. This technique provides user selectable interpolation algorithms and can be monitor drug selection and discriminations.

2.7.3 Interpolation Techniques and Error in Topographic Brain Mapping

The nearest neighbors, planar spline techniques and the spherical spline techniques are the interpolation techniques used in topographic brain mapping. There were evaluated by A. C. Soong et al. [42], by using cross-validation method. This evaluative method records montage predicted by interpolation from the other sites of scalp. Four measurements were used to measure and predict errors including

inaccuracy, precision, bias and tolerance. It was found that none of the interpolation techniques performed well. Further, the global techniques performed significantly better than the local technique. They concluded that electrode densities of the order cannot be used with interpolation. In addition, these techniques do not increase the spatial resolution of the electroencephalogram nor estimate quantitative EEG such as radial-current density analysis.

E.M. Fletcher et al. [43], estimated interpolation errors in scalp topographic mapping via computer simulation. It was found that adequate electrode density is more important among the best interpolation methods. For shallow sources, local interpolation error correlates with potential gradient and lesser correlates with distance to nearest electrode. The greatest correlation is with the product of gradient and distance. Therefore, we can control interpolation error by adjusting inter-electrode distance inversely proportional to the expected potential gradient. High apparent gradient at shallow sources probably has high interpolation error like all areas far from electrode.

Further to P. Anderer et al [44], they suggested that must minimize or remove EOG artifacts from the EEG signal before using topographic brain mapping because EEG artifacts can lead to error in the mapping method.

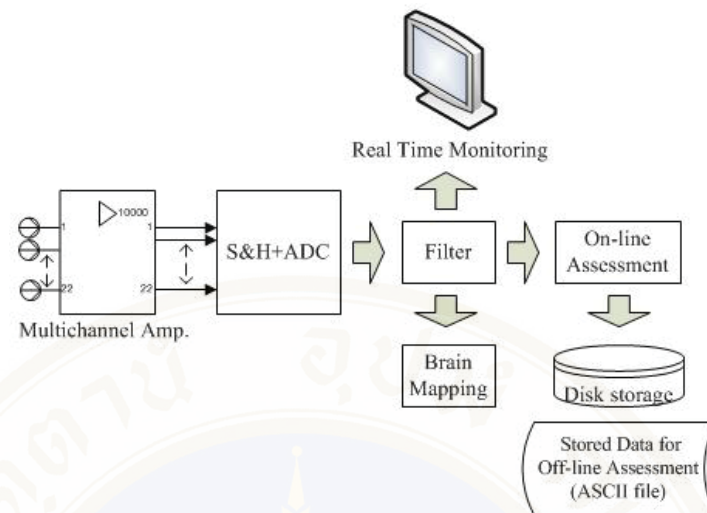
CHAPTER III

METHODOLOGIES OF PROTOTYPE HARDWARE AND SOFTWARE

3.1 System Overview

In this thesis, the prototypes of both hardware and software of the 19-channel EEG monitoring system are developed. Designed system block diagram is shown in Figure 3.1. The system which develops in this project is the digital EEG monitoring system for acquiring and monitoring EEG signal from scalp surface. The band width of EEG amplifiers and band pass analog filters are from 0.5 to 45 Hz. In order to maintain the diagnostic information of EEG signals, the quantization level of 16 bit is selected.

For the software, in on-line mode, multichannel EEGs signal will be filtered with finite impulse response (FIR) band-pass digital filter with adjustable cut-off frequencies to remove artifact and real time multichannel EEG will display on a monitor of computer. The movement and power line (50 Hz) artifacts level will be estimated and display. The artifact level will update and instant report to user for signal quality assessment during measure EEG signals. The software can perform EEG analyses in order to power spectral density and 2D-brain mapping (topographic EEG analysis). In case of long term monitoring and record, the data can be saving in the hard disk of the computer. For off-line assessment, stored data which was saved in ASCII file formats will be loaded and assessed. In this project, the eye-blink removal method based on the robust minimum variance beamforming (RMVB) and a simple digital filter is also developed to remove eye-blink artifact in off-line mode.



(a)



(b)

Figure 3.1 Designed system; (a) block diagram and (b) prototype hardware

3.2 The Prototype Hardware

The raw EEG signals have very low amplitudes in the scale of μvolts . To retain the efficient information the signals have to be amplified before filtering to reduce the noise and make the signals suitable for processing and visualization. Analog to digital converter (ADC) is also applied in order to interface the hardware with computer.

3.2.1 Electrodes

To avoid the potential shifts due to electrode polarization, the (Ag-AgCl) electrodes are used to record scalp EEG. The system using a standard EEG-cap (an ElectroCap™, [Electro-Cap International, Inc.,]), is shown in Figure 3.2. The EEG monitoring device in this thesis is equipped with 19 Ag/AgCl electrodes at the positions defined by the international 10-20 system and 1 Ag/AgCl electrodes for ground connection. The additional Oz electrode could be added when perform topographic brain mapping.

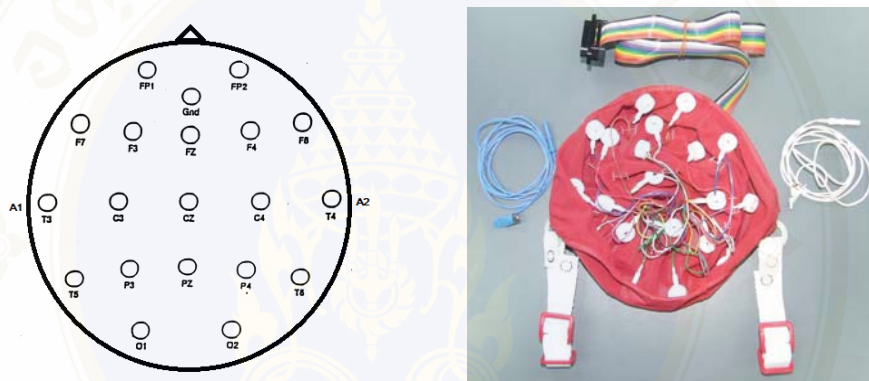


Figure 3.2 EEG electrodes position and cap

The disk electrodes which have approximately 3 mm in diameter are fixed on a cap and connected to amplifiers via long flexible leads. The electrode cap can be placed and removed rapidly and caused a minimal unpleasant feeling in long term monitoring.

3.2.2 Analog Amplifiers and Filters

This system consists of 22 channels analog amplifier which amplification gain of each channel is approximately 10,000. It provided 19 channels for EEG signal and 3 additional channels are also provided for further development such as used for measuring electrooculogram (EOG), electrocardiogram (ECG) and Electromyogram (EMG).

This project designed for acquiring the EEG signal which contain frequency component from 0.5 Hz. up to 45 Hz. The amplifier circuit developed based

on exiting circuit, called OPENEEG, recommended by Tom De Rybel. This circuit consisted of a differential amplifier, a right leg driven circuit, a high pass filter with variable gain, and a 2nd order Besselworth low pass filter. Finally, 50 Hz notch filter is implemented to eliminate power line noise. The schematic is shown in Figure 3.3 (a).

a) Differential Amplifier

Normally, the operational amplifier that able to operate under low voltage power supply with high input impedance and low output impedance would be recommended. The differential amplifier recommended by OPENEEG is the INA114 chip manufactured by TI. These chips internally have three operational amplifiers with internally connected feedback resistors which allow it to offer excellent accuracy. The INA114 can also operate off a single supply as low as 2.25V and draws a maximum of 3mA, which implies that this device consumes very little power. The operational amplifier recommended by OPENEEG is the TLC277IP manufactured by TI.

The resistors and the capacitors used to construct this project would have an error of 1% and 5%, respectively.

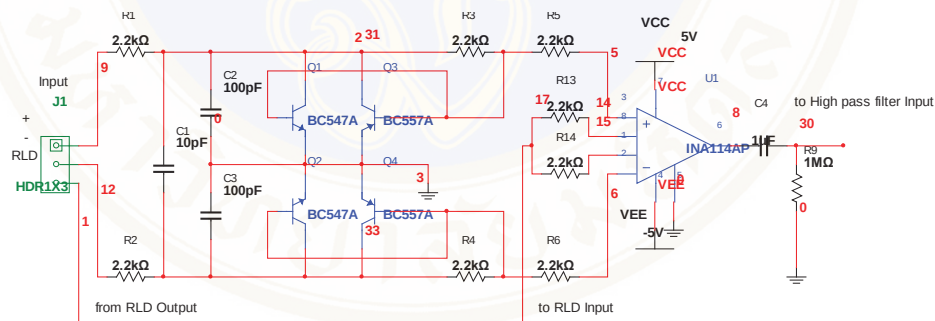


Figure 3.3 Protection circuit and Differential amplifier

b) Right Leg Driven Circuit

Initially, the differential amplifier able to eliminate the entire common mode noise that generated by the body. To improve the ability to reject common mode noise of differential amplifier, up to 100 times more than the differential amplifier alone, the right leg driven circuit has been implemented. The purpose of right leg driven circuit is to reduce common mode noise by driving the differential amplifier with another source of common mode noise generated by the body.

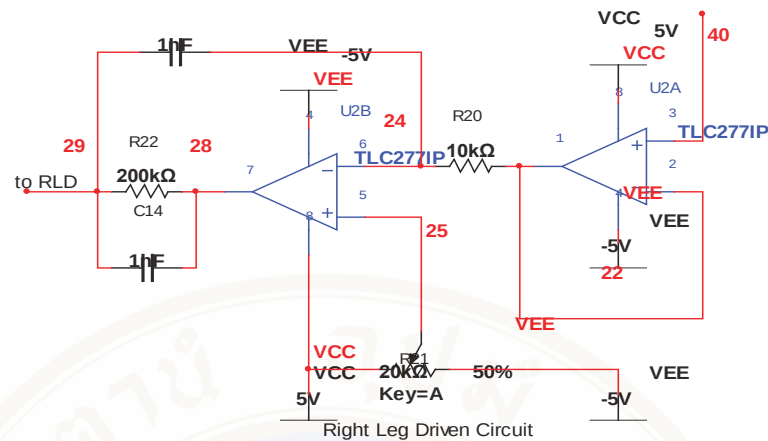


Figure 3.4 Right Leg Driven Circuit

c) High Pass and Low Pass Filter

High pass filter with a cut of frequency of 0.16 Hz and includes a potentiometer which varies its gain are used to remove the disturbing very low frequency components. The high pass is necessary to eliminate the fluctuating DC offsets generated by charge buildup on the electrodes.

On the other hand, high frequency noise is mitigated by using low pass filters with a cut of frequency of 59 Hz 2nd order Besselworth filter, meaning that it exhibited both Bessel and Butterworth filter characteristics.

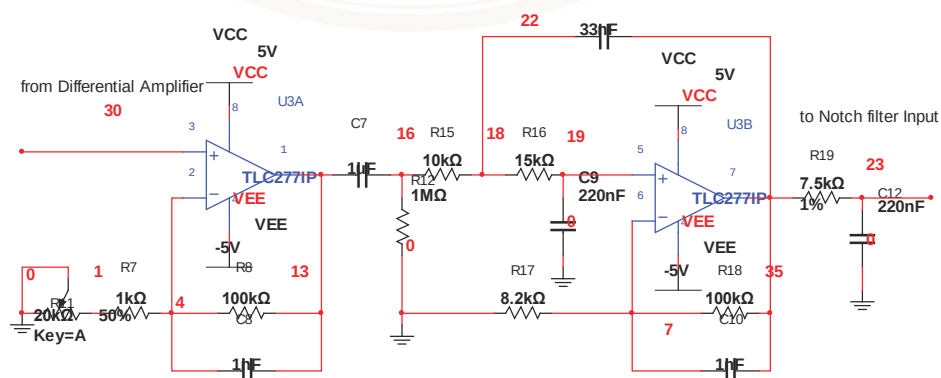


Figure 3.5 High pass and low pass filter

d) Notch Filter

After the assembly and testing of the high and low pass filters recommended on OPENEEG, 50 Hz power line noise did not reject. The 50 Hz notch filter is implemented to ensure that any frequency contributions at 50 Hz will be eliminated.

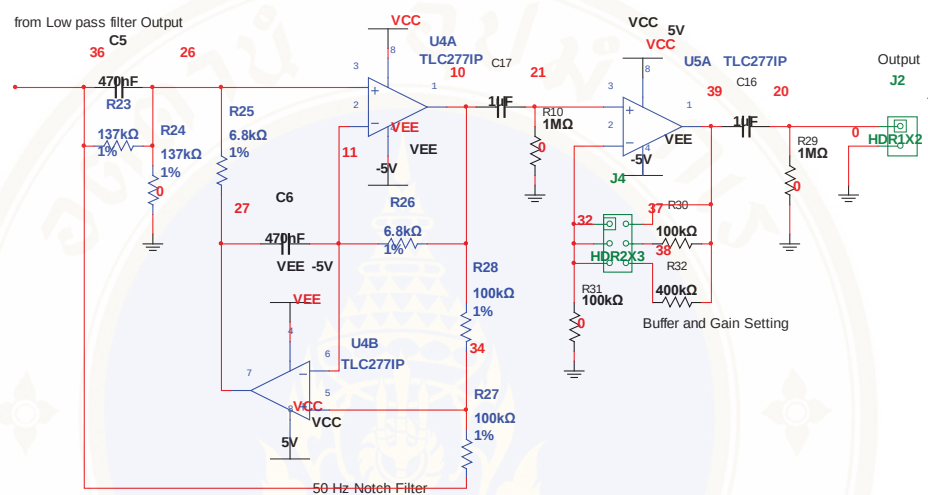


Figure 3.6 50 Hz Notch filter circuit

The schematic diagram and printed circuit board of an analog amplifier and filters for one channel is represented in Figure 3.7 and frequency response is shown in chapter 4. This filter behaved perfectly. Using the signal generator to test the frequency response of the actual circuit, it was found that any frequency higher than 46 Hz was completely cut off.

The system consists of 11 printed circuit board (PCB) of amplifiers. Each PCB has 2 channels of amplifier, high pass and low pass filters. Notch filter PCB is separately designed and each PCB designed for 4 channels. We can easily add the number of channel of the system by add the number of PCB.

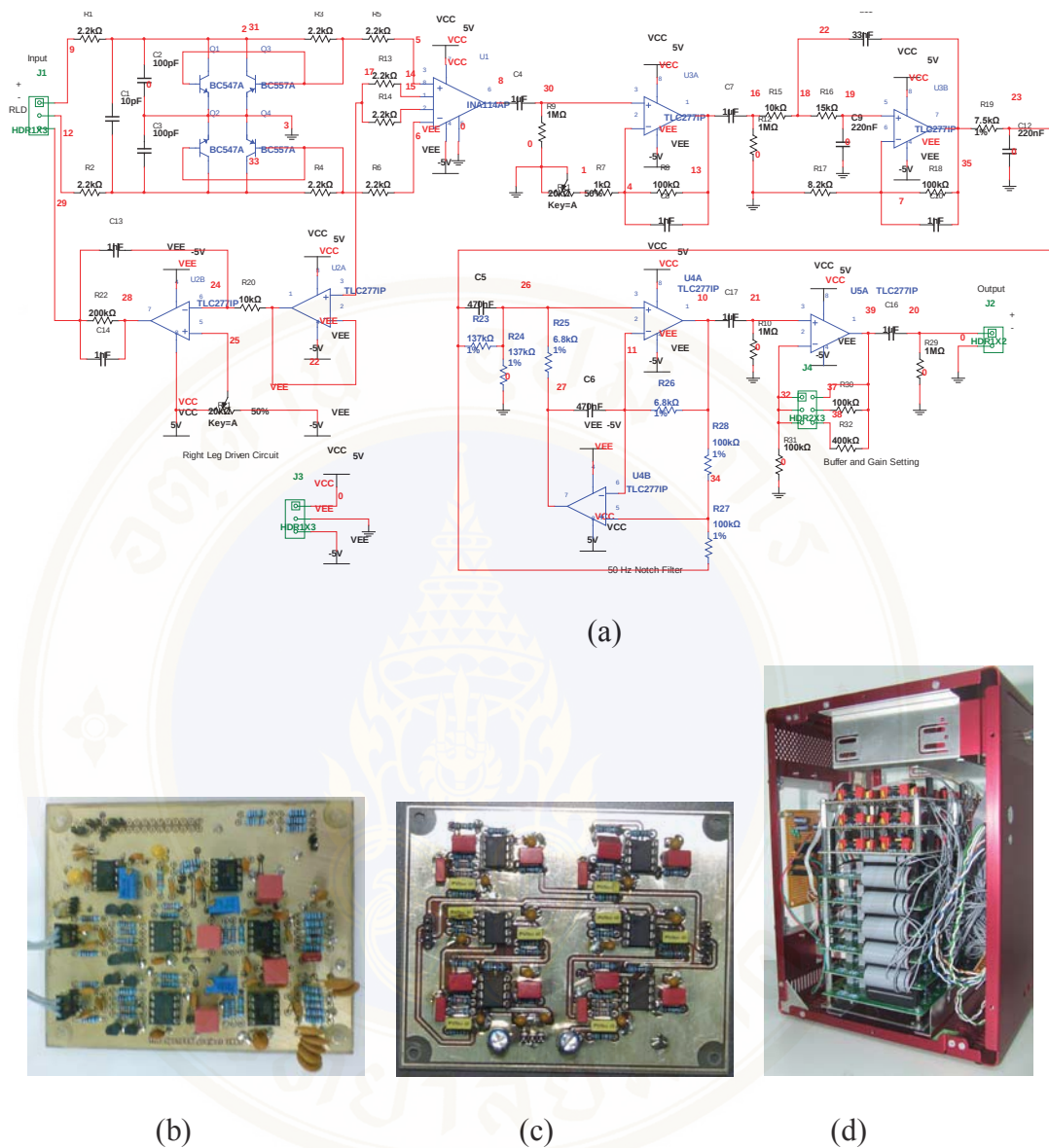


Figure 3.7 Designed EEG amplifier and analog filter; (a) The schematic diagram for 1 channel, (b) PCB for 2 channel of amplifiers and (c) 4 channel of notch filters, (d) Hardware assembly

3.2.3 Isolated Power Supply and Signal Isolation

Electrical safety is the issues that must be considered when we design the medical equipment. The related standards are also discussed and implemented. In this project, the electrical hazards are protected by using DC-DC converter isolated power supply. The devices (RS3-0505D) that has specification meet to the medical standard,

EN-60601-1 Certified, has been used to develop the isolated power supply. The component and PCB of isolated power supply is illustrated in Figure 3.8. The input voltage range of the circuit is 4.5 – 9 VDC. In this project the 9 VDC adaptors is used for input voltage. The rated output voltage of power supply is ± 5 VDC and output current full load is ± 300 mA. It can provide efficient power for the system which has power consumption approximately 200 mA.

