國立交通大學

生醫工程研究所

碩 士 論 文

時序特徵分類與投票之三選項腦機界面系統

Three-choice Brain-Computer Interface System through Classification and Voting of Temporal Features

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中 華 民 國 九 十 八 年 六 月

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A Thesis

Submitted to Institute of Biomedical Engineering

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in partial Fulfillment of the Requirements

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摘要

腦機界面系統(BCI)提供一個單靠腦部活動來取代平常使用的肌肉做為和外界溝通的管道。而腦電波圖(EEG)廣泛的應用在腦機界面系統中。透過記錄和分析使用者執行特定任務時的腦部活動,可以將分析過後的結果轉換成對應的指令而達到像是控制義肢或指標、打字或回答問題。時至今日，像是運動想像腦機界面或事件相關腦機界面等許多腦機界面系統蓬勃發展。在現存的腦機界面研究中，以 P300 為基礎的腦機界面因穩定且不需預先訓練受試者的優點，因而被廣泛研究。

為了達到降低訓練時間和降低使用者的負擔,我們使用一個三選項的界面實作以 P300 為基礎腦機系統。我們並使用一個經典的 P300 分析方法步進線性鑑別分析(Stepwise linear discriminant analysis)做為特徵選取和分類。並提出一投票策略來達到系統可自動且即時的依使用者做調整，以增進線上系統的效能。更具體來說，我們結合步進線性鑑別分析和活動窗口(moving window)來產生時序特徵做投票。透過這些時序特徵我們可以決定門檻值使得線上系統可以在維持一定的分辨率的條件下動態決定結果。因此,我們可以增進線上系統溝通的效能和效率。

三個健康的受試者被邀請參與離線和線上的實驗。研究結果顯示，我們的系統比 Sellers 和 Donchin 在 2006 所發表的四選項腦機系統有更好的效能。在離線分析我們在 83.4%的分辨率下達到 7.7 bits/min 的轉移率，而當線上系統達到 5.23 bit/min 的轉移率時則有 100%的分辨率。這些結果都證明了比四選項系統在 97%的分辨率下達到 1.8 bit/min 有更好的效能，也顯示了適應性在腦機界面系統上的優點。

Abstract

Brain-computer interface (BCI) provides a channel to communicate with external world only through cerebral activity, thus replacing the normal pathway of communication by using muscles. The electroencephalography (EEG) is commonly used in the BCI system. When a subject is performing specific tasks, the EEG signals induced by the subject’s neuronal activities are recorded and analyzed. Then, the analyzed EEG signals will be translated to the corresponding commands to control prosthesis or cursor, spell words, answer questions. Nowadays, there are many development of BCI systems such as Motor-imagery based BCI systems, ERP-based BCI systems. In the existing BCI studies, P300-based BCI systems are commonly conducted, because P300 ERP can be reliably measured without initial user training.

To reduce training time and subjects’ burden, our P300-based BCI system is implemented by using a three-choice paradigm. We use a typical P300 analysis method, stepwise linear discriminant analysis (SWDA) for feautre selection and classification. To improve the system, we propose a ”voting strategy” to automatically make the online system adaptable to users. More specifically, we combine SWDA with moving window to produce the temporal features for voting. Through the temporal features which can decide the threshold, the online system can dynamically make decision while maintaining the accuracy of classification. In this way, we improve the performance and efficiency of communication in online BCI system.

Three able-body subjects are recruited to participate in the offline experiments, and seven able-body subjects are recruited to participate in online experiments. The results of this study present better performances than those in the four-choice offline system provided by Sellers and Donchin (2006). In offline analysis, the transfer rates can be achieved up to 7.7 bits/min with an accuracy of 83.4%, while the transfer rates of online testing can be achieved up to 5.28 bits/min with an accuracy of 100%. These results suggest that the performances of our system are better than four-choice system in which transfer rate is 1.8 bits/min with accuracy of 97%, thus indicating the advantage of the adaptability in BCI system.

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Chapter 1

Introduction

In this first chapter we give some background knowledge to this thesis. We briefly introduce from the Electroencephalography to brain-computer interfaces to event-related potentials (ERPs). In Section 1.2 we give some introduction to Electroencephalography (EEG), so called brain wave. The measurement way, some basic analyses and researches are presented. In Section 1.3 we give a brief introduction to brain-computer interfaces (BCI). In Section 1.4, we give a description of the ERPs that can be used in BCI system. The detail of BCI systems will be provided in the next Chapter.

1.1 Motivation

Diseases like Amyotrophic Lateral Sclerosis (ALS) make patients being unable to communicate with the external world through the normal pathway, such as talking or taping. However, their brain is still healthy, even thouhgh they have the paralyzed body. Nowadays, to help those who suffer from diseases like ALS, the development of brain-computer interface can provide a new way to communicate with external world. In other words, a Brain-computer interface is defined as a communication system which does not depend on the brains normal output pathways of peripheral nerves and muscles. Specifically, subjects can communicate with the external world only with barin waves.

In order to provide a realistic application in daily life, a pratical brain-computer interface system should have real time response and felxibility in various situations. A real time BCI system, the so-called online BCI system, can facilitate subject to express ideas or to have direct communication with other people. In addition, a flexible online BCI system can adapt to differnt subjects, thus improving the efficiency of the system.

Even though the developement of BCI systems thrives in recent years, usability is still a debatable issue in BCI systems. For instance, subjects under some BCI systems have to move their eyes to gaze at differet stimulus in order to transmit commends. However, if disabled patients can move their eyes or even one muscle in a controlled way, other interfaces based on eye-gaze or EMG switch technology are more efficient than some existing BCI systems. Moreover, some systems require long subjects training time, and some may be only suitable for certain subjects. Thus, an online BCI system with short training time and simple tasks can reduce subjects' burden and make the system eazier to use. Consequently, if a practical online BCI system is established, it may be widely used. In this case, subjects are more willing to accept this system. Thus, this research project is of great worth.

1.2 Electroencephalography

1.2.1 Introduction to Electroencephalography

There exists various non-invasive techniques to monitor the brain activity such as functional Magnetic Resonance Imaging (fMRI), magnetoencephalography (MEG), and Electroencephalography (EEG). EEG is used to measure the electrical activity of the brain. This activity is generated by billions of nerve cells, called neurons. Each neuron is connected to thousands of other neurons, and the neurons send action potentials to other neurons when they are communicating. When we measure the EEG, we actually measure the combined electrical activity of millions of neurons on the cerebral cortex because the potential of a single neuron is too small to be measured. A typical EEG measuring device consists of several components, including EEG electrode cap that receives the electrical avtivity from the scalp, EEG amplifier that amplifys the signal, computers that record the data, and monitors that give the subjects visual stimulus. The devices are shown in Figure 1.1.

The EEG signal has a good temporal resolution, but it has a poor spatial resolution, which depends on the electrode number of an EEG electrode cap. The electrode layout on an EEG electrode cap has a international standtard called the international 10-20 system, as Figure 1.2 shows. When we are measureing EEG, we often put some single electrodes surrounding the eye. This is used to measure the electrical activity of eye movement and eye blinking, which is called EOG. This EOG contaminates the EEG signal badly, so by measuring it we can remove the trials that was affected. This processing is called EOG rejection.

When we use an EEG electrode cap to measure EEG, we have to fill each electrode with the electrolyte gel using a blunt needle. This makes the electrodes contact the scalp and lower the impedance. In an EEG experiment we often wait until all the electrodes have an impedence lower 3k ohm before we start the signal acquisition.

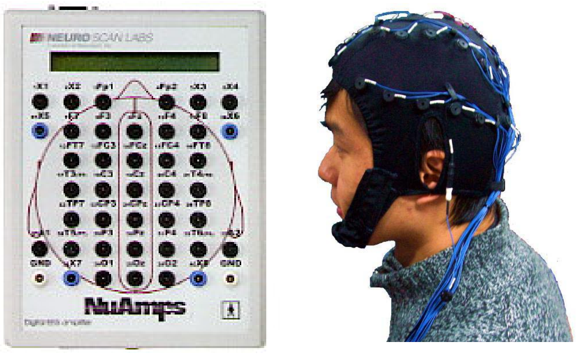


Figure 1.1: EEG measuring devices. From right to left is the EEG amplifier and the electrode cap.

1.2.2 Basic Analysis of Electroencephalography

There are some basic EEG analyses, mainly described here as time domain and frequency domain analysis.

Time domain analysis

Usually we use time domain analysis to observe an Event-related Potential (ERP). An ERP is a potential change in the EEG when a particular event or stimulus occurs. The potential change is time-locked and phase-locked, it is a very small potential change and can not be easily observed in a single trial. So we have to average a few trials to observe it. Because of the time-locked and phase-locked characteristic, by the averaging technique we can eliminate the random noise and enhance the signal-to-noise ratio (SNR). That is the common technique to observe an ERP. Another technique that is often used to separate these signals from background activity and noise is lowpass or bandpass filter. It is rereasonable because most of the energy of ERP is concentrated at low frequencies. Some well-known ERP-based BCI have employed filtering and averaging, including P100 in the Visual-evoked Potential (VEP), P300, N400, and Audio-evoked Potential (AEP).

