Bio-Signal Based Human-Computer Interface for Geometric Modeling

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A Thesis

in

The Department

of

Mechanical and Industrial Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of Doctor of Philosophy (Mechanical Engineering) at

Concordia University

Montreal, Quebec, Canada

December 2013

CONCORDIA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: **Lan Wu**

Entitled: **Bio-Signal Based Human-Computer Interface for Geometric Modeling**

and submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY (Mechanical Engineering)

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ABSTRACT

Bio-Signal Based Human-Computer Interface for Geometric Modeling

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Concordia University, 2013

Modern techniques drive the development of bio-signal controlled assistive devices such as prosthetics, wheelchairs, etc. The control of these devices needs the accurate acquisition of bio-signal features and the accomplishment of multiple control intentions. The limited bio-signal sources limit the amount of available bio-signal features. Therefore, the accomplishment of multiple control intentions in some cases can't only depend on the classification of bio-signals. In this thesis, we develop a bio-signal controlled real-time 3D geometric modeling design platform, which focus on the study of two aspects: 1) Identifying the control capabilities of bio-signals, 2) Developing 3D geometric modeling. In the study of control capabilities of bio-signals, we propose three efficient bio-signal feature extraction approaches and develop logic control panels which are used to achieve the multiple control intentions.

In this thesis, four main original contributions are made in developing bio-signal controlled geometric modeling design platform as follows:

First, three types of bio-signal controlled Human-Computer Interface(HCI), Electromyography(EMG) based HCI, Electrooculography(EOG) based HCI and

Electroencephalography(EEG) based HCI are designed, in which the bipolar electrodes are used for bio-signal acquisition and the bio-signal sources that can generate strong signal patterns are identified. The identified bio-signal sources maintain the acquired bio-signals with a relative high Signal-to-Noise Ratio (SNR), thus simplifying the signal feature extraction methods.

Second, in order to achieve multiple control intentions, an approach of logic control panels is proposed in EMG and EOG based HCI systems. The logic control panels are designed with two advantages. One advantage is that it accomplishes the control intentions; the other is that it reduces the fatigue of the bio-signal sources so that the accuracies and stabilities of the control from the bio-signals are maintained well.

Third, a new approach is proposed to extract signal features based on a Steady-State Visual Evoked Potential (SSVEP). Due to the periodic feature of the stimulation signals, the scientific research indicates that the same periodic features exist in EEG responses. Hence, in time domain a weak periodic signal detection algorithm (WPSDA) is proposed, which aims at detecting the brain's weak responses to the visual periodic stimulation signals under heavy noisy background. This algorithm is depicted by Lorenz system which describes a nonlinear dynamic system. Such a nonlinear dynamic system is sensitive to its system parameters. Once the parameters are carefully calibrated, Lorenz system equations can detect the input waves (stimulation signal patterns) inside of the response waves (EEG signals) if brain positively responds to the stimulation.

Last, the control accuracy of the extracted signal features was verified on the corresponding bio-signal controlled geometric modeling systems. The geometric modeling systems are formed mainly by free-form parametric splines, parametric surfaces and rotation geometries. Through online tests, the control accuracy rate up to 100% was obtained for the EMG and EOG based HCI systems and up to 75% control accuracy rate was obtained for the EEG based BCI system.

Dedicated to my mother, Yu Zhen Li, and to my family members

ACKNOWLEDGEMENTS

I would like to acknowledge that without the assistance and support of many people directly or indirectly, I would not have completed this thesis.

First and foremost, I would like to express my thanks and appreciate to my supervisor Dr. Ali Akgunduz for his constructive advice, constant guidance, financial support and encouragement throughout this work. His constructive advice and constant guidance played the significant role in this thesis. Without the assistance from him, this thesis would not have been existed.

I would like to thank my mother and all my family members for their continuous encouragement and support during my Ph.D. I express my gratitude to all faculty members and staffs of the Department of Mechanical and Industrial Engineering at Concordia University not only for providing me a nice studying and working environment but also for contributing to my educations.

Finally, thanks to all those people who provided me help during my Ph.D.

Lan Wu

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

ϑ:	Number of received bio-signals
A:	An array that is used to store the received EMG signals
d:	Amplitude difference of two adjacent EMG signals
E:	EMG signals received from the equipment
ε:	Set of thresholds used to validate the occurrence of range of signal features
β:	$=\begin{cases} 1 & if\ feature\ is\ detected \\ 0 & otherwise \end{cases}$
L:	Record the number of the detected signal features
S:	Time interval determined by the same amount of EMG signals
Q:	Set of user intentions
h	The amplitude difference between the adjacent negative peak value and positive peak value
g	Time difference between two time instances when the signal amplitudes cross the zero line from the negative value to the positive value and from the positive value to the negative value
l	Time difference between two adjacent low peak values.
p	Index for identifying sampling period of EEG data
λ_i^p	The value of single EEG data in period$p$

Λ^p	Acquired EEG data set in period p
ω_∇	Detected angle frequency $\omega_\nabla = 2\pi f_\nabla$
f_∇	Detected frequency
$sin\ (\omega_\nabla t)$	Embedded sine function
ω	Characteristic angle frequency of testing system
k_e	EEG signal intensity coefficient
λ_i	Detected signals for $i = \{0, 1, \cdots, N-1\}$
∇	The number of detected SSVEP responses
x	Displacement of Lorenz attractor along *x* direction
y	Displacement of Lorenz attractor along *y* direction
z	Displacement of Lorenz attractor along *z* direction
B	Baseline value for determining the existence of z(t)peak values of Lorenz attractor
T	Threshold value used for determining the existence of external stimulus signals to the Lorenz system
u_T	Average value of T data set
ε_T	The minimum difference between mean values in order to make the decision
L^c	Initial state of Lorenz system
X	Acquired raw EEG data set in time domain
$C(x_n)$	EEG data point's auto-correlation data
φ_k	Frequency data of auto-correlated data $C(X)$
$\overline{\psi_k}$	Average PSD at the specified frequency range
Ψ_k	PSD at the specified frequency with improved SNR

CHAPTER 1
INTRODUCTION

Body bio-signals are associated with different body functions and can be collected from the body itself. For handicapped people, these body bio-signals are good candidates, which can be used to replace the hands functions to manipulate the assistive devices such as wheelchairs, computers, etc. Hence, in recent years, the studies for the bio-signals have been performed by a large body of researchers. The objective is to improve the control capability of the bio-signals, thus positively contributing to the development of bio-signal controlled assistive devices. Under this motivation, this thesis investigates the control capabilities of three types of bio-signals such as EMG, EOG, and EEG signals. Our objective is to develop a bio-signal controlled geometric modeling design system particularly tailored for handicapped people in order to bring their ideas into the products design process.

In the bio-signal based researches and applications, the control capability of the bio-signals is affected by two factors: 1) the acquisition of bio-signals; 2) signal processing techniques. In general, the acquisition of bio-signals is determined by the acquisition approaches and available bio-signal sources. Nowadays, the advances in the techniques of bio-signal acquisitions and signal processing are bringing the application of bio-signals close to the objective that is less dangerous and has high control accuracy.

1.1The acquisition approaches of bio-signals

According to the current literature, there are two main branches for bio-signal acquiring method. The first one is an invasive approach, which needs to implant electrodes into the patients' body. Another is called non-invasive approach, which acquires body signals by putting electrodes on the scalp or skin epidermis. Comparison of research results for these two signals' acquiring approaches indicates that the invasive approach can generate a more accurate control because of signals acquired from implanted electrodes enjoying a higher Signal to Noise Ratio (SNR), namely, less noise interferences. But research results also show that with the aging of implanted electrodes, the performance of acquired signals will degenerate so that the control accuracy will follow to decline. Besides, the implant surgery itself will bring patients some extent of injury and patients need a certain recovery process. In non-invasive signal acquisition approaches, signals acquired from the skin or scalp show a lower SNR. But as alternative options, non-invasive approaches provide certain advantage, namely, they bring less dangerous to the users. Hence, in signal acquisition approaches, non-invasive signal acquisition approaches have been widely used in various HCI systems.

1.2Bio-signal sources

In current bio-signal based applications, three categories of body bio-signals are widely used and studied, they are EMG, EOG, and EEG signals. These bio-signals are excited by corresponding body activities and carry the specific information which people want to express. At this point, EEG signals reflect brain neuron activities such as motor imagination, etc. EOG signals recode eyes' movement and EMG signals reflect muscles' activities. In the non-invasive signal acquisition research area, an international 10/20 system that is followed by most of research bodies to acquire EEG signals is used to specify the positions of electrodes. So far, the EEG signals are acquired mainly from the electrodes pasted on the locations specified by this standard.

1.3Basic structure of bio-signal based HCI systems

To achieve a bio-signal based application, the most direct way is to construct a control system, in which the input is the bio-signals and the output is the responses of the controlled devices. In the research of bio-signals, such a control system is known as bio-signal based Human-Computer Interface (HCI) system. Concerning such HCI systems, in general, their configuration consists of three blocks. The first block is used to acquire bio-signals. The second block is used to extract the signal features from acquired bio-signals. Finally, the last block is used to convert the extracted bio-signal features to perform desired operations. These three blocks form a basic frame of bio-signal based HCI systems (See Figure 1 below as illustration).

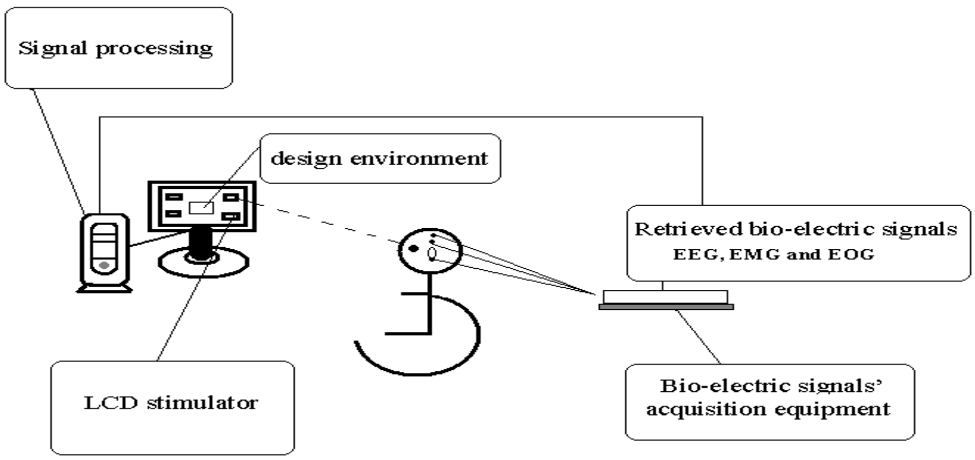


Figure 1: A basic structure of a bio-signal based HCI

The performance of such HCI systems is influenced by advances of techniques in both signal acquiring and signal processing.

1.4 Current applications of bio-signals

Currently, the most research works in bio-signal field are associated with the needs of the handicapped people, such as body function restoration, manipulating computer, controlling wheelchair, etc.

The body function restoration is one of the most important research branches in bio-signal field. Concerning the researches for body function restoration, in the past few years, Function Electrical Stimulation (FES) devices' muscle implantation has been used in clinical settings for the restoration of grasp functions for tetraplegic patients (Cornwall et al. 2004). The applications of these assistive devices in clinical studies have shown that patient life standards have been improved (Taylor et al. 2002). In the non-invasive bio-signal research area, the research for the restoration of grasp functions can be found from the works of Nathan (1995), and Pfurtscheller et al. (2003). The objective of the FES of non-invasive approach is to replace the application of invasive FES devices. In FES of non-invasive approach, the surface electrodes are used to collect bio-signals and stimulate the patient's paralyzed hand's muscles to carry out the desired grasp tasks.

In the research of bio-signal applications, one of the most attractive applications is associated with the manipulation of computers. In this aspect, Trejo et al. (2006), Li et al. (2010), and Citi et al. (2008) proposed a lot of approaches which address the issue about moving a cursor in Brain-Computer Interface (BCI) system. In the BCI systems, an accurate and efficient cursor movement control approach will bring many potential applications for handicapped people. One of these applications is that the manipulating a virtual keyboard to complete a text spelling such as an e-mail, a short message, etc., which can help handicapped people to complete the communication with outside world. Other potential applications related with BCI based cursor control include file reading, web navigation (Bensch et al. 2007 and Sirvent et al. 2010), and game playing (Gentiletti et al. 2009), etc. BCI based direct virtual keyboard control with improved spelling rate proposed by Sugiarto et al. (2009) and Scherer (2004) can be found in the literature.

As alternative control tools, Tsui et al.(2007), Philips et al. (2007), Lin et al. (2010), and Rebsamen et al. (2007) have introduced EMG, EOG, and EEG signals into the wheelchair control unit to navigate the wheelchair's movement to replace the traditional control input approaches such as a hand-input, a voice control, etc.. The research studies in this field include both real world wheelchair control (Ubeyli 2008) and virtual environment wheelchair navigation (Leeb et al. 2007). Furthermore, advanced researches for accurate and efficient signal processing algorithms have been proposed in many works (e.g. Sun et al. 2005, Delorme et al. 2007, Brunner et al. 2007, Medvedev et al. 2008 and Gao et al. 2010). All of these researches are bringing the body bio-signal direct control HCI system's wheelchair from the lab settings to reality to better serve the handicapped people.

Bio-signal based robot applications not only provide the benefit for handicapped people but also provide benefit in some industries such as aerospace industry, game industry, etc. Pineau et al. (2003) developed a bio-signal based robot, which is used as a machine nurse controlled by paralyzed patients directly to serve their daily life. In aerospace area, a P300 BCI based camera carrier has been reported by Yang et al. (2009). This camera carrier has six-direction movements and has grasp/release functions. It can be controlled to hold the camera to take photos in outer space. In computer-aided design area, a BCI for CAD system has been proposed by Esfahani et al. (2012). The EEG signals used in this BCI are generated from the imagination process for five primitive shapes. Multiple electrodes EEG handset is used as signal acquisition hardware. Through using proposed data processing techniques, five primitive shapes are distinguished by users. As alternative control approaches for joystick, keyboard, etc., the researches of BCI based computer games have been developed in game industry area, many works can be found (Ko et al. 2009, and Finke et al. 2009). These BCI based games provide opportunities for the handicapped people to meet their entertainment needs.

Bio-signal based applications are helping handicapped people to achieve improved life quality.

1.5 Handicapped people and esthetic of product design

While several HCI based applications have been covered in both academic researches and industry in order to improve the lives of handicapped people, to the best of our knowledge, there has not been any significant work done to enable handicapped people to express their artistic natures in the form of 3D geometric modeling. While many products are particularly designed for handicapped people, when it comes to receive their inputs in the form of 3D geometric modeling, geometric modeling designers mainly depend on either their expertise or surveys. We believe that one can best contribute to the esthetic of a design being developed by through involving in the design stage. Hence, the objective of this research is to outline the fundamentals of a prototype geometric modeling platform that can be used by handicapped people. In this research, the target group is handicapped people who are not able to use their hands to control computer. The hand functionalities are replaced by signals received from the body in the forms of EMG and EOG signals as well as EEG. The results of this research will enable handicapped people to be involved in the geometric modeling design process more closely and to express their artistic nature in 3D environment.

1.6 Motivation and progress

In our research lab, a real-time free-form sketching platform was developed in order to provide designers a virtual environment to perform 3D sketching at the early stage of product design (conceptual design). The free-form sketching application enables a designer to create 3D geometries in the form of free-form parametric splines and surfaces. In this sketching system, a virtual hand with key board control or 5DT data glove control is used as the sketching tool (See Figure 2 below). The manipulations of the key board or 5DT data gloves are from the hands' control (input control resource).

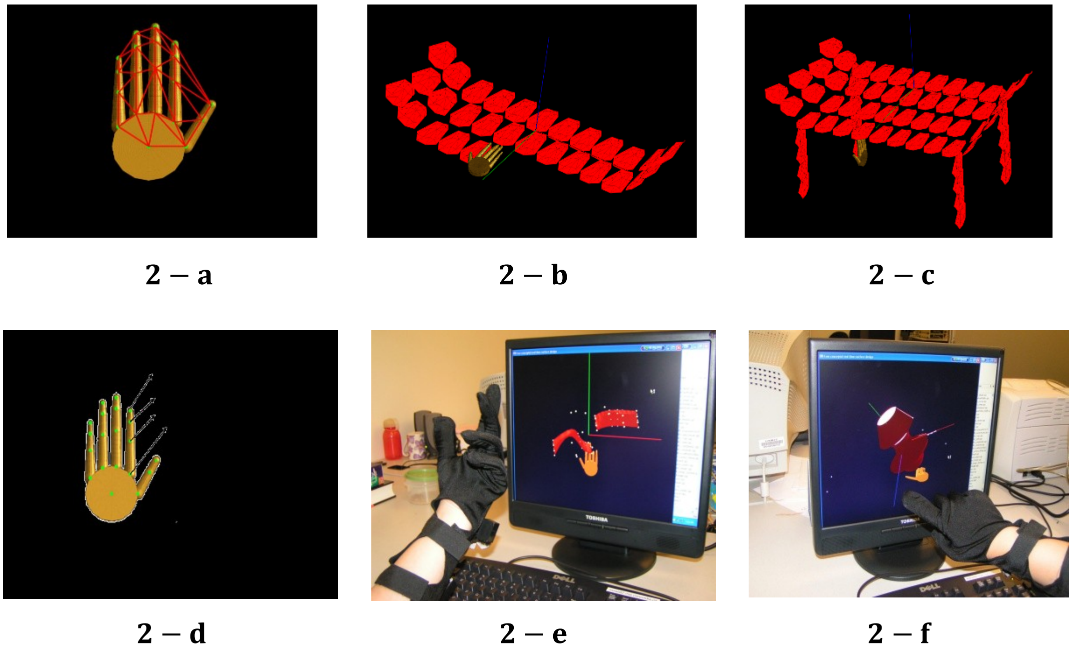


Figure 2: (a)-(c) 3D sketching system developed by Huang Yu and Ali Akgunduz (2006);(d)-(f) 3D sketching system extended by Lan Wu and Ali Akgunduz (2008)

In this thesis, we attempt to introduce bio-signals as input control resources to replace hands' input control and combine existing sketching approaches to achieve product conceptual design in the form of 3D geometric modeling in a fully computerized 3Denvironment.The objectives are presented as follows.