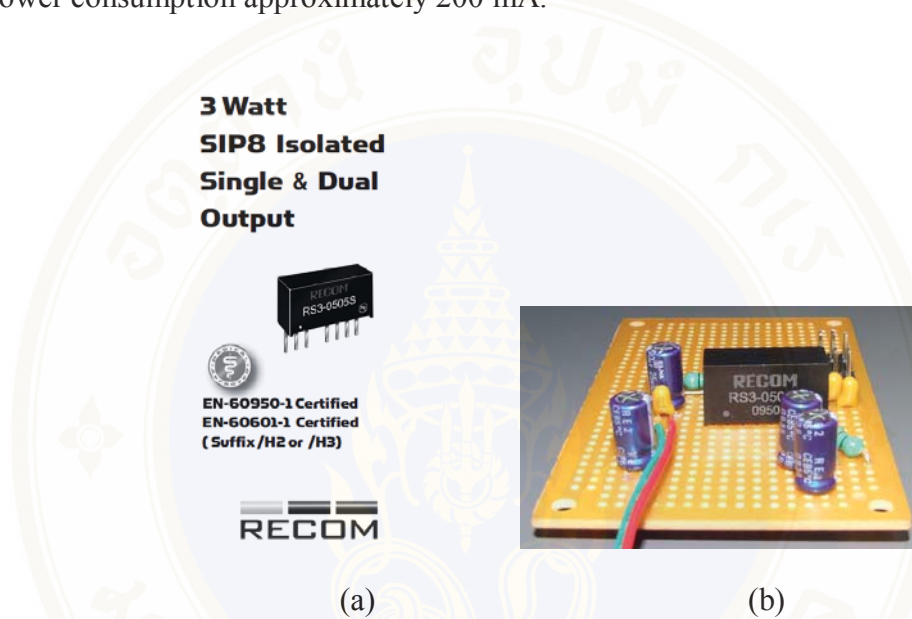


Figure 3.8 Isolated power supply (a) component and (b) PCB

In case of signal isolation, we performed by the advantages of National Instrument Data Acquisition device (NI USB 6218, 16-Bit, 250 kS/s Isolated M Series MIO DAQ, Bus-Powered). The 60 V CAT I isolation is provided by that device.

3.2.4 Analog to Digital Converter (ADC)

By the advantages of designed software, which developed based on labVIEW 8.5 and National Instrument Data Acquisition device (NI USB 6218, 16-Bit, 250 kS/s Isolated M Series MIO DAQ, Bus-Powered), sample rates of an ADC which samples and measures continuous analog EEG can be set from 128 and up to 1,024 Hz., if necessary. Data Acquisition device is presented in Figure 3.9.



Figure 3.9 Data Acquisition device (NI USB 6218)



Figure 3.10 The Prototype Hardware

3.3 Function of Prototype Software

The prototype software has been developed for interface to the prototype hardware (Figure 3.10) via USB port. The following function has been provided to user for filtering, waveform display, signal quality assessment, EEG analysis and recording. It was developed based on LabVIEW 8.5 [45]. The display/control panel of the system is represented in Figure 3.11.

3.3.1 Digital Filters

In this system FIR band-pass digital filter with adjustable cut-off frequencies is applied to remove artifact in on line mode. The software also selects type of filter such as Butterworth, Chebychev, Inverse chebychev, Illiptic and Bessel

filter. Normally, the raw signals will display while the filter type selected at the normal.

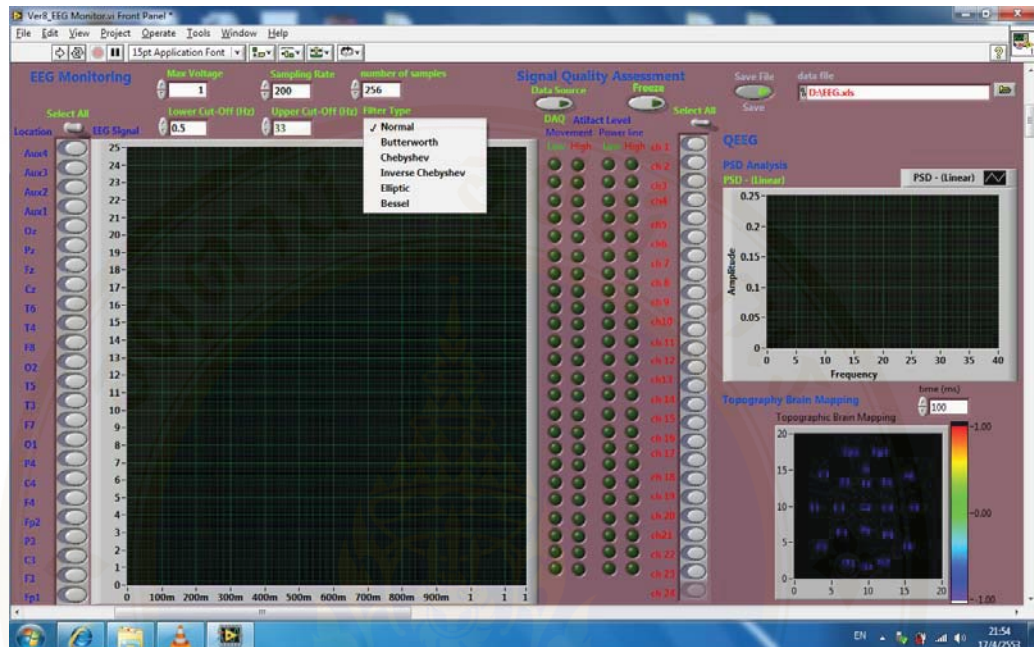


Figure 3.11 Display/control panel of the system

3.3.2 Waveform Display

The real time multichannel EEG signals will display on a computer monitor. Each channel has separately switches to turn on or off the waveform.

3.3.3 Signal Quality Assessment

For EEG signal quality assessment, low-quality signals can be identified by visual inspection or visually assessment. The method that used in this system is a visual inspection of the artifacts to manage risk of low-quality signals. The signal to noise ratio (SNR) is estimated using Fast Fourier Transform (FFT) by the Spectrum Average Method as performed in [31] and reported as noise level. The movement and power line (50 Hz) artifacts level will be estimated and display. The artifact level will update and instant report to user for signal quality assessment during measure EEG signals.

3.3.4 EEG Analysis

The software can perform EEG analyses in order to power spectral density and 2D-brain mapping (topographic EEG analysis). The PSD analysis [45, 46] of all channel or some of them can selected to display on the monitor.

The 2D topographic brain mapping which performed by using cubic spline interpolation technique [47] will also display. This tool gives us the ability to view the dynamic changes taking place throughout the brain during monitoring.

3.3.5 EEG Storage

For long term monitoring and record, the data can be saving in the hard disk of the computer as ASCII file format. The necessary memory volume can calculate by the example that, for a one hour recording from 19 channel sampled at 200 sample/s a memory size of $19 \times 60 \times 60 \times 200 \times 16 \approx 219$ Mbits or ≈ 27.4 Mbyte.

3.4 The Method for Artifacts Removal

Artifacts can be removed in on-line mode by using FIR band-pass digital filter that can adjust the cut-off frequency to reject the unwanted frequency or maintain wanted frequency.

For off line mode, the method for eye-blink removal is proposed for enhancing the quality of the eye blink artifacts removed EEG signals. The method based on RMVB and a simple digital filter. The results of testing and evaluating of this method presented in chapter 4.

3.4.1 Eye-Blink Artifacts Removal Improvement (1st phase)

Eye-blink artifact removal method that proposed in this project developed from the previous method, called conventional method as shown in Figure 3.12 (a), that proposed by K. Nazarpour et al. [27]. After the removal of the EB artifacts from EEG signals based on the conventional method we found by inspection that some components of EEG signals are oversmoothed and distorted as shown in Figures 3.12 (b) and (c). Therefore, the simple but efficient method is proposed in order to enhance the results of the conventional method.

In this phase, the RMVB and digital filter knowledge will be employing for enhancing the quality of the EB artifacts removed EEG signals. After that, to validate this method in term of reliability and fast algorithm the EB artifacts removed EEG signals will be evaluated. The reconstructed EEG will be evaluated by the validation criterion in frequency, spatial and time domain.

3.4.1.1 The conventional method

a) RMVB based EB artifacts removal. This section aims to review the conventional method in [27] for recovering the clean multi-channel EEG back from the EB contaminated one by employing the RMVB) [27], [48]. The prior knowledge used in the RMVB is obtained via the STF-TS model [49]. Specifically, let $\mathbf{s}(t) = [s_1(t), s_2(t), \dots, s_N(t)]^T$ be N zero-mean real mutually uncorrelated point geometrically stationary sources which are mixed by an $N \times N$ full column rank matrix (mixing matrix) $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_N]$ where $\mathbf{a}_i$ is the i -th column of $\mathbf{A}$. The vector of a time mixture signal (N -channel EEG signal at each time stem t) $\mathbf{x}(t) = [x_1(t), x_2(t), \dots, x_N(t)]^T$ which is shown in Figure 3.12 (a) can be formulated as

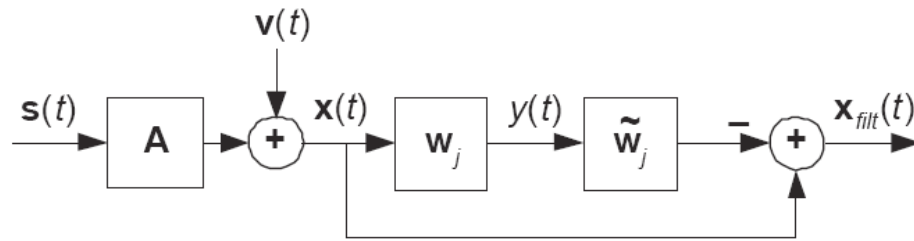
$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{v}(t) \quad (1)$$

where $\mathbf{v}(t) = [v_1(t), v_2(t), \dots, v_N(t)]^T$ is the additive white Gaussian zero-mean noise which is assumed to be spatially and temporally uncorrelated with a multi-channel EEG. The goal is we try to remove the EB source $y(t)$ in Figure 3.12 (a) from the multi-channel EEG, $\mathbf{x}(t)$.

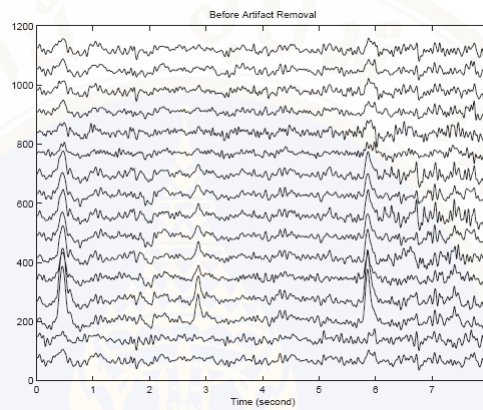
b) Implementation of the RMVB. According to Figure 3.12 (a) since $\mathbf{a}_i$ performs as the steering vector of the j -th source (which is assumed to be the source according to EBs), we may write $y(t)$ which is denoted as an estimation of the source $s_j(t)$ as

$$y(t) = \mathbf{w}_j^T \mathbf{x}(t), \quad (2)$$

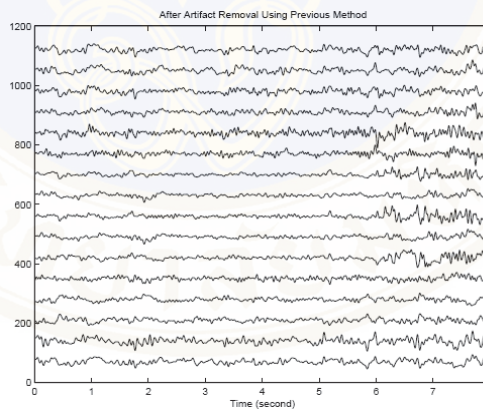
where $\mathbf{w}_j$ acts as a spatial filter. $\mathbf{w}_j$ can be found by minimizing the energy of $y(t)$ subject to the prior knowledge on how the EB artifacts are spatially distributed. Since the prior knowledge we can find is usually not the ideal one,



(a)



(b)



(c)

Figure 3.12 (a) Conventional method for extracting an EB component from a multi-channel EEG [27], The result of Conventional method, (b) before and (c) after eyeblink artifact removal.

w_j can be found by solving the worst-case performance optimization [50] where the estimated prior knowledge can be used. In general, we can write this problem as

$$\text{Minimize } J_c = \mathbf{w}_j^T \mathbf{R} \mathbf{w}_j \text{ subject to } \min_{\|\delta\| < \varepsilon} \left| \mathbf{w}_j^T \hat{\mathbf{a}}_j + \mathbf{w}_j^T \delta \right| = 1$$

where $\mathbf{R} = \frac{1}{K} \sum_{k=1}^K \mathbf{R}_{XX}^k$, $\hat{\mathbf{a}}_j$ is the estimated steering vector of source j-th, ε

is the setting mismatch norm, and $\delta = \mathbf{a}_j - \hat{\mathbf{a}}_j$. By using the Lagrange multiplier method, differentiating J_c with respect to $\mathbf{w}_j$ and setting it to zero, the spatial filter $\mathbf{w}_j$ can be computed as follows:

$$\mathbf{w}_j = \left[\mathbf{R} + \frac{\varepsilon}{\rho} \mathbf{I} \right]^{-1} \hat{\mathbf{a}}_j, \quad (3)$$

where $\rho = \|\mathbf{w}_j\|$ and $\mathbf{I}$ denotes the identity matrix.

By following the method suggested in [51], we can use ρ that satisfies the following equation:

$$\sum_{i=1}^N \left(\frac{|g_i|}{\varepsilon + \rho \sigma_i} \right)^2 - 1 = 0, \quad (4)$$

where $\mathbf{g} = [g_1, \dots, g_N]^T = \mathbf{U}^T \hat{\mathbf{a}}_j$. $\mathbf{U}$ is an $N \times N$ matrix whose columns are eigenvectors of $\mathbf{R}$ and $\sigma_i (i = 1, \dots, N)$ are their corresponding eigenvalues [50].

The clean multi-channel EEG without the EB contamination, $\mathbf{x}_{flt}(t)$, can be obtained by deflation method [52], that is

$$\mathbf{x}_{flt}(t) = \mathbf{x}(t) - \tilde{\mathbf{w}}_j y(t), \quad (5)$$

where $\tilde{\mathbf{w}}_j$ can be found so that $\mathbf{x}_{flt}(t)$ has minimum energy when the EB source $y(t)$ is removed from the contaminated source $\mathbf{x}(t)$. Specifically, $\tilde{\mathbf{w}}_j$ can be obtained by minimizing $J_j(\tilde{\mathbf{w}}_j)$ with respect to $\tilde{\mathbf{w}}_j$ where

$$\begin{aligned} J_j(\tilde{\mathbf{w}}_j) &= E[\mathbf{x}_{flt}^T(t) \mathbf{x}_{flt}(t)] \\ &= E[\mathbf{x}^T(t) \mathbf{x}(t)] - 2 \tilde{\mathbf{w}}_j^{\square T} E[\mathbf{x}(t) y(t)] + \tilde{\mathbf{w}}_j^{\square T} \tilde{\mathbf{w}}_j E[y(t)^2]. \end{aligned}$$

Hence,

$$\tilde{\mathbf{w}}_j = \frac{E[\mathbf{x}(t)y^T(t)]}{E[y(t)^2]} = \frac{E[\mathbf{x}(t)\mathbf{x}^T(t)]\mathbf{w}_j}{E[y(t)^2]}. \quad (6)$$

c) Space-time-frequency-time/segment model (STF-TS model). According to section b, the estimated prior knowledge $\hat{\mathbf{a}}_j$ of the beamformer can be found via the space signature of the STF-TS model proposed in [49]. This section aims to review the basic concept of the STF-TS model.