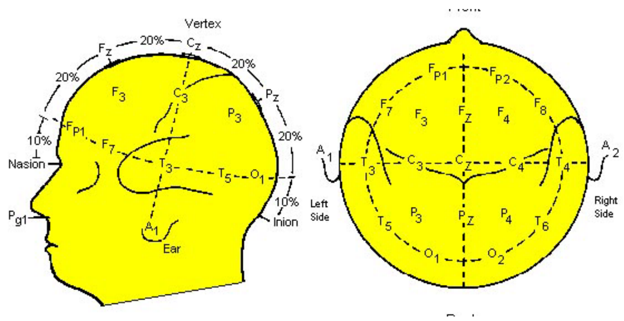


Figure 1.2: The international 10-20 system. The "10" and "20" means the 10% and 20% interelectrode distance. The 'F', 'C', 'P', 'O', 'T' represent with respect to frontal, central, parietal, occipital, temporal lobe. The odd number is placed in the left side and the even number the right side [3]

Frequency domain analysis

Frequency domain analysis are used to observe the changes in oscillatory activity. Such changed can be evoked by presentation of stimulus or by concentration of the subject on a specific mental task. Usually, the phase of oscillatory activity is not time-locked to the stimulus or to mental task of subject. Thus, time domain analysis technique cannot be used. Instead, frequency domain analysis are used to observe the oscillatory activity. For instance, SSVEP have band power in the harmonics of the visual stimulation frequency at occipital cortex. Fast Fourier transform can be used to estimate the band power as features. Another example in systems based on motor imagery, the bandpower in the mu and beta rhythm over the sensorimotor cortex is used as features.

1.3 Brain-computer Interface

Over the past few decades, the EEG has been used mainly for evaluation of neurological disorders in the clinic and for the investigation of brain functions. Until recently, researchers found it possible to translate some specific EEG to commands. That is, people can communicate with others or control devices directly by their brain activity, without using any normal pathways of the peripheral nerves. This communication and control technique was then called Brain-computer Interface [22] . Among the methods to measure electrical activity, MEG and EEG are more suitable for a BCI system because they can give the instantaneous continuous recording of brain activity. And EEG is even more suitable because of the following advantages, the devices to measure EEG are more portable and cheaper, and we don't have to be in a shielding room when measuring EEG. Although the EEG signal is having low spatial resolution compared to the others. Almost all BCI researches are using EEG signal nowadays.

A general BCI has many components. The BCI system goes through the data acquisition, then some signal processing, followed by a command translation, in the end output commands to communicate with others or to control cursors or devices. The details of a BCI system will be described in the next Chapter.

1.4 Event-related Potentials

Servel kind of internally or externally paced events will result in time-locked and phase-locked brain signals. Almost all of these kinds evoked activities have a more or less fixed time-delay to the stimulus. These time-locked and phase-locked called event-related potentials (ERP) or evoked potentials (EP). ERP can be viewed as potential changes of the neurons when our brain deal with mental tasks. Usually the brainsignals of mental task is smaller than the ongoing brain signals, thus concealed in the irregular and noisy ongoing brain signals. In order to extract the ERPs, synchronous averaging are performed, implying we have toexecute the same mental tasks more than once, after applying synchronous averaging, most of the noise will be eliminated, therefore enhancing the signal-to-noise ratio and obtaining the time-locked and phase-locked signals, ERP. Here, we introduce four common ERPs.

SCP

SCPs are the slow voltage changes of the brain cortex, with a 0.5-10.0s potential shifts. They are settled in the frequency range below 1-2Hz. SCPs can be divided into two types, negative and positive. Negative SCPs represent the mobilization or readiness while positive SCPs represent ongoing congnitive and inhibition of neuronal activity [21].

VEP

Visual evoked potential (VEP) is induced when the user's eyes are stimulated by looking at a test pattern which often is a flashing pattern. To measure VEPs, the recording electrodes are placed over the visual cortex [19].

SSVEP

The SSVEP is brain oscillations recorded at occipital cortex that elicited by a brief visual stimulus modulated at a specific frequency. The visual stimulus flick at different frequencies lead to brain oscillation at the same frequency and at harmonics and subharmonics of the stimulation frequency.

P300

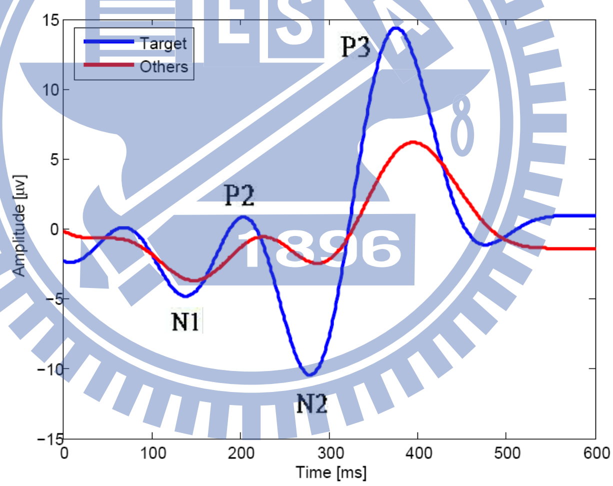


Figure 1.3: The P300 wave. The P300 (P3) is a positive deflection in the EEG, which appears approximately 300 ms after presentation of a rare or suprising stimulus. A series of negative and positive components (N1, P2, N2) procede the P3. While the P3 reflect high-level processing of stimuli, the earlier components reflect low-level, automatic processing of stimulus.

The P300 is a positive deflection in the EEG, appearing approximately 300 ms after the presentation of rare or surprising (Figure 1.3), task-relevant stimulus. [10, 20] It is one of the endogenous ERPs are the result of later, more conscious processing of stimulus and have characteristics that depend mainly on the stimulus context. Specifically, subjecs should pay attention to the stimulus that presented in experiment. Many different stimulus modalities can be used to evoked the P300, such as visual, auditory, tactile, gustatory or olfactory. The P300 is a common research topic because it can be reliably measured and because the characteristics of the P300 waveform. For instance the latency and amplitude can be influenced by various factors. Some important factors influencing the P300 are listed below.

- Target probability

  The amplitude of P300 is inversely related to the probability of the stimulus. High amplitude of P300 are elicited while the probability of the target stimulus is low. In practice, the target stimulus usually presented around 10% probability to elicited a stable P300 response [18].

- Interstimulus interval

  In recent study, the interstimulus interval (ISI) are positively related tothe P300 peak amplitude. The longer the ISI be used, the larger the P300 amplitude are presented.

- Attention

  The amplitude of the P300 depand on how the subjects focus on the stimuluse. In an oddball paradigm, the P300 can't be elicited while the subjcets don't concentrate on the target stimulus.

- Task Difficulty

  The difficult task in the P300 experiment lead to the latency increases and amplitude decreases. For instance the P300 amplitude decreases while it is difficult to discriminate the target and non-target stimulus [8].

Two typical paradigms are used in P300 experiments, oddball paradigm and three stimulus paradigm. In the first paradigm, two different stimulus are used, target stimulus and non-target stimulus. The target stimlus are presnted rarely and the non-target stimulus are presented frequently in a random successive order. Subjects are asked to focus on the target stimulus. In three-stimulus paradigm, a novelty stimulus or a distracter stimulus are used besides target and non-target stimulus. This paradigm is modified from the oddball paradigm. The different type of P300 so-called P3a are elicited by the distracter stimulus that differ from P300 are elicited by oddball pradigm. The P3a could be elicited even though subjecs completely ignore the distractor stimulus. Nevertheless, the P300 so-called P3b are mostly used in BCI system.

1.5 Thesis Overview

Chapter 2 provides the overview of BCI systems, including the basic components and key-issues. We also introduce some present-day BCIs and some P300-based BCIs. The methods used in our BCI will be introduced in Chapter 3. Chapter 4 provides the experiment steup and detail of the online system we designed, and we show the analysis results of the offline experiment and onilne testing. In Chapter 5, we give some brief discussion. In Chapter 6 we give this thesis some conclusion.

Chapter 2

Survey of Brain-computer Interface

In this chapter we will give an overview to BCI systems. We first introduce some categories of BCI systems, then we briefly introduce some present-day BCIs and some P300-based BCIs. Next we list and explain some basic components and nowaday key-issues in a BCI system. In the end of this chapter we provide the thesis scope.

2.1 Categories of Brain-computer interface systems

Invasive and non-invasive systems

We have mentioned th non-invasive brain monitor techinques in previous cheapter. The BCI systems based on these techniques are non-invasive BCI systems and among these techniques, EEG is the most suitable for a BCI system. The ”non-invasive” means we don’t hav to directly record the brain activity by putting the electrodes into the brain, in which the user will be at medical risks. Therefore, the non-invasive BCIis less debatable. The disadvantages of the non-invasive BCI is the influence of the volume conductor effect, thus the quality of electrodes containing other noise overlappoing the brain activity.

On the contrary, for the invasive BCI systems, we have to put the electrodes into a user’s skull to monitor the brain directly. This is the main drawback of invasive BCI systems. The other disadvantage of the invasive ones is that the quality of the signals decades over time. However, the signals in a invasive BCI is of higher signal-to-noise ratio.

Due to the medical risks, present-day almost all of the BCI systems are non-invasive.