1.7 Objectives

In our previous work, we developed a free-form sketching application for product designers to express themselves in 3D environment freely in order to shape their products at the conceptual design phase. The main input for controlling the sketching application was the combination of mouse and keyboard as well as data-glove signals. In this sketching system, hands are input control resources. In current research work, we propose to use bio-signals as input control resources to further improve the functionalities of the sketching application in order to give handicapped people an opportunity to be involved in product design process. Moreover the results of the proposed research work will enable handicapped people to express their artistic natures in a 3D environment using our solution. Hence, the main goal of this research work is to investigate the control capabilities of the bio-signals and the possibilities to use them in the geometric modeling design. In order to reach our goal, following objectives were pursued:

1) Identify reliable bio-signal sources/features.
2) Design a LCD type stimulator, which is integrated with the application environment.
3) Develop efficient bio-signal feature extraction approaches for EMG, EOG, and EEG signals.
4) Develop interface in order to utilize the retrieved body bio-signals.
5) Develop geometric modeling design platform.
6) Test the developed methods for robustness.

1.8 Contributions and Organization of the Thesis

Based on the proposed objectives, in this thesis, the following contributions are made:

1) Identified EMG, EOG, and EEG signal sources/features.
2) Designed a LCD stimulator, which is integrated with the application environment.
3) Developed efficient EMG, EOG and EEG signal feature extraction approaches
4) Designed logic control panels, which are used to accomplish the multiple control intentions for EMG/EOG based HCI system.
5) Developed bio-signal based 3D geometric modeling design platform.
6) Tested the control accuracy of extracted signal features.

In Chapter 1, a brief introduction on bio-signals and their applications is given. Also, the proposed problems with possible research solutions are identified. A literature review based on types of bio-signals and signal feature extraction methods is conducted in Chapter 2. In Chapter 3the methodology for signal feature extractions is developed. In Chapter 4, discussions are presented. In Chapter 5, three types of bio-signal based 3D geometric modeling HCI systems and future works are summarized to conclude this thesis.

CHAPTER 2
RELATED WORK

In this chapter, we review the previous works in two categories: 1) Bio-signals based HCI systems. 2) Conceptual design in fully computerized 3D environment

2.1 Bio-signal based HCI systems

Literature on bio-signal and its application covers a large spectrum. Medicine, psychology, engineering and marketing science are main contributors to the literature on this topic. In this part, we include only the literature directly related to our research.

The general HCI system aims at using bio-signals to achieve the control functions and the direct information exchange between human and computers with hands-free operation. In recent years, advances in both signal acquiring equipment and signal processing techniques are bringing the bio-signal based HCI systems outside the laboratory environment to their real-world applications. Several applications such as EEG and EMG based wheelchair design, EEG based internet browser design, EMG based prosthetic limbs' design, EEG and EMG based spelling devices' design and so on have been developed, which provide handicapped people an improved quality of life.

As alternative control sources, the body bio-signals have received great attention from a large number of researchers. Major research topics in bio-signals are signal acquisition and signal processing, as well as their applications. Currently, the bio-signals are mainly categorized as three types: EEG, EMG, and EOG signals. The majority of existing HCI systems is based on these three types of bio-signals. These systems are the categorized as EEG based Brain-Computer Interface (BCI) systems, EMG based HCI systems, and EOG based HCI systems. Regardless of the methodology being applied, the common objective in such research is to achieve direct information exchange between human and computers or machines by means of body bio-signals to transfer human's intentions.

In the current EEG based BCI systems, a large number of works in the signal processing and their application area depend on the signal generation methods, the number of electrodes, and the signal acquisition locations. EEG signals reflect the brain activities. Commonly, two different methods are used to trigger brain to send signals: external stimulation; brain's natural response to the situations which is a pure imagination processes. Based the two methods, the literature on EEG signal based BCI systems are summarized as follows.

2.1.1 Visual Evoked Potential (VEP) based BCI systems

Wang et al.(2006), Wang et al.(2008), and Bin et al.(2009)provided an overview of EEG signals generated from external stimulations; the studies for Visual Evoked Potentials (VEPs) BCI systems are discussed. This kind of BCI systems can capture small changes in brain electrical potentials that are the brain's responses to the external stimulation signals in the occipital region. For these BCI systems, the researchers can use the spectral analysis techniques to detect the corresponding response's features from either amplitude peak value (Wang et al. 2006, Cheng et al. 2002, Gao et al. 2003, and Muller-Putz et al. 2005), or phase changes (Kluge et al. 2007 and Jia et al. 2010) at the stimulation frequencies.

Furthermore, studies on VEP based BCI systems are categorized in two groups: the Steady State Evoked Potentials (SSVEPs) BCI systems (Muller-Putz et al. 2008); and Transient State Evoked Potentials (TVEPs) BCI systems (Sutter 1992). The difference between SSVEPs and TVEPs systems is the frequency rates used for stimulation signals. For TVEPs systems, the stimulation signal repetition frequency is below 2Hz. On the other hand, for SSVEPs systems the stimulation signal's repetition frequency is above 6Hz.

In terms of the number of the electrodes, for the multi-electrode EEG acquisition equipments the proposed methods (BSS- blind source separation and ICA-independent component analysis) can be used to reject the interference from the artifacts and optimize the arrangement of the electrodes so that one can obtain the optimized signals for each individual subject (Wang et al. 2004). Besides, works presented by Muller-Putz (2005) and Middendorf (2000) show that O1 and O2 locations (see Figure 4) are suitable signal acquisition locations for most subjects. Because for the bipolar electrodes arrangement, the background noises from O1 and O2 can be cancelled to some extent so that BCI system can obtain the clean signals. As one of the SSVEP based BCI applications, Gao et al. (2003) developed an environment controller. By converting the time domain signals into its spectral domain using a 4-35 Hz band pass filter and 1024-point FFT (Fast Fourier Transformation) based on sample rate 200, a 0.195 frequency resolution can be obtained. As a result, a total of 48 flicker targets are identified. Finally, identified flicker targets are used in the design of stimulator in the frequency range of 4-35Hz. Successfully separating the user responses for all 48 flickers stimuli, one can develop a user interface that enables user to provide 48 different intentions using brain signals.

For the SSVEP based BCI systems, the selection for the different type of stimulators are a crucial factor. In the current literature, there are three types of stimulators (Light-emitting diode (LED) stimulator, Cathode Ray Tube (CRT) stimulator, and Liquid Crystal Display (LCD) stimulator). Wu et al. (2008) provided an investigation for the performances of these three different types of stimulators. Among the three types of stimulators, LED type stimulators provide the strongest simulation intensity, but it also brings visual fatigue and uncomfortable senses to the users. In order to reduce the visual fatigue, LCD type stimulators are studied. Since the intensity of the stimulation signals generated by this type of stimulator is the weakest among these three types of stimulators, the stimulated periodic signals are usually buried in the strong noise signals. In order to effectively detect the weak periodic response signals from LCD stimulator stimulated EEG signals, a weak periodic signal detection approach is introduced. Methods used to detect weak periodical signals have been studied for many years. Many applications are from radar design, equipment/machinery fault diagnostic, and seismic activity research as well as communication industry. Chen et al. (2007) proposed an approach, which detects the existence of weak square wave signals under strong noisy background based on chaos theory. Li (2005) proposed a method to improve the accuracy of the detection of weak periodic signals. His method is based on the combination of the second FFT and chaotic oscillator. Works for weak signal detection in terms of the sensitivity of the nonlinear dynamic system to its parameters are presented by Birx et al. (1992) and Wang et al. (1999).

2.1.2 P300 based BCI systems

Another type of EEG based BCI system which depends on the external stimuli is the P300 based BCI systems. In P300 based systems, the stimulation is generated by events where events only occur occasionally. In the literature, the brain-stimuli interaction is called event-related potential (ERP). P300 is EEG responses to an external rare stimulus over parietal cortex and reflects as a positive wave shape change around 300ms after that rare stimulus happens (Piccionea et al. 2006, Sellers et al. 2006, and Hoffmann 2008). The research on the applications of P300 based BCI systems from Citi et al. (2008) demonstrated the possibility of realizing the control functions by only using brain signals such as the work of P300 based mouse' analogue control. As other popular applications of P300 based BCI systems, Omori et al. (2009), Krusienski et al. (2006), and Rebsamen et al. (2006) investigated P300 BCI based spelling devices and wheelchair control. By using P300 based spelling devices, users can perform the spelling task by picking the letters one by one form a matrix of alphabet table. The studies for P300 based game applications can be found in the work of Finke et al. (2009). In recent years, several research studies use P300 based BCI systems for feature extraction applications (Dal Seno et al. 2008, Liang et al. 2008, Yang et al. 2007, and Ishita et al. 2007). Furthermore, some researchers (e.g. Li et al. 2008 and Lu et al. 2009) focused on algorithms to improve the system performance by reducing computational complexity and the time required for calibration. Since the algorithms used in these two systems have poor initial performance, Lotte et al. (2009) proposed a minimal calibration time approach to serve an efficient P300 based BCI system. Mugler et al. (2008) developed a P300 event-related potential based internet browser control. In this work, several participants with various health problems were tested to perform web page navigation, hyperlink selection, and page scrolling tasks by selecting symbols from an independent screen.

2.1.3 *Mu* rhythm based BCI systems

The research for the bio-signals shows that in their spectral domain, four types of main spectrum component exist. These spectrums are associated with four different statuses of brain activities. These four spectrum components are: i) delta wave band from 0-3Hz; ii) theta wave band from 4-7Hz; iii) alpha wave band from 8-14 Hz; and iv) beta wave band from 15-30 Hz. Furthermore, research studies on brain activities have revealed that one can achieve the control of the rhythm of their brain activities at sensory motor area through taking the neuron-feedback training. This sensory motor rhythm is usually called *mu* rhythm and for most subjects, its range is from 12-15Hz. The current research shows that the amplitude of the *mu* rhythm as the brain sensory motor area is in its idle states higher than that of the brain sensory motor area are in the motion preparing and focusing attention states. Cheng et al. (2004) and Fruitet et al. (2010) investigated a *mu* rhythm based application for moving the cursor on the computer screen. Based on the literature, the *mu* rhythms from the motion imaginations often suffer the interference from the alpha wave of occipital region, thus making the detection of *mu* rhythms difficult. In the works of Guo et al. (2010), Royer et al. (2009), and Schalk et al. (2008), the feature extraction from *mu* rhythm EEG signals is discussed.

2.1.4 Slow cortical potential based BCI systems

In addition, the applications of Slow Cortical Potentials (SCP) represent another important type of EEG based BCI system. Slow cortical potentials from the cortex are one of features of the brain activities. They occur in the frequency range 1-2Hz, and usually have the voltage Root Mean Square (RMS) amplitude from 10-100uv. Hinterberger et al. (2004) revealed that the SCP has the polarity characteristics. This polarity feature reflects that the brain responses with respect to the tasks, namely, the negative voltage will occur when brain responds to a task, whereas it takes a positive shift if the task disappears and brain is in its idle states. Usually the duration for the SCP will be 0.5-10s. Similar to the *mu* rhythm, the research results prove that the SCP can be learned and self-regulated through training processes. As specific applications, the thought translation devices (TTD) are developed by Birbauner et al. (2000), Kübler et al. (1999), and Birbauner et al. (2003) and the results show that a paralyzed patient can achieve communication on a PC screen by controlling their brain potentials. Bensch et al. (2007) explored a web browser controlled by SCP. This web browser provides paralyzed patients the capabilities to access not only any links on a web page but also e-mail, virtual keyboards, wide range hypertexts opening, etc. A SCP based BCI system using audio as stimuli is presented in the work of Pham et al. (2005), which aims to provide paralyzed patients with visual impairments opportunities to communicate with the outside world.

2.1.5 EMG signal based HCI systems

The muscles' contractions provide another source for bio-signals, namely, EMG signals. EMG signals are voltage or current changes which are caused by the muscles' activities. These EMG signals usually have the features such as strong amplitudes, insensitive to noise, etc. In the recent years, the researches for EMG based function prosthetic applications such as the prosthetic hand, etc. are studied in many works e.g. Boostani et al. (2003), and Yokoi et al. (2004). In the work of Crawford et al. (2005), a 4 freedom robotic arm control by using EMG signals from human forearm is elaborated. The extracted feature in this system is the amplitude of the EMG signals from each channel. The feature vector consisting of 7 values is used as the input of linear support vector machine. The outputs are used to identify the gestures from the forearm muscles' movements. Since the EMG signals have the features of strong amplitude and insensitive to noise, an approach to control a computer by using unprocessed EMG signals is presented by Felzer et al. (2002).

2.2Conceptual design in fully computerized 3D environment

As the initial stage of the product design process, many conceptual design works have been done by pioneers. In this section, we review the related works to our research objective which is to use our existing sketching approaches to develop a 3D geometric modeling design platform that can be used by handicapped people. Hence, the literature below in the field of conceptual design is associated with the Virtual Reality (VR) based sketching methods.

In general, sketching methods in VR can be classified into two groups: 1) Spline based methods; 2) Surface based methods. In the first group of works, the generating sketches are based on parametric or non-parametric spline patterns. In the second group of works, the initial sketches are generated by using surface patches. We give a brief review on these two classes of design techniques.

Wesche et al. (2000) developed a responsive workbench to perform conceptual design in a virtual reality environment. This responsive workbench is a spline based free-form sketching toolkit. In this responsive workbench, the stylus is the input device and used to draw Bezier curves. Through editing the drawn Bezier curves to generate a curve network and filling the multisided patch with closed boundary surrounding it, a surface model with G^n continuity along the patch boundaries is obtained in VR environment. Xu et al. (2000) proposed a sketching method, which uses data-glove as input device to construct curves based on the collection of data points. Schkolne (2006) developed an intuitive sketching method. Through tracking the trajectory of hands by using a 6-degree of freedom tracker, a polygon surface-based 3D geometric object which is formed by the trajectory of the hands is drawn in VR based 3D environment. Akgunduz et al. (2004) presented a three-step approach to perform the free-form conceptual design in 3D. Using this method, first, an approximate shape of the designed object is created in 3D. Then, various reference points are selected on the surface of the initial design, and then selected reference points are used to generate the parametric surface. Finally, the parametric surface is improved by various modification operations. Based on this sketching approach, we proposed an improved sketching method (2008) based on the real-time free-form parametric surface expressions. This improved method uses data-glove/keyboard as input device. By using reverse engineering approach to fit the drawn data points, one can design the real-time free-form parametric surface-based 3D geometric objects in 3D environment.

2.3 Gap in literature and our contribution

In the above noted literature, we review the works in the bio-signal field. The works reviewed cover a lot of content, but the main works focus on the exploration of the control capabilities of bio-signals. The accurate and efficient control capabilities from the bio-signals are the key factor to achieve hands-free manipulations. The control capabilities of bio-signals depend on available bio-signal features and the achievement of the multiple control intentions. In order to obtain the accurate and efficient control capabilities from bio-signals, the proposed works in the literature focus on the improvements of the bio-signal feature extraction algorithms and classification algorithms of the multiple bio-signal features.

In this thesis, we select to use bipolar electrode arrangement to acquire the bio-signals. Hence, during the whole application process, only one bio-signal source works to generate bio-signals with features. Under this circumstance, the available signal features are very limited. Hence, methods only based on classifying available bio-signal features to obtain required amount of control intentions can not meet the request for multiple control intentions in developing bio-signal controlled geometric modeling design system. In order to solve this problem, in this thesis, an approach of logic control panels is proposed. The use of logic control panels extends the users' control intentions to the desired amount, thus enabling the bio-signal controlled 3D geometric modeling design to be possible in EMG and EOG controlled HCI systems.

In SSVEP based HCI systems, due to the periodic feature of the stimulation signals, the same periodic features have been found in brain's EEG responses to the stimulation signals. In the literature, such periodic features' extractions are mostly performed in the frequency domain. The EEG signal features are extracted from the amplitude or phase of the PSD at stimulation frequency. When the acquired EEG signals have a relatively low SNR, the stability of the extracted EEG features is affected by the intensity of the noise signals, e.g. the EEG responses to a LCD stimulator. In order to improve the control accuracy from the extracted EEG features, in this thesis, we introduce a weak periodic signal detection algorithm. Using this algorithm, we successfully detect the brain's weak periodic response to the visual periodic flicking targets under strong noisy background.

Based on the noted above, a comparison is made between the literature and the thesis work and shown in table 1 below.

Table 1: Comparison of the literature and thesis work

Methods in comparison	Literature	Thesis work
Methods used to achieve the multiple control intentions	Approaches: The classification of the available bio-signal features.	Approaches: Logic control panels.
	Limitation: The available bio-signal features are limited.	Advantage: Can extend the desired control intentions to the desired amount without suffering the limitation from the amount of available bio-signal features.
EEG feature extraction approaches in SSVEP based BCI systems	Approaches: 1. PSD methods based on amplitude peak value detections. 2. PSD methods based on the phase feature detections	Approach: Weak periodic signal detection method
	Limitations: The stability of the extracted EEG features is affected by the uncontrollable factors such as: noise signals.	Advantages: Can detect the existence of the brain's weak periodic response to the visual periodic stimulation signals under strong noisy background.

In this section, we review the fundamental works closely related to bio-signal based geometric design. Motivated by these studies, in this thesis, we aim at developing a methodology to build a bio-signal controlled geometric modeling design platform which can be used by handicapped people. In order to achieve this objective, the control capabilities of three types of bio-signals are the most important factors. Therefore, three types of bio-signal based HCI systems are constructed first. Then the detailed works for identifying control capabilities of bio-signals are performed in each of HCIS. The general workflow in each type of bio-signal based HCI is that first, identifying bio-signal sources; then, extracting signal features; finally, testing control accuracy in applications.

The detailed methodology about determining bio-signal sources, extracting signal features and testing control accuracy are discussed in Chapter 3 below.