For a long-term EEG signal, the calculations of both the time-frequency transform and the PARAFAC [29] for constructing the STF model [53] are very complex. Computational complexity can be reduced by dividing the time domain into segments. After that, the time-frequency transform is applied individually to each segment forming a 4-D array signal, $\hat{\mathbf{y}}(n_1, s_t, f_1, t_1)$ (denoted in array form as $\hat{\mathbf{Y}}$), where n_1 is the channel index ranging from 1 to N_1 , s_t is the time/segment index ranging from 1 to S_t , f_1 is the frequency index ranging from 1 to F_1 , and t_1 is the time index ranging from 1 to T_1 . The 4-way PARAFAC is then applied to this 4-D array signal. The 4-way PARAFAC model of the 4-D array $\hat{\mathbf{Y}}$ can be formulated as follows:

$$\hat{\mathbf{Y}}_{N_1 \times S_t \times F_1 \times T_1} = f(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}) + \hat{\mathbf{E}}_{N_1 \times S_t \times F_1 \times T_1}, \quad (7)$$

where the 4-way PARAFAC model (STF-TS model) is

$$f(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}) = \sum_{m=1}^M \hat{a}(n_1, m) \hat{b}(s_t, m) \hat{c}(f_1, m) \hat{d}(t_1, m),$$

and $\hat{\mathbf{E}}$ is now a 4-D array residual of the model. Each column of $\hat{\mathbf{A}}_{N_1 \times M}$ denotes the space (spatial) signature of the m -th component ranging from 1 to M where its matrix elements are denoted as $\hat{a}(n_1, m)$. Each column of $\hat{\mathbf{B}}_{S_t \times M}$ denotes the time/segment signature where its matrix elements are denoted as $\hat{b}(s_t, m)$. Each column of $\hat{\mathbf{C}}_{F_1 \times M}$ denotes the frequency signature where its matrix elements are denoted as $\hat{c}(f_1, m)$. Each column of $\hat{\mathbf{D}}_{T_1 \times M}$ denotes the time signature where its matrix elements are denoted as $\hat{d}(t_1, m)$. $\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}$, and $\hat{\mathbf{D}}$ can be estimated by using the alternate least square algorithm (ALS) [54] where the cost function is

$$\operatorname{argmin}_{\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}} \left\| \hat{\mathbf{Y}} - f(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}) \right\|.$$

In this section, the column of $\hat{\mathbf{A}}_{N_i \times M}$ which illustrates how EBs are spatially distributed is employed as the estimated prior knowledge $\hat{\mathbf{a}}_j$.

3.4.1.2 Proposed Method (Model I Method). After the removal of the EB artifacts from EEG signals based on the conventional method mentioned, we found by inspection that some components of EEG signals are oversmoothed and distorted as shown in Figure 3.12 (c). Therefore, in this section, the simple but efficient method called Model I method is proposed in order to enhance the results of the conventional method.

a) Proposed EB Artifacts Removal Method. According to (2), the EB source $y(t)$ is obtained via the worst-case performance optimization [50]. Hence, it may lack of some physical structures of the real EEG signals. Theoretically, the EB source should contain only the frequency bands of the EB which is around 2-4 Hz. However, the EB source obtained from the previous method seems to have some other frequency bands which might be related to the structures of the EEGs. Therefore, we propose to apply the lowpass filter to the EB source. Then, this filtered EB source is employed instead of the traditional one in the process of deflation in (5).

b) Issue on Selecting Lowpass Filter. Instead of using the ideal lowpass filter or its approximation, e.g. high order IIR filter, we employ FIR lowpass filter of order 30 for the reason of simplicity. Since the EB source is of size 1600 samples, order of 30 FIR lowpass filter is practical. In addition, the frequency response of the FIR filter is not as selective as the IIR filter, thus we select the cut-off frequency of our lowpass filter as 10 Hz. This number is selected to delete the frequency bands that may relate to EEG while maintaining the frequency bands related to the EB.

In this phase, the eye-blink artifacts removal method have been developed and improved (see Figure 3.13). It proposed for extracting an eye-blink component from multichannel EEG in this project. The preliminary simulation results, in chapter 4, show that the corrected EEG has less distortion than the conventional method.

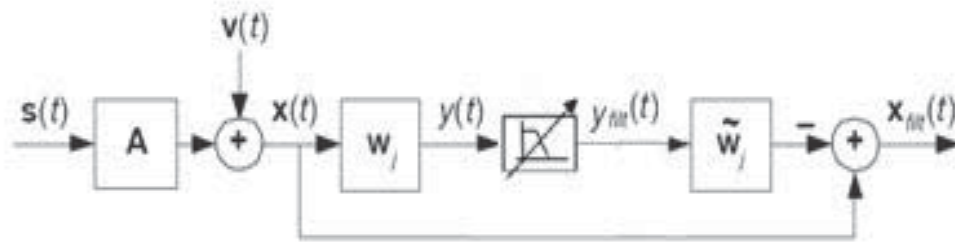


Figure 3.13 Model I method

3.4.2 Eye-Blink Artifacts Removal Improvement (2st phase)

The previous method as show in Figure 3.14 proposed by Y. Wongsawat [55], instead of using the RMVB to find the global eyeblink source, local eyeblink sources of each group of EEG channels are calculated. The results show that the computational complexity is reducing from the conventional method and the correlation of the resulting clean EEG with the eyeblink sources is as low as the correlation obtained from the conventional method.

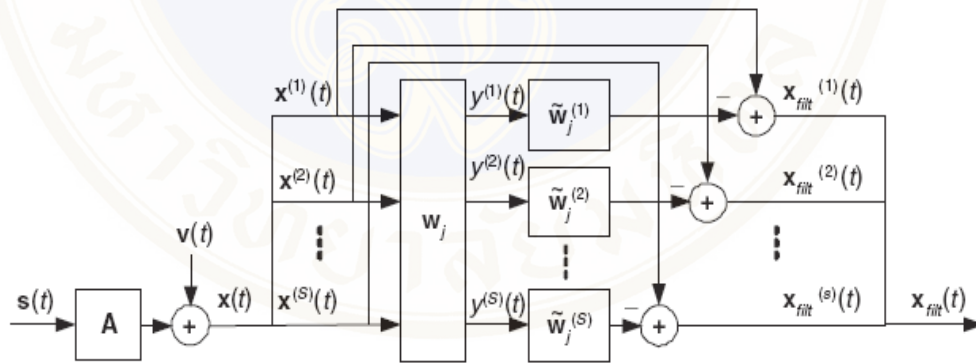


Figure 3.14 Previous method proposed by Y. Wongsawat [55].

In this phase, we propose a combination of the previous method (RMVB-based method) [55] with a simple FIR filters to reshape the EB source before using to reconstruct the corrected EEG, in order to correct the oversmooth effect of method [27, 55] and maintain the efficient computational load as well as previous method [55]. Furthermore, we also propose the method to quantitatively assess the quality of the EB-removed EEGs by employing the frequency domain information.

3.4.2.1 Efficient Implementation of RMVB for Eye-blink Artifact Removal of Multi-channel EEG. According to (3), if the number of channels of the multi channel EEG is high, finding ρ and the inverse of $\{\mathbf{R} + \frac{\varepsilon}{\rho}\mathbf{I}\}$ would require high computational complexity. In this section, we propose the new problem formulation which results in reducing the computational complexity on finding the spatial filter $\mathbf{w}_j$ while maintaining the similar eyeblink removal results with the conventional method in [27]. The overview of the method is similar to the one shown in Figure 3.14 without the filtering part. In order to find the eyeblink source $y(t)$, we need to find $\mathbf{w}_j$ such that the energy of $y(t)$ is minimized given that we know the prior knowledge about the extracted source which is the space signature of the STF-TS model. Intuitively speaking, when we filter $\mathbf{x}(t)$ using $\mathbf{w}_j$, we have to obtain the source $y(t)$ so that $y(t)$ would not take any information besides eyeblink artifacts from $\mathbf{x}(t)$. Previously, we minimize J_c which is the energy of $y(t)$, i.e.

$$J_c = \mathbf{w}_j^T \mathbf{R} \mathbf{w}_j \text{ subject to } \min_{\|\delta\| \leq \varepsilon} \left| \mathbf{w}_j^T \hat{\mathbf{a}}_j + \mathbf{w}_j^T \delta \right| = 1$$

Now, let $\|y(t)\|^2 = \|\mathbf{w}_j^T \mathbf{x}(t)\|^2 = \sum_{s=1}^S \left\| \mathbf{w}_j^T \mathbf{x}^{(s)}(t) \right\|^2$, we instead minimize

$$J_c = \hat{\mathbf{w}}_j^T \left\{ \sum_{s=1}^S \mathbf{R}^{(s)} \right\} \hat{\mathbf{w}}_j$$

subject to

$$\min_{\|\delta\| \leq \varepsilon} \left| \hat{\mathbf{w}}_j^T \left\{ \sum_{s=1}^S \hat{\mathbf{a}}_j^{(s)} \right\} \hat{\mathbf{a}}_j^{(s)} + \hat{\mathbf{w}}_j^T \delta \right| = 1$$

where $\hat{\mathbf{w}}_j$ is the spatial filter which can be used to extract the j -th source from $\mathbf{x}^{(s)}(t)$ ($s = 1, \dots, S$). $\mathbf{x}^{(s)}(t)$ of size $\frac{N}{S} \times T_1$ is $\mathbf{x}(t)$ of the s -th group of EEG channels where T_1 is the number of samples in time of each EEG channel, and S is the total number of groups, i.e. $\mathbf{x}(t) = [\mathbf{x}^{(1)}(t), \dots, \mathbf{x}^{(S)}(t)]^T$. $\hat{\mathbf{a}}_j^{(s)}$ of size $\frac{N}{S} \times T_1$ is $\hat{\mathbf{a}}_j$ of the s -th group of EEG channels, i.e. $\hat{\mathbf{a}}_j = [\hat{\mathbf{a}}_j^{(1)}, \dots, \hat{\mathbf{a}}_j^{(S)}]^T$.

$\mathbf{R}^{(s)}$ of size $\frac{N}{s} \times \frac{N}{s}$ is $\mathbf{R}$ of the s -th group of EEG channels. Similar to (3), we can show that

$$\hat{\mathbf{w}}_j = \left[\left\{ \sum_{s=1}^S \mathbf{R}^{(s)} \right\} + \frac{\varepsilon}{\rho} \mathbf{I} \right]^{-1} \left\{ \sum_{s=1}^S \hat{\mathbf{a}}_j^{(s)} \right\}. \quad (8)$$

ρ can be obtained by (4) where the columns of $\mathbf{U}$ are eigenvectors of $\sum_{s=1}^S \mathbf{R}^{(s)}$, and $\sigma_i (i=1, \dots, \frac{N}{s})$ are their corresponding eigenvalues. It should be noted that $\hat{\mathbf{w}}_j$ is of size $\frac{N}{s} \times 1$. Hence, eyeblink source of each group (s) can be obtained individually by

$$y^{(s)}(t) = \hat{\mathbf{w}}_j^T \mathbf{x}^{(s)}(t) \quad (9)$$

The clean multi-channel EEG can be obtained by cascading the clean signals of each group together. Specifically,

$$\mathbf{x}_{filt}(t) = [\mathbf{x}_{filt}^{(1)}(t), \dots, \mathbf{x}_{filt}^{(S)}(t)]^T, \quad (10)$$

where

$$\tilde{\mathbf{x}}_{filt}^{(s)}(t) = \mathbf{x}^{(s)}(t) - \tilde{\mathbf{w}}_j y^{(s)}(t), \text{ and}$$

$$\tilde{\mathbf{w}}_j^{(s)} = \frac{E[\mathbf{x}^{(s)}(t) \mathbf{x}^{T(s)}(t)] \hat{\mathbf{w}}_j}{E[y^{(s)}(t)^2]}.$$

3.4.2.2 Proposed Method (Model II Method). The overview of the proposed method is described as follows:

a) Proposed eye-blink removal method. According to (2), the EB source $y(t)$ is obtained via the worst-case performance optimization [50]. Hence, it may lack of some physical structures of the real EEG signals. Theoretically, the EB source should contain only the frequency bands of the EB which is around 2-4 Hz. However, the EB source obtained from the previous method seems to have some other frequency bands which might be related to the structures of the EEGs. Therefore, we propose to locally apply the lowpass filter to the EB sources. Then, this filtered EB sources are employed instead of the traditional one in the process of deflation in (5).

The proposed system called Model II method can be summarized in Figure 3.15. The number of the group of EEG channel, (S in Section 3.4.2.1) is selected as 1, 2, and 4. Finding the optimal number of group need more research and is listed as our future work.

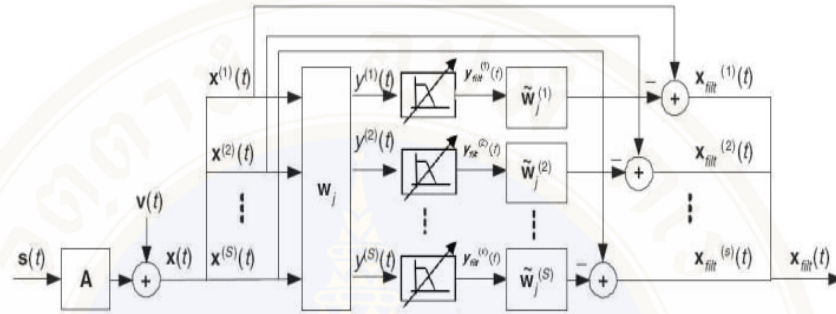


Figure 3.15 Model II method for extracting an eyeblink component from a multi-channel EEG

b) Issue on Selecting Lowpass Filter. Instead of using the ideal lowpass filter or its approximation, e.g. high order IIR filter, we employ FIR lowpass filter of order 30 for the reason of simplicity. Since the EB source is of size 1600 samples, order of 30 FIR lowpass filter is practical. In addition, the frequency response of the FIR filter is not as selective as the IIR filter, thus we select the cut-off frequency of our lowpass filter as 10 Hz. This number is selected to delete the frequency bands that may relate to EEG while maintaining the frequency bands related to the EBs. The proposed algorithm is applied to real EEG measurements. The results were shown in chapter 4.

CHAPTER IV

TESTING RESULTS AND DISCUSSIONS

4.1 Designed Hardware

Electrodes, EEG Amplifier and Analog Filter

The system using a standard EEG-cap to collected EEG signal. It widely used in many research. This recording device is equipped with 19 Ag/AgCl electrodes at the positions defined by the international 10-20 system and 1 Ag/AgCl electrodes for ground connection. All electrodes were reusable Ag/AgCl electrodes.

Normally, the frequency range of the original signal is distorted largely by the electrode properties. Because of the advantages of Ag/AgCl electrodes, which has low resistive component, the signal amplitudes of the system are only attenuated significantly for frequencies below 1 Hz.

The EEG electrode is connected to the positive input of the amplifier, as represented in Figure 4.1, and the reference electrode is connected to the negative input. Electrodes at the ear lobe positions (A1 and A2) were chosen as references. The signals from both electrodes were connected together to the negative input. This electrode montage has the advantages that the signals from all electrodes are directly comparable to each other.



Figure 4.1 Designed hardware

Table 4.1 The frequencies respond of the amplifiers and analog filters

Frequency (Hz)	Gain
0.5	9170
1	10550
5	10970
10	10900
15	10780
20	10620
25	10440
30	10180
35	9900
40	9600
45	9000
46	8100
47	6840
48	4830
49	2150
50	500
51	2540
52	3920
53	4800
54	5380
55	5760
60	6430
65	6320
70	6060

This measurement technique helps to eliminate the common mode signal such as power line noise or increase the common mode rejection ratio (CMRR) of the

system. The CMRR is an accepted measure to quantify the ability of the amplifier to reject the common mode signal. Normally, acceptable CMRRs must be larger than 100000:1 (100 dB) and can calculate as follow;

$$\text{CMRR} = \text{amplification of the EEG signal} / \text{amplification of the common mode signal}$$

The CMRR of the designed amplifier is approximately 113 dB minimum at 50 Hz.

The frequency response of the amplifiers and analog filters has been verified to ensure that the information of EEG signal is not distorted. The frequencies response, bandwidth –3dB, of designed system is 46 Hz. The amplification gains, at some frequency, of the hardware are show in Table 4.1.

The hardware that has been designed can used to collected EEG signal which have frequency range from 0.5 to 45 Hz.

4.2 Designed Software

The software that can perform some EEG analyses has been developed. The display screen is divided to three sections; there are EEG Monitoring, Signal Quality Assessment and EEG Analysis. The 15 Hz sine wave signal with 100 micro-Volts in amplitude from function generator was used as the testing signal and connected to input of some channel such as O₁, F₇, T₃, T₅, O₂, F₈, T₄ and T₆ the results are show in Figure 4.2.

4.2.1 EEG Monitoring

Each channel of EEG signal can be selected by channel selector switch to display the signal which acquiring. The “Select All” switch used to turn on or turn off all channel. This software is very flexible because the user can set the sampling rate and number of samples during monitoring. In addition, it provide many type (Butterworth, Chebychev, Inverse chebychev, Illiptic and Bessel filter) of band pass digital filter with adjustable cut-off frequencies to remove artifacts in on line mode or limit the band width of signal.