Pattern-recognition-based and operant-conditioning-based systems

The pattern-recognition-based BCI is based on congitive mental tasks. This kind system are often predefined. Commonly used mental tasks in current BCI system include motor imagery, arithmetic, visual, spatial operations. And user will perform more tha once these mental tasks to train a classifier used to recoginze his wish. The operant-conditioning-based BCI is based on the self-regulation of the EEG response. In other words, we train a user to control the BCI systems by regulate his brain signals. The representative work is Wolpaw μ-rhythm BCI and SCP BCI [22].

Synchronous and asynchronous systems

In a synchronous BCI, the user is notified to perform a mental activity when a specific external cue is shown. That means this kind of system operates in a cue-based mode and has the information about the onset of the mental activity in advance. The analyses and classification of the brain signals in the system is limited to the predefined fixed time period. Besides, the system is active only during the predefined period as well. BCI systems based on evoked potentials and ERPs belong to this category, such as P300, SCP. Besides EPRs, the BCI developed in Graz that analyzed the spontaneous EEG are also synchronous BCIs.

The BCI that a user can intend a mental activity whenever he wishes to perform such mental activity is an asynchronous BCI. In the asynchronous BCI, the brain signals are analyzed and classified continuously. We have to not only classify from the redefined mental tasks but also discriminate events from noise and nonevents such as resting or idling states. Such a BCI system is more flexible and attractive to be utilized in practice. Besides the above advantages, it also offer a rapider response time than synchronous ones. However, the classification in an asynchronous BCI system is not accurate enough today.

2.2 Basic components in BCIs

Signal pre-processing

The goal of the stage is to enhance the signal-to-noise ratio. Typical procedures include amplification, filtering, possible artifact removal. For the filtering, the bandpass filtering is usually applied. In addition, a notch filter is also used to suppress the 60 Hz power line interference. As for the artifact removal, almost all BCIs rule out the signals if the EOG or EMG is detected to be used or over a predefined threshold.

Feature extraction

In this stage, certain features are extracted from the preprocessed signals. ERP, ERD/ERS and brain rhythms are typically used features in a BCI system. Besides the above features, various feature extraction methods have been studied to extract more discriminative features, such as discrete wavelet transform, continuous wavelet transform, autoregress model(AR) or adaptive autoregress (AAR) model, power spectrum. All the above methods can be found in BCI competition 2003 papers.

Classification

The features extracted from feature extraction are fed to train a classifier. Many classification methods have been proposed in pattern recognition field. The classifier in a BCI can be anything from a simple linear model to a complex nonlinear or a machine learning models. In general, the BCI has two phases training phase and testing phase. The training phase consists of a repetitive process of cue-based mental tasks to train a classifier. In the testing phase, we use the classifier built in the training phase to recognize different mental tasks.

Command translation

The goal of this step is to translate the classification output in previous step to an operator command. The command can be, e.g. a letter in a spelling system, choice of multi-choice system, a movement of a course on the user's screen or nothing to be performed when the classification is "resting" or "idle". The design of translation algorithm and device control depends on what applications the BCI want to provide with.

Biofeedback

A feedback which make the user more easily adaptive to the system is a very important component for a BCI system. A feedback can indicate how well the asked mental activity was recognized by the system. When the system gives the feedback to a user, he will create a biofeedback which is the process that the user receives information about his biological state.

By Biofeedback, the user can monitor his physiological states, shape his brain electrical behavior, and voluntary modification of his EEG response. Today, nearly all BCI systems provide a feedback to users.

2.3 Present-day BCI systems

Here we introduce some present-day BCI systems, we mainly introduce two kinds of BCI systems, the ERP-based BCI and the motor-imagery based BCI.

2.3.1 ERP-based BCI

The event-related potential(ERP) is evoked by the external events, so this kind of BCI usually depends on the gaze of the user. We can always detect the ERP as long as we have enough trials. This kind of BCI has its advantages like the short training time and high accuracy. The drawbacks are the transition rate may be slow and the users may habituate to the system and lower the performance. Here we introduce three main ERP-based BCI, the P300-based, SSVEP-based BCI and SCP-based BCI.

P300-based BCI

The basic idea underlying P300-based BCI system is to use an similar oddball paradigm. Subjects decide which stimulus plays the role of the target stimulus. As the P300 occurs only if subjects voluntarily response to a specific stimulus, the specific stimulus chosen by the user can be automatically inferred from the EEG recorded during stimulus presentation. More specifically, the typical procedure in a P300-based BCI is as follows. First, the user decides a command which he wants to execute by the help of the BCI. Then, the stimulus are presented in the screen and the user focus on the selected stimulus. Finally, the recorded data is analyzed to infer which stimulus was chosen by the subject. This kind of BCI system had the advantage that needed a short training time and requiring no initial user training. The variant application of P300-based BCI are describe in Section 2.4

SSVEP-based BCI

The SSVEP is Steady-state Visual Evoked Potential. It is a response to a visual stimulus with a specific high frequency. The EEG signal power will increase at the specific stimulus frequency. Therefore with some different frequency stimulus on the screen we can detect which one has the user's gaze. There are lots of BCI application using SSVEP, such as

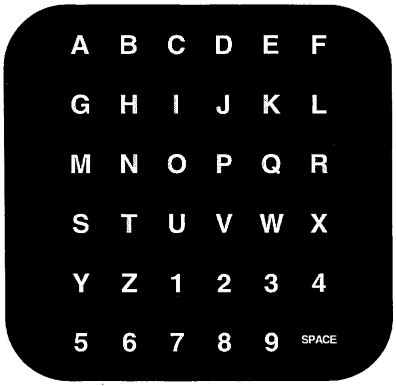
Pfurtscheller [11], his team deveoped a application to control an electricla proschesis using SSVEP.

SCP-based BCI

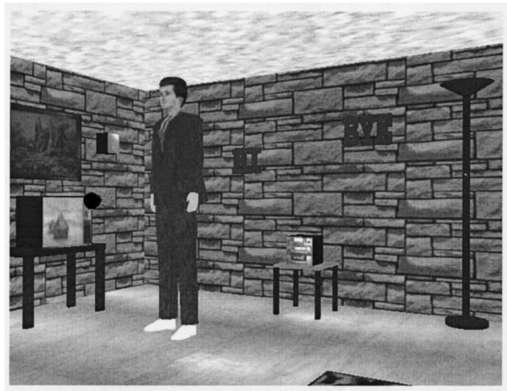
This BCI is also called thought translation device (TTD) proposed at the University of Tbingen in Germany. TTD is an operant conditioning based BCI. The user is trained to control the BCI system for a long time by means of self-regulating his SCP. In the system, the user faces a screen and choose to move the cursor to the top or the bottom on the screen by controlling his amplitude of SCP. [2] The system will have a well performance if a user is completely trained. However, the drawback that hase to take a long time to train a user to fulfill self-regulation.

2.3.2 Motor-imagery based BCI

This kind of BCI basically no need to depend on the user's gaze. The motor-imagery is a spontaneously induced EEG signal. Therefore this kind of BCI is more difficult to develop since the imagery and the concentration of each user may be different. One of the most successful BCI using motor-imagery tasks is Graz BCI is proposed by Gert Pfurtscheller. [12, 13] The development is mostly based on the detection of the ERD and ERS pattern in a motor-imagery task. Actually the concept of ERD and ERS was proposed by Pfurtscheller. In their works there are lots of research about different movement that causes different kind of ERD and ERS. They intend to left/right hand movement imagery, foot movement imagery, or tongue movement imagery. They use spatial filter as Common Spatial Pattern (CSP) or morlet wavelet transforms to extract the features. This kind of BCI has its advantages like high transition rate, and users may improve the performance through constant training. The drawbacks are, the training time is longer than a ERP-based BCI, and the user's concentration is very improtant.



(a) Speller



(b) Virtual aparment

Figure 2.1: (a)An typical 6 x 6 P300-based Speller [5, 7] (b)Controling objects in virtual apartment base on P300 [1]

2.4 Review of P300-based BCI systems

P300 speller

The fisrt P300-based BCI has been presented by Farwell and Donchin in 1988. [5, 7] In this system, users are gazing at a 6x6 matrix on the screen.(Figure 2.1 (a)) In the matrix there are letters, numbers, and symbols. When the system starts, it flashes each row and column in the matrix with random sequence. The user is asked to focus his attention on the symbol he wants to select and count the number of time that this symbol is flashed. To infer which symbol the subject wanted to select, it was thus sufficient to find out which flashes evoked a P300. The principle of this system based on the less probability of the target symbol. The probability of each symbol are 1/6. The low probability led to evoke the P300 response.

Since the work of Farwell and Donchin several researchers have proposed extensions and modification of the basic P300 speller paradigm. Otherwise, many other studies were concerned with classification algorithms for the P300 speller.

Virtual apartment

A departure from the P300 spellerparadigm was initiated by Bayliss who tested if the P300 could be evoked in a virtual reality environment [1]. In the system, subjects viewed a virtual apartment as Figure 2.1(b) that alternatively on a monitor or through a head-mounted display. Subjects control five items in the virtual apartment, for instance switching on/off the television or stereo. The system work by concentrating on small spheres that were flashing in randm order over thecontrollable items. They reveal the small variance of P300 reponse between monitor and head-mounted display conditions. It was shown that virtual controllable experimental environments is an interesting alternative to implement a P300 paradigm.