CHAPTER 3
METHODOLOGY

In this chapter, the detailed methods about identifying bio-signal sources, extracting signal features, and testing control accuracy are discussed respectively in the following HCI systems: 1) EMG based HCI system;2) EOG based HCI system; 3) EEG based HCI system. Since the research of bio-signals depends on the signal acquisition and the signal communication approaches such as sampling rate, TCP/UDP protocol, hence, we first introduce the bio-signal acquisition equipment and corresponding software support used in this research work.

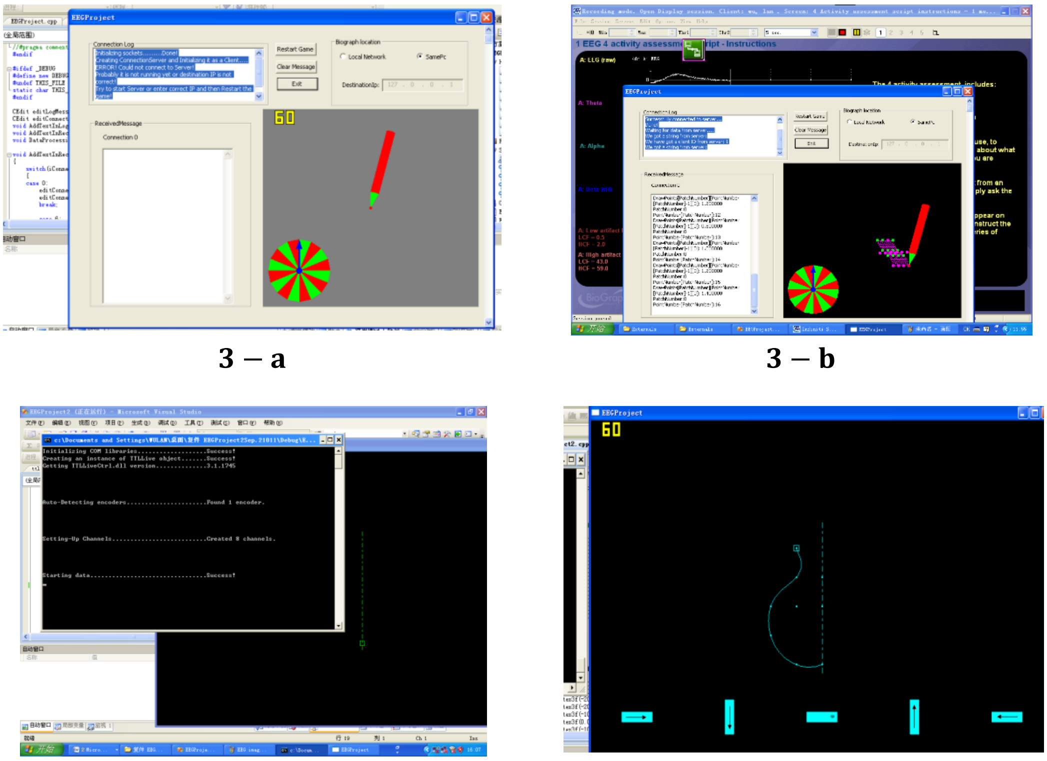
3.1 Hardware and software support from the bio-signal acquisition equipment

In this research work, the bio-signal acquisition equipment is selected as Infinity ProComp2, which is manufactured by Thought Technology Ltd. It is non-invasion bio-signal acquisition hardware. Four electrodes and a EEG extender cable are included in a TT-EEG kit, that is, one positive electrode (blue color and disk shape),one negative electrode (yellow color and disk shape) and two reference electrodes (black color and ear clip) as well as the EEG extended DIN cable. To retrieve the bio-signals, two types of electrode configurations can be set up by users. One is BIPOLAR configuration, which connect three electrodes (one positive electrode and one negative electrode as well as one reference electrode) to the equipment. Another electrode arrangement is MONOPOLAR configuration, which only one positive electrode and two reference electrodes are used. In this thesis the bipolar electrodes are selected for hardware configuration. Five steps are followed for hardware connection.

1) Chose the three electrodes (one positive electrode, one negative electrode, and one reference electrode) from the TT-EEG electrode kit (T8750).
2) Plug these three electrodes into EEG extender DIN cable (T8740).
3) Connect the EEG extender DIN cable directly to the ProComp 2 input A which has EEG sensor build-in.
4) Connect ProComp 2 to TTUSB.
5) Connect TTUSB to computer.

In order to support the applications from a third party, two software packages are provided by the hardware manufacturer. One is the connection instrument software development kit version 3.0. This software package provides the third party a graphic user interface (GUI). The third party can read data signals from the screen data channel into the specific application (e.g. 3D geometric modeling design in this research case).The TCP protocol is used for collecting bio-signals from the body and guarantees 100% signals are able to reach to the destination. The UDP protocol is used for sending data to the third party’s application. This data communication protocol can not guarantee the third party side being able to receive 100% data signals. Hence, the connection instrument software development kit version 3.0 can’t provide the support for developing EEG based HCI. Another software package is the TTLAPI. TTLAPI is a COM DLL and runs on Windows platform (e.g. Windows 98, 2000, XP and Vista.). This software package provides an interface between the hardware and the third party’s applications, which guarantees 256 sampling rate/s and 100% data communication between the hardware and the third party’s applications. Therefore, TTLAPI supports the applications of three types of bio-signal based HCI systems.

The following Figure 3 shows a comparison of the two GUIS we developed. These two GUI are supported by aforementioned two software kits respectively.



3 − a **3 − b**

3 − c **3 − d**

Figure 3: (a)-(b) GUIS supported by connection instrument software development kit version 3.0; (c)-(d) GUIS supported by TTLAPI

In this research work, these two types of signal acquisition software kits are used respectively. Hence, the application programs are written in openGL and VC++/C++ code based on the library functions provided by the connection instrument software development kit version 3.0/ TTLAPI.

After setting up the hardware configuration and selecting the signal acquisition software kit, the detailed works about determining the bio-signal sources, extracting signal features and designing control panels in EMG, EOG, and EEG signal based HCI systems are discussed individually below.

3.2 EMG based HCI system

Following the aforementioned hardware and software interface configuration, in this section, we discuss methods about the determination of bio-signal sources, the extraction of signal features and design of control panels for EMG based HCI in details.

3.2.1 Identifying signal sources for EMG based HCI

For a bio-signal based HCI system, the performance of the HCI system extremely depends on the stability of the bio-signal features. In the literature, the previous work revealed that the selection of the bio-signal sources can ensure the collected bio-signals a relative high SNR, thus maintain the stability and reliability of the extracted signal features. Hence, the EMG signal sources are identified first. The determination of EMG signal sources depends on the signal features that the signal sources generate. In this work, an on-off switch featured signal feature is expected to be obtained from the available bio-signal sources. Based on the desired signal feature, three EMG signal sources are identified through offline data analysis and the observation for the graph of the collected raw EMG signals. One identified signal sources for EMG signals is detected at upper lip (positive electrode) and lower lip (negative electrode) as well as left ear (reference electrode). The rest two are identified at G (negative electrode) and F8/F7 (positive electrode) as well as left ear (reference electrode) which follows the international 10/20 system. See Figure 4 below.

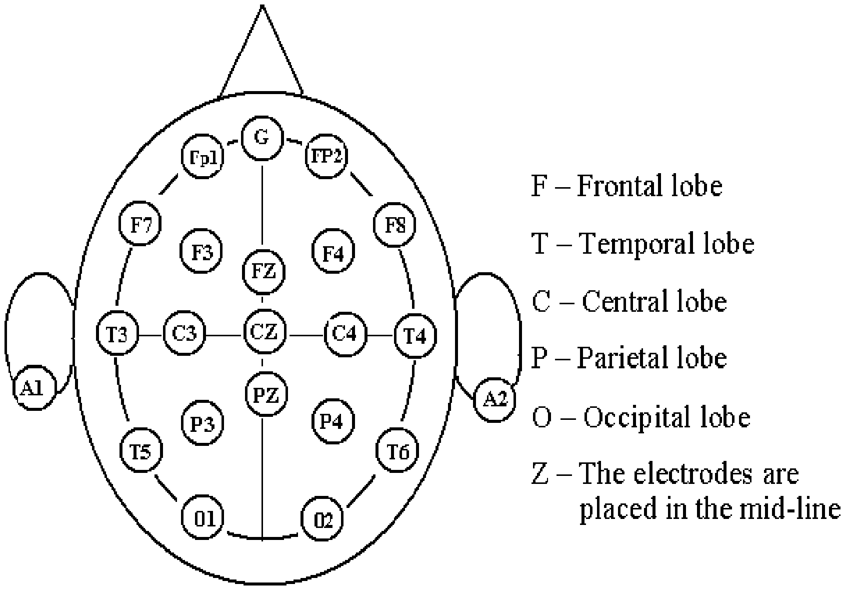


Figure 4: Positions of the electrodes in international 10/20 system

Three identified EMG signal sources can generate the similar signal features, which accord with the preferable on-off switch signal feature (see Figure 6 below). In Figure 5, a sample of raw EMG signals, which is collected from the ProComp 2software development kit version 3.0 is illustrated. The output screen chosen for this test is 4 activity assessment script instructions-1 monitor. The collected raw EMG signals are from the eye muscle's intentional contractions or mouth muscles' intentional contractions. In Figure 5, following the sequence from up to down, the numbers of the rectangular waves correspond to the numbers of the eye muscle's contractions or mouth muscles' contractions.

Figure 5: The graph of the collected raw EMG signals from the identified signal sources

3.2.2 EMG signal feature analysis

The EMG signals in the designed HCI system are generated by eye muscles' or mouth muscles' intentional contractions, namely, eye's intentional blinks or lips' closes. These eyes' intentional blinks or lips' closes cause a series of voltage potential differences between the positive electrode F8/F7 and the negative electrode G or between positive electrode on the upper lip and negative electrode on the lower lip. Through the linked data reading channel, the raw EMG signals are obtained. These raw EMG signals record the information about the eye's blinks or lips' closes and can be monitored through the screen graph. Through online observation and offline analysis, the result shows that once eye's blink or once lips' close causes the amplitudes of two adjacent instant raw EMG signals to generate twice abrupt and cross zero line's changes. (See Figure 6 below, the rising edge and falling edge). This change shows a roughly rectangular wave shape EMG signal output. Moreover, once eye's blink or once lips' close produces one rectangular raw EEG wave shape output. Besides, the Figure 6 shows that with the end of eye's blinks or lips' closes, the amplitudes of raw EMG signals have a slowly increasing from negative value to positive value and cross the zero line (zero amplitude and time axis).

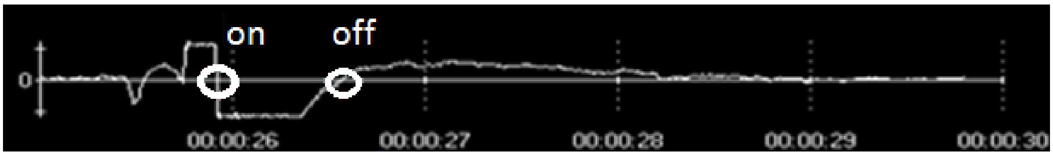


Figure 6: The identification of EMG signal features

These are two signal features obtained through the observation of the data graph. Based on this online observation and offline data analysis, the signal features are summarized as follows:

1) One eye's blink or lips' close produces one rectangular raw EMG signal output, and the amplitudes of two adjacent instant raw EMG signals with zero line in between lying on its falling edge have an abrupt change and the difference of these two signals' amplitudes is less than -200 (threshold 1). Similarly, the amplitudes of two adjacent instant raw EMG signals with zero line in between lying on its rising edge have an abrupt change and the difference of these two signals' amplitudes is greater than 100 (threshold 3).

2) Accompanying the end of eye's blinks or lips' closes, there is a slowly increasing and crossing the zero line process on the amplitude of raw EMG output signals. In this increasing process, the amplitude difference between two adjacent instant EMG signals with zero line in between is usually above 6 (threshold 2) and less than 100 (threshold 3).

In the process of raw EMG signal collection, the reference electrode is used to eliminate the interference from the outside environment and power line, etc. The threshold1, threshold 2 and threshold3 are determined through offline data analysis.

3.2.3 EMG signal feature extractions

Through the online observation and offline analysis, we found the eye's blink or lips' close will cause roughly rectangular wave shape raw EMG signal output and relationship between the numbers of eye's blink or lips' closes and obtained rectangular EMG waves is one to one mapping relationship. Therefore, we map the numbers of the eye's blinks or lips' closes into control intentions. It is well known that the EMG signals are highly dynamic signals, therefore, algorithm must be able to capture its dynamic change features and can't consume too more memory space. To meet these requirements, a one dimension array is defined and used to store the amplitudes of two adjacent instant raw EMG signals. The amplitudes of these two adjacent EMG signals are stored in this array, one is the amplitude of the current received EMG signal and the rest is the amplitude of the previous instant EMG signal. The real-time update of the amplitudes of these two adjacent instant EMG signals guarantees the real-time update of their amplitude difference. If the amplitude difference computed is less than the threshold 1, in our test, it was set up as -200, and then counter adds one number (once eye's blink or once lips' close was detected). Similarly, if the amplitude difference computed is greater than the threshold 2 (in our test, it was set up as 6) and less than the threshold 3(in our case, it was set up as 100), then output the number of detected rectangular EMG waves (the end of eye's blinks or lips' closes). As analyzed above, the EMG signal features are extracted, that reflect the number of eye's blinks or lips' closes. Through mapping these extracted EMG signal features into control intentions, the users can control a 3D cursor to perform geometric modeling drawing task.

In the flow chat Figure 7, the EMG signal feature extraction process isdemonstrated.

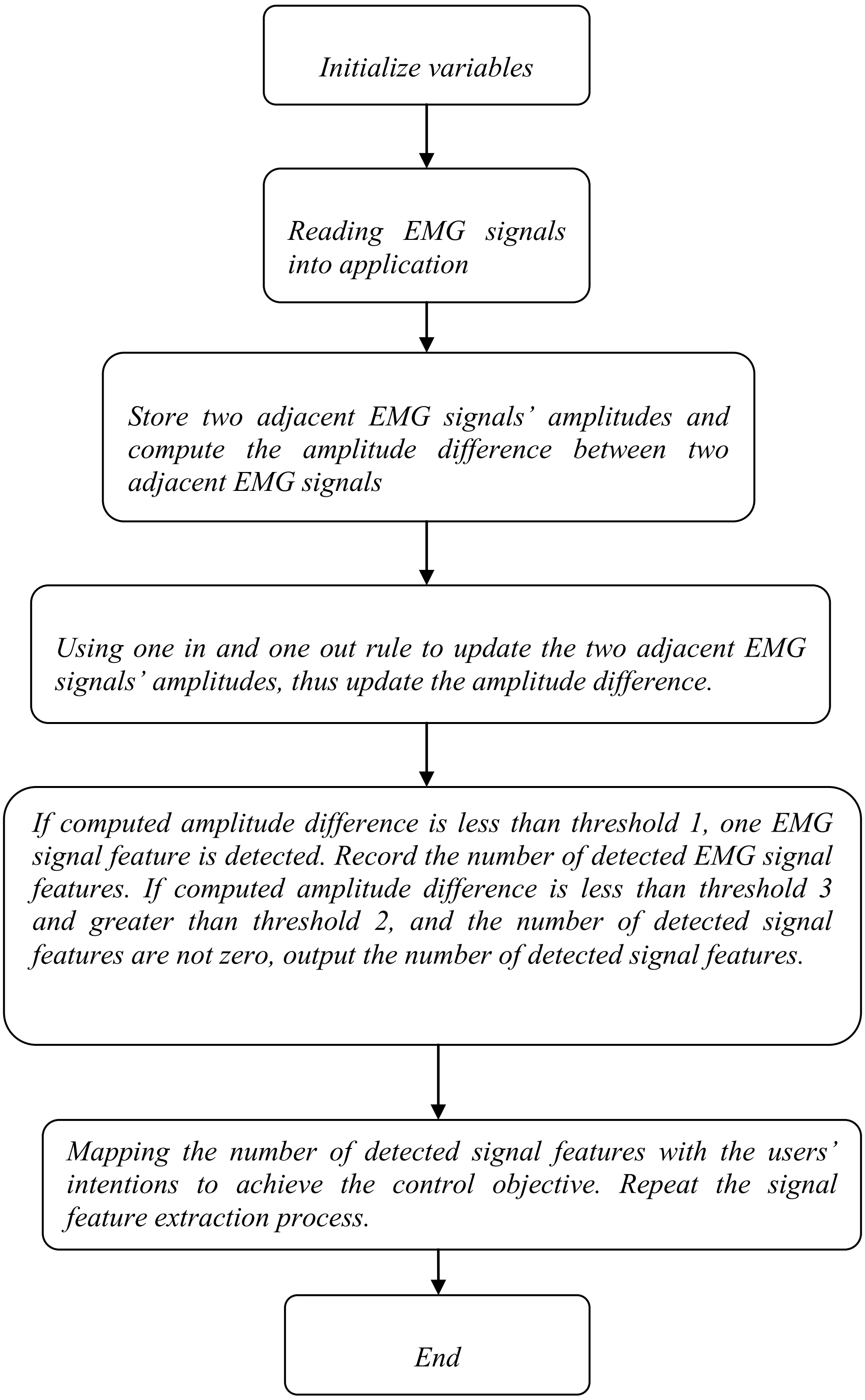


Figure 7: Flow chart of EMG signal feature extraction process

Then EMG signal feature extraction is demonstrated in the flow chart Figure 8 below:

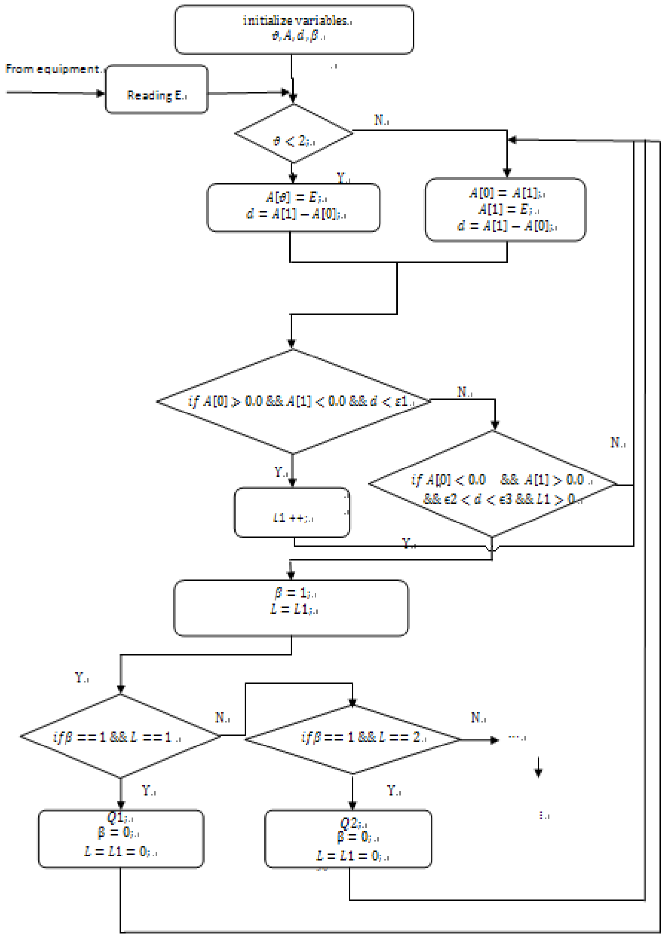


Figure 8: Flow chart of EMG signal feature extraction

Table 2: Variables of flow chart of EMG signal feature extraction

ϑ:	Number of received bio-signals
A:	An array that is used to store the received EMG signals
d:	Amplitude difference of two adjacent EMG signals
E:	EMG signals received from the equipment
ε:	Set of thresholds used to validate the occurrence of range of signal

	features
β:	$=\begin{cases} 1 & if\ feature\ is\ detected \\ 0 & otherwise \end{cases}$
L:	Record the number of the detected signal features
S:	Time interval determined by the same amount of EMG signals
Q:	Set of user intentions

3.2.4 Control panel design

In this thesis, based on the bipolar electrodes arrangement, each time, only one identified bio-signal source can be used to acquire the bio-signals. It brings two limitations to the specified applications: 1) the amount of available bio-signal features is limited; 2) high physical needs for the single bio-signal source are easy to cause the fatigue of the bio-signal source, thus degrading the available bio-signal features. For example, in our EMG based application, the available bio-signal features are identified as the number of eye's blinks or lips' closes. Although by identifying the numbers of eye's blinks or lips' closes, the users can control a 3D cursor to achieve the intended drawing. But, these rectangular EMG wave shape outputs are difficult to keep stable for an extended amount of time (a typical drawing task requires hours of work). The experiments indicate that the fatigue is easy to experience due to the high physical demand on eyes/lips. In this case, the possibility of error in accurate identification of the number of eye's blinks or lips’ closes is significantly high. (See Figure 9 below)

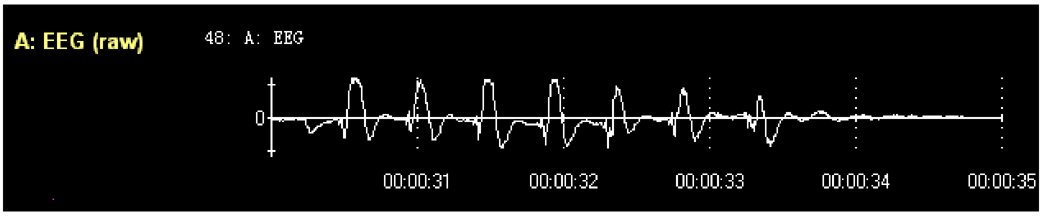


Figure 9: Degraded EMG signals

Under this circumstance, in order to achieve the complicated control task, it is necessary to develop methodology to overcome these two shortcomings, namely, accomplish the multiple control intentions and reduce the fatigue of the bio-signal source. To achieve this objective, special attentions are paid to the Graphical User Interface (GUI) design.

The objective to develop GUI that incorporates various options is to enable a user to convey his/her intentions with limited number of body signals (in this research case it is the number of eye's blinks or mouth muscles' contractions). One of the options that is proposed in order to handle multiple user intentions is to integrate logic control panels into the 3D geometric modeling system. These logic control panels are designed as a series of round disks and each of them has a rotating pointer on it. The pointer rotates around the disk at a speed which is controlled by the received signal amount, and the disk is divided into sectors. Each sector corresponds to a control intention. In this way, if the pointer rotates into the desired region, then the required control intention can be determined by an on-off switch signal feature through once eye's blink instead of multiple blinks so that the muscles 'fatigue caused by the frequent blinks can be released. Accordingly, the control accuracy can be improved. Moreover, by expanding this method, the multiple control intentions can be achieved.

That is similar to the root directory approach. First, a round disk is used as a root directory which has several sectors designed on it. Each of these sectors corresponds to a set of sub directory disks. These sub directory disks correspond to required control intentions. For example, on the root disk, one sector corresponds to the motion control intention, the users can use their body signals to open its sub directory disk which has at least seven sectors designed on it. One is used to back to the root disk and six of them correspond to six direction motion control intentions. Likewise, with more sectors designed on it, the control intentions can be expanded layer by layer, thus making the control intentions to reach the desired amount.

It is worth noting that the rotating speed of the pointer is determined by the amount of received bio-signals.

See the Figure 10 below for the illustration of this extending process.

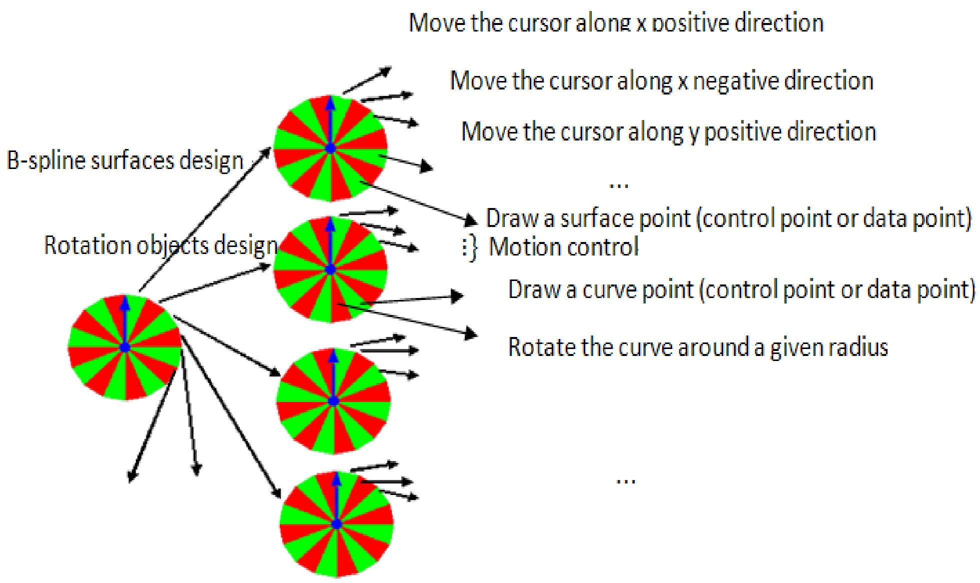


Figure 10: Control panel extending

In the flow chart Figure 11, the EMG signal feature extraction process with control panel application is demonstrated

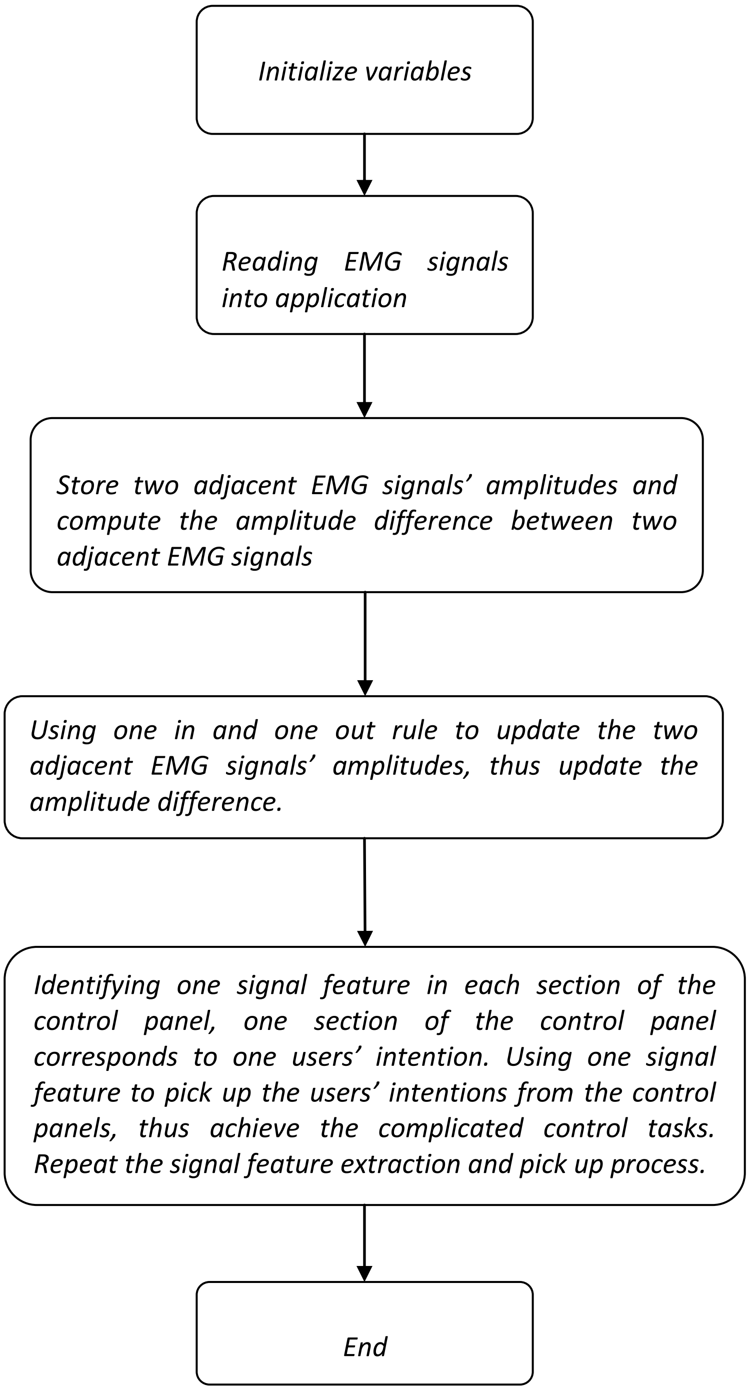


Figure 11: Flow chart of EMG signal feature extraction process with control panel application

Then EMG signal feature extraction with control panel application is demonstrated in flow chart 12 below:

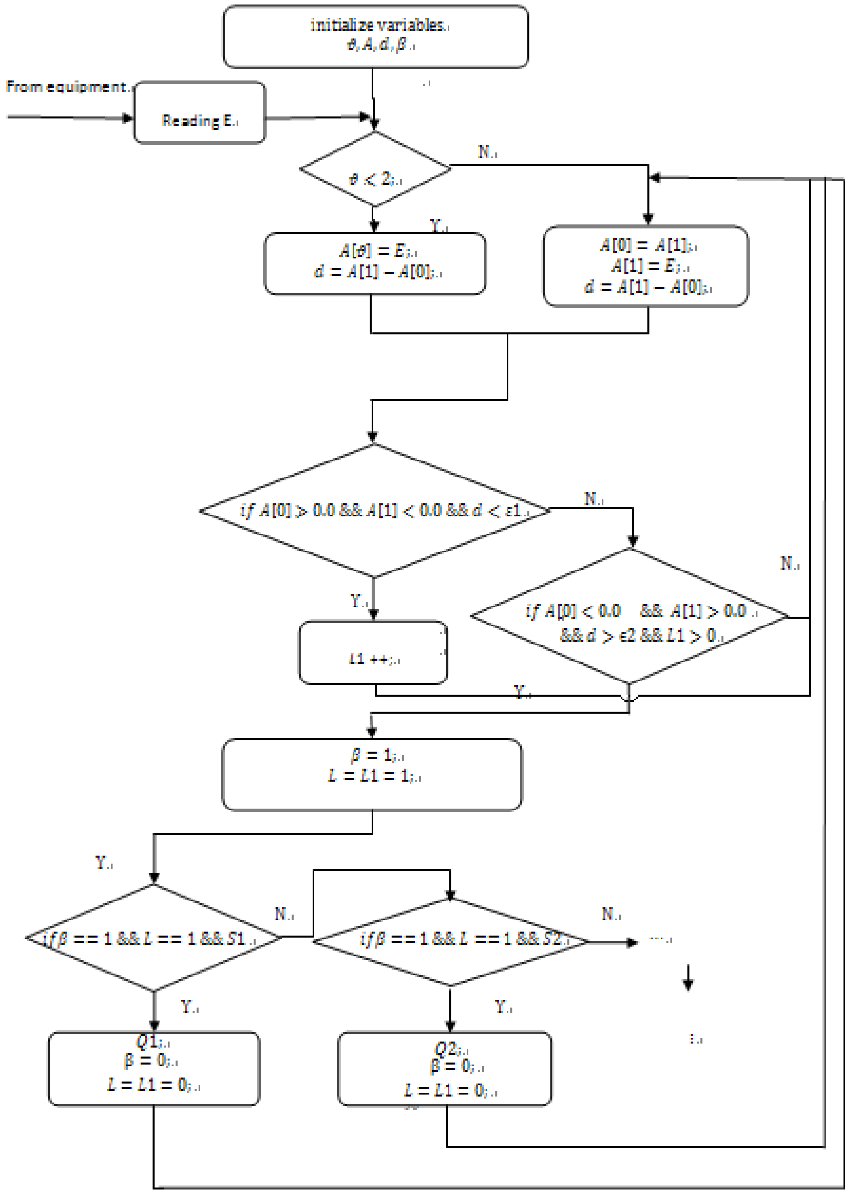


Figure 12: Flow chart of EMG signal feature extraction with control panel application

3.2.5 Experiments and results

- **System design and set-up**

In this research work, two types of signal acquisition software kits are provided by the hardware manufacturer. As noted above, these two signal acquisition software kits are connection instrument software development kit version 3.0 and TTLAPI. Hence, based on these two signal acquisition software kits, two GUIs are developed and used in EMG based geometric modeling design system respectively. The experiments have proved that the same EMG signal patterns can be acquired using any one of signal acquisition software kits.In order to test the possibility for using extracted EMG signal features and designed logic control panels to do 3D geometric modeling design in computer-based environment, the following experiment is designed, in which the design of GUI and the acquisition of EMG data are based on connection instrument software development kit version 3.0. The detailed experiment steps are described as follows:

Steps:

1) Prior to the experiments, clear instructions are given to all subjects.
2) No previous training was provided to all subjects.
3) Subjects were positioned in front of a LCD computer monitor. The interface of the computer screen is given in Figure 3-a.
4) Configure thresholds for designed BCI system.

Once the thresholds were configured, the online drawing experiment was started. A series of control intentions are designed on the logic control panel. During the experiments, the subjects were asked to use their EMG signals as controller to pick up desired control intentions from the control panels, for example, move cursor (here, is a designed pen) along desired directions, draw points, generate spline curve, surface, etc. Several drawing experiments were performed, and results are discussed as follows.

- **Results of 3D geometric modeling using designed EMG signal based HCI**

The use of the logic control panels extends the control intentions to the desired amount. Therefore, it enables the 3D geometric modeling design to be possible in EMG based HCI systems. On this basis, the corresponding 3D geometric modeling design platform is constructed in the EMG based HCI system. In this geometric modeling design platform, all the geometric modeling is generated by using B-spline curves, Bezier curves, B-spline surfaces and rotation geometries. The specified drawing options are achieved by means of the logic control panels. Some examples are displayed in Figure 13 and Figure 14, that are designed by using the above noted geometric generation techniques and GUIsupported by connection instrument software development kit version 3.0. A detailed generation approach is displayed in the Figure 13 and used to give the illustration for the achievement of a bio-signal controlled geometric modeling in EMG based HCI. In these drawing experiments, the results show that up to 100% accuracy rate has been achieved.