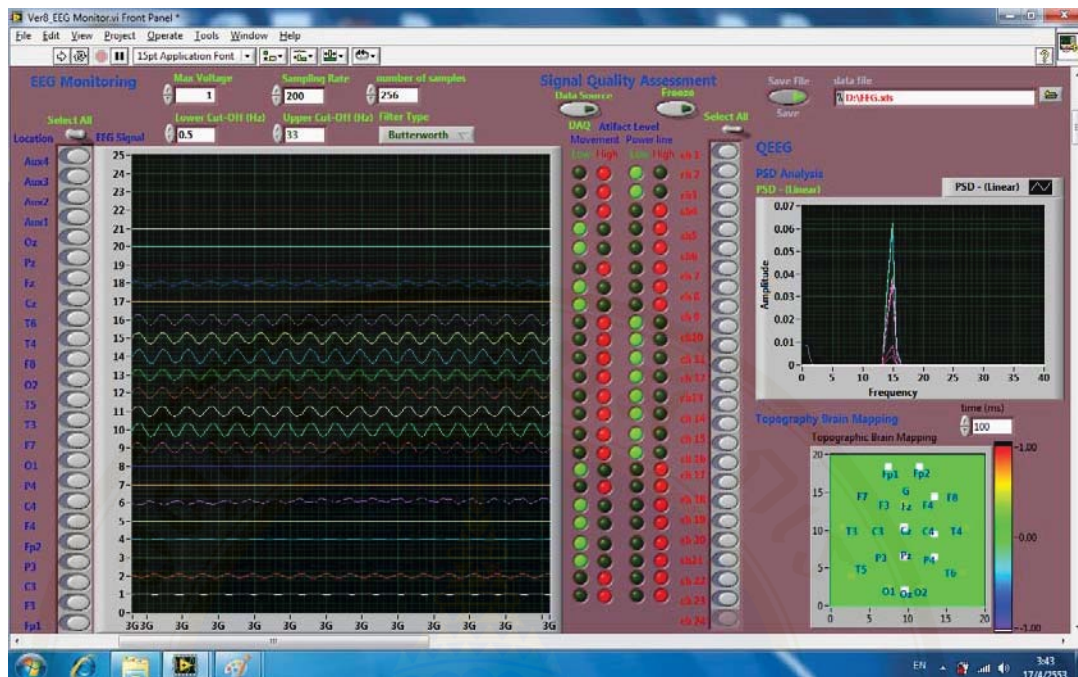


Figure 4.2 The display/control panel of the system, using 15 Hz sine wave signal connected to input of channel O₁, F₇, T₃, T₅, O₂, F₈, T₄ and T₆.

4.2.2 Signal Quality Assessment

The movement artifact and power line (50 Hz) noise is observed and reported to the user in term of “Artifact Level”. The artifact levels of each channel are indicated in low or high level. This application is helpful to improve the accuracy of EEG recording technical skill. User can stop the EEG wave form to evaluate the signal during monitoring by “Freeze” button.

4.2.3 EEG Analyses

4.2.3.1 PSD Analysis. Each channel of EEG signal can be selected by channel selector switch for EEG PSD analysis (see Figure 4.3). The “Select All” switch also used to turn on or turn off all channel. This implementation can be used to quantify EEG component, by observed the power of each frequency, on the brain during monitoring. Figure 4.3 show that the PSD of input signal are maximum at 15 Hz.

4.2.3.2 Topographic Brain Mapping. The 2 dimensions (2D) topographic brain mapping (see Figure 4.3) is plotted using the digitized data as recorded from each of 19 EEG electrodes from EEG-cap and additional Oz electrode. The Oz electrode is connected to the additional amplifier that provided for other bio signal. The on-line topographic brain map is presented for monitoring the subject brain activity. This representative view can be used to observe the alterations of EEG amplitude of each location.

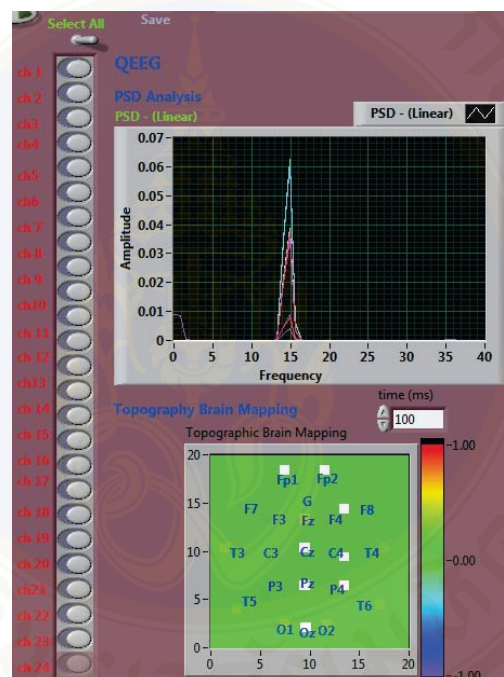


Figure 4.3 PSD Analysis and Topography Brain Mapping

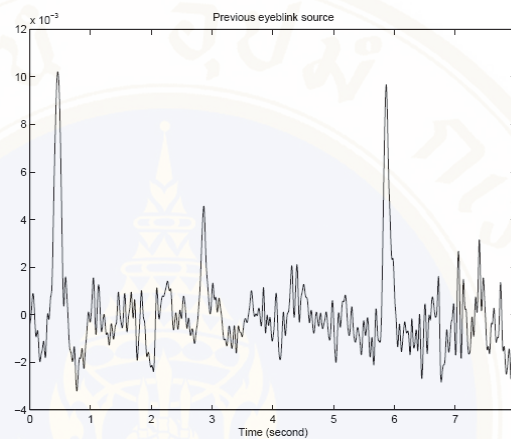
4.3 Simulation Results of the Proposed Eye-Blink Artifact Removal Method

4.3.1 Simulation Results of Model I Method (in section 3.4.1.2)

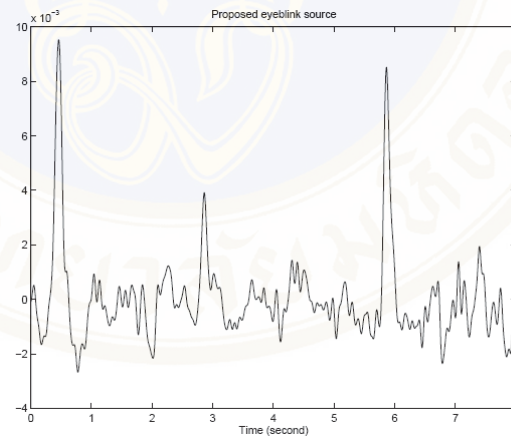
The Model I method is applied to real EEG measurements. The EB artifact database is provided by the School of Psychology, Cardiff University, UK. The scalp 16-channel EEG was obtained using Silver/Silver-Chloride electrodes placed at

locations defined by the 10-20 system. The 8-second of 16-channel EEG was sampled at 200 Hz, and band pass filtered with cut-off frequencies of 2 Hz and 30 Hz.

EB sources obtained from the convention method and Model I method are shown in Figures 4.4(a) and (b), respectively. Obviously, some high frequency bands which may relate to the structures of the EEGs are filtered out.

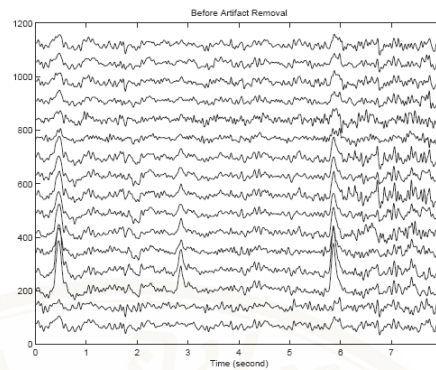


(a)

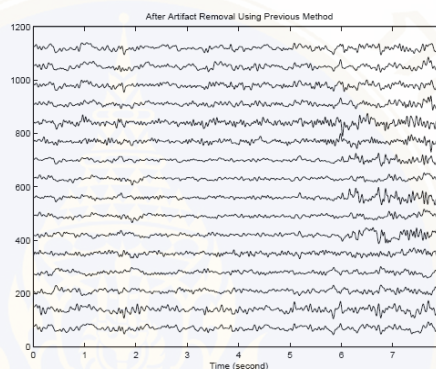


(b)

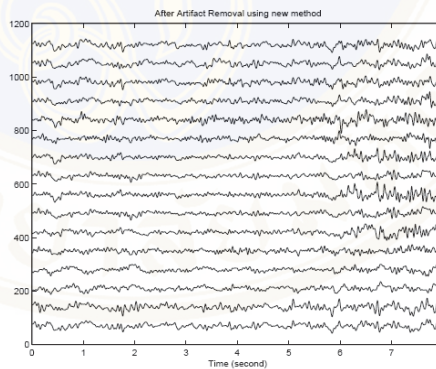
Figure 4.4 The EB sources which are calculated by (a) the conventional method and (b) the Model I method.



(a)



(b)



(c)

Figure 4.5 The results of the Model I EB artifact removal method for a set of real EEGs: (a) Original EB contaminated 16-channel EEG, (b) Resulting artifact removed 16-channel EEG obtain from the previous method, and (c) Resulting artifact removed 16-channel EEG obtain from the Model I method. From bottom to top channels: Cz, Pz, FP1, FP2, F7, F8, F5, F6, F3, F4, T7, T8, C5, C6, C3, C4.

Figure 4.5(a) illustrates the original EB-contaminated 16-channel EEG. According to Figure 4.5(c), by using our Model I method, the EB artifacts at the time of 0.5, 3, and 6 seconds are efficiently removed. It can be observed that the EB-removed EEGs obtained from the Model I method (Figure 4.5(c)) are visually less oversmoothed than the one obtained from the previous method (Figure 4.5(b)).

In order to quantitatively evaluate the merit of our Model I method, the segments of EEGs from 4 to 5 seconds of channels FP1, FP2, F7, F8, F5, F6, F3 and F4 (which are the regions that tend to be oversmoothed by the previous method) are used to evaluate the performance of our Model I method. Table 4.2 demonstrates the mean squared errors (MSE) of the selected regions of the data obtained from the previous and the Model I methods with respect to the original data of the same regions. According to Table 4.2, we can see that EB artifacts can be removed by the Model I method with lower distortions to the original underlying brain signals than those removed by the conventional method.

Table 4.2. Comparison of the mean squared errors (MSE) obtained by conventional and Model I method compared to the original data of the selected regions.

Channels	Convention	Model I
FP1	74.65	70.18
FP2	71.7	67.41
F7	21.07	19.81
F8	27.35	25.72
F5	21.9	20.59
F6	27.58	25.93
F3	19.97	18.78
F4	23.41	22.01
Avg.	35.95	33.8

4.3.2 Simulation Results of Model II Method (in section 3.4.2.2)

The proposed algorithm (Model II method) is applied to real EEG measurements using the same data as Model I method testing. The simulation results are presented in Figure 4.6. Figure 4.6 (a) illustrates the original EB-contaminated 16-channel EEG. According to Figure 4.6(e), by using our Model II method, the EB artifacts at the time of 0.5, 3, and 6 seconds are efficiently removed. It can be observed that the EB-removed EEGs obtained from the Model II method (Figure 4.6 (e)) are visually less oversmoothed than the one obtained from the conventional method (Figure 4.6(b)). Figures 4.6(f) and (g) present the resulting clean multichannel EEGs using the Model II method when the eyeblink contaminated multi-channel EEGs are divided into 2 and 4 groups ($S = 2, 4$), respectively.

When using the Model II methods, we can visually see that the eyeblink artifacts are efficiently removed and less oversmoothed than the one obtained from the previous method in Figures 4.6 (c) and (d), respectively.

In order to quantitatively evaluate the merit of our Model II method, the segments of EEGs from 4 to 5 seconds of channels FP1, FP2, F7, F8, F5, F6, F3 and F4 (which are the regions that tend to be oversmoothed by the previous method, called the selected regions) are used to evaluate the performance of our Model II method. The mean square error, in frequency domain which using the single-sided amplitude spectrum of the selected regions by taking the fast Fourier transform (FFT), obtained from the previous and the Model II methods with respect to the original data of the same regions is calculated and demonstrated in Table 4.3. According to Table 4.3, we can see that EB artifacts can be removed by the Model II method with lower distortions (low error) to the original underlying brain signals than those removed by the previous method.

Even though, according to Table 4.4, the computational complexity of Model II method is insignificant increase from conventional method. It is noted that the computational complexities obtained in this paper are measured in MATLAB Software (www.mathworks.com) and performed on the laptop computer with a 1.8 GHz Intel® Core™ 2 Duo processor T7100.

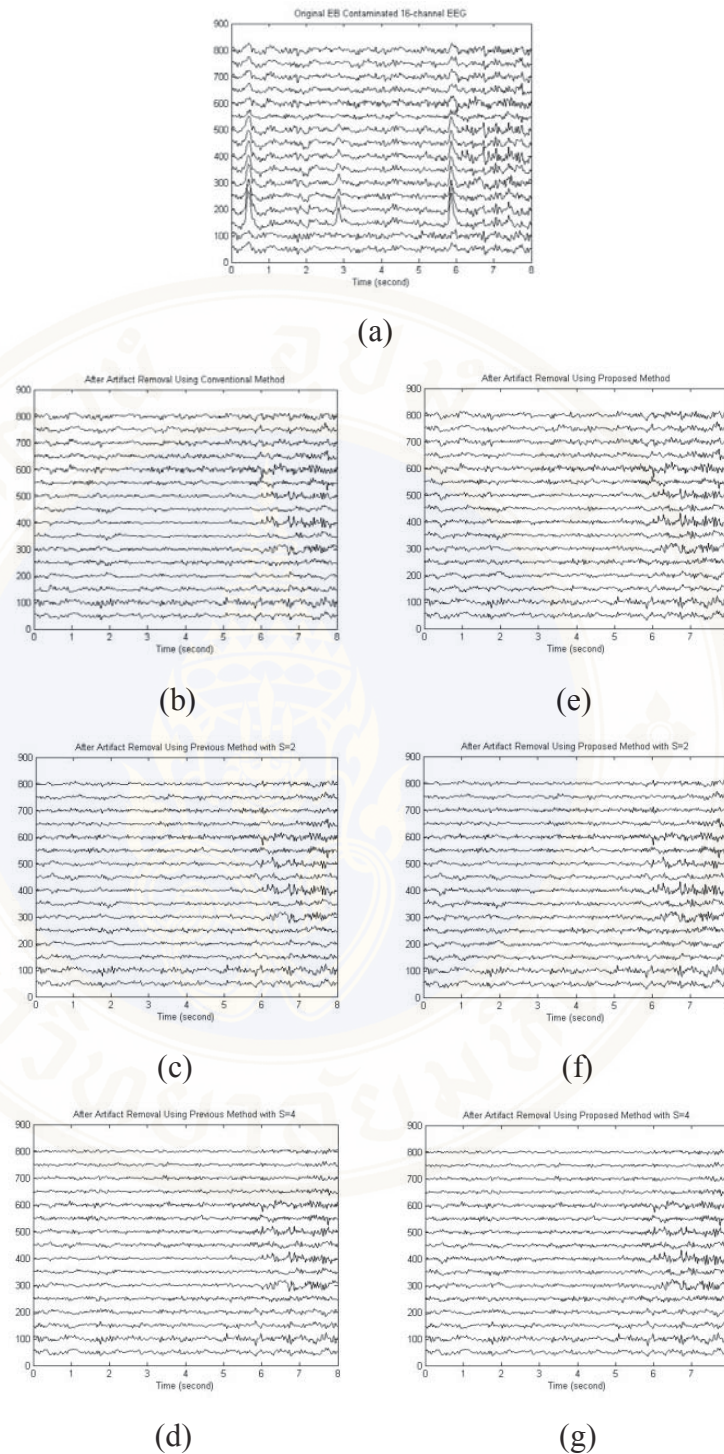


Figure 4.6 The results of the Model II method for a set of real EEGs: (a) Eyeblink-contaminated EEGs before artifact removal, (b) EEGs after removing the artifact using previous method, EEGs after removing the artifact using previous method with (c) $S = 2$ and (d) $S = 4$ and EEGs after removing the artifact using Model II method (e), with (f) $S = 2$ and (g) $S = 4$. The bottom line corresponds to channel 1 and the top line corresponds to channel 16.

TABLE 4.3 Comparison of the mean squared errors (MSE) obtained by conventional (Convent.), previous (Pre.) and Model II (M II) method compared to the original data of the selected regions in frequency domain.

Ch.	Convent.	Pre.	Pre.	M II	M II	M II
		S=2	S=4	S=1	S=2	S=4
FP1	0.0164	0.0196	0.0186	0.0144	0.0142	0.0121
FP2	0.0151	0.0173	0.0141	0.0112	0.0120	0.0092
F7	0.0095	0.0087	0.0104	0.0063	0.0055	0.0069
F8	0.0094	0.0088	0.0102	0.0058	0.0056	0.0063
F5	0.0099	0.0086	0.0106	0.0062	0.0051	0.0070
F6	0.0132	0.0116	0.0147	0.0076	0.0067	0.0078
F3	0.0108	0.0124	0.0108	0.0064	0.0071	0.0057
F4	0.0112	0.0136	0.0152	0.0064	0.0102	0.0100

TABLE 4.4 Comparison of time complexity (second) of the conventional, previous and Model II method.