(a) Curser control (b) Brain-controlled wheelchair

Figure 2.2: (a) Controling the curser by gazing on each arrows. [14] (b)Controling the wheelchair to nine places in the building. [15]

Cursor control

One system allow subjects to contorl a two-dimensional cursor with the help of P300 was presented by Piccione. [14]. In this paradigm, Visual stimuli consisting of four arrows (up, right, down,left) were randomly presented in peripheral positions on the screen.(Figure

2.4(a)) Participants hade to pay attention to the arrow indicating the correct direction for a ball to move. They proposed the system that had the well performance for healthy subjects but not suitable for locked-in sndrome patients.

Brain-controlled wheelchair

Another P300 BCI paradigm was presented by Rebsamen. [15]. The system presented a 3 x 3 matrix consist nine place choices in a building.(Figure 2.4(b)) This paradigm is similar to the P300 speller for reduce the matrix. It is implemented on a conventional wheelchair with embedded system. That is the first application of P300-based BCI for controlling a realistic object.

Four-choice BCI

A initial study of using P300-based BCI for disabled subjects that presented by Sellers and Donchin [16]. Four smtimulus (YES, NO, END, PASS) with successive order presented randomly on the screen. The purpose of this paradigm was to simplify the system for disabled subjects who might have visual deficits. Because it is hardly to concentrate on a small item on a screen for disable subjects, and they also can't do too much eye movements. In this study, two different stimulus are tested, auditory and combinations of visual and auditory. The results show the system based on visual and combinations of visual and auditory stimulus had better performance than only using auditory. Futhermore they proved that communicating with external world by P300-based BCI was possible for the disabled subjets.

2.5 Limitations

Although the BCI systems we introduced above looks well, there are still some limitations in present-day BCI systems. Here we list some normal difficulties when doing researches on BCI systems.

Habituation

In a ERP-based BCI, we use the evoked potential from the subejcts to develop a BCI system. For the evoked potential is not controlled by our own will, we may get used to the BCI system and that affects the performance [4].

Noise

As we mentioned before, the EEG signal is poor on the Signal-to-noise ratio. The artifact noise is always a big problem in analysing EEG signals. Eye blinking, eye movements, the heart beating, any possible single small movement causes artifact noises to the EEG signal. Furthermore, not only an artifact causes noises. The interference from the environment, the power line, or the devices, they are also contaminating the EEG signal. In a BCI system, we detect the spontaneous EEG signals or the evoked potential. Both are very small changes and can be easily affected by these noises. In addition to the artifacts and interference, a distraction of the user also causes noises to the EEG signal. As a human being is very complicated, every little cognitive task has its own response on the EEG signal. We can't be sure that every user of the BCI system are always concentrating to the system, one may easily lose concentration and that reduces the performance of a BCI.

Fatigue

Another limitation to BCI systems is the fatigue of the users. As we introduced in the previous section, the ERP-based BCI keeps giving stimulus to the users and detect their responses. These stimuli may be some quickly changed pictures or flashing, and these fatigue a user easily. Even if in a motor-imagery based BCI, the users may get tired easily because of the continuous concentrate on the imagenery.

2.6 Key-issues in BCI systems

Here we list some key-issues in BCI systems. The future researches on BCI systems may be mostly about these difficult issues.

Noise Reduction

As we mentioned in the previous section, the noise is a limitation to the EEG analyses and BCI systems. How to reduce the noise and the non-interested signals is an issue. Today there are some practical methods to reduce the noises, such as EOG rejection, bandpass filtering, Independent component analysis (ICA), or Laplacian spatial filtering. In this thesis, we use EOG rejection, bandpass filtering and averaging to reduce the noise.

Features

How to find significant features from the EEG signal is an important issue. People have been trying with many methods to extract significant features from the raw EEG data. In this work, we use the SWDA to select significant features from time points.

Adaptation

There are two adaptation issues in a BCI system. The first is the users should adapt themselves to the system, that is, self-training of the users. The second is, the BCI system should adapt itselves to the users, that is a machine learning issue. Both adaptation issues are important, and these two issues work totally different. If we are trying to self-training a user, we should lower the variability of the BCI system, or the users may not be able to get himself trained well because the feedback keeps changing. If we want to make the system adapt itselves to the users, the system should have more flexibilty that adative for variant subjects with variant situation. In our study, we using a threshold to online adaptive to stoping. We will describe in Chapter 3.

Biofeedback

As we mentioned before, the biofeedback is a important component in the BCI system. Nearly all BCI systems need a biofeedback to the users. This issue is about how the biofeedback affects the users, and how to design useful biofeedback. The design of different biofeedback may result in different mental work and stimulus, which influences on the signal. Is is helpful for subjects to adapt themself to improve the performance. However, not all the influence of a biofeedback is beneficial, it may be harmful as well. For example, the biofeedback stimulus may distract the user from the task. In this work, we using a simple online feedback while the system making a predict.It is described in the Chapter 4.

2.7 Thesis scope

In this thesis, we propose a P300-based three-choice brain computer interface. in reality, there are many questions with binary answers such as yes/no, positive/negative...and so on. However, users cannot always have a sure answer on the questions with binary answers. The mainly idea to design a three-choice system is to provide two correct choices and another flexible choice for this kind of question. To develop this system, the sucessive stimulus are presented in the middle of the screen in a random order, and subjects don't have to do more eye movements and can't be distracted from constantly searching the stimulus on the screen. The subjects can pay attention on the target stimulus. In this system, we using Yes, No, End as the choices to answer some basic questions.

The purpose of our system is to make it automatically stop as long as the predicted result has higher standard of reliability. Thus, the voting method is to compute the standard of reliability by temporal features produced by moving window and SWDA. We use moving window equally sampling the data trials and produce averaging data from each combination of trials. And then, SWDA is used to compute predicted results from each averaging data. The predicted results can be seen as temporal features, and the votes can be derived from the temporal features. Additionally, we can use the percentage of votes to be the standard of reliability. Compare to the system using fixed number of trials to predict the result, our system using voting method can save time of predicting while the standard of reliability show that the number of recorded trials is enough to make a correct predict. In this sense, if the predicted result has low standard of reliability, we can record more data to reduce the probability of errors through this technique.In this thesis, we perform two parts, offline analysis and online testing. In offline analysis, we use performance evaluation to examine the techinque, and then decide the parameter setup for the online testing. Addiionally, we validate the system performance by way of online testing.

Chapter 3

Proposed P300-based BCI System

In this chapter we will introduce about the techniques we use in this work, including the data preprocessing methods, the stepwise linear discriminate method (SWDA), the voting strategy for online system, and the performance evalution technique including bootstrap method and bit rate. The offline and online experiments will be provided in the next chapters.

3.1 Data preprocessing

Preprocessing

We mainly use two preprocessing techniques here: The artifact removal and the bandpass filtering.

As we mentioned in the previous Chapter, the artifact exists in EEG signal and significantly affects the data. We apply the EOG rejection to avoid eye blinking and eye movement in our data. The EOG rejection is to simply decide a threshold. Then we remove any single trial that has a single sample exceeds the threshold. This procedure may reduce the trial number used in the further analysis. The threshould we use here is 100 muV.

As for the bandpass filtering, we use a Butterworth bandpass filter to filter the data. We filter the data from 1Hz to 40Hz, this will eliminate the 60Hz power line effect on the signal, the low frequency heart beating (ECG), and the high frequency EMG effects. Before the further analysis on the discriminate analysis, we filter the data from 1Hz to 8Hz. This is due to the observation result from our experiments.

3.2 Stepwise linear discriminant analysis

3.2.1 Introduction

Stepwise linear discriminant analysis (SWDA) is presented by Draper and Smith in 1981 [6]. It is a technique to select suitable predictor variables to be included in a multiple regression model. It can be considered to be efficient because the terminating heuristic is implemented in an economical manner. Additionally, it can reduce the data size but keep the most useful features in the model. In a sense, SWDA has the advantage which include automatic feature extraction, that is helpful for improving efficiency of data analysis in BCI. Wolpaw and Sellers provide a comprehensive comparison in stepwise linear discriminant analysis, Person's correlation method (PCM), Fisher's linear discriminant (FLD), linear support vector machine (LSVM) and Gaussian support vector machine (GSVM) for P300 speller [9]. They indicated that out of the five examined methods, SWDA provided the best overall combination of training and performance characteristics for P300 classification. In this section, we will introduce the techiques in SWDA, including the linear regression, forward selection method, the backward elimination method and the stepwise procedure.