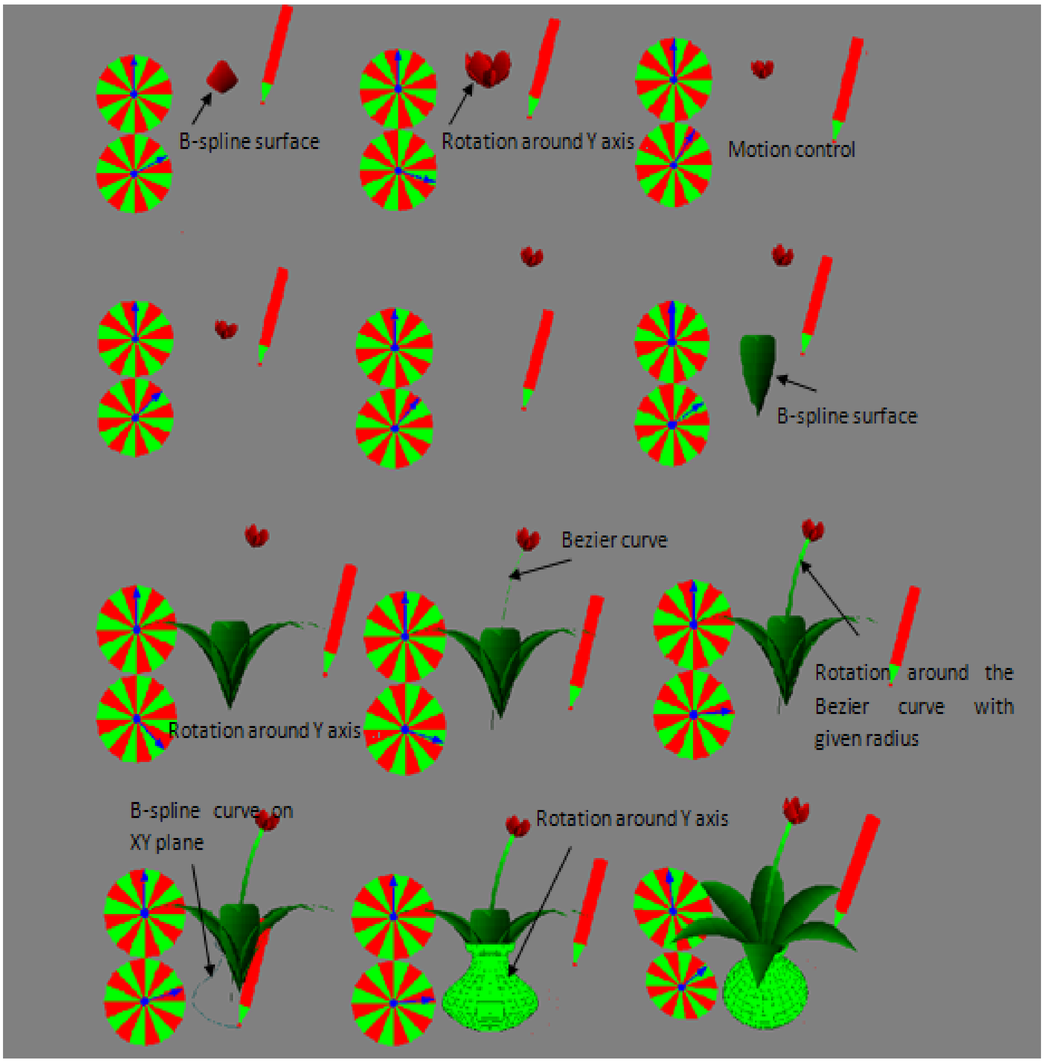
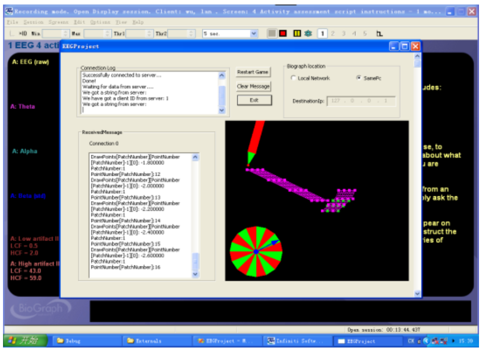
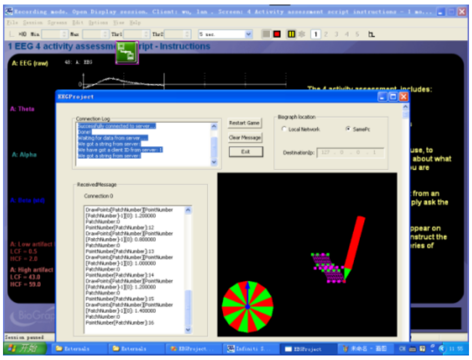


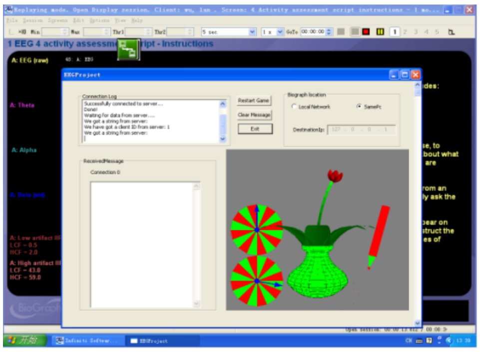
Figure 13: Integrated application of geometric modeling

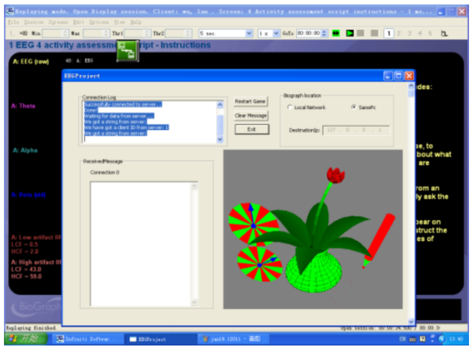


14 – a

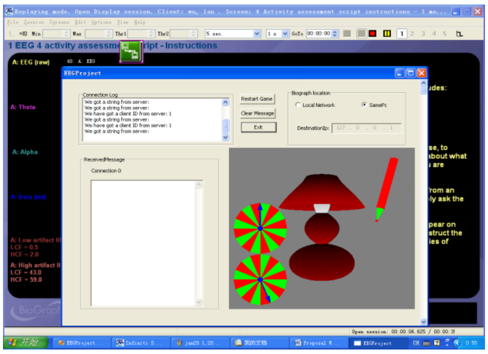


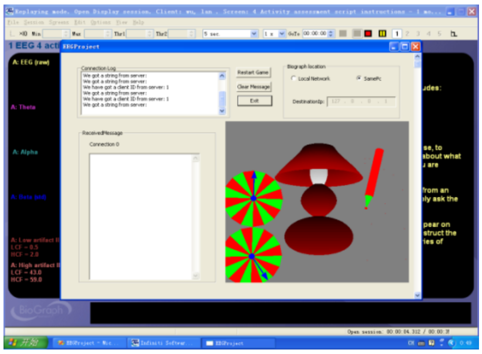
14 – b



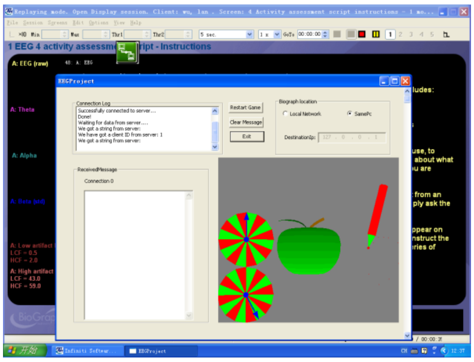


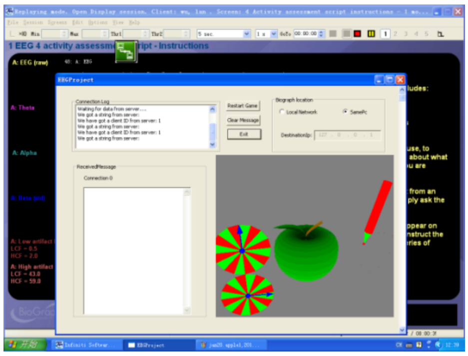
14 – c **14 – d**





14 – e **14 – f**





14 – g **14 – h**

Figure14: 3D geometric modeling in the EMG based HCI system

3.3 EOG based HCI system

After testing the extracted EMG signal features in geometric modeling. In this section, EOG signal based HCI is studied, detailed methods about identifying bio-signal sources, extracting signal features are presented below.

3.3.1 Identifying signal sources of EOG signal based HCI

Through graph observation for collected EOG signals, the bio-signal sources in EOG based HCI are identified at the G (negative electrode) and F8/F7 (positive electrode) as well as the left ear (reference electrode). The Figure 15 below is the graph of the captured raw EOG signals from the identified EOG signal sources.

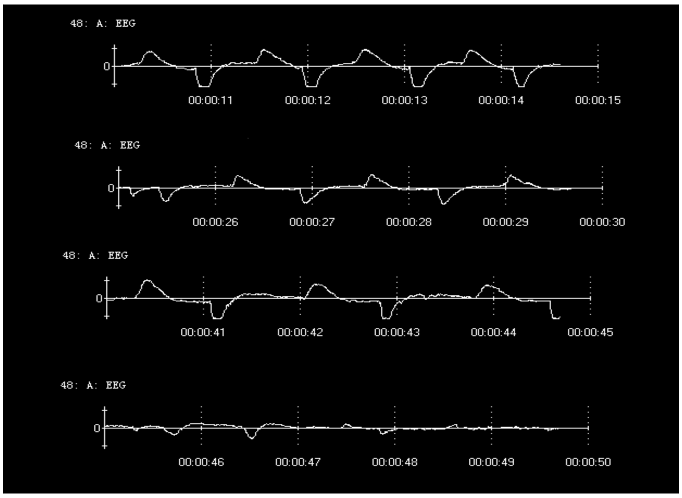


Figure 15: The graph of the collected raw EOG signals from the identified EOG signal sources.

In Figure 15, from up to down, the first three EOG signal graph record the eye balls' movement from the central point of the screen to the right direction and from the right direction to the central point (G, F8, and left ear are data collection locations). The fourth graph records the right eye balls' movement from the central point to the up direction and from the up direction to the central point. The comparison of these figures shows that the eye ball's right/left movements generate the strong and repeatable signal patterns. The eye balls' up movement shows a relative weak signal feature. Based on this observation, the eye balls' right/left movements are selected as the generation approaches of EOG signals.

Note: The experiment has proved that the similar signal patterns can be collected from G, F7, and left ear locations when the eye balls move from the central point of the screen to the left direction and from the left direction to the central point.

3.3.2 EOG signal feature analysis

In terms of the seleced EOG signal generation approach, EOG signals are collected from the eye balls'right/leftmovements.

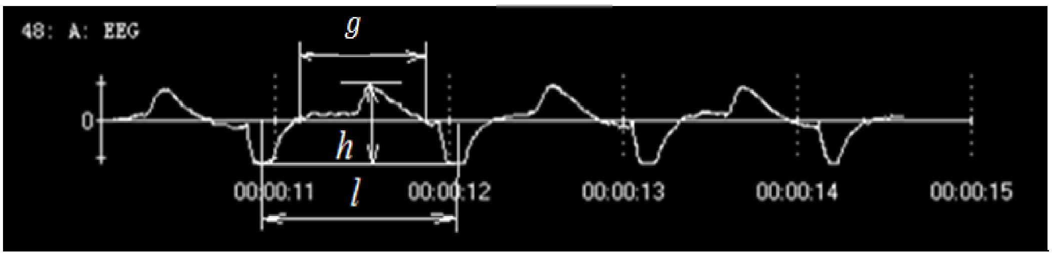


Figure 16: The identification of EOG signal features

Above Figure 16 shows the graph of EOG signals(collected from G, F8,and left ear locations) when the subject repeatly moves the eye ballsfrom the central point of the screen to the rightand moves eye balls from the right back to the screen centeral points, strong and repeatable EOG signal patterns are obtained.Inone cycle of the eye balls' movement (from the center point to right and from right to the centre point) the amplitudes of EOG signals generate a change from the negative peak value to the positive peak value and from the positive peak value back to the negative peak value, thus form a one to one mapping between eye balls' one cycle movement and one EOG signal pattern. Multiple online tests show the reliability and repeatability of the generated EOG signal patterns.Based on these observations, the EOG signal features are summrized as follows:

1) One cycle of eye balls' right/left movement causes the amplitudes of EOG signals having a change from the negative peak value to the positive peak value and from the positive peak value to the negative peak value.
2) EOG signal patterns generated by eye balls' right/left movements are strong and repeatable.
3) Three obvious features are selected through the observation of the EOG signal graphic output:
   i. The amplitude difference between the adjacent negative peak value and positive peak value, which is denoted by *h*.
   ii. The time difference between two adjacent negative peak values, which is denoted by *l*.
   iii. The third is the time difference *g* between two time instants when the signal amplitudes cross the zero line from the negative value to the positive value and from the positive value to the negative value.

3.3.3 EOG signal features extraction

Through the online observation and offline analysis, three signal features are identified (see Figure 16 above). One is the amplitude difference *h* between the adjacent negative peak value and positive peak value. One is the time difference *l* between two adjacent negative peak values. The third is the time difference *g* between two time instances when the signal amplitudes cross the zero line from the negative value to the positive value and from the positive value to the negative value.

In terms of this result, the EOG signal features are extracted that are based on each 2 seconds data segments (sampling rate is 256 records per second). The signal feature extraction process is displayed by Figure 17 below:

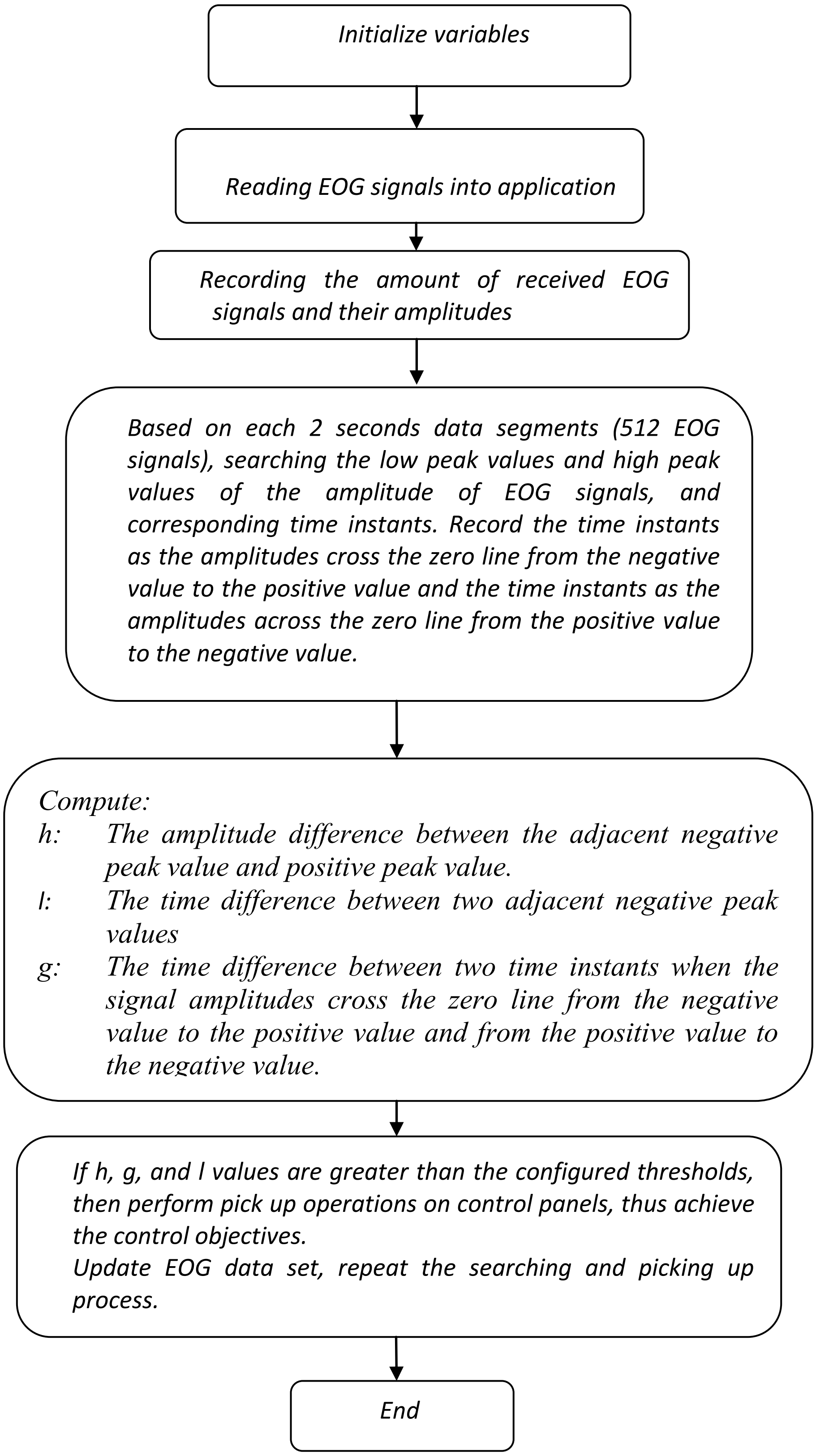

Initialize variables
Reading EOG signals into application
Recording the amount of received EOG signals and their amplitudes
Based on each 2 seconds data segments (512 EOG signals), searching the low peak values and high peak values of the amplitude of EOG signals, and corresponding time instants. Record the time instants as the amplitudes cross the zero line from the negative value to the positive value and the time instants as the amplitudes across the zero line from the positive value to the negative value.
Compute:
h: The amplitude difference between the adjacent negative peak value and positive peak value.
l: The time difference between two adjacent negative peak values
g: The time difference between two time instants when the signal amplitudes cross the zero line from the negative value to the positive value and from the positive value to the negative value.
If h, g, and l values are greater than the configured thresholds, then perform pick up operations on control panels, thus achieve the control objectives.
Update EOG data set, repeat the searching and picking up process.
End

Figure 17: Flow chart of EOG signal feature extraction process

3.3.4 Experiments and results

- **System design and set-up**

The design of EOG based geometric modeling system is completely the same as that of EMG based geometric modeling system, except that the signal feature extraction algorithms are different. Hence, the same GUI supported by connection instrument software development kit version 3.0 was used in the experiments. The objective of the experiment is to extract the EOG features noted above and use them to achieve the control purposes. The experiments were performed to detect the EOG signal features and the results are summarized below.

- **Results**

The experiments were performed for EOG signal feature extraction show that the extracted EOG signal features are robustness. Based on the robustness of the extracted EOG signal features, we draw a conclusion that using extracted EOG signal features, the control accuracy rate up to 100%can be achieved.

Similarly, the same EOG signal patterns can be acquired by using TTLAPI software kit.

It is worth noting that the researches described in this thesis are focused on two steps works. The first step work is focused on the study for bio-signals which includes the signal acquisition, signal feature analysis and signal feature extraction. The second step work is focused on the geometric modeling creation methods. In our current EMG and EOG based HCI system, the studying results from the EMG and EOG demonstrated the robustness of the extracted signal features in achieving the control tasks. But, for 3D geometric modeling generation, currently, only single-data-point generation approach is integrated in the designed HCI systems. Due to the limitation from the signal generation approach (e.g. muscles' contractions) and the number of the electrodes, the multiply control commands can only be generated by means of the use of logic control panels. Hence, using single-data-point generation approach to create the complex 3D geometric modeling is a time-consuming process. In order to enable the designed HCI system more applicable, the efficiency of the generation of 3D geometric modeling needs to be improved. The specified methods such as multi-data-point approach (see Figure 1) and drawing tools with pre-defined trajectories and shapes can be taken into consideration to integrate into current existing HCI systems to improve the drawing efficiency.

Besides, for bipolar electrode arrangement, EEG based BCI system has potentials to obtain more signal features. Consequently, it is possible to improve the drawing efficiency through an EEG based HCI. Hence, in the following section, we propose an EEG based HCI. The objective is to identify the control capability of EEG signals and its capability in improving the drawing efficiency.

3.4 EEG based HCI system

As one of three main bio-signals, EEG signals reflect brain neuron activities. Based on the literature, since the SSVEP based applications have the advantages of less training time and easy to trigger out, etc., in this research work, we integrate SSVEP based bio-signal control into developed 3D geometric modeling design environment.