Methods	Convent.	Pre.	Pre.	M II	M II	M II
		S=2	S=4	S=1	S=2	S=4
Complexity	8.25	0.26	0.17	8.43	0.37	0.28

4.4 DISCUSSIONS

4.4.1 Hardware

The accuracy of data acquisition device for collecting EEG signal is very important. The specification of the device must be suitable for the data that acquired. For this project, the hardware that has been developed can use for acquiring the scalp EEG with frequency range between 0.5 to 45 Hz.

In addition, safety is the issues that must be considered when we design the medical equipment. The related standards are also discussed; the electrical hazards are protected by using DC-DC converter isolated power supply and isolated data acquisition device. In the further work, the system should be tested and evaluated to meet the standard.

The dimension of the hardware is also considered in hardware design. The size of the hardware is approximately 6 x 8 x 10 inch in dimension. The advantage of small size hardware is it very comfortable, conversely it cause to high cost.

The amplifiers of the system consist of 11 printed circuit board (PCB) and each PCB has 2 channel of amplifier. From this reason, we can increase or decrease 2 channel of the system by add or remove a PCB.

4.4.2 Software

Normally, commercial software will design to use with their product. For specific research, we must be developing the appropriate hardware and software.

The software that developed in this project is the initiate tool for EEG monitoring, filtering, recording, signal quality assessment and EEG analysis. It can also used to evaluate the system. It should be develop to perform montage setup, on-line eye blink or other artifacts removal, on-line signal quality assessment and 3D-brain mapping.

4.4.3 Eye-Blink Artifact Removal Method

The proposed eye-blink artifact removal method mentioned in chapter 3 and the simulation results that presented in chapter 4. A model II method is the final version of eye-blink artifact removal method development. The results show that EB artifacts can be removed by the Model II method with lower distortions (low error) to the original underlying brain signals than those removed by the previous method. The computational complexity of Model II method is significant decrease from conventional method. The advantage of decreasing of the computational complexity is that this method could be applied to remove the eye-blink artifact in on-line mode.

CHAPTER V

CONCLUSIONS AND FUTURE WORKS

The several expected results were formulated, as section 1.3, to fulfill the project of a multichannel EEG monitoring system. These results are summarized as follows.

5.1 Summary of Contribution

A prototype of 19-channel EEG monitoring system that employs the local resources has been developed. The system consists of 19 channels analog amplifiers with amplification gain 10,000 defined for EEG signal from Ag/AgCl electrodes which fixed on cap according to 10-20 system. The system also provided 3 additional channels analog amplifiers for future development. The additional channels could be applied for measuring other bio signal, e.g. EOG, ECG, and EMG. The system suitable to measure scalp EEG which has frequency range between 0.5 to 45 Hz. For electrical hazards protection, the standard device such as isolated power supply and signal isolation has been designed and implement to the system.

Eye-blink artifact removal method (RMVB-based Eye-blink Artifacts Removal via STF-TS Modeling and Digital Filtering) has been proposed. It has been developed for enhancing the quality of the EB artifact removed EEG signals. The algorithms and methods, mentioned in chapter 3, were simulation test. The results show that it can remove the eye-blink artifact from multichannel EEG signal with low distortion and low computation time. This algorithm also could be applied in BCI system. The proposed method has been presented on IEEE ISBME 2009 conference.

The prototype software for EEG assessment that can be used in conjunction with real time monitoring has also been developed. The EEG signal from each channel can selected for monitoring and also saved in ASCII file format. The movement artifact and power line (50 Hz) noise of each channel are reported to user in

term of artifact level. The artifacts level is helpful to correct the recording technique for low signal quality avoidance. The software can perform some other EEG analyses. The user can limit the range of EEG frequency to the band of interest using FIR band pass filter that provided by this software. The power spectral density and 2D-brain mapping, the important tool for quantitative EEG analysis are also performed.

In the other hand, the proposed system that has been developed is inexpensive and can develop the software respect to specific problem. This system could be use with other multichannel bio-signals systems e.g., multichannel EMG, electrical impedance tomography.

5.2 Future Works

For further improvement, the hardware of the system should be developed for wireless EEG monitoring system, small size and low power consumption. Electrode impedance testing module should also be developed and added to the system.

The software that can perform montage setup, 3-D brain mapping, more patterns recognizes and source localization should be considered for the future works. Furthermore, this system could be applied to BCI system and intraoperative monitoring research.

REFERENCES

1. Teplan M. Fundamentals of EEG measurement. *Measurement science review*. 2002; 2(2):1-11.
2. Sanei S, Chambers JA. *EEG Signal Processing*. New York: JohnWiley & Sons; 2007.
3. Garcia GN. Direct brain-computer communication through scalp recorded EEG signals [Ph.D. Thesis in Sciences]. Lausanne: École Polytechnique Fédérale de Lausanne (EPFL); 2004.
4. Claassen J, Mayer SA. Continuous electroencephalographic monitoring in neurocritical care. *Curr Neurol Neurosci Rep*. 2002; 2(6):534-40.
5. Stacey L. "EEG Machine." How Products are Made [Online]. eNotes.com.2006. Available from: <http://www.enotes.com/how-products-encyclopedia/eeg-machine> [Accessed 2009 Jun 20].
6. Macdonald G. Long-term EEG monitoring in the Neonatal Intensive Care Unit. *Conf Proc IEEE Eng Med Biol Soc*. 2005; 3:2483-5.
7. Alan W, Mutch C. EEG Monitoring to Assess Emergence From Neuroanesthesia. [Online]. ClinicalTrials.gov. Available from: <http://clinicaltrials.gov/ct2/show/NCT00443807> [Accessed 2009 Jun 20].
8. Willmann K, Springman S, Rusy D, Daily E. A preliminary evaluation of a new derived EG index monitor in anesthetized patients. *J Clin Monit Comput*. 2002; 17(6):345-50.
9. Fatourech M, Bashashati A, Ward RK, Birch GE. EMG and EOG artifacts in brain computer interface systems: A survey. *Clin Neurophysiol*. 2007 ; 118(3):480-94.
10. Choi S, Cichocki A, Park HM, Lee SY. Blind source separation and independent component analysis: a review. *Neural Inf Process-Lett Rev*. 2005; 6:1–57.

11. Schlögl A, Keinrath C, Zimmermann D, Scherer R, Leeb R, Pfurtscheller G. A fully automated correction method of EOG artifacts in EEG recordings. *Clin Neurophysiol.* 2007; 118(1):98-104.
12. Ting KH, Fung PC, Chang CQ, Chan FH. Automatic correction of artifact from single-trial eventrelated potentials by blind source separation using second order statistics only. *Med Eng Phys.* 2006; 28(8):780-94.
13. Shoker L, Sanei S, Chambers JA. Artifact removal from electroencephalograms using a hybrid BSS-SVM algorithm. *IEEE Signal Processing Letters.* 2005; 12(10):721-4.
14. Shoker L, Sanei S, Wang W, Chambers JA. Removal of eye blinking artifact from the electro-encephalogram incorporating a new constrained blind source separation algorithm. *Med. Biol. Eng. Comput.* 2005; 43:290-5.
15. Nazarpour K, Wongsawat Y, Sanei S, Chambers JA, Orintara S. Removal of the eye-blink artifacts from EEGs via STF-TS modeling and robust minimum variance beamforming. *Conf Proc IEEE Eng Med Biol Soc.* 2007; 29:6211-4.
16. Puthusserypady S, Ratnarajah T. H^∞ adaptive filters for eye blink artifact minimization from electroencephalogram. *IEEE Signal Processing Letters.* 2005; 12(12): 816-9.
17. Lagerlund TD, Sharbrough FW, Busacker NE. Spatial filtering of multichannel electroencephalographic recordings through principal component analysis by singular value decomposition. *J Clin Neurophysiol.* 1997; 14(1):73-82.
18. Jung TP, Makeig S, Humphries C, Lee TW, Mckeown MJ, Iragui V, Sejnowski TJ. Removing electroencephalographic artifacts by blind source separation. *Psychophysiology.* 2000; 37: 163-178. Cambridge University Press. Printed in the USA.
19. Nazarpour K, Sanei S, Chambers JA. A novel semiblind signal extraction approach incorporating PARAFAC for the removal of the removal of eye-blink artifact from EEGs. *Proceedings of the 15th International Conference on Digital Signal Processing (DSP '07);* 2007 July; Cardiff, UK.127-130.

20. Li XL, Zhang XD. Sequential blind extraction adopting second-order statistics. *IEEE Signal Processing Letters*. 2007; 14(1):58–61.
21. James CJ, Gibson OJ. Temporally constrained ICA: an application to artifact rejection in electromagnetic brain signal analysis. *IEEE Transactions on Biomedical Engineering*. 2003; 50(9): 1108–16.
22. Hesse CW, James CJ. On semi-blind source separation using spatial constraints with applications in EEG analysis. *IEEE Transactions on Biomedical Engineering*. 2006; 53(12):2525–34.
23. Hesse CW, James CJ. The fast ICA algorithm with spatial constraints. *IEEE Signal Processing Letters*. 2005; 12(11):792–5.
24. Lu W, Rajapakse JC. Approach and applications of constrained ICA. *IEEE Transactions on Neural Networks*. 2005; 16(1):203–12.
25. Ille N. Artifact correction in continuous recording of the electrode and magnetoencephalogram by spatial filtering. [Ph.D. thesis]. University of Mannheim, Mannheim, Germany, 2001.
26. Parra LC, Spence CD, Gerson AD, Sajda P. Recipes for the linear analysis of EEG. *NeuroImage*. 2005; (28)2: 326–41.
27. Nazarpour K, Wongsawat Y, Sanei S, Orintara S, Chambers J. A robust minimum variance beamforming approach for the removal of the eye-blink artifacts from EEGs. *Proceedings of International Conference of the IEEE Engineering in Medicine and Biology Society*, May 2007.
28. Li J, Stoica P, editors. *Robust Adaptive Beamforming*. Wiley, 2005.
29. Bro R. PARAFAC: Tutorial and applications. *Chemometrics Intell. Lab. Syst.* vol. 1997; 38:149–71.
30. Nakamura M. Technical quality evaluation of EEG recording based on electroencephalographers' knowledge. *Medical Engineering & Physics*. 2005; 27: 93-100.
31. Jenq YC. Discrete-Time Method for Signal and Noise Measurement. *Proceeding of Instrumentation and Measurement Technology Conference IMTC/95 'Integrating Intelligent Instrumentation and Control'*; 1995 Apr 23-25; IEEE, 1995. p. 68.

32. Eckert O. Automatic artefact detection in intraoperative EEG monitoring. *Biomed Tech (Berl)*. 1998; 43(9):236-42.
33. Ferree TC, Luu P, Russell GS, Tucker DM. Scalp electrode impedance, infection risk, and EEG data quality. *Clin Neurophysiol*. 2001; 112(3):536-44.
34. Grönlund C, Roeleveld K, Holtermann A, Karlsson JS. On-line signal quality estimation of multichannel surface electromyograms. *Med. Biol. Eng. Comput*. 2005; 43(3):357-64.
35. Niedermeyer E, Lopes da Silva FH. *Electroencephalography: Basic Principles, clinical Applications and Related Fields*. 5th ed. Chapter 18 p. 366, chapter 56 p.1141-1153. Philadelphia: Lippincott Williams & Wilkins; 2005.
36. Niedermeyer E, Lopes da Silva FH. *Electroencephalography: Basic Principles, clinical Applications and Related Fields*. 5th ed. chapter 59 p. 1239. Philadelphia: Lippincott Williams & Wilkins; 2005. Quantitative information
37. Crossroadsinstitute. What is Brain mapping? [Online]. Available from: <http://www.crossroadsinstitute.org/learningcenter/qeeg/what-is-brainmapping.html> [Accessed 2009 Jun 20].
38. Sabbatini RME. EEG Brain topography [Online]. Available from: <http://www.cerebromente.org.br/n03/tecnologia/eeg.htm#topography> [Accessed 2009 Jun 20].
39. Medical application EEG topography. Available from: <http://www.economicexpert.com/a/EEG:topography.html> [Accessed 2009 Jun 20].
40. Walerjan P, Tarnecki R. PC based EEG mapping system. *Acta Neurobiol.Exp*. 1995;55(4):307-15.
41. Itil TM, Mucci A, Eralp E. Dynamic brain mapping methodology and application, *International Journal of Psychophysiology*. 1991; 10(3):281-91.
42. Soong AC, Lind JC, Shaw GR, Koles ZJ. Systematic comparisons of interpolation techniques in topographic brain mapping. *Electroencephalography and clinical neurophysiology, Electroencephalogr Clin Neurophysiol*. 1993; 87(4):185-95.

43. Fletcher EM, Kussmaul CL, Mangun GR. Estimation of interpolation errors in scalp topographic mapping. *Electroencephalography and Clinical Neurophysiology*. 1996; 98(5):422-34.
44. Anderer P, Semlitsch HV, Saletu B, Barbanoj M J. Artifact processing in topographic mapping of electroencephalographic activity in neuropsychopharmacology. *Psychiatry Res*. 1992; 45(2):79-93
45. Kehtarnavaz N. Digital Signal Processing System Design, LabVIEW-Based Hybrid Programming. 2th ed. Burlington: Elsevier Academic Press; 2008.
46. Ingle VK, Proakis JG. Digital Signal Processing using MATLAB Toronto: Thomson; 2007.
47. McKinley S, Megan L. Cubic Spline Interpolation. [Online]. Available from: <http://online.redwoods.cc.ca.us/instruct/darnold/laproj/fall98/Skymeg> [Accessed 2010 Jan 10].
48. Vorobyov SA, Gershman AB, Luo ZQ. Robust adaptive beamforming using worst case performance optimization. *IEEE Transactions on Signal Processing*. 2003; 51(2): 313–24.
49. Wongsawat Y, Oraintara S, Rao KR. Reduced complexity space-time-frequency model for multichannel EEG and its applications. *Proceedings of IEEE International Symposium on Circuits and Systems*; 2007; 1305–08.
50. Zarifi K, Shahbazpanahi S, Gershman AB, Luo ZQ. Robust blind multiuser detection based on the worst-case performance optimization of the MMSE receiver. *IEEE Transactions on Signal Processing*. 2005; 53(1): 295–305.
51. Cichocki A, Amari S. Adaptive Blind Signal and Image Processing. New York: John Wiley and Sons; 2002.
52. Bro R, Multi-way Analysis in the Food Industry: Models, Algorithms and Applications. MATLAB toolbox available [online] at <http://www.models.kvl.dk/users/rasmus/>: Ph.D. Thesis, University of Amsterdam and Royal Veterinary an Agricultural University.
53. Miwakeichi F, Martinez-Montes E, Valdes-Sosa PA, Nishiyama N, Mizuhara H, Yamaguchi Y. Decomposing EEG data into space-time-frequency

components using parallel factor analysis. *NeuroImage*. 2004; 22: 1035–45.





ENHANCEMENT OF ROBUST MINIMUM VARIANCE BEAMFORMING BASED EYE-BLINK ARTIFACT REMOVAL FROM EEGS VIA DIGITAL FILTERING

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ABSTRACT

This paper proposes a method to enhance the performance of the minimum variance beamforming (RMVB)-based eyeblink (EB) artifact removal from the electroencephalograms (EEG) by employing a simple digital filter. By removing the EB artifacts from EEG signals based on a space-time frequency (STF) model of EEGs and the RMVB, we found that some components of EEG signals have been lost. Therefore, the lowpass FIR filter is combined with the RMVB based method to reshape the EB source. The results show that EB artifacts can be efficiently removed by the proposed method with lower distortions to the original underlying EEG signals than the previous method.

1. INTRODUCTION

The electrooculogram (EOG) generated by eye movements, or blinks is found to be the most significant and common artifact in EEG analysis [1]. Suppressing eye-blink (EB) over a sustained recording course is particularly difficult due to its amplitude which is of the order of ten times larger than the average cortical signals, lasting approximately 300 msec. Due to the reasonably high magnitude of the EB artifacts and the high resistance of the skull and scalp tissues, EOG may contaminate majority of the electrode signals, even those in the occipital area. In recent years, it has become very desirable to effectively remove the EB artifacts without distorting the underlying brain activity. In this regard, reliable and fast, either iterative or batch, algorithms for EB artifact removal are of great interest for diverse applications such as brain computer interfacing (BCI) and ambulatory EEG settings.

Various methods for EB artifact removal from EEGs have been documented that are mainly based on independent component analysis (ICA) [1], linear regression [2], and references therein. Approaches, such as trial rejection, eye fixation, EOG subtraction, principal component analysis (PCA) [3], blind source separation (BSS) [4–6], and robust beamforming [7] have also been documented as having varying success. A hybrid BSS-SVM method for removing EB artifacts along with a temporally constrained BSS algorithm have been recently developed in [5, 6]. Moreover, methods based on H^∞ adaptive [8] and spatial filters [9] have also been presented in the literature for EB removal. It has been shown that the regression- and BSS-based methods are most reliable [1], despite no quantitative comparison for any reference dataset being available.