3.2.2 Linear regression

Linear regression analysis commonly performed when investigator wish to examine the relationship between two interval or ratio variables. In many situations, a straight-line relationship can be valuable in summarizing the observed dependence of one variable on another. For example, we take two corresponding observation X and Y, assume that the

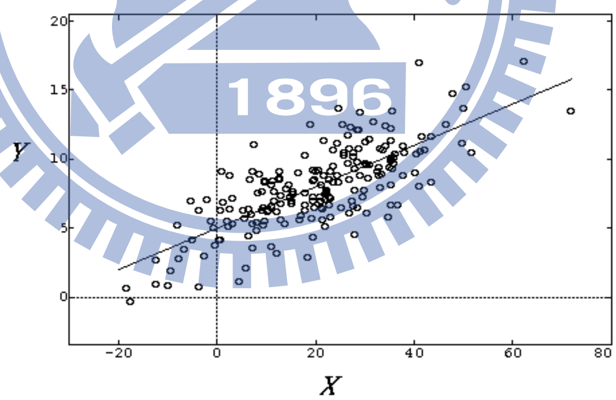


Figure 3.1: Regression fitted straight line.

regression line of dependent variable which we shall denote by Y, on variable X has the form $\beta_0 + \beta_1 X$. Then we can write the linear first-order model

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{3.1}$$

,that is, for a given X, a corresponding observation Y consists of the value $\beta_0 + \beta_1 X$ plus an amout ϵ, the increment by which any individual Y may fall off the regression line as Figure 3.1.The equation of such a straight line can be obtained by the method of least squares when data are available. Regression and correlation analysis can be used for either of two main purposes. One is examining the kind of relationship and its strength. Otherwise, The equationn relating Y and X can be used to predict the value of Y for a given value of X. Prediction intervals can also be used to indicate a likely range of the predicted value of Y.

3.2.3 Forward selection method

The forward selection method is a procedure that to select the variable with the highest absolute value of the simple correlation, each time adding one variable to the model, until a specified stopping rule is satisfied. The most commonly used stopping rule is based on the F test of the hypothesis that the partial correlation of the variable entered is equal to zero. General, the rule to reject variables entering when the F is less than a specified value, This cutoff value is often called the minimum F-to-enter. Equivalently, the P value corresponding to the computed F statistic could be claculated and the forward selection stopped when this P value is greater than a specified level. Note that here also the p value is affected by the fact that the variables are selected from the data and therefore should not be used in the hypothesis-testing context.

3.2.4 Backward elimination method

An alternative strategy for variable selection is the backward elimination. This technique begins with all of the variable in the equation and proceeds by eliminating the least useful vatiables one at a time. The parial F value is calculated for every predictor variable treated as it were the last variable to enter the regression equation. The F-to-remove is computed for testing that each coefficient is zero or not. The process continues until no variable can be removed according to the stopping rule.

3.2.5 Stepwise procedure

One very commonly used techinque that combines both of the forward and backward methods is called the stepwise procedure. In stepwise prcedure, the forward stepwise method would be applied to adding a variable to the predictive equation step by step. In addition, the backward elimination method is so-called the backward stepwise method is used to remove the least useful variable from the model.

The standard stepwise selection procedure begins with the empty regrassion model, and subsequently adjust the variables in the equation until the stopping rule is reached. At first, the standard procedure do forward selection to select variables. At each step the variables observe the computed F-to-enter. If one variable with highest computed F-to-enter, and the F-to-enter is greater than the preselected significance level F-to-enter. The variable would be included in the regression model. After the variable is entered, the F-to-remove is computed for all the variable in the model. Moreover, the variable with the minimum F-to-remove less than preselected significance level F-to-remove is removed. After the variable removed, then next variable with the large enough computed F-to-enter would be selected. Repeat two forward and backward prcedure until no variables can be deleted or added.

The choice of the significance level affects both the nature of the selection process and the number of variables. The significance level value F-to-remove must large than significance level value F-to-enter. Otherwise, the process is essentially forward selection. In many situations it is useful for investigator to examine the full sequence until all variables are entered. This step can be accomplished by setting the minimum F-to-enter equal to a small value, such as 0.1 (or a corresponding P value of 0.01). In our study, we set the P value of < 0.1 for adding a variable, and a P value of > 0.15 to eliminate variables. We examine the time points as our feature points. Using stepwise procedure, we have the candidate points that have a better chance to be useful.

The regression coefficients were computed after the process of stepwise feature selection. We derive the regression coefficients as the classification weights. Each variable of weights could be seen as the contribution of each corresponding feature point. In other words, the points that strongly represent the characteristic P300 as defined by the training data. Additionally, the weights show the significant level of corresponding point for representing the characteristic of P300. Thus, the regression model is taken as the sum of scored feature vectors. The result of the regresion model represent the possibility of each feauture vectors with the characteristic of P300.

$$s = w \cdot x \tag{3.2}$$

The **s** is taken as the score to predict the result. In our study, it is taken to predict which epoch is the target epoch with highest possibility.

3.3 Voting

In order to design one compatible online brain computer interface with good performance for all subjects, efficiency and flexibility are important issue. However, EEG data has the low singla-to-noise ratio. In order to solve this problem, averaging is a good way to enhance the signal-to-noise ratio. Thus we can extract more information we want by averaging more repetitious epochs. Additionally, the fixed repetition of trials generally be set before experiment. For instance, most online P300-based brain computer interface terminate in fixed repitition of stimulus according offline analysis result. Even though the repitition of times could be set according different subjects. But the quality of different experiment data is varied from the same subject. So, if we can compute the significant response degree of the P300 or the standard of reliability of the discrimination results, less trial repetitions are needed in experiments. In this case, we want to design a algorithm to compute the standard of reliability that can make the online system automaticlly adapt to stop. Serby presented a threshold method to make the decision [17]. A maxmum likelihood be applied to calculate the possibility that P300 be included. Additionally, a decision was made if the corresponding threshold was reached. They conclude the method is helpful for online performance. In addition, the study prove the adative online system is actually needed. In this section, we propose a algorithm to extract more information from current data. The moving window be applied to compute different size of averaging data. In addition, the voting strategy is used to estimate the standard of reliability of the discrimination result.

3.3.1 Moving window

Successive trials are recorded from the P300 experiments. As we mentioned before. For increasing the SNR and extracting the P300 ERP, the discrimination result is generally computed from averaging all of the current trials. For instance, the trials are recored in

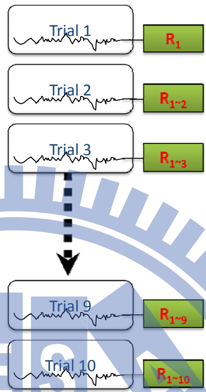


Figure 3.2: Succesive trials and discrimination results of online experiment. Each dixcrimination results are computed from averaging all the recorded trials.

online testing as Figure 3.2. The first discrimination result $\mathbf{R}_1$ is derived when the first trial is recored. Following, the next trial is recorded, and then the second discrimination result $\mathbf{R}_{1\sim 2}$ is derived from averaging trial 1 and trial 2. The $\mathbf{R}_{1\sim 3}$ is derived from trial 1, trial 2 and trial 3. On the analogy of this, the process continue until the number of trial reach the limit, and then output the result. We observed the successive results $\mathbf{R_1}, \mathbf{R}_{1\sim 2}...\mathbf{R}_{1\sim n}$ have the property of coincidence. Thus, the sequential results can be seen as temporal features. If most of the results consist with each other, then it has the large reliability to ensure the result. However, it also has the disadvantage for this evidence, the early recorded trials have the larger influence on the last result. For instance, the first trial must effect all of the successive results. If the first trial reflect the wrong response from the subject. Then at least one of the temporal feature is wrong, and the other features is affected by the wrong trial. Thus, it isn't reasonable way to compute the evidence. For this reason, producing

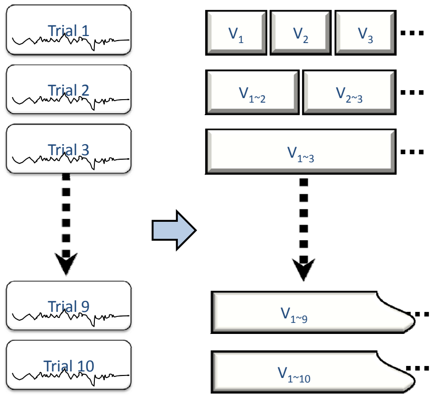


Figure 3.3: Using a moving window to produce the combination of trials. Computing predicit results so-called temporal features using SWDA by averaging all the combination of trials.

all the combination of n trials is the equitable way to produce the temporal features. But, that is not realistic for a online system, the cost of the system is too much. Thus, using a moving window to produce the combination of the n trials is reasonable and suitable. The one discrimination result is as one vote to make the decision. As shown in Figure 3.3, the votes are derived from different windows size of trials. The windows size means the number of trials which are included to average and compute the vote. In this flow chart, the first vote $\mathbf{V_1}$ will be computed when the first trial is recored. After the first trial, the vote $\mathbf{V_2}$ and $\mathbf{V_{1\sim2}}$ are derived when the second trial is recorded. $\mathbf{V_2}$ is derived from the trial 2, and $\mathbf{V_{1\sim2}}$ is derived from the averaging trial 1 and trial 2. Following, $\mathbf{V_3}$, $\mathbf{V_{2\sim3}}$ and $\mathbf{V_{1\sim3}}$ are derived when trial 3 is recorded. On the analogy of this, the process continue until the number of trials reach the limit. The number of votes increase depend on the number of trials. We can observe a lot of knowledge from all of the votes. However, the standard of reliability of votes are varied that computed from different window size. Thus, the process to combine all the information will discuss in Section 3.3.2.