A SSVEP BCI system is a brain-computer interface which utilizes extracted EEG features (generated under the action of the periodic visual stimulations) to generate control functions to achieve hands-free manipulations. It uses periodic visual flicking targets to provide periodic visual stimulations to users. The stimulation signal's repetition frequency is above 6Hz.In general, an SSVEP based BCI is formed by three basic units: 1) Stimulator; 2) Signal processing unit; 3) Commands performing unit. In the following sections, they are discussed in details.

3.4.1 LCD stimulator design

One of the methods to accomplish a BCI system is to design a control system that responds to external stimulator signals. In order to reduce the visual fatigue and create a convenient application environment for users, we design an LCD type stimulator to achieve various control functionalities in a BCI system. Stimulation of the brain is achieved by sending a certain frequency signal from a LCD monitor. Based on 60 Hz LCD monitor refresh rate, from 1 Hz to 30 Hz frequency range can be used to model stimulation frequencies (Figure 18 illustrates the structures of stimulation signals). Each modeled stimulation frequency can be used to achieve a certain control capability in the computer. While, we only experimented with the frequency bands: 15Hz, 14Hz, 13Hz, 12Hz, and 10Hz, several other frequency combinations can be used to increase the number of control functionalities in the given BCI system. A flicking target is used to send intended stimuli signals to the user's brain. Consequently, five unique control commands are achieved through designing five different flicking targets as shown in the Figure 19.

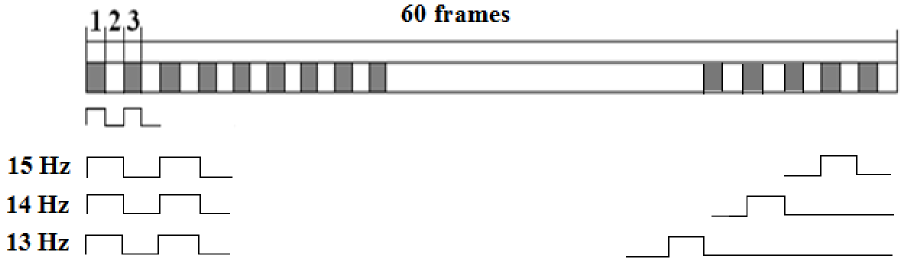


Figure 18: Structure of stimulation frequencies on a LCD stimulator

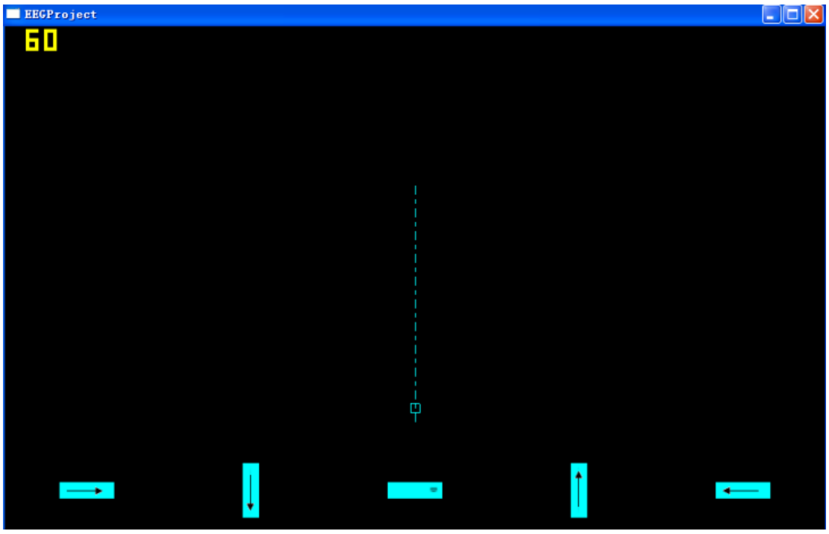


Figure 19: The configuration of flicking targets for current online BCI (frequencies for flicking targets from left to right are 12Hz, 10Hz, 13Hz, 15Hz, and 14Hz)

3.4.2 Data-acquisition

In the designed online experiments, five flicking targets were used to provide stimulation signals. Each flicking target worked cyclical Target is activated for 4 seconds for flicking which followed by a 4 seconds break. Hence, the data acquisition and analysis were based on the data collected during each 4 seconds time-frame includes both flicking and pause periods.

3.4.3 Electrodes arrangement

Literature suggests that the SSVEP responses can be widely observed if the signals are collected from occipital region and parietal region (Bin et al. 2009). Our experiments also support the findings of the literature and we found the strong SSVEP responses from the occipital region. Consequently, we set-up an EEG signal acquisition system using bipolar electrode arrangement by placing negative and positive electrodes on O1 and O2 respectively and reference electrode on left ear. A sampling rate of 256 Hz was used.

3.4.4 Signal processing

Data is collected for each 4 second period. Let us denote index$p$ for identifying the sampling period. Since the sampling rate is 256 records per second, each 4 second periods consists of 1024 data points. Let λ_i^p be the value of single EEG data in period$p$, then $\Lambda^p = \{\lambda_0^p, \lambda_1^p, \cdots, \lambda_{N-1}^p\}$ for$N = 1024$. The details for the signal processing method used in our method are discussed below.

3.4.4.1 Weak periodic signal detecting system

At this point we have a BCI system that includes an artificial stimulus signal as an input and EEG signals as output. Brain is a highly complex organism that responds to many external and internal factors. The stimulus signals used in the proposed BCI system are periodic. Hence, it is expected brain to response in the similar way and general periodic EEG signals. However, stimulated SSVEP response is weak and mixed with large amount of noise signals due to the intensity of LCD stimulator. Therefore, it is not trivial to link the disturbance on brain activities with the stimulus signals. Lorenz system (Lorenz 1963) is a nonlinear dynamic system. Since a nonlinear dynamic system such as Lorenz system is highly sensitive to its parameters, a small perturbation of system parameters can cause obvious changes on the motion orbit of the Lorenz attractor.

Due to its unique features, we reformulated Lorenz system to detect weak sine responses from EEG signals. The system model and its parameters are discussed as follows.

i. System model and system parameters

$$\dot{x} = \omega_{\nabla}\sigma(y - x)/\omega \quad (1)$$

$$\dot{y} = \omega_{\nabla}\{r[1 + ksin(\omega_{\nabla}t) + k_e\lambda_i]x - y - xz\}/\omega \quad (2)$$

$$\dot{z} = \omega_{\nabla}(xy - bz)/\omega \quad (3)$$

Where

ω_{∇}:	Detected angle frequency $\omega_{\nabla} = 2\pi f_{\nabla}$
f_{∇}:	Detected frequency
$sin\ (\omega_{\nabla}t)$:	Embedded sine function
ω:	Characteristic angle frequency of testing system
k_e:	EEG signal intensity coefficient
λ_i:	Detected signals for $i = \{0, 1, \cdots, N-1\}$
∇:	The number of detected SSVEP responses
x:	Displacement of Lorenz attractor along *x* direction
y:	Displacement of Lorenz attractor along *y* direction
z:	Displacement of Lorenz attractor along *z* direction

Following values are used for system parameters:

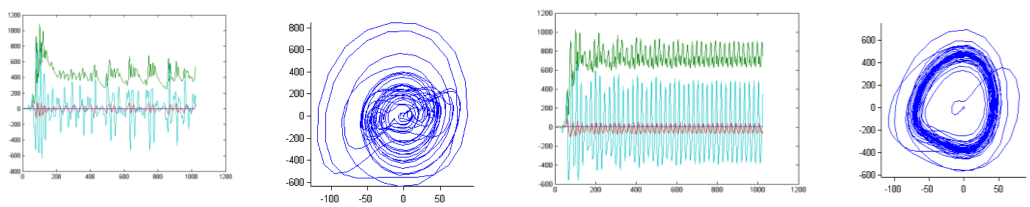
$\sigma = 10,\ r = 168,\ b = 8/3,\ \omega = 70\ \mathrm{rad/s}$, and $k = 2.45$.

To solve the Lorenz equations, the initial values for the Lorenz attractor are: $\begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$

The feature extraction methodology used for identifying the presence of the weak-periodic signal is discussed in the following section.

ii. Feature analysis

In its initial state($\lambda_i = 0,\ \forall i$), the Lorenz system is in a chaos situation (denote it as L^c) as shown in Figure 20-aandFigure 20-b. Figure 20-a provides critical Lorenz system outputs ($x(t),\ y(t)$, and $z(t)$) in its chaos state for sampling duration of t. In an ideal situation where only sine signals $\lambda_i = sin\,(\omega_{\nabla} t)$ are input to the system (no noise signal-mix is in the input signal set), the system is in a non-chaos state when the EEG signal intensity coefficient k_e is increased into a certain range. For instance, if the EEG signal intensity coefficient k_e is increased in the 0.675~0.74 range for stimulus frequencies ($\nabla = \{15\ Hz, 14\ Hz, 13\ Hz, 12\ Hz, 10\ Hz\}$in our case) , the chaos state is broken. We observe that, during non-chaos state, the corresponding outputs $x(t), y(t)$, and $z(t)$ tend to be regular oscillations as shown in Figure 20-c. Moreover, a periodic motion around an orbit in x-y plane is detected as shown in Figure 20-d.



20-a **20-b** **20-c** **20-d**

Figure 20: (a)-(b) Illustration of outputs of testing system with chaos states; (c)-(d) Outputs of testing system as sine signal is detected.

In BCI systems, the response to a given stimulus signal should be identified in real-time. In online experiments, the parameter k_e was determined empirically.The value of $k_e$varies for different subjects and different bio-signal sources as well as the different expected identified periodic signals. In order for the proposed BCI system to perform with high accuracy, test runs were performed on each subject for calibration purpose. Consequently, the value of EEG signal intensity coefficient k_e is estimated from Lorenz system's outputs by visual observation.

iii. Features extractions

If there is a brain response to the external stimulation, periodic disturbance should be visible on displacement of Lorenz attractor along z direction.Let us define$T = \{T_0, T_1, \cdots, T_{m \leq N-1}\}$ as the time between two peak values of$z(t)$ above a baseline(B) where the baseline is determined during calibration. The experiments show that, when the designed Lorenz system received the disturbance from the certain intensity pure weak periodic signals, the values of T is significantly reduced (see Figure 21 and Figure 22). Therefore, we conclude that sudden reduction on T corresponds to the existence of weak periodic signals. On Figure 21 and Figure 22, the horizontal axis represents the number of samplings in each 4 seconds data segment. The vertical axis represents the amplitude output of $x(t), y(t),$ and $z(t)$. Let us define $\mu_T$as average of T. Similarly, the reduction of μ_T values reflects the existence of weak periodic signals. Hence, μ_T is used as the threshold to determine if the brain responds to external periodic stimulations.

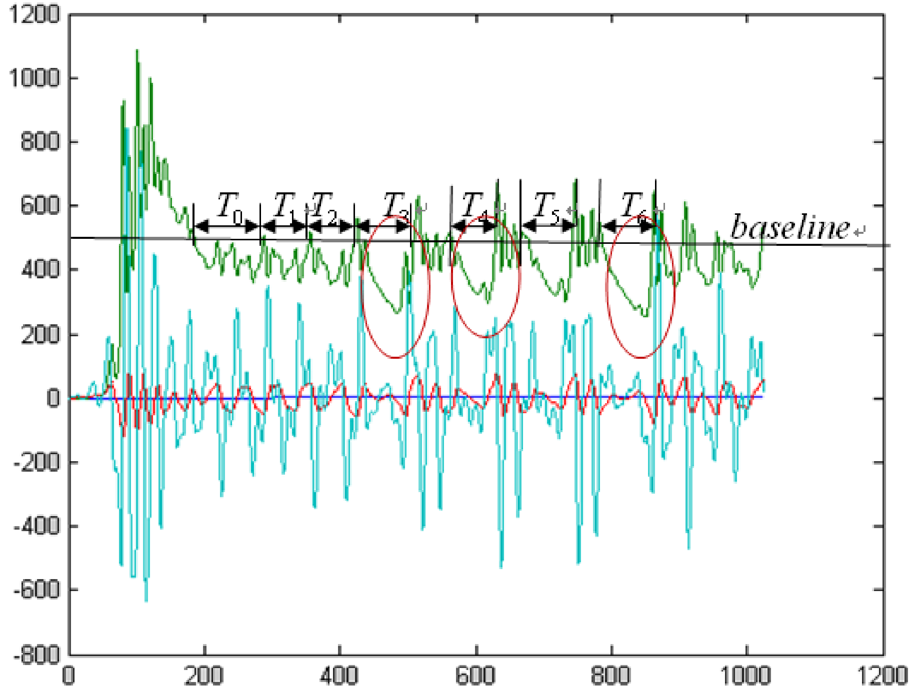


Figure 21: Features (marked by T) of z(t) from the output of critical $\omega=\omega_\nabla=70$ rad/sLorenz testing system

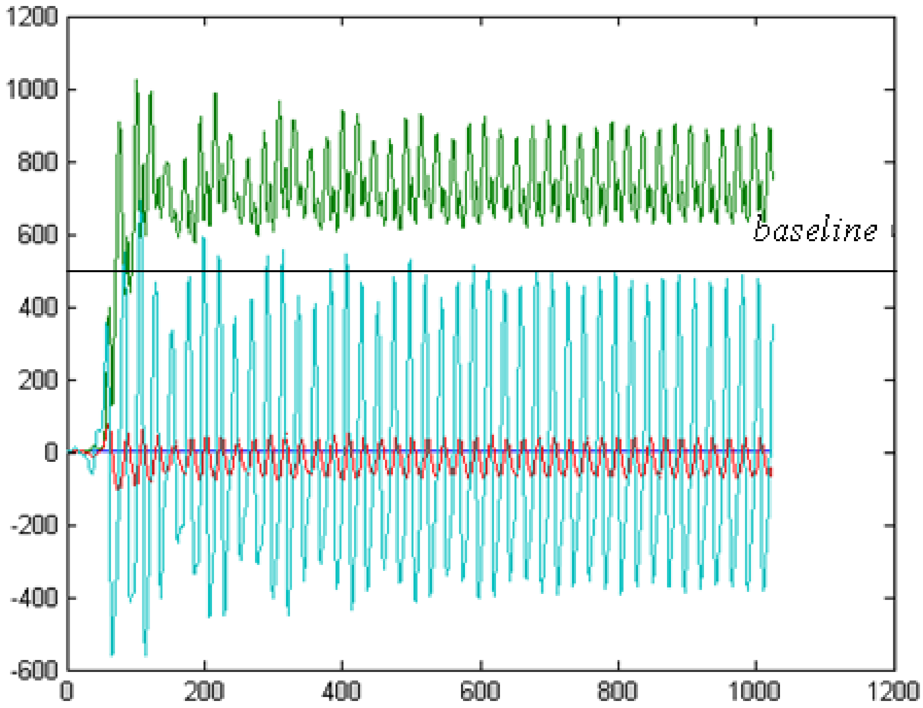


Figure 22: Features of output from $\omega=\omega_\nabla$=70 rad/s Lorenz system with $k_e\lambda_i = (0.675{\sim}0.74)\sin(70t)$ periodic signal input

The baseline(B) is determined offline from the output of $z(t)$of Lorenz system for $\lambda_i = 0,\ \forall i$. The threshold for $T(u_T)$on the other hand is determined during initialization at the beginning of the experiments. Feature extraction method utilized in our research is summarized in the flow chart given in Figure 23.

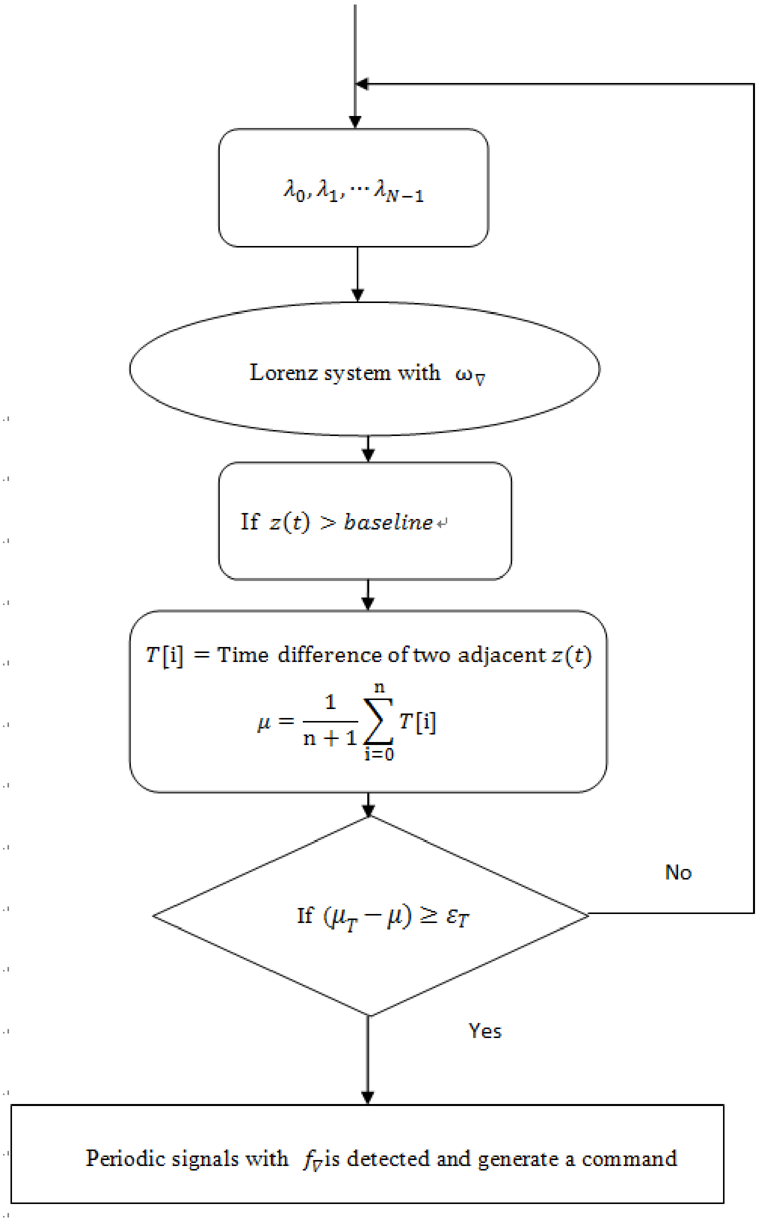


Figure 23: The flow chart of EEG feature extraction based on WPSDA

iv. The calibration of the baseline and the thresholds

- **The calibration of the baseline**

In its chaos state ($\lambda_i = 0, \forall i$), Lorenz system output along z direction produces a feature as a sudden increase from its lowest values (highlighted area in Figure 21). A baseline(B) is determined in such way that all peak values(z^*) of $z(t)$that consistof Lorenz system features at its chaos state, are above the selected line. Initial value of B is determined empirically by observation from fluctuation of $z(t)$ data.