Recently, Nazapour et al. [7] have presented one efficient type of the BSS-based method by employing the STFTS model and RMVB. However, in some dataset (especially with high amplitude EB artifacts), this method seems to oversmooth the original EEG signals. Hence, in this paper, we propose a combination of the RMVB-based method [7] with a simple FIR filter in order to correct the oversmooth effect. The results in term of both visually and quantitatively assessment illustrate that the proposed method causes less distortion to the original underlying brain activities compared to the previous work.

This paper is organized as follows. Section 2 discusses the principles of the previous work on removal of the EB artifacts. The proposed method which results in lower EEGs signals distortions

after the EB artifact removal are described in Section 3. In Section 4, the simulation results are shown. The conclusions of this study are stated in Section 5.

2. ROBUST BEAMFORMING MINIMUM VARIANCE –BASED EYE-BLINK ARTIFACT REMOVAL

This section aims to review the previous method proposed in [7] for recovering the clean multi-channel EEG back from the EB-contaminated one by employing the robust minimum variance beamforming (RMVB) [10], [11]. The prior knowledge used in the RMVB is obtained via the STF-TS model [12]. Specifically, let $\mathbf{s}(t) = [s_1(t), s_2(t), \dots, s_N(t)]^T$ be N zero-mean real mutually uncorrelated point geometrically stationary sources which are mixed by an $N \times N$ full column rank matrix (mixing matrix) $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_N]$ where $\mathbf{a}_i$ is the i -th column of $\mathbf{A}$. The vector of a time mixture signal (N -channel EEG signal at each time stem t)

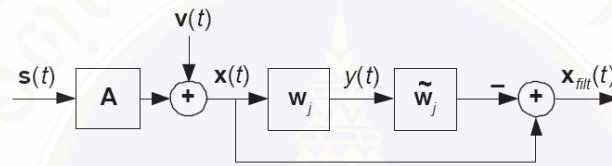


Figure 1. Conventional system in [7] for extracting an EB component from a multi-channel EEG.

$\mathbf{x}(t) = [x_1(t), x_2(t), \dots, x_N(t)]^T$ which is shown in Fig.1 can be formulated as

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{v}(t) \quad (1)$$

where $\mathbf{v}(t) = [v_1(t), v_2(t), \dots, v_N(t)]^T$ is the additive white Gaussian zero-mean noise which is assumed to be spatially and temporally uncorrelated with a multi-channel EEG. The goal is we try to remove the EB source $y(t)$ in Fig.1 from the multi-channel EEG, $\mathbf{x}(t)$.

2.1. Implementation of the RMVB

According to Fig.1, since $\mathbf{a}_i$ performs as the steering vector of the j -th source (which is assumed to be the source according to EBs), we may write $y(t)$ which is denoted as an estimation of the source $s_j(t)$ as

$$y(t) = \mathbf{w}_j^T \mathbf{x}(t), \quad (2)$$

where $\mathbf{w}_j$ acts as a spatial filter. $\mathbf{w}_j$ can be found by minimizing the energy of $y(t)$ subject to the prior knowledge on how the EB artifacts are spatially distributed. Since the prior knowledge we can find is usually not the ideal one, $\mathbf{w}_j$ can be found by solving the worst-case performance optimization [11] where the estimated prior knowledge can be used. In general, we can write this problem as

$$\text{Minimize } J_c = \mathbf{w}_j^T \mathbf{R} \mathbf{w}_j \text{ subject to } \min_{\|\delta\| < \varepsilon} \left| \mathbf{w}_j^T \hat{\mathbf{a}}_j + \mathbf{w}_j^T \delta \right| = 1$$

where $\mathbf{R} = \frac{1}{K} \sum_{k=1}^K \mathbf{R}_{XX}^k$, $\hat{\mathbf{a}}_j$ is the estimated steering vector of source j -th, ε is the

setting mismatch norm, and $\delta = \mathbf{a}_j - \hat{\mathbf{a}}_j$. By using the Lagrange multiplier method, differentiating J_c with respect to $\mathbf{w}_j$ and setting it to zero, the spatial filter $\mathbf{w}_j$ can be computed as follows:

$$\mathbf{w}_j = \left[\mathbf{R} + \frac{\varepsilon}{\rho} \mathbf{I} \right]^{-1} \hat{\mathbf{a}}_j, \quad (3)$$

where $\rho \equiv \|\mathbf{w}_j\|$ and $\mathbf{I}$ denotes the identity matrix.

By following the method suggested in [13], we can use ρ that satisfies the following equation:

$$\sum_{i=1}^N \left(\frac{|g_i|}{\varepsilon + \rho \sigma_i} \right)^2 - 1 = 0, \quad (4)$$

where $\mathbf{g} = [g_1, \dots, g_N]^T = \mathbf{U}^T \hat{\mathbf{a}}_j$. $\mathbf{U}$ is an $N \times N$ matrix whose columns are eigenvectors of $\mathbf{R}$ and $\sigma_i (i = 1, \dots, N)$ are their corresponding eigenvalues [10].

The clean multi-channel EEG without the EB contamination, $\mathbf{x}_{filt}(t)$, can be obtained by deflation method [14], that is

$$\mathbf{x}_{filt}(t) = \mathbf{x}(t) - \tilde{\mathbf{w}}_j y(t), \quad (5)$$

where $\tilde{\mathbf{w}}_j$ can be found so that $\mathbf{x}_{filt}(t)$ has minimum energy when the EB source $y(t)$ is removed from the contaminated source $\mathbf{x}(t)$. Specifically, $\tilde{\mathbf{w}}_j$ can be obtained by minimizing $J_j(\tilde{\mathbf{w}}_j)$ with respect to $\tilde{\mathbf{w}}_j$ where

$$\begin{aligned} J_j(\tilde{\mathbf{w}}_j) &= E[\mathbf{x}_{filt}^T(t) \mathbf{x}_{filt}(t)] \\ &= E[\mathbf{x}^T(t) \mathbf{x}(t)] - 2 \tilde{\mathbf{w}}_j^T E[\mathbf{x}(t) y(t)] + \tilde{\mathbf{w}}_j^T \tilde{\mathbf{w}}_j E[y(t)^2]. \end{aligned}$$

Hence,

$$\tilde{\mathbf{w}}_j = \frac{E[\mathbf{x}(t) y^T(t)]}{E[y(t)^2]} = \frac{E[\mathbf{x}(t) \mathbf{x}^T(t)] \mathbf{w}_j}{E[y(t)^2]}. \quad (6)$$

2.2. Space-time-frequency-time/segment model (STF-TS model)

According to section 2.1, the estimated prior knowledge $\hat{\mathbf{a}}_j$ of the beamformer can be found via the space signature of the STF-TS model proposed in [12]. This section aims to review the basic concept of the STF-TS model.

For a long-term EEG signal, the calculations of both the time-frequency transform and the PARAFAC [15] for constructing the STF model [16] are very complex. Computational complexity can be reduced by dividing the time domain into segments. After that, the time-frequency transform is applied individually to each segment forming a 4-D array signal, $\hat{\mathbf{y}}(n_1, s_t, f_1, t_1)$ (denoted in array form as $\hat{\mathbf{Y}}$), where n_1 is the channel index ranging from 1 to N_1 , s_t is the time/segment index ranging from 1 to S_t , f_1 is the frequency index ranging from 1 to F_1 , and t_1 is the time index ranging from 1 to T_1 . The 4-way PARAFAC is then applied to this 4-D array signal. The 4-way PARAFAC model of the 4-D array $\hat{\mathbf{Y}}$ can be formulated as follows:

$$\hat{\mathbf{Y}}_{N_1 \times S_t \times F_1 \times T_1} = f(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}) + \hat{\mathbf{E}}_{N_1 \times S_t \times F_1 \times T_1}, \quad (7)$$

where the 4-way PARAFAC model (STF-TS model) is

$$f(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}) = \sum_{m=1}^M \hat{a}(n_1, m) \hat{b}(s_t, m) \hat{c}(f_1, m) \hat{d}(t_1, m),$$

and $\hat{\mathbf{E}}$ is now a 4-D array residual of the model. Each column of $\hat{\mathbf{A}}_{N_1 \times M}$ denotes the space (spatial) signature of the m -th component ranging from 1 to M where its matrix elements are denoted as $\hat{a}(n_1, m)$. Each column of $\hat{\mathbf{B}}_{S_t \times M}$ denotes the time/segment signature where its matrix elements are denoted as $\hat{b}(s_t, m)$. Each column of $\hat{\mathbf{C}}_{F_1 \times M}$ denotes the frequency signature where its matrix elements are denoted as $\hat{c}(f_1, m)$. Each column of $\hat{\mathbf{D}}_{T_1 \times M}$ denotes the time signature where its matrix elements are denoted as $\hat{d}(t_1, m)$. $\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}$, and $\hat{\mathbf{D}}$ can be estimated by using the alternate least square algorithm (ALS) [15] where the cost function is

$$\text{argmin}_{\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}} \left\| \hat{\mathbf{Y}} - f(\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}, \hat{\mathbf{D}}) \right\|.$$

In this paper, the column of $\hat{\mathbf{A}}_{N_1 \times M}$ which illustrates how EBs are spatially distributed is employed as the estimated prior knowledge $\hat{\mathbf{a}}_j$.

3. PROPOSED EYE-BLINK (EB) REMOVAL METHOD

After the removal of the EB artifacts from EEG signals based on the previous method mentioned in Section 2, we found by inspection that some components of EEG signals are oversmoothed and distorted as shown in Fig. 2(b). Therefore, in this section, the simple but efficient method is proposed in order to enhance the results of the previous method in [7].

3.1. Proposed Method

According to (2), the EB source $y(t)$ is obtained via the worst-case performance optimization [11]. Hence, it may lack of some physical structures of the real EEG signals. Theoretically, the EB source should contain only the frequency bands of the EB which is around 2-4 Hz. However, the EB source obtained from the previous method seems to have some other frequency bands which might be related to the structures of the EEGs. Therefore, we propose to apply the lowpass filter to the EB source. Then, this filtered EB source is employed instead of the traditional one in the process of deflation in (5).

3.2. Issue on Selecting Lowpass Filter

Instead of using the ideal lowpass filter or its approximation, e.g. high order IIR filter, we employ FIR lowpass filter of order 30 for the reason of simplicity. Since the EB source is of size 1600 samples, order of 30 FIR lowpass filter is practical. In addition, the frequency response of the FIR filter is not as selective as the IIR filter, thus we select the cut-off frequency of our lowpass filter as 10 Hz. This number is selected to delete the frequency bands that may relate to EEG while maintaining the frequency bands related to the EB.

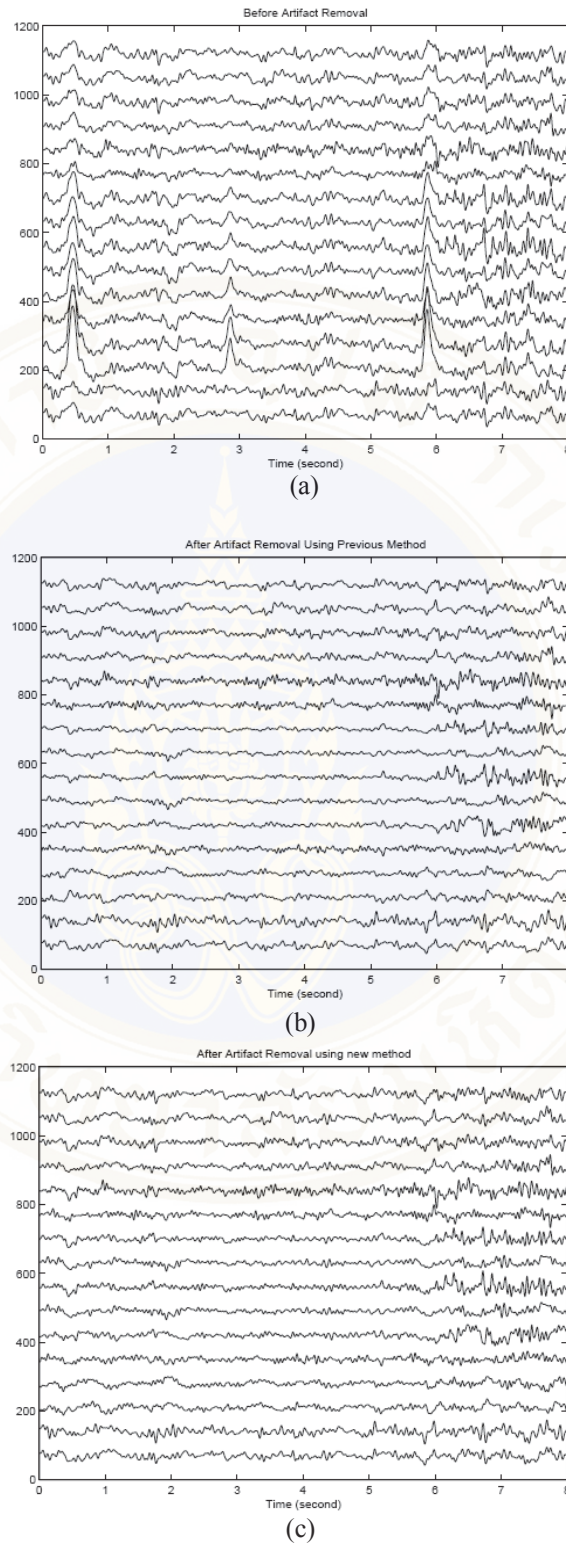


Figure 2. The results of the proposed EB artifact removal method for a set of real EEGs: (a) Original EB contaminated 16-channel EEG, (b) Resulting artifact removed 16-channel EEG obtain from the previous method, and (c) Resulting artifact removed 16-channel EEG obtain from the proposed method. From bottom to top channels: Cz, Pz, FP1, FP2, F7, F8, F5, F6, F3, F4, T7, T8, C5, C6, C3, C4.

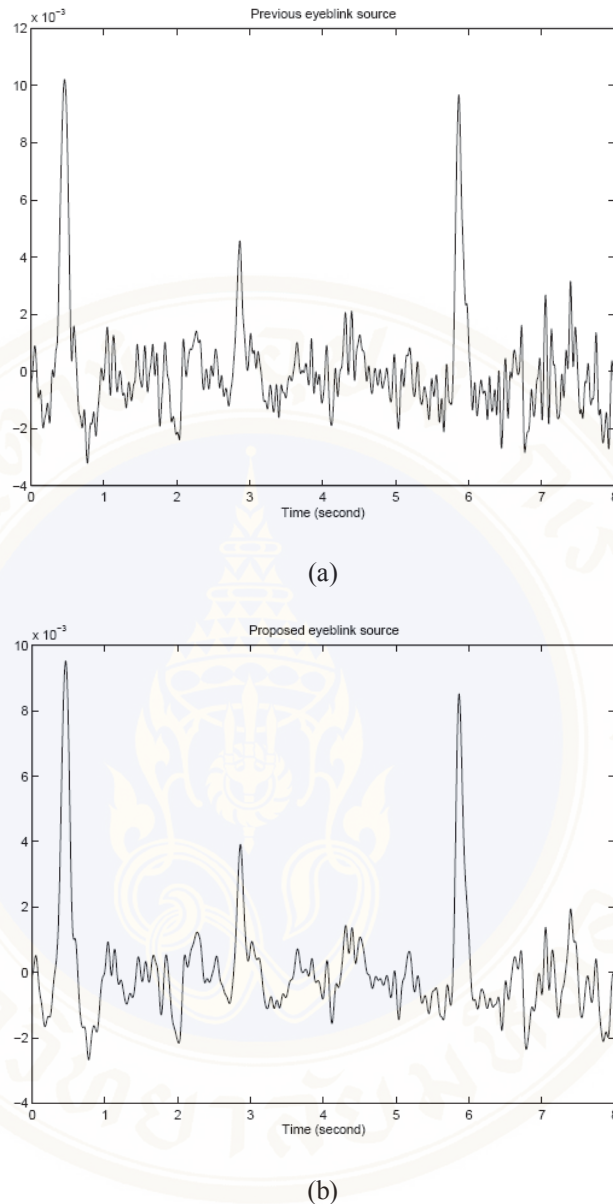


Figure 3. The EB sources which are calculated by (a) the previous method and (b) the proposed method.

4. SIMULATION RESULTS

The proposed algorithm is applied to real EEG measurements. The EB artifact database is provided by the School of Psychology, Cardiff University, UK. The scalp 16-channel EEG was obtained using Silver/Silver-Chloride electrodes placed at locations defined by the 10-20 system [1]. The 8-second of 16-channel EEG was sampled at 200 Hz, and bandpass filtered with cut-off frequencies of 2 Hz and 30 Hz.

EB sources obtained from the previous and proposed (lowpass filtered version of the previous EB source with the cut-off frequency of 10 Hz) methods are shown in Fig. 3(a) and (b), respectively. Obviously, some high frequency bands which may relate to the structures of the EEGs are filtered out.

Fig. 2(a) illustrates the original EB-contaminated 16-channel EEG. According to Fig. 2(c), by using our proposed method, the EB artifacts at the time of 0.5, 3, and 6 seconds are efficiently

removed. It can be observed that the EB-removed EEGs obtained from the proposed method (Fig.2(c)) are visually less oversmoothed than the one obtained from the previous method (Fig. 2(b)).