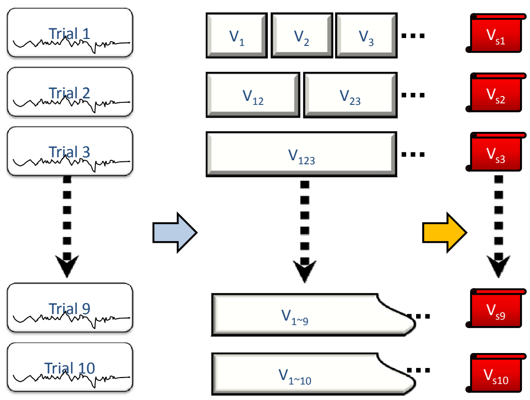


Figure 3.4: Flow chart of producing the votes. The votes derived from each window size of temporal features subsets.

3.3.2 Voting strategy

The votes are represented the discrimination result of three condition(Yes, No and End). Collecting all of the votes and counting the number of three condition of votes that is the simple way to make a dicision. However, the votes are computed from averaging more trials that actually have higher standard of reliability than the votes from averaging less trials. Because the signal-to-noise ratio can be reduced by averaging more repetitions trials. Thus, in the process, the vote subset of the same windows size are represented one vote to make the decision. In other words, all the votes of same window size that have to gather statistics and produce one least result. For instance, in Figure 3.4, the $\mathbf{V_{s1}}$ computed from gathering statistics of the vote sets $\mathbf{V_1}, \mathbf{V_2}, ...\mathbf{V_n}$. Finally, n votes $\mathbf{V_{s1}}, \mathbf{V_{s2}}, ...\mathbf{V_{sn}}$ are derived when n trials are recorded. Additionally, the n votes can be seen as n temporal features to make a decision. The percentage of votes of three condition results could be seen as the authentic level. Thus, if we have the prior knowledge, a decision was made only after a predefined threshold had been reached; otherwise, the next trials are recorded. The percentage of votes are shown in Table 3.1. It exhibit different possibility that achieving the percentage of votes in different number of trials. On the other words, the possibility to reach the same

Percentage of votes

$Vote\backslash Numberoftrials$	1	2	3	4	5	6	7	8	9	10
1	100	50	33.3	25	20	16.6	14.2	12.5	11.1	10
2		100	66.6	50	40	33.3	28.5	25	22.2	20
3			100	75	60	50	42.8	37.5	33.3	30
4				100	80	66.6	57.1	50	44.4	40
5					100	83.3	71.4	62.5	55.5	50
6						100	85.7	75	66.6	60
7							100	87.5	77.7	70
8								100	88.8	80
9									100	90
10										100

Table 3.1: Percentage of votes in 10 successive trials. The X axis represents the number of votes, and the Y axis represents the number of trials. Each block represents the percentage of votes in each number of votes and trials.

threshold of percentage of votes increase according the numbers of epochs. For instance, if the threshold is set to 80%, a decision is made which all the votes indicate the same result while three epochs are observed. On the other side, if above eight votes indicate the same result, then a decision is made while ten epochs are recorded. Thus, the threshold can be seen as adapting according different numbers of epochs. Moreover, a probability of making a decision is based on the number of epochs and subject's performance. However, too strict threshold lead to decrease the probablity of achievement. Thus,design a suitable threshold values depend on the offline performane of the subject. The minimum number of trials required to reach a decision with the required threshold of certainty was three. In order to ensure a reasonable experiment time, a decision was made at most 10 trials even if the percentage of votes had not been reached.

3.4 Performance evaluation

3.4.1 Bootstrap method

Bootstrap method is presented by Efron in 1979. This method is the practice of estimation properties of an estimator by measuring those properties when sampling from an approximating distribution. On the other words, bootstrap provides an estimate of a properties in the absence of adequate data on its sampling distribution by obtaining many random sub-samples from the available data and computing the properties afresh for each of these sub-samples. The distribution of these values approximates the actual distribution. In this

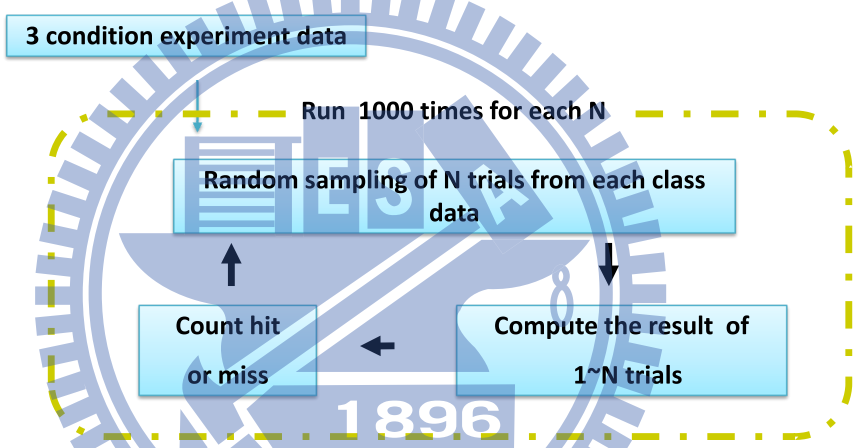


Figure 3.5: Flow chart of bootstrap.

work, we randomly chose N trials from each condition data. Following, we sequentially exame the results in 1 trials, 2 trials, ..., N trials from the random N trials. Repeat this process until reach 1000 times. Classification accuracy could be estimated by this procedure. It also provide the prior knowledge for online implementation.

3.4.2 Bit rate

An information transfer rate, a bit rate, can be used in order to take into account both accuracy and speed of a BCI. The bit rate is a standard measure of any communication system(which a BCI basically is). It tells the amount of information communicated per time unit. The bit rate R measures the achievable information rate per unit time, given the decision accuracy and duration. The number of achievable bits per decision is given by following equation [22]

$$C = log_2 N + Plog_2 P + (1-P)log_2(\frac{(1-P)}{(N-1)}) \tag{3.3}$$

where N is the number of possible selections and P is the correct classification rate. The bitrate R in bits/minute is given by $R = CM$ where C is the number of bits per decision (bits/trial), and M is the average number of decisions per minute. The bit rate as a function

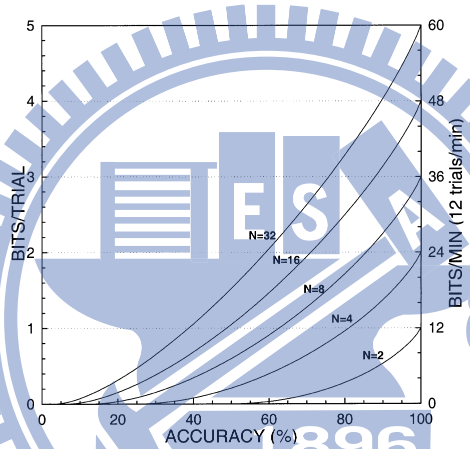


Figure 3.6: Bit rate in bit/trial and bits/min(assuming 12 trials/min), when the number of possible selections N is 2, 4, 8, 16 and 32 [22].

of accuracy for a different number of choice can be examined in Figure 3.6.

Chapter 4

Experiments

4.1 Offline

4.1.1 Experiment paradigm

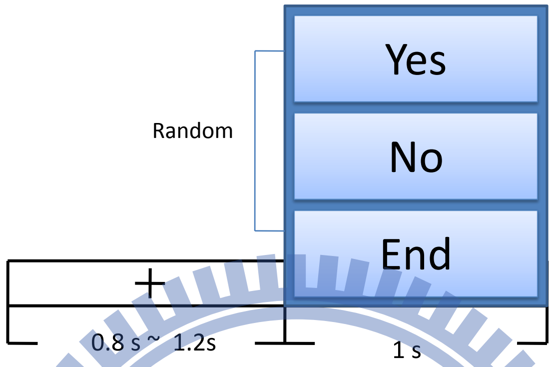


Figure 4.1: Experiment paradigm

Experiment paradigm. This figure shows the experiment paradigm of one trials. The time interval indicates the duration of stimulus and fixation are shown on the screen.

The experiment paradigm is as Figure 4.1. At the begining of each stimulus, a fixation apears on the screen indicating the subjects to focus. The fixation is presented for 800 ms to 1200 ms per time, after than the stimulus were presented randomly in three type of stimulus (YES, NO, END). Three type of stimulus duration were the same in 1000 ms. Each tirals consist one of each type of stimulus with probability of 0.33. Subjects were asked to attend to a specific stimulus, either YES, No or END. In addition, the specific stimulus are presented infrequently in a random sequential series, then the P300 response would be elicited while the subject attending to the stimulus series. Because the sepecific stimulus is the rare event with 0.33 probabilty, and the other event could be seen as the non-target with 0.66 probabilty. The P300 response is shown in Figure 4.2.

There are some task that could hlep subject to focus on the target stimulus. We will discuss the effect of different task in Section 4.1.2. In addition, two way were uesed to decide the specific target were , one was defined by the experimenter at the beginning of each run, another was depand on the subject's answer of the question which provided from

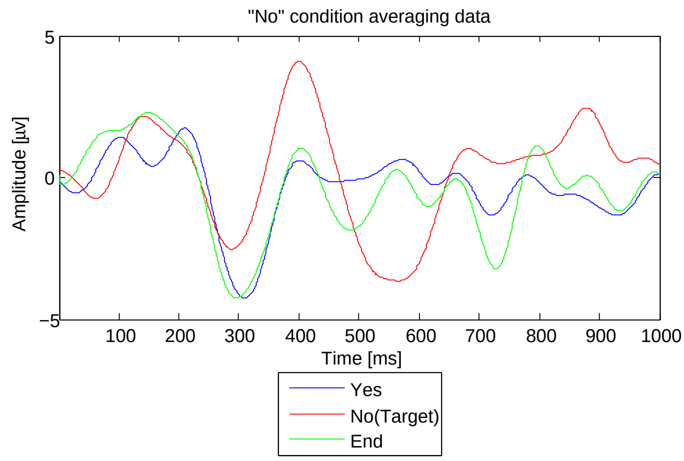


Figure 4.2: No condition averaging data

experimenter.