- **The calibration of the threshold for$T$**

A threshold value for T is used for determining the existence of external stimulus signals to the Lorenz system. Once a threshold value for B is determined, a series of T are identified from $z(t)$ which is the output of Lorenz system in its chaos state(L^c). Consequently a threshold value (T^*) is identified from T. Since a typical BCI system includes multiple command capabilities, a unique T_∇^* for all stimulus signals is identified. In our model we use the average of T as a threshold($T^* = \mu_T$).

In our case we designed our SSVEP BCI system to handle five control-commands (four commands for motion control, and one command for drawing). Four flicking targets for $\nabla = \{15Hz, 14Hz, 12Hz, 10Hz\}$ frequencies were used to model the motion control (up, left, right and down cursor movements). The user interface of the developed stimulator is illustrated earlier in Figure 19.

The details for the threshold selection process are provided below:

1) At $p = 0$, solve Lorenz system for $\lambda_i^0 = 0$ for $i = \{0,1,\cdots,N-1\}$. Based on the given input parameters (ω, $\omega_\nabla, r, \sigma, k, k_e$) a baseline and consequently set of $T$are retried from$z(t)$. Let T^0 be the initial set of T.

2) Next, Lorenz system is solved for a given raw EEG dataΛ^p. Subsequently, a new set of$T$ is obtained. Let this new set of T be represented by T^p.

3) If $\mu_{T^0} - \mu_{T^p} \geq \varepsilon_T$ than we conclude that there is an external stimulus to the brain where ε_T is the minimum difference between mean values in order to make the decision. The value of ε_T is sensitive to the users. Hence a number of experiments with a unique stimulation signal are performed on each subject to calibrate ε_T . If required, k_e is modified accordingly to calibrate ε_T. The experiments are repeated until a reliable value for ε_T is obtained.

4) Similarly, thresholds for all stimulation frequencies $\left(\varepsilon_{T_\nabla}\right)$ are determined.

5) Adapt the determined threshold in the designed SSVEP BCI system to move cursor and perform drawing action.

v. Experiments and results

- **System design and set-up**

In order to test the capabilities of the proposed weak periodic signal detection and EEG feature extraction algorithm, an online SSVEP BCI system was modeled to perform simple 3D geometric modeling. The objective of the designed SSVEP BCI system is to draw 3D images on a computer monitor by controlling five unique operations. Only input to the computer is the EEG signals received from the user's brain. Hence these experiments were performed to test if five unique response signals can be retrieved from EEG signals. The experiment steps are described as follows:

Steps:

- Prior to the experiments, clear instructions are given to all subjects.
- In order to familiarize with the system, sufficient training was provided to all subjects
- Subjects were positioned in front of a LCD computer monitor by keeping about 45 cm distance between subject and the monitor. The interface of the computer screen is given in Figure 19.
- Configure all parameters and thresholds for designed BCI system.

  Through experiments, thresholds for T and B are determined for all five commands so that intention of user can be successfully retrieved during the experiment. After determining the thresholds for T and B, the accuracy of the proposed model is tested on a subject. In the accuracy test, the subject was asked to move a cursor in four directions (up, down, left and right). The accuracy rates given in Table 3 are obtained.

Table 3: Percentage of desired movements

Movements	Frequency	Percentage of desired movements
up	15 Hz	71%
down	10 Hz	75%
left	14 Hz	83%
right	12 Hz	85%

- Once the satisfactory accuracy rates were obtained for the given thresholds, geometric modeling tests were performed. Subjects were asked to gaze the flicking targets (15Hz, 14Hz, 12Hz and 10Hz) focus on the ones that corresponds to their intentions so the cursor can be moved to the intended direction. In order to activate the drawing function, the fifth stimulus, a 13Hz flicking target was used.

- **Results:**

Results clearly show that the designed Lorenz systems successfully detected the existence of periodic response signals as the subject gazed the corresponding flicking target. Subjects were asked to perform two different drawing tasks. First subjects were asked to follow pre-defined data points which are necessary to model a vase as shown in Figure24-c. At the beginning of the experiments, subjects were told to draw the image given in Figure 24-a. Next, each subject starts modeling on an empty screen. Initially, the cursor is located on the lower end of the centerline. While the subject attempts to reach the next correct data point, all the errors are recorded. One female subject with corrected eyesight and three male subjects with normal eyesight participated in the online experiments. Figure 24-d shows that the female subject performed only one error (circled in the figure) during first 6 steps cursor move. After all the data points are successfully determined, the vase given in Figure 24-f is created by revolving data points about the center line. The trajectory was formed by using the B-spline to fit the data points. The test results show that all subjects were able to reach the desired shape with the average control accuracy rate is 73%.

In the second part of the experiments, subjects were asked to design a vase of their own choice. An example for this experiment is given in Figure 24-g-i. Since there was no correction mechanism, the process did not always result in the intended shape. However, movement towards the intended direction was achieved successfully in most cases. As seen in Figure 24-g, cursor was moved to upward, left and right as it was intended.

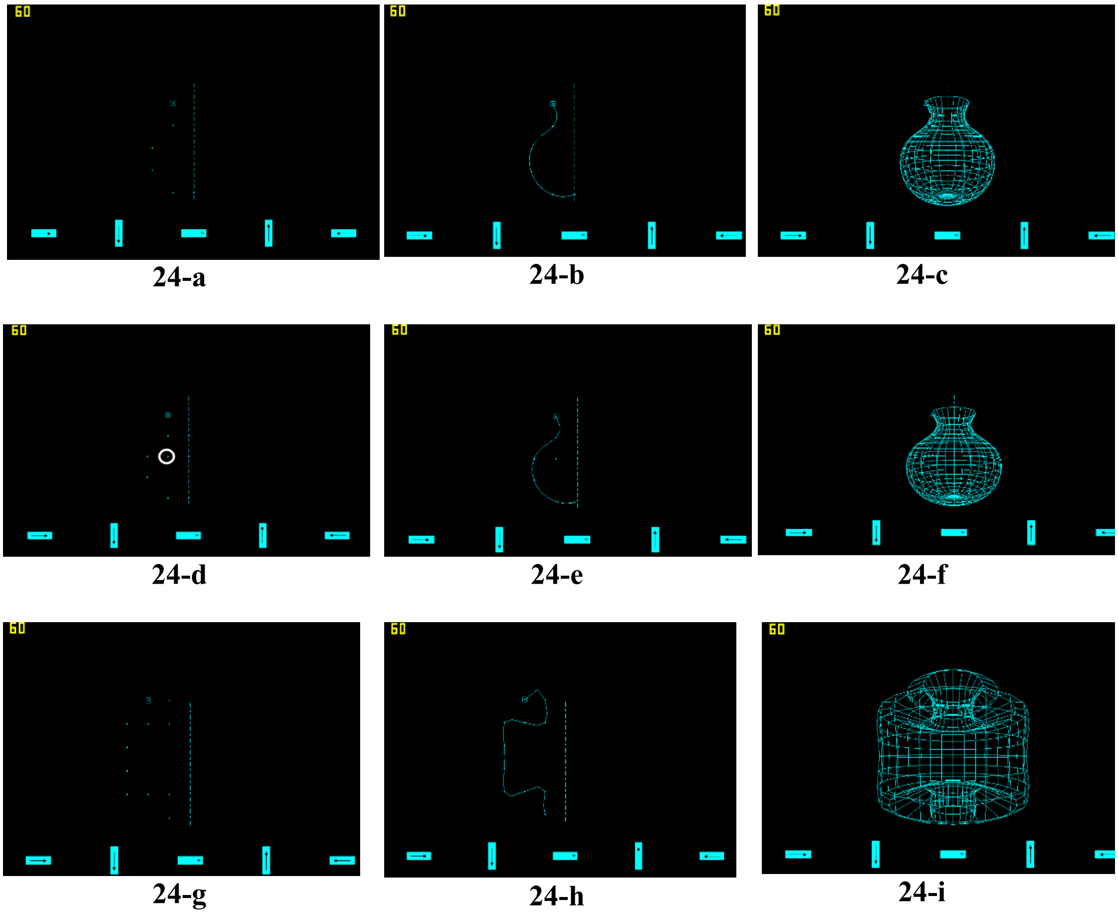


Figure 24: (a)-(c) a desired trajectory of a bottle; (d)-(f) a real drawn bottle image; (g)-(i) a real trajectory of a bottle image.

- **Discussion of weak periodic signal detection approach**

It is obvious that during each drawing process, the undesired controls always exist. Although the appropriate configuration of the thresholds and the parameter k_e improve the classification accuracy to a desirable level at the setup stage, due to visual fatigue, the interference from the other flicking targets, brain's own activities as well as environment noise, undesired controls occur inevitably to some extent in each drawing experiment. In Figure 24-d-i, some undesired drawings are found. Although such undesired controls were included in drawing experiments, the drawing results show that approximate trajectories can always be attained using the proposed SSVEP based controller. Finally, it should be noted that the appropriate thresholds and parameter k_e are key factors in the process of improving the online classification accuracy (reducing undesired controls).

3.4.4.2 Power Spectral of Density (PSD) approach

i. EEG feature detection using PSD approach

In SSVEP based BCI system, since the periodic features of the external visual stimulation signals, by gazing the specified flicking target, the corresponding frequency information will be included in the acquired brain's EEG responses. In order to extract such frequency features from the acquired EEG signals, spectral analysis approaches are followed by a large body of researchers. In frequency domain, the PSD method is widely considered as a fast and stable method which is used to extract frequency features. Hence, in this thesis, besides the weak signal detection approach, PSD method is also integrated into our BCI for 3D geometric modeling. The detailed signal processing algorithm is provided below.

ii. Signal processing algorithm based on PSD approach

Steps:

1) Auto- correlation processing.

Let X be the acquired raw EEG data set in time domain where $X = \{x_1, x_2, \cdots, x_{N-1}\}$.For each EEG data point x_n, auto-correlation datais established as:

$$C(x_n) = \frac{\sum_{j=n}^{N-1}(x_j x_{j-n})}{N} \text{ for } n = \{0, 1, \cdots, N-1\} \tag{4}$$

2) Convert the obtained auto-correlated EEG data set $\mathrm{C}(X)$ into frequency domain by performing FFT operation.

Let φ_k be the equivalence of an EEG data in frequency domain which is a complex number. After applying FFT operation on the auto-correlated data $C(X)$, frequency data φ_k is obtained as:

$$\varphi_k = \sum_{\mathrm{n}=0}^{\mathrm{N}-1} C(x_n)\mathrm{e}^{-\mathrm{i}2\pi\mathrm{k}\frac{n}{N}} \text{ for } k = \{0, 1, \cdots, N-1\} \tag{5}$$

3) Calculate PSD at the specified frequency.

4) Let $\psi_k$be the PSD data set,

Consequently,

$$\psi_k = \frac{|\varphi_k|^2}{\mathrm{N}} \tag{6}$$

$$frequency = k\frac{f_s}{N}, \qquad f_s{:}\, Sampling\ rate \tag{7}$$

5) Let $\overline{\psi_k}$be the average PSD at the specified frequency range $k-4 \leq k \leq k+4$

$$\overline{\psi_k} = \frac{\sum_{\mathrm{t=k-4}}^{\mathrm{t=k+4}} \psi_t}{9} \text{for k>4} \tag{8}$$

6) Let Ψ_k be the PSD at the specified frequency with improved SNR

$$\Psi_\mathrm{k} = \psi_k / \overline{\psi_k} \text{fork>4} \tag{9}$$

iii. Feature analysis

Applying signal processing algorithm (described in equations (4-9)) on the acquired EEG signal data set, a PSD data set Ψ_k ($k = \{4, 5, \cdots, N-5\}, N = 1024$) is obtained. This PSD data set displays the energy change of the brain at each unit of the frequency resolution. Gazing frequency specified flicking targets causes an increase on the brain's energy. Hence, the peak value of PSD can be used to verify if there exist brain responses to the visual periodic stimulation signals. Figure25 below demonstrates the changes of PSD values at 10 Hz frequency. The displayed PSD values are obtained by using equations (4-9). The stimulator works on 4s-based switch on-off states.

iv. Determine the threshold to validate if the brain is responding to the stimulus

Once we determine the PSD values at the specified frequency range with improved $\mathrm{SNR}(\Psi_k)$, we now can select an appropriate threshold from the determined PSD values and use it as a standard to adjudge if the brain responses to the specified stimulation signals. For example, Figure 25 below, the threshold is selected as 0.15. In this case, three PSD values exceed this selected threshold, therefore, we determine them as three PSD peak values and validate that in three time intervals (each time interval lasts 4 seconds), and the brain responds to the stimulation signals. In Figure 25, the horizontal axis represents the number of EEG data segments; the vertical axis represents the PSD values at 10Hz stimulation frequency in each 4 seconds time intervals. And the flicking target is a picture-based stimulation pattern in which the picture is sunflower.

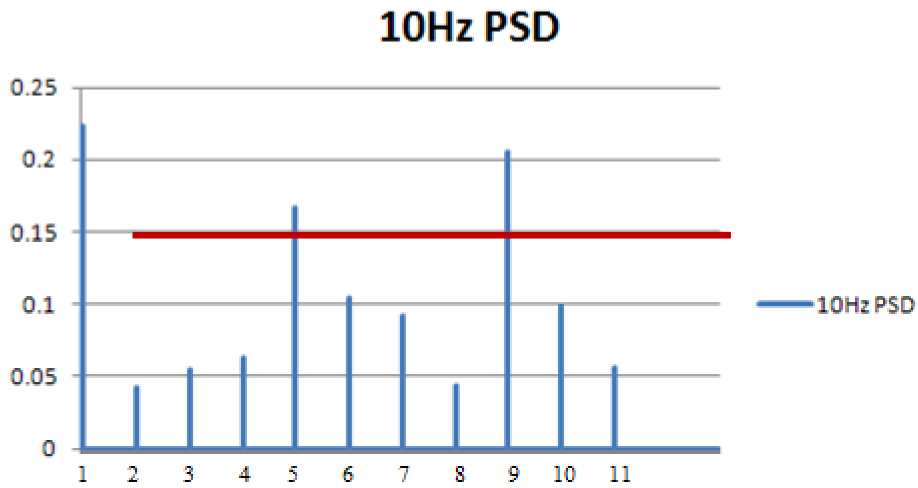


Figure 25: PSD at 10 Hz frequency and detected on the location of O1 and O2

Note: The original threshold is determined empirically through offline data analysis (e.g. graph observation), and then they are re-calibrated to meet the need for control accuracy at the beginning of the online experiments.

v. Experiment and result

- **System design and set-up**

In order to test control capability of extracted EEG features, the same SSVEP BCI system that was modeled for testing weak periodic signal algorithm was used in the following experiments. The objective is to use PSD method to identify five flicking targets from the stimulated EEG responses, and then use them to control cursor to achieve a simple geometric modeling design. The experiment steps are described as follows:

Steps:

1) Prior to the experiments, clear instructions are given to all subjects.

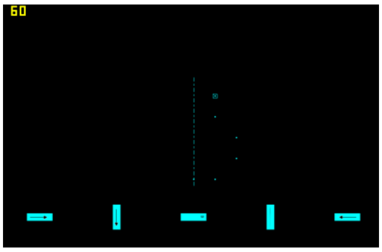
2) In order to familiarize with the system, sufficient training was provided to all subjects
3) Subjects were positioned in front of a LCD computer monitor by keeping about 45 cm distance between subject and the monitor. The interface of the computer screen is given in Figure 19.
4) Configure all thresholds for designed BCI system.

In order to reach the desired control accuracy rate, the subjects were asked to move a cursor in four directions (up, down, left and right) by gazing four corresponding flicking targets (15Hz, 10Hz, 12Hz and 14Hz). And then the thresholds were modified until a desired control accuracy rate in all four directions was achieved.

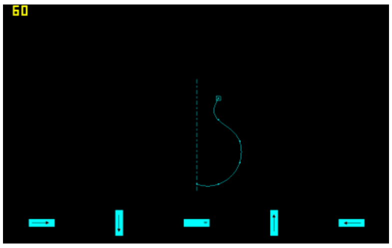
Once reaching the desired result for control accuracy rate, geometric modeling tests were performed. Subjects were asked to gaze the flicking targets (15Hz, 14Hz, 12Hz and 10Hz) and focus on the one that corresponds to their intentions so the cursor can be moved to the intended direction. In order to activate the drawing function, a fifth control frequency, 13Hz flicking target was used.

- **Results:**

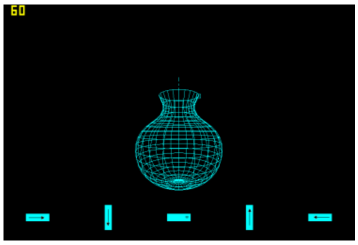
As part of the experiment, subjects were asked to perform a simple geometric modeling task. First, subjects were trained on an ideal drawing trajectory (modeling of a vase in our case as shown in Figure 26-a-c). Next, the subjects were asked to perform the drawing task by following the desired trajectory using their brain's EEG responses as controller (Figure 26-d-f. As shown in Figure 26-d-f), subjects occasionally deviate from the desired trajectory. Yet, all subjects were able to complete the given task with control accuracy rate 70%. The experimental results also show that all subjects stay in the right side of the center line and above the starting point. This indicates that, despite some errors occurs in reading user's intentions through proposed SSVEP BCI system, strong correlations with the users' intention and the interpretation of the raw EEG signal.