In order to quantitatively evaluate the merit of our proposed method, the segments of EEGs from 4 to 5 seconds of channels FP1, FP2, F7, F8, F5, F6, F3 and F4 (which are the regions that tend to be oversmoothed by the previous method) are used to evaluate the performance of our proposed method. Table 1. demonstrates the mean squared errors (MSE) of the selected regions of the data obtained from the previous and the proposed methods with respect to the original data of the same regions. According to Table 1, we can see that EB artifacts can be removed by the proposed method with lower distortions to the original underlying brain signals than those removed by the previous method.

5. CONCLUSION

In this paper, we have presented the method used for enhancing the quality of the EB-removed EEG signals. It is visually found that EEG components are more efficiently recovered after applying the modified EB sources (lowpass filtering with a cutoff frequency of 10 Hz) for reconstructing the EB-removed EEGs. Moreover, comparison of the original EEGs with the EB-removed EEGs (in the selected segments) shows that the proposed method identifies and removes the effect of the EB artifact with less distortion in the sense of MSE compared to the previous method.

Table 1. Comparison of the mean squared errors (MSE) obtained by previous and proposed method compared to the original data of the selected regions.

Channels	Previous	Proposed
FP1	74.65	70.18
FP2	71.70	67.41
F7	21.07	19.81
F8	27.35	25.72
F5	21.90	20.59
F6	27.58	25.93
F3	19.97	18.78
F4	23.41	22.01
Avg.	35.95	33.80

6. ACKNOWLEDGEMENT

The author would like to thank Dr. Kianoush Nazarpour and Prof. Saeid Sanei, the school of engineering, Prof. Edward Wilding, the school psychology, Cardiff University, for kindly discussions and providing the dataset.

REFERENCES

- [1] S. Sanei and J. A. Chambers, *EEG Signal Processing*. West Sussex, England: John Wiley and Sons, 2007.
- [2] A. Schlögl, C. Keinrath, D. Zimmermann, R. Scherer, R. Leeb, and G. Pfurtscheller, "A fully automated correction method of EOG artifacts in EEG recordings," *Clinical Neurophysiology*, vol. 118, pp. 98–104, 2007.
- [3] M. Fatourehchi, A. Bashashati, R. K. Ward, and G. E. Birch, "EMG and EOG artifacts in brain computer interface systems: A survey," *Clinical Neurophysiology*. 2007, in Press.
- [4] K. H. Ting, P. C. W. Fung, C. Q. Chang, and F. H. Y. Chan, "Automatic correction of artifact from single trial event-related potentials by blind source separation using second order statistics only," *Medical Engineering and Physics*, vol. 28, pp. 780–794, 2006.

- [5] L. Shoker, S. Sanei, and J. A. Chambers, "Artifact removal from electroencephalograms using a hybrid BSS-SVM algorithm," *IEEE Signal Processing Letters*, vol. 12, no. 10, pp. 721–724, 2005.
- [6] L. Shoker, S. Sanei, W. Wang, and J. A. Chambers, "Removal of eye blinking artifact from electroencephalogram, incorporating a new constrained blind source separation algorithm," *Medical and Biological Engineering and Computing*, vol. 43, pp. 209–295, 2005.
- [7] K. Nazarpour, Y. Wongsawat, S. Sanei, S. Orintara, and J. Chambers, "A robust minimum variance beamforming approach for the removal of the eye-blink artifacts from EEGs," in *Proceedings of International Conference of the IEEE Engineering in Medicine and Biology Society*, May 2007.
- [8] S. Puthusserypady and T. Ratnarajah, "Robust adaptive techniques for minimization of EOG artefacts from EEG signals," *Signal Processing*, vol. 86, pp. 2351–2363, 2006.
- [9] T. D. Lagerlund, F. W. Sharbrough, and N. E. Busacker, "Spatial filtering of multichannel electroencephalographic recordings through principal component analysis by singular value decomposition," *Clin. Neurophysiol.*, vol. 14, pp. 73–82, 1997.
- [10] J. Li and P. Stoica, *Robust Adaptive Beamforming*. Hoboken, NJ: John Wiley and Sons, 2005.
- [11] S. A. Vorobyov, A. B. Gershman, and Z. Q. Luo, "Robust adaptive beamforming using worst case performance optimization," *IEEE Transactions on Signal Processing*, vol. 51, no. 2, pp. 313–324, 2003.
- [12] Y. Wongsawat, S. Orintara, and K. R. Rao, "Reduced complexity space-time-frequency model for multichannel EEG and its applications," in *Proceedings of IEEE International Symposium on Circuits and Systems*, pp. 1305–1308, May 2007.
- [13] K. Zarifi, S. Shahbazpanahi, A. B. Gershman, and Z.- Q. Luo, "Robust blind multiuser detection based on the worst-case performance optimization of the MMSE receiver," *IEEE Transactions on Signal Processing*, vol. 53, no. 1, pp. 295–305, 2005.
- [14] A. Cichocki and S. Amari, *Adaptive Blind Signal and Image Processing*. New York: John Wiley and Sons, 2002.
- [15] R. Bro, *Multi-way Analysis in the Food Industry: Models, Algorithms and Applications*. MATLAB toolbox available [online] at <http://www.models.kvl.dk/users/rasmus/>: Ph.D. Thesis, University of Amsterdam and Royal Veterinary and Agricultural University.
- [16] F. Miwakeichi, E. Martinez-Montes, P. A. Valdes-Sosa, N. Nishiyama, H. Mizuhara, and Y. Yamaguchi, "Decomposing EEG data into space-time-frequency components using parallel factor analysis," *NeuroImage*, vol. 22, pp. 1035–1045, 2004.

Enhancement and Assessment of the RMVB-based Eyeblink Artifact Removal from the Multi-channel EEG

Pinyo Khumkaew, Yodchanan Wongsawat

Abstract—This paper proposes a method to enhance the performance of the fast implementation of robust minimum variance beamforming (RMVB)-based eyeblink (EB) artifacts removal from the multi-channel electroencephalogram (EEG). The prior knowledge, i.e. the EB source, is reshaped via the designed filters before employing to solve the RMVB problem. The method used to quantitatively assess the quality of the EB-removed EEGs in frequency domain is also proposed. Simulation results show that the proposed method can efficiently remove EB artifacts, especially at the frontal channels, from the multichannel EEG with low computational time.

I. INTRODUCTION

The electrooculogram (EOG) generated by eye movements or blinking is found to be the significant and common artifact in EEG analysis [1]. In recent years, it has become very desirable to effectively remove the EB artifacts without distorting the underlying brain activity. In this regard, reliable and fast, either iterative or batch, algorithms for EB artifact removal are of great interest for diverse applications such as brain computer interfacing (BCI) and ambulatory EEG settings. Furthermore, another interesting problem to be solved for the researchers (in the area of EEG analysis) is about the validation of various artifact removal methods. Currently, the suitable method for validating artifact removal algorithms is not proposed [2]. The method that usually used for algorithms validating is a visual inspection of the cleaned signal. The criterion for systematically validating artifact removal methods is necessary and needed to be developed.

Various methods for EB artifact removal from EEGs have been documented. In [3], the linear regression method is used to calculate the correction coefficients of the artifact component. This component is then used to subtract with the artifact contaminated signal resulting in the clean EEG signal. Even though this method yields good results, it would be problematic when the reference channels are not provided. By assuming that artifact is uncorrelated with EEG, principal component analysis (PCA) is also used to decompose EOG contaminated signal into distinct components [2]. Similarly, blind source separation (BSS) [4-6] using independent component analysis (ICA) can be employed by assuming that the artifacts and EEG are independent [5], i.e. space-time information of the EEG is exploited. One of the reliable results using all space, time and frequency as the prior information has been developed via the robust minimum variance beamforming (RMVB) method [7].

Unlike the high complexity method in [8] where the forward solution is used to calculate the eyeblink source, in [7], space signature (according to the artifact) of the space time frequency time-segment (STF-TS) model [9] is employed.

However, in [7], if the number of channels is high, calculating the solution for the RMVB also consumes high computational load. In addition, in some dataset (especially with high amplitude EB artifacts), the results of this method seems to oversmooth the original EEG signals.

The previous work [10], instead of using the RMVB to find the global eyeblink source, local eyeblink sources of each group of EEG channels are calculated. The results show that the computational complexity is reducing from the method in [7] (called conventional method) and the correlation of the resulting clean EEG with the eyeblink sources is as low as the correlation obtained from the conventional method.

Manuscript received September 30, 2009; revised on November 10, 2009.

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In this paper, we propose a combination of the previous work (RMVB-based method) [10] with a simple FIR filters to reshape the EB source before using to reconstruct the corrected EEG, in order to correct the oversmooth effect of method [7, 10] and maintain the efficient computational load as well as previous method [10]. Furthermore, we also propose the method to quantitatively assess the quality of the EB-removed EEGs by employing the frequency domain information.

This paper is organized as follows. Section II discusses the principles of the previous work on removal of the EB artifacts. The proposed method which results in lower EEG signal distortions after the EB artifact removal is described in Section III. In Section IV, the simulation results and the assessment method are presented. The conclusions of this study are stated in Section V.

II. ROBUST MINIMUM VARIANCE BEAMFORMING-BASED EYE-BLINK ARTIFACT REMOVAL

This section aims to review the previous method proposed in [7, 10] for recovering the clean multi-channel EEG back from the EB-contaminated one by employing the robust minimum variance beamforming (RMVB) [11,12]. The prior knowledge used in the RMVB is obtained via the STF-TS model [9]. Specifically, let $\mathbf{s}(t) = [s_1(t), s_2(t), \dots, s_N(t)]^T$ be N zero-mean real mutually uncorrelated point geometrically stationary sources which are mixed by an $N \times N$ full column rank matrix (mixing matrix) $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_N]$ where $\mathbf{a}_i$ is the i -th column of $\mathbf{A}$. The vector of a time mixture signal (N -channel EEG signal at each time stem t)

$\mathbf{x}(t) = [x_1(t), x_2(t), \dots, x_N(t)]^T$ which is shown in Fig.1 can be formulated as

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{v}(t) \quad (1)$$

where $\mathbf{v}(t) = [v_1(t), v_2(t), \dots, v_N(t)]^T$ is the additive white Gaussian zero-mean noise which is assumed to be spatially and temporally uncorrelated with a multi-channel EEG. The goal is we try to remove the EB source $y(t)$ in Fig.1 from the multi-channel EEG $\mathbf{x}(t)$.

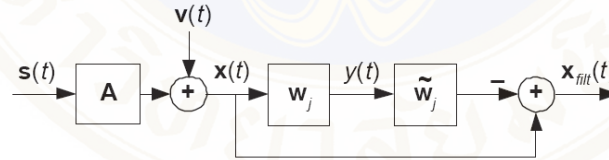


Fig. 1. Conventional system in [7] for extracting an EB component from a multi-channel EEG.

1) Implementation of the RMVB

According to Fig.1, since $\mathbf{a}_i$ performs as the steering vector of the j -th source (which is assumed to be the source according to EBs), we may write $y(t)$ which is denoted as an estimation of the source $s_j(t)$ as

$$y(t) = \mathbf{w}_j^T \mathbf{x}(t), \quad (2)$$

where $\mathbf{w}_j$ acts as a spatial filter. $\mathbf{w}_j$ can be found by minimizing the energy of $y(t)$ subject to the prior knowledge on how the EB artifacts are spatially distributed. Since the prior knowledge we can find is usually not the ideal one, $\mathbf{w}_j$ can be found by solving the worst-case performance optimization [12] where the estimated prior knowledge can be used. In general, we can write this problem as

$$\text{Minimize } J_c = \mathbf{w}_j^T \mathbf{R} \mathbf{w}_j \text{ subject to } \min_{\|\delta\| \leq \epsilon} \left| \mathbf{w}_j^T \hat{\mathbf{a}}_j + \mathbf{w}_j^T \delta \right| = 1$$

where $\mathbf{R} = \frac{1}{K} \sum_{k=1}^K \mathbf{R}_{XX}^k$, $\hat{\mathbf{a}}_j$ is the estimated steering vector of source j -th, ε is the setting mismatch norm, and $\delta = \mathbf{a}_j - \hat{\mathbf{a}}_j$. By using the Lagrange multiplier method, differentiating J_c with respect to $\mathbf{w}_j$ and setting it to zero, the spatial filter $\mathbf{w}_j$ can be computed as follows:

$$\mathbf{w}_j = \left[\mathbf{R} + \frac{\varepsilon}{\rho} \mathbf{I} \right]^{-1} \hat{\mathbf{a}}_j, \quad (3)$$

where $\rho \equiv \|\mathbf{w}_j\|$ and $\mathbf{I}$ denotes the identity matrix.

By following the method suggested in [13], we can use ρ that satisfies the following equation:

$$\sum_{i=1}^N \left(\frac{|g_i|}{\varepsilon + \rho \sigma_i} \right)^2 - 1 = 0, \quad (4)$$

where $\mathbf{g} = [g_1, \dots, g_N]^T = \mathbf{U}^T \hat{\mathbf{a}}_j$. $\mathbf{U}$ is an $N \times N$ matrix whose columns are eigenvectors of $\mathbf{R}$ and $\sigma_i (i=1, \dots, N)$ are their corresponding eigenvalues [11].

The clean multi-channel EEG without the EB contamination, $\mathbf{x}_{filt}(t)$, can be obtained by deflation method [14], that is

$$\mathbf{x}_{\text{filt}}(t) = \tilde{\mathbf{x}}(t) - \mathbf{w}_j y(t), \quad (5)$$

where $\tilde{\mathbf{w}}_j$ can be found so that $\mathbf{x}_{filt}(t)$ has minimum energy when the EB source $y(t)$ is removed from the contaminated source $\mathbf{x}(t)$. Specifically, $\tilde{\mathbf{w}}_j$ can be obtained by minimizing

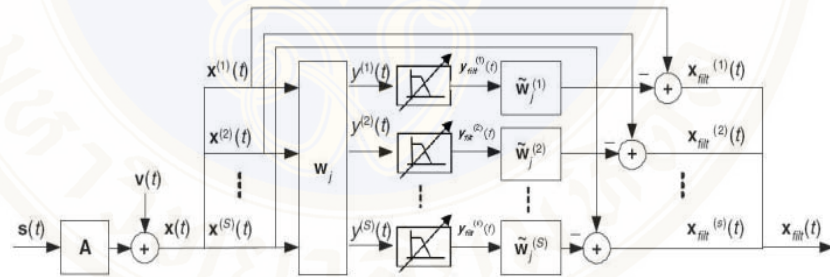


Fig. 2. Proposed system for extracting an eyeblink component from a multi-channel EEG.

 $J_j(\tilde{\mathbf{w}}_j)$ with respect to $\tilde{\mathbf{w}}_j$ where

$$\begin{aligned} J_j(\tilde{\mathbf{w}}_j) &= E[\mathbf{x}_{\text{filt}}^T(\mathbf{t})\mathbf{x}_{\text{filt}}(\mathbf{t})] \\ &= E[\mathbf{x}^T(\mathbf{t})\mathbf{x}(\mathbf{t})] - 2\tilde{\mathbf{w}}_j^T E[\mathbf{x}(\mathbf{t})y(\mathbf{t})] + \tilde{\mathbf{w}}_j^T \tilde{\mathbf{w}}_j E[y(\mathbf{t})^2]. \end{aligned}$$

Hence,

$$\tilde{\mathbf{w}}_j = \frac{E[\mathbf{x}(t)y^T(t)]}{E[y(t)^2]} = \frac{E[\mathbf{x}(t)\mathbf{x}^T(t)]\mathbf{w}_j}{E[y(t)^2]}. \quad (6)$$

For space-time-frequency-time/segment model (STF-TS model), according to the implementation of the RMVB, the estimated prior knowledge $\hat{\mathbf{a}}_j$ of the beamformer can be found via the space signature of the STF-TS model proposed in [9].