4.1.2 Experiment setup

Experiment setup

We prepared two computers and an 32-channel EEG cap connecting to an amplifier. The subject is asked to wear the EEG cap and sit on a comfortable chair, putting his/her hands on the table and keep them relax. There is a 17" LCD monitor set in front of the the subject, and the screen shows the visual stimulus described in Section 4.1.1. This paradigm is controlled by computer A. The timing of each triger is sent from computer A through a parallel port to computer B, which is connected to the amplifier and records the data along with the triger points. The data acquisition is under 1000Hz sampling rate. It is recorded at the Seven channels (Fz, Fcz, Cz, Cpz, P3, Pz, P4) as Figure 4.3. We start the experiment after the impedence of all 7 channels are below 3k ohm.

Subjects

We invited three subjects in offline experiment, including two males and one female, all aged 22-24. Moreover, we invited 7 subjects in online experiment, including four males

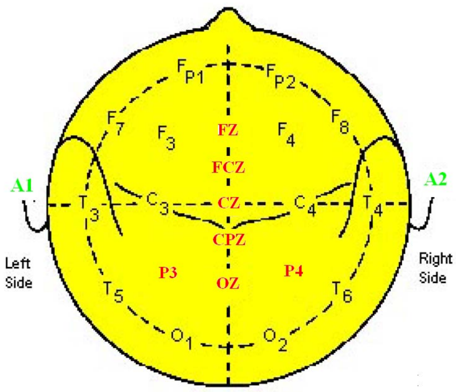


Figure 4.3: Seven channels (Fz, Fcz, Cz, Cpz, P3, Pz, P4) were used

and three female, all aged 22-24. All subjects were healthy university students. In offline experiment, each subject participates three offline experiments session. Each of the sessions consisted of nine runs, one run consisted 20 of trials. Each trials consisted with three type of stimulus (YES, NO, END). We asked these subjects to participate one offline experiment session about every a week. In online experiment, seven subjects participant nine run of online experiments.

Task

The performance of this P300 experiment significantly depend on subject's concentration. There are three common way to confirm that subject actually focus on the target stimulus, mental counting, taping the keyboard or noting of the target. However, the resonable task is mental counting or noting, because motor responses are not possible for a disable patients, the current study has adopted mental counting of attending to target stimulus.

4.1.3 Experiment result

Bootstrap analysis

As we decribe in Section 3.4.1, bootstrap is a method to estimante performance from sampling recorded data. In this analysis, we examine the probability of achievement and accuracy in different voteing threshold. Because we need to observe the analysis to select the suitable voting threshold described in Section 3.3.2. In addition, we also compare the accuracy between voting method and only SWDA be used.

- The analysis results of Subject 1 in three condition data are shown in Figure 4.4.

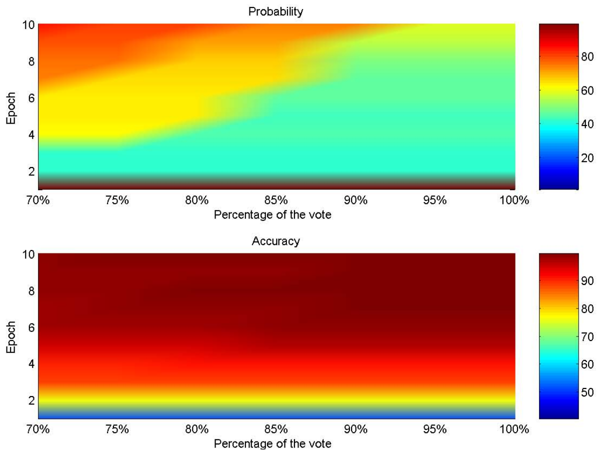
  The results show the equal performance in three condition analysis. In addition, the high enough accuracy with high enogh probability of achievement is presented while setting the threshold to 85%. The comparsion of accuracy of three analysis are shown in the figure right colum.

- The analysis results of Subject 2 in three condition data are shown in Figure 4.5.

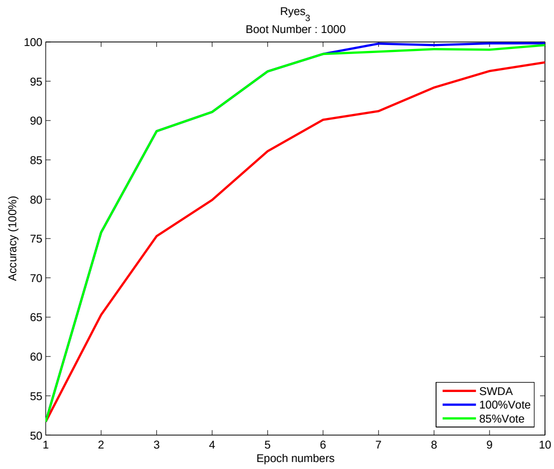
  The results of subject 2 have the better performance in yes and no condition. The probability of achievement in end condition are lower than the others. However, the accuracy in end condition is similar to yes and no condition whhile the threshold is stted above 80%.

- The analysis results of Subject 3 in three condition data are shown in Figure 4.6.

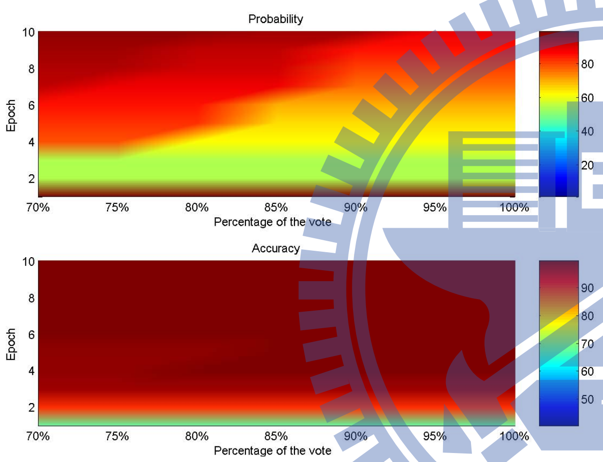
  As the comparsion of accracy show in the figure right column, the accuracy are significantly improved by using threshod in different percentage of votes. In addition, the reslut of no condition present the best performance.