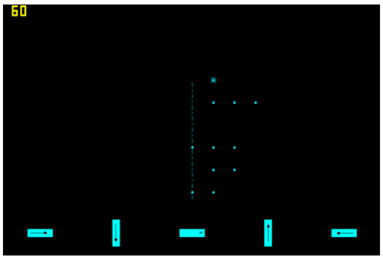
26-a



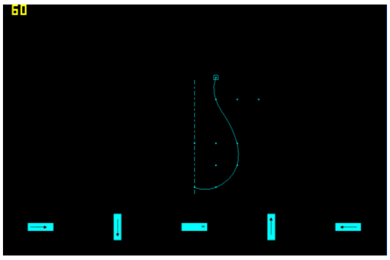
26-b



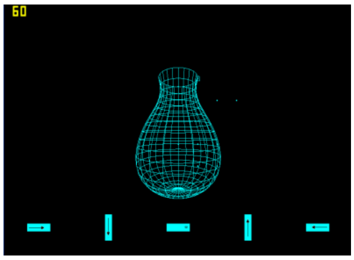
26-c



26-d



26-e



26-f

Figure 26: (a)-(c) Desired drawing results; (d)-(f) Real drawing results

In above noted drawing process, a LCD stimulator (see Figure 19) with five flicking targets was used to trigger the presence of the EEG responses. Through detecting the PSD peak values at specified stimulation frequencies, five EEG responses are identified, and then used as five control intentions to achieve the cursor control and drawing task. The experiment results show that using PSD method the approximate drawing trajectory can be obtained. But, in most cases, the drawing results are highly affected by the noise signals such as artifacts, environment interferences, and other uncontrollable factors from the brain, etc. In Figure 26-d, undesired drawn points are shown clearly. These undesired drawn points show the affects from the above noted noise signals.

3.4.4.3 A comparison of weak periodic signal detection algorithm (WPSDA) and PSD algorithm

In this thesis, two EEG signal feature extraction methods are proposed. They are used to extract the EEG signal features to achieve the control purposes. One is weak periodic signals detection method, and another is PSD method. Both methods are used to extract EEG responses via a SSVEP based BCI. The same flicking targets are used in the experiments. These two EEG signal feature extraction algorithms work in the time domain and frequency domain respectively. A performance comparison is performed and features are summarized in the Table 4.

Table 4: A comparison of weak periodic signal detection algorithm and PSD algorithm

Components in comparison		Weak periodic signal detection algorithm	PSD algorithm
Stimulation signals	Feature	periodic stimulations	periodic stimulations
	Frequency range	15Hz, 14Hz, 13Hz, 12Hz, 10Hz	15Hz, 14Hz, 13Hz, 12Hz, 10Hz
Brain response signals: Expected Signal Features		The existence of periodic response signals with the same frequency as that of stimulation signals	The occurrence of PSD peak value at stimulation frequency
Detection method	Working principle	*Design a Lorenz system in which its system parameters are set up to maintain the motion of the Lorenz attractor in a critical chaos state, input EEG signals including stimulation periodic signals as a small perturbation in one of system parameters to stimulate the motion of the Lorenz attractor to generate the periodic changes, in this way to detect the existence of the periodic stimulation signals inside the EEG signals.*	*Utilize the FFT conversion to find the amplitude or phase changes at the stimulation frequencies to detect the existence of the stimulation signals inside the EEG signals. Since the stimulation signals can cause PSD peak value output or stimulation signal phase output, PSD peak value output or stimulation signal phase output can reflect the existence of the stimulation signals inside the EEG signals.*

	Features	*1. Time domain analysis.* *2. Can detect the periodic signals in a continuous frequency range.* *3. Can detect to the weak periodic signals from stimulated EEG signals under low SNR*	*1. Frequency domain analysis.* *2. Frequency spectrum is discrete.* 3. *For the weak periodic stimulation actions, the stability of the extracted EEG frequency features is affected by noise signals.*

CHPATER 4
DISCUSSIONS

4.1 Discussions on LCD stimulator design

At the early stage of our research work, we modeled the LCD stimulator on an Acer TravelMate 3200 laptop, where the screen refresh rate is configured at 100 Hz which is synchronous with the graphic card's frame rate. Based on 100 Hz refresh rate, frequency range from 1 Hz to 50 Hz can be used to model stimulation frequencies. We developed a number of alternative configurations within the stimulation frequency range. First, single pattern stimulation target (See Figure 29-a) was used to trigger the presence of the SSVEP. In order to improve the SNR and to reduce the early occurrence of the visual fatigue caused by the gazing single signal pattern stimulus, a set of picture-based stimulation patterns that varies with time were experimented as stimulation targets (Figure 27 illustrates the design -- autumn leaves, butterfly, and sunflower etc. are used as stimuli). In order to test the performance of the designed LCD stimulator, a series of experiments were performed online. The details of the experiment configurations and results are discussed below.

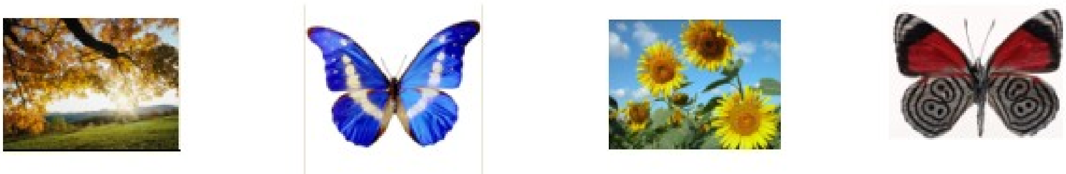


Figure 27: Time-varied stimuli pictures

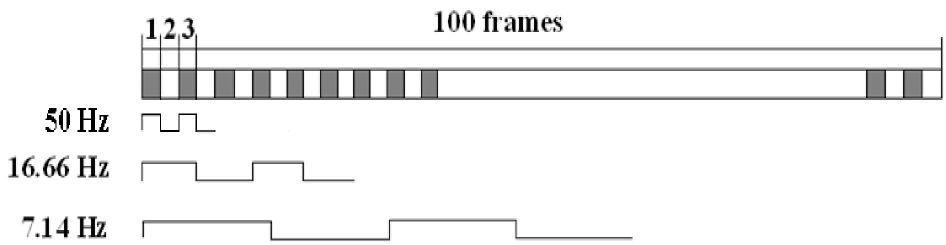


Figure 28: Structure of stimulation frequencies on time-varied LCD stimulator

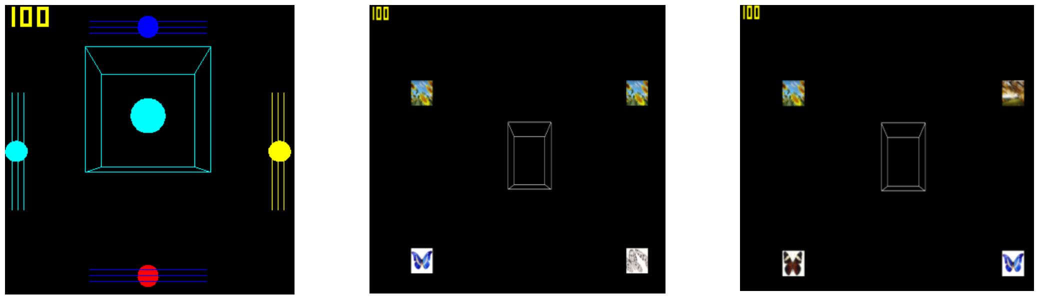


Figure 29: (a) Single signal pattern stimuli; (b) Time varying stimuli patterns

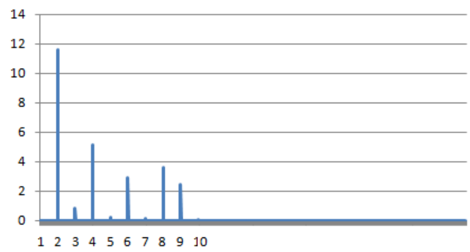
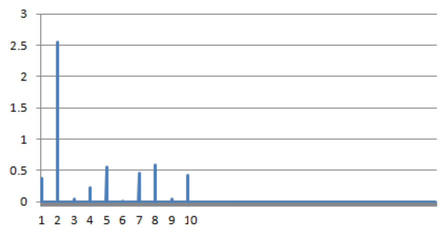
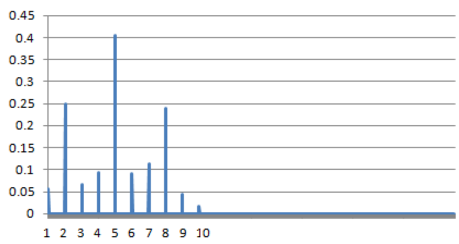
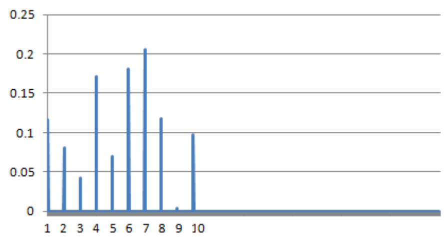
4.1.1 Experimental set up for testing time-varied LCD stimulator

The experiments were performed based on a trail of 1 second flicking followed by 1 second break. Each experimented included a total of 5 trials lasted 10 seconds (1 second flicking, 1 second break). We invited two subjects to take part in the experiments. For each subject, two experiments were constructed to test the SSVEP responses for designed LCD stimulator with time-varied flicking targets. We only tested the performance of the stimulator design on 50 Hz stimulation frequency (the structure of stimulation frequency is displayed in Figure 28).Equal interval rectangle wave shaped stimulation signal structure and time varied stimuli patterns (all of them flicking simultaneously in the test) were used as inputs. In the test 1, bipolar electrodes arrangements (O1 negative electrode and O2 positive electrode, left ear as reference) were used to collect data. For tests 2, bipolar electrodes arrangements (Fp1 negative electrode and Fp2 positive electrode, left ear as reference) were used for signal acquisition. As sampling rate, 256 Hz was used. When the test began, each subject was asked to gaze the 50Hztarget patterns (see Figure 29-b) without body movements and eyes' blinks at the same time.

4.1.2 Results

Based on the PSD signal processing approach, the data analysis results based on equations (4-6) are presented on Table 5.For the following figures shown in table 5, the horizontal axis represents the number of data segments (in10s time period); the vertical axis represents the amplitudes of the PSD values at 50 Hz stimulation frequency.

Table 5: A comparison of PSD values for two subjects at 50 Hz

Tests / Subjects	Test one (O1,O2,and left ear for electrodes)	Test two (FP1,FP2, and left ear for electrodes)
Subject1		
Subject2		

Based on the data analysis, the following results were summarized:

1) The SSVEP responses for each subject on O1 and O2 locations are stronger than those on FP1and FP2 locations.
2) At the same electrode locations, the intensity of SSVEP responses for two subjects is different.
3) The SSVEP responses from the subject one are stronger than those from subject two.
4) The brain's responses to the external visual periodic stimulations and brain own same frequency activities as well as the same frequency noise signals, the phases of these signals themselves enable the SSVEP peak values not always be identified in the data segments which correspond to the flicking states.
5) The modeled LCD stimulator with time varied stimuli patterns and equal interval rectangle wave stimulation signal structure increases the intensity of the stimulation signals and reduce the visual fatigue of the eyes to a certain extent.

The test results show that the accuracy and efficiency of the detection of the PSD peak values are promising. However, several shortcomings were identified when the designed LCD stimulator was tested on a real-time 3D geometric modeling exercise.

1) Time varied picture based stimuli patterns are not convenient for users to memorize the control intentions.
2) Interferences from each flicking targets are very strong, SSVEP peak values at different stimulation frequencies may be identified at the same time, thus affecting the control accuracy.

3) It is not convenient for users to focus their attentions on geometric modeling design due to the separate configuration of the flicking targets.
4) Gazing these separate configured flicking targets, eyes' movements introduce a lot of noise signals.

In terms of these results, in order to solve these problems, we designed and tested the current flicking targets patterns and configurations (see Figure 19). In the current application, each control intention is directly indicated on the corresponding flicking target and all flicking targets are configured at the bottom of the screen, thus making the users easily focus their attentions on both intention selections and the geometric modeling design. Since all flicking targets are configured at the bottom of the screen, the range of the eyes' movements are reduced so that the noise signals caused by the eyes movements are reduced to a minimum level. But the intensity of the stimulations from the current designed light blue flicking targets' patterns is weaker than that from time-varied flicking targets' patterns. The tests' results show that the brain's responses to current designed stimulator are weaker than it's responses to the time-varied stimulator. In order to increase the SNR to improve control accuracy, 4 seconds based flicking and break patterns are set up for the stimulator. Meanwhile, 4 seconds based data collection and equations 8-9 are used in the signal processing. In terms of these modifications, online tests were performed. The online experiments show that control accuracy in the drawing process gets improvement. And due to the application of the light blue color to all flicking targets' patterns, the visual fatigue of the eyes to be released to a certain extent.

4.2 A comparison of proposed control techniques

In this thesis, we investigate the control capabilities of three types of bio-signals (e.g. EMG, EOG and EEG) and possibilities for using them to achieve the complex tasks. A comparison of proposed control techniques is summarized as follows:

Table 6: A comparison of proposed control techniques

Method	Advantages	Disadvantage
EMG	1. Generated signal features are repeatable, stable, and strong. 2. Can be used to achieve the complex tasks. 3. Not sensitive to the noise signals. For example, some small ranges of body activities and eyes' nature blinks 4. Control accuracy can be up to 100%in our designed HCI.	For bipolar electrode arrangement, the achievement of a complex task is time consuming process in current designed system
EOG	1. Generated signal features are repeatable, stable, and strong. 2. Can be used to achieve the complex tasks. 3. Not sensitive to the noise signals. For example, some small ranges of body activities and eyes' nature blinks. 4. Control accuracy can be up to 100% in our designed HCI.	For bipolar electrode arrangement, the achievement of a complex task is time consuming process in current designed system
EEG	1. For bipolar electrode arrangement, EEG based BCI system has promising future in reducing the time used to achieve the complex tasks.	1. Compared with the EMG signals and EOG signals, EEG signals are sensitive to the noise signals. 2. Compared with the EMG signals and EOG signals, EEG signal features are not stable and reliable all the time in current designed BCI system. 3. Only up to 75% accuracy rate is achieved when doing a simple drawing task.

CHAPTER 5
CONCLUSIONS

In this thesis, three types of bio-signal based 3D geometric modeling design environments are developed. The objective is to investigate the possibilities to use bio-signals as input approaches to achieve the 3D geometric modeling. Through the online signal processing and experiments, the conclusions for three types of bio-signal HCI systems are drawn as follows:

5.1 Summary: EMG signal based HCI system

In this research work, the EMG signals are collected from the eye/lip muscles' intentionally contractions. Compared with the EOG signals and EEG signals, the collected EMG signals show the strongest signal features. Through perform designed online experiments, EMG based 3D geometric modeling HCI has been proved the best performance in control stability and accuracy. With the application of the control panels, the more complicated control functions can be extended to meet the task requirements. In terms of these research results, we draw the conclusion for EMG based HCI that it is possible to develop the EMG based 3D geometric modeling design environment to enable certain group of handicapped people to be involved into the product design process.

In terms of the stable and accurate signal feature, the future work for EMG based 3D geometric modeling design environment can be focus on the improvement of the design efficiency. And this objective can be achieved by means of the integration of several sketching skills such as using shape pre-defined drawing tools, pre-defined graphic libraries, etc.

5.2 Summary: EOG signal based HCI system

As one of three bio-signals, in this thesis, we also investigated the EOG signals. The objective is to explore more useful body signals. The studied EOG signals are generated from the eye balls' movements. By means of the online graph output, the collected EOG signals demonstrate a repeatable and stable signal patterns. Therefore, we extracted three signal features from the raw EOG signals and tagged them to the control commands. The online test shows the robustness of the extracted signal features.

Therefore, combine with the control panels and geometric modeling design environment used for EMG based HCI, the EOG based 3D geometric modeling design HCI also is a promising candidate which can be used by certain group of handicapped people to do 3D geometric modeling creation.

Similarly, in order to make the EOG based 3D geometric modeling design HCI more accessible, the improvement of the drawing efficiency will be the work which should be figured out in the future.

5.3 Summary: EEG signal based HCI system

In this research work, the collected EEG signals are stimulated from a SSVEP based BCI. In order to provide the users a convenient application environment, a LCD stimulator is designed and integrated with the geometric modeling design environment. Compared to EMG and EOG signals, the acquired EEG signals are mixed with a large amount of noise signals. In order to explore the useful signal features to meet the requirements for the control objective, two types of signal processing approaches are studied in this thesis. One is the PSD approach. The robustness of this approach in control stability has been proved by a large body of researchers. Hence, we integrated this approach into our 3D geometric modeling design environment. Through the online experiments, the results show that using PSD approach is possible to roughly trace the desired trajectory, but control accuracy is weaker than that of EMG and EOG systems. Another signal processing method used in this study is the weak periodic signal detection approach. It works on the time domain EEG signals. The proposed approach uses the Lorenz system to detect the existence of the SSVEP responses. The online experiments show that this algorithm can dig out the SSVEP responses from the heavy noisy EEG signals. Hence, compared with the PSD approach, it is also a good candidate in developing the EEG based 3D geometric modeling design systems.

In this chapter, we summarize the results from three bio-signal based 3D geometric modeling design environment. The results show a promising future to further develop the bio-signal based 3D geometric modeling design platform.

5.4 Future Works

In chapter 3, for EMG, EOG, and EEG based HCI systems, the bio-signal sources that can generate the strong signal patterns are identified respectively. These identified bio-signal sources provide the strong, repeatable, and stable signal features. Based on the identified bio-signal sources (e.g. F7, G, and left ear or F8, G, and left ear), the future work can consider combining current existing EMG and EOG based HCI systems together. The combination of EMG and EOG based HCI can bring two advantages. First, the EMG and EOG signal features can be used alternatively so that the fatigue of the muscles can be released. Next, the increase of available signal features would improve the drawing efficiency. Moreover, in order to improve the drawing efficiency, number of options available to perform the geometric modeling such as pre-defined trajectory tools, shape pre-defined objects etc. can be increased significantly. Finally, more advanced filtering techniques can be considered in order to improve the performance of the proposed EEG based BCI system.

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