2) Efficient Implementation of RMVB for Eyeblick artifact Removal of Multi-channel EEG

According to (3), if the number of channels of the multi-channel EEG is high, finding ρ

and the inverse of $\{\mathbf{R} + \frac{\varepsilon}{\rho}\mathbf{I}\}$ would require high computational complexity. In this section, we propose the new problem formulation which results in reducing the computational complexity on finding the spatial filter $\mathbf{w}_j$ while maintaining the similar eyeblink removal results with the conventional method in [7]. The overview of the method is similar to the one shown in Fig. 2 without the filtering part. In order to find the eyeblink source $y(t)$, we need to find $\mathbf{w}_j$ such that the energy of $y(t)$ is minimized given that we know the prior knowledge about the extracted source which is the space signature of the STF-TS model. Intuitively speaking, when we filter $\mathbf{x}(t)$ using $\mathbf{w}_j$, we have to obtain the source $y(t)$ so that $y(t)$ would not take any information besides eyeblink artifacts from $\mathbf{x}(t)$. Previously, we minimize J_c which is the energy of $y(t)$, i.e.

$$J_c = \mathbf{w}_j^T \mathbf{R} \mathbf{w}_j \quad \text{subject to} \quad \min_{\|\delta\| \leq \varepsilon} \left| \mathbf{w}_j^T \hat{\mathbf{a}}_j + \mathbf{w}_j^T \delta \right| = 1$$

Now, let $\|y(t)\|^2 = \|\mathbf{w}_j^T \mathbf{x}(t)\|^2 = \sum_{s=1}^S \left\| \mathbf{w}_j^T \mathbf{x}^{(s)}(t) \right\|^2$, we instead minimize

$$J_c = \hat{\mathbf{w}}_j^T \left\{ \sum_{s=1}^S \mathbf{R}^{(s)} \right\} \hat{\mathbf{w}}_j$$

subject to

$$\min_{\|\delta\| \leq \varepsilon} \left| \hat{\mathbf{w}}_j^T \left\{ \sum_{s=1}^S \hat{\mathbf{a}}_j^{(s)} \right\} \hat{\mathbf{a}}_j^{(s)} + \hat{\mathbf{w}}_j^T \delta \right| = 1$$

where $\hat{\mathbf{w}}_j$ is the spatial filter which can be used to extract the j -th source from $\mathbf{x}^{(s)}(t)$ ($s = 1, \dots, S$). $\mathbf{x}^{(s)}(t)$ of size $\frac{N}{S} \times T_1$ is $\mathbf{x}(t)$ of the s -th group of EEG channels where T_1 is the number of samples in time of each EEG channel, and S is the total number of groups, i.e. $\mathbf{x}(t) = [\mathbf{x}^{(1)}(t), \dots, \mathbf{x}^{(S)}(t)]^T$. $\hat{\mathbf{a}}_j^{(s)}$ of size $\frac{N}{S} \times T_1$ is $\hat{\mathbf{a}}_j$ of the s -th group of EEG channels, i.e. $\hat{\mathbf{a}}_j = [\hat{\mathbf{a}}_j^{(1)}, \dots, \hat{\mathbf{a}}_j^{(S)}]^T$.

$\mathbf{R}^{(s)}$ of size $\frac{N}{S} \times \frac{N}{S}$ is $\mathbf{R}$ of the s -th group of EEG channels. Similar to (3), we can show that

$$\hat{\mathbf{w}}_j = \left[\left\{ \sum_{s=1}^S \mathbf{R}^{(s)} \right\} + \frac{\varepsilon}{\rho} \mathbf{I} \right]^{-1} \left\{ \sum_{s=1}^S \hat{\mathbf{a}}_j^{(s)} \right\}. \quad (7)$$

ρ can be obtained by (4) where the columns of $\mathbf{U}$ are eigenvectors of $\sum_{s=1}^S \mathbf{R}^{(s)}$, and $\sigma_i (i=1, \dots, \frac{N}{S})$ are their corresponding eigenvalues. It should be noted that $\hat{\mathbf{w}}_j$ is of size $\frac{N}{S} \times 1$. Hence, eyeblink source of each group (s) can be obtained individually by

$$y^{(s)}(t) = \hat{\mathbf{w}}_j^T \mathbf{x}^{(s)}(t) \quad (8)$$

The clean multi-channel EEG can be obtained by cascading the clean signals of each group together. Specifically,

$$\mathbf{x}_{\text{filt}}(t) = [\mathbf{x}_{\text{filt}}^{(1)}(t), \dots, \mathbf{x}_{\text{filt}}^{(S)}(t)]^T, \quad (9)$$

where

$$\mathbf{x}_{filt}^{(s)}(t) = \mathbf{x}^{(s)}(t) - \tilde{\mathbf{w}}_j^{(s)} y^{(s)}(t), \text{ and}$$

$$\tilde{\mathbf{w}}_j^{(s)} = \frac{E[\mathbf{x}^{(s)}(t)\mathbf{x}^{T(s)}(t)]\hat{\mathbf{w}}_j}{E[y^{(s)}(t)^2]}.$$

III. PROPOSED EYE-BLINK (EB) REMOVAL METHOD

After the removal of the EB artifacts from EEG signals based on the previous method [10] mentioned in Section 2, we found by inspection that some components of EEG signals are oversmoothed and distorted as shown in Fig. 3(b, c and d). Therefore, in this section, the simple but efficient method is proposed in order to enhance the results of the previous method. The overview of the proposed method is described as follows:

1) Proposed Method

According to (2), the EB source $y(t)$ is obtained via the worst-case performance optimization [11]. Hence, it may lack of some physical structures of the real EEG signals. Theoretically, the EB source should contain only the frequency bands of the EB which is around 2-4 Hz. However, the EB source obtained from the previous method seems to have some other frequency bands which might be related to the structures of the EEGs. Therefore, we propose to locally apply the lowpass filter to the EB sources. Then, this filtered EB sources are employed instead of the traditional one in the process of deflation in (5). The proposed system can be summarized in Fig. 2. In this paper, the number of the group of EEG channel, (S in Section II) is selected as 1, 2, and 4. Finding the optimal number of group need more research and is listed as our future work.

2) Issue on Selecting Lowpass Filter

Instead of using the ideal lowpass filter or its approximation, e.g. high order IIR filter, we employ FIR lowpass filter of order 30 for the reason of simplicity. Since the EB source is of size 1600 samples, order of 30 FIR lowpass filter is practical. In addition, the frequency response of the FIR filter is not as selective as the IIR filter, thus we select the cut-off frequency of our lowpass filter as 10 Hz. This number is selected to delete the frequency bands that may relate to EEG while maintaining the frequency bands related to the EBs.

IV. SIMULATION RESULTS

The proposed algorithm is applied to real EEG measurements.

The EB artifact database is provided by the School of Psychology, Cardiff University, UK. The scalp 16-channel EEG was obtained using Silver/Silver-Chloride electrodes placed at locations defined by the 10-20 system [1]. The 8-second of 16-channel EEG was sampled at 200 Hz, and bandpass filtered with cut-off frequencies of 2 Hz and 30 Hz.

Fig. 3(a) illustrates the original EB-contaminated 16-channel EEG. According to Fig. 3(e), by using our proposed method, the EB artifacts at the time of 0.5, 3, and 6 seconds are efficiently removed. It can be observed that the EB-removed EEGs obtained from the proposed method (Fig. 3(e)) are visually less oversmoothed than the one obtained from the conventional method (Fig. 3(b)). Figs. 3(f) and (g) present the resulting clean multichannel EEGs using the proposed method when the eyeblink contaminated multi-channel EEGs are divided into 2 and 4 groups ($S = 2, 4$), respectively. When using the proposed methods, we can visually see that the eyeblink artifacts are efficiently removed and less oversmoothed than the one obtained from the previous method in Figs. 3(c) and (d), respectively.

In order to quantitatively evaluate the merit of our proposed method, the segments of EEGs from 4 to 5 seconds of channels FP1, FP2, F7, F8, F5, F6, F3 and F4 (which are the regions that tend to be oversmoothed by the previous method, called the selected regions) are used to evaluate the performance of our proposed method. The mean square error, in frequency domain which using the single-sided amplitude spectrum of the selected regions by taking the fast Fourier transform (FFT), obtained from the previous and the proposed methods with respect to the original data of the same regions is calculated and demonstrated in Table I. According to Table I, we can see that EB artifacts can

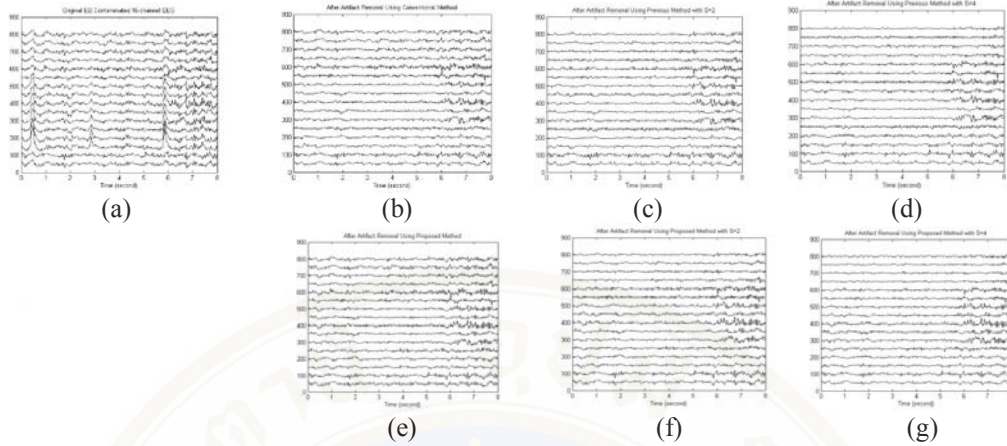


Fig. 3. The results of the proposed eyeblink artifact removal method for a set of real EEGs: (a) Eyeblink-contaminated EEGs before artifact removal, (b) EEGs after removing the artifact using conventional method, EEGs after removing the artifact using previous method with (c) $S = 2$ and (d) $S = 4$ and EEGs after removing the artifact using proposed method (e), with (f) $S = 2$ and (g) $S = 4$. The bottom line corresponds to channel-1 and the top line corresponds to channel-16.

TABLE I Comparison of the mean squared errors (MSE) obtained by conventional (Convent.), previous (Pre.), and proposed (Pro.) method compared to the original data of the selected regions in frequency domain.

Ch.	Convent.	Pre. S=2	Pre. S=4	Pro.	Pro. S=2	Pro. S=4
FP1	0.0164	0.0196	0.0186	0.0144	0.0142	0.0121
FP2	0.0151	0.0173	0.0141	0.0112	0.0120	0.0092
F7	0.0095	0.0087	0.0104	0.0063	0.0055	0.0069
F8	0.0094	0.0088	0.0102	0.0058	0.0056	0.0063
F5	0.0099	0.0086	0.0106	0.0062	0.0051	0.0070
F6	0.0132	0.0116	0.0147	0.0076	0.0067	0.0078
F3	0.0108	0.0124	0.0108	0.0064	0.0071	0.0057
F4	0.0112	0.0136	0.0152	0.0064	0.0102	0.0100

TABLE II Comparison of time complexity (second) of the conventional, previous and proposed method.

Methods	Convent.	Pre. S=2	Pre. S=4	Pro.	Pro. S=2	Pro. S=4
Complexity	8.25	0.26	0.17	8.43	0.37	0.28

be removed by the proposed method with lower distortions (low error) to the original underlying brain signals than those removed by the previous method.

Even though, according to Table II, the computational complexity of proposed method is insignificant increase from previous method. It is noted that the computational complexities obtained in this paper are measured in MATLAB Software (www.mathworks.com) and performed on the laptop computer with a 1.8 GHz Intel® Core™ 2 Duo processor T7100.

V. CONCLUSION

In this paper, we have presented the method used for enhancing the quality of the EB-removed EEG signals. It is visually found that EEG components are more efficiently recovered after

applying the modified EB sources (lowpass filtering with a cutoff frequency of 10 Hz) for reconstructing the EB-removed EEGs. Moreover, comparison of the original EEGs with the EB-removed EEGs (in the selected regions) shows that the proposed method identifies and removes the effect of the EB artifact with less distortion, especially at the frontal channels, in the sense of MSE (in frequency domain) compared to the previous method. The computational complexity of proposed method is dramatically improvement when compare with the conventional method and insignificant increase from previous method.

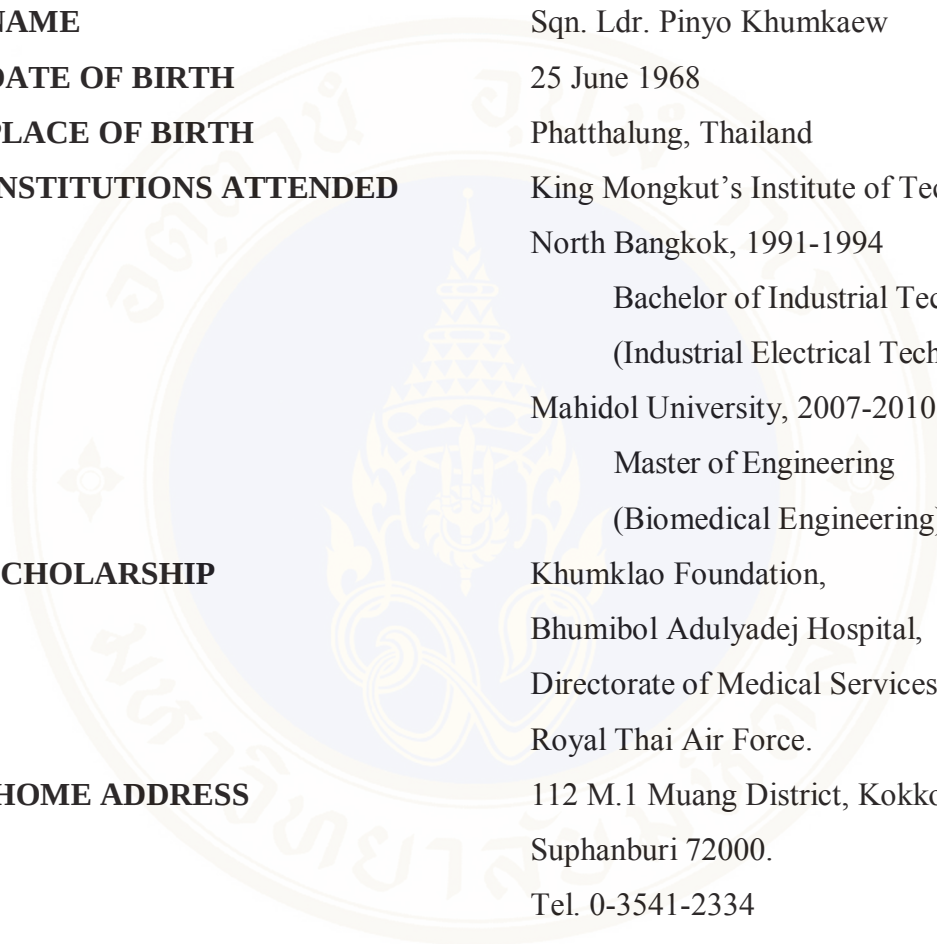
ACKNOWLEDGEMENT

The author would like to thank Dr. Kianoush Nazarpour and Prof. Saeid Sanei, the school of engineering, Prof. Edward Wilding, the school psychology, Cardiff University, for kindly discussions and providing the dataset.

REFERENCES

- [1] S. Sanei and J. A. Chambers, *EEG Signal Processing*. West Sussex, England: John Wiley and Sons, 2007.
- [2] M. Fatourehchi, A. Bashashati, R. K. Ward, and G. E. Birch, "EMG and EOG artifacts in brain computer interface systems: A survey," *Clinical Neurophysiology*, vol. 118, no. 3, pp. 480-494, 2007.
- [3] A. Schlögl, C. Keinrath, D. Zimmermann, R. Scherer, R. Leeb, and G. Pfurtscheller, "A fully automated correction method of EOG artifacts in EEG recordings," *Clinical Neurophysiology*, vol. 118, no. 1, pp. 98-104, 2007.
- [4] K. H. Ting, P. C. W. Fung, C. Q. Chang, and F. H. Y. Chan, "Automatic correction of artifact from single trial event-related potentials by blind source separation using second order statistics only," *Medical Engineering and Physics*, vol. 28, no. 8, pp. 780-794, 2006.
- [5] L. Shoker, S. Sanei, and J. A. Chambers, "Artifact removal from electroencephalograms using a hybrid BSS-SVM algorithm," *IEEE Signal Processing Letters*, vol. 12, no. 10, pp. 721-724, 2005.
- [6] L. Shoker, S. Sanei, W. Wang, and J. A. Chambers, "Removal of eye blinking artifact from electroencephalogram, incorporating a new constrained blind source separation algorithm," *Medical and Biological Engineering and Computing*, vol. 43, pp. 209-295, 2005.
- [7] K. Nazarpour, Y. Wongsawat, S. Sanei, S. Orintara, and J. Chambers, "A robust minimum variance beamforming approach for the removal of the eye-blink artifacts from EEGs," in *Proc. Int. Conf. IEEE Engineering in Medicine and Biology Society*, May 2007.
- [8] J. C. Mosher, R. Leahy, and P. S. Lewis, "EEG and MEG: forward solutions for inverse methods," *IEEE Trans. Biomedical Engineering*, vol. 46, no. 3, pp. 245-259, 1999.
- [9] Y. Wongsawat, S. Orintara, and K. R. Rao, "Reduced complexity space-time-frequency model for multichannel EEG and its applications," in *Proc. IEEE International Symposium on Circuits and Systems*, pp. 1305-1308, May 2007.
- [10] Y. Wongsawat, "Efficient Implementation of RMVB for eyeblink Artifacts Removal of EEG via STF-TS Modeling," in *Conf. ROBIO 2008 IEEE Int. Conf.* pp. 1567 - 1572.
- [11] J. Li and P. Stoica, *Robust Adaptive Beamforming*. Hoboken, NJ: John Wiley and Sons, 2005.
- [12] S. A. Vorobyov, A. B. Gershman, and Z. Q. Luo, "Robust adaptive beamforming using worst case performance optimization," *IEEE Trans. Signal Processing*, vol. 51, no. 2, pp. 313-324, 2003.
- [13] K. Zarifi, S. Shahbazpanahi, A. B. Gershman, and Z.Q. Luo, "Robust blind multiuser detection based on the worst-case performance optimization of the MMSE receiver," *IEEE Trans. Signal Processing*, vol. 53, no. 1, pp. 295-305, 2005.
- [14] A. Cichocki and S. Amari, *Adaptive Blind Signal and Image Processing*. New York: John Wiley and Sons, 2002.

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