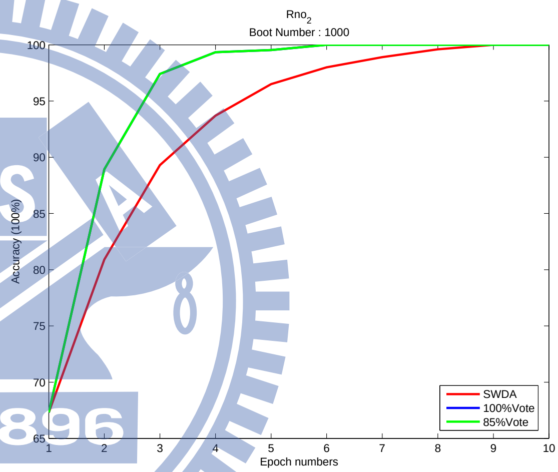
(a) Yes condition



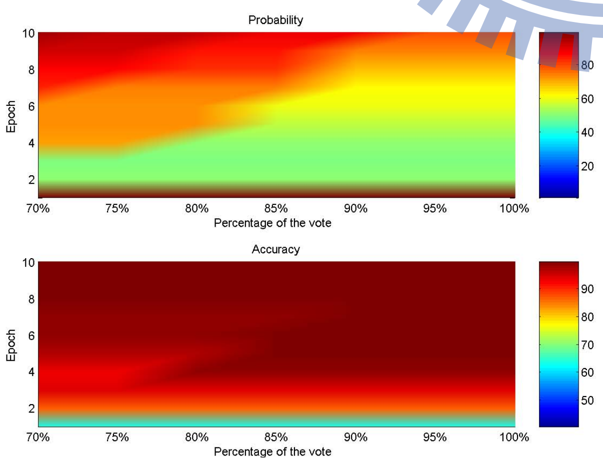
(b) Yes condition



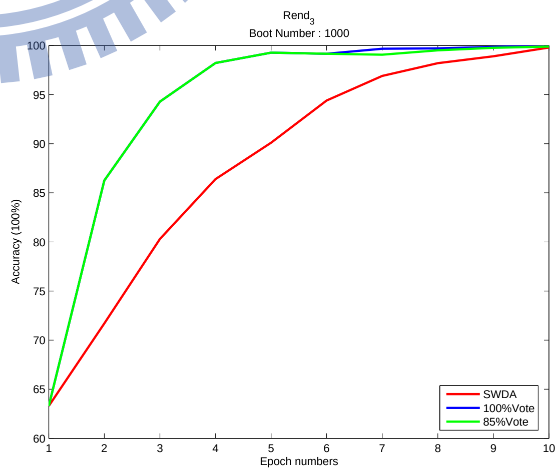
(c) No condition



(d) NO condition

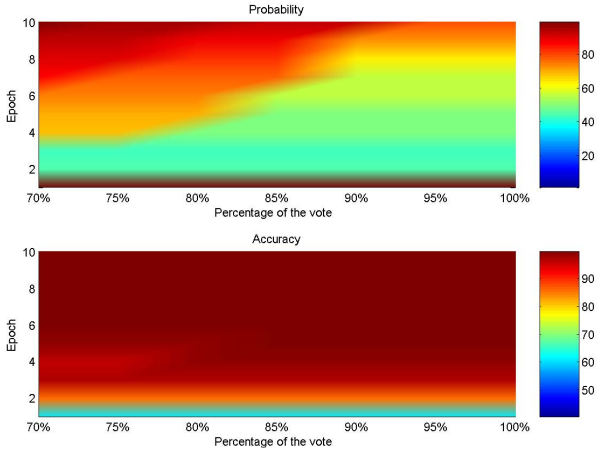


(e) End condition

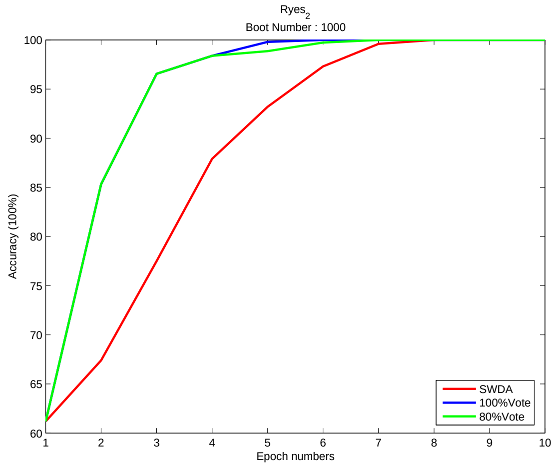


(f) End condition

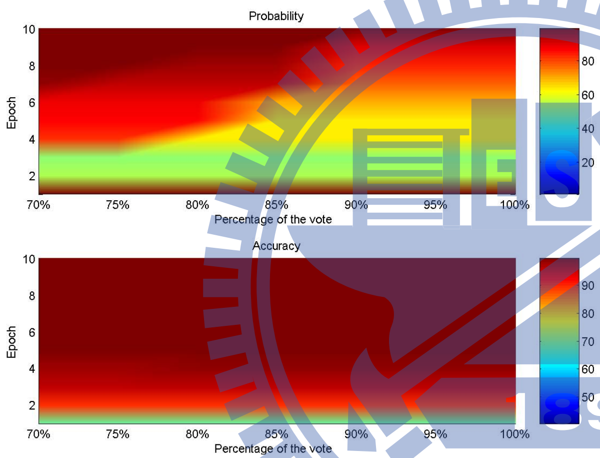
Figure 4.4: Analysis results in different percentage of votes from Subject 1. Figure a,c and e show the probability of achievement and discriminant accuracy in seven threshold (70, 75, 80, 85, 90, 95, 100 percentage of votes), and the epoch number range from 1 to 10. The colors in the figure are defined in the color bar which show the degree. Figure b, d and f show the comparison of accuracy of the threshold be set to 85%, 100% and only using SWDA.



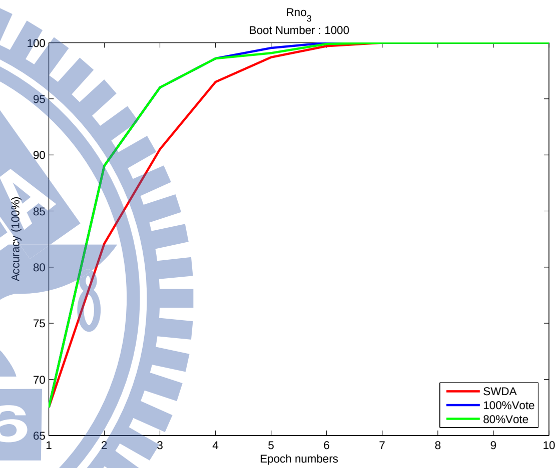
(a) Yes condition



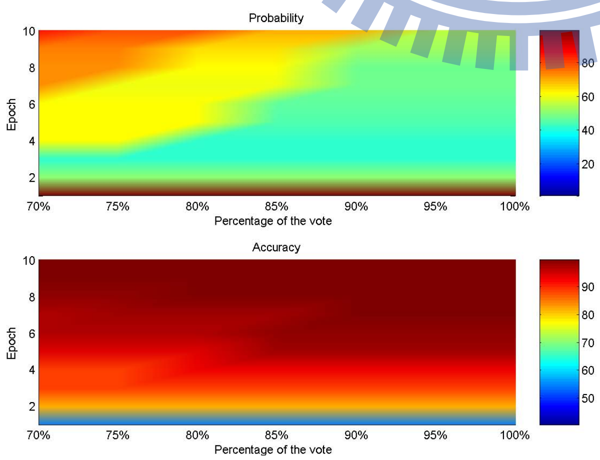
(b) Yes condition



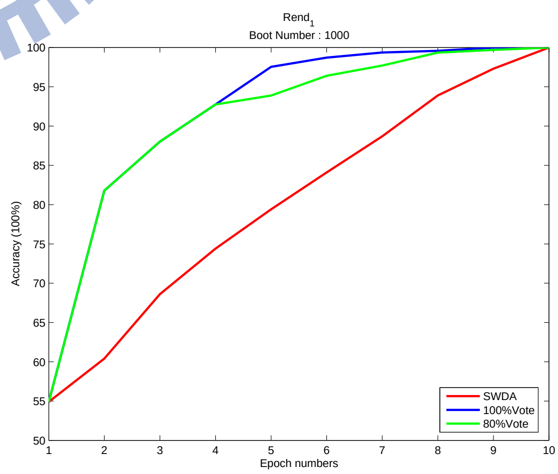
(c) No condition



(d) No condition

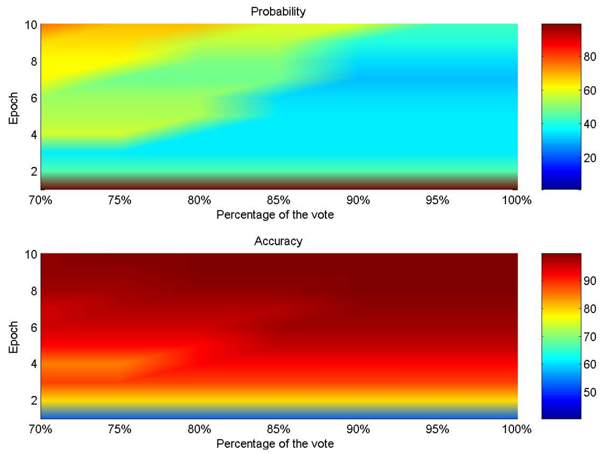


(e) End condition

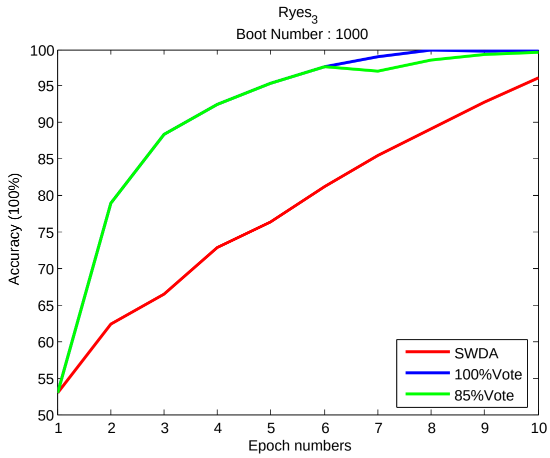


(f) End condition

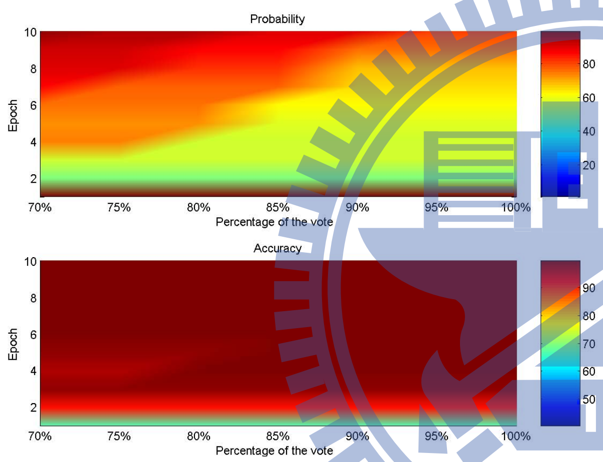
Figure 4.5: Analysis results in different percentage of votes from Subject 2. Figure a,c and e show the probability of achievement and discriminant accuracy in seven threshold (70, 75, 80, 85, 90, 95, 100 percentage of votes), and the epoch number range from 1 to 10. The colors in the figure are defined in the color bar which show the degree. Figure b, d and f show the comparison of accuracy of the threshold be set to 80%, 100% and only using SWDA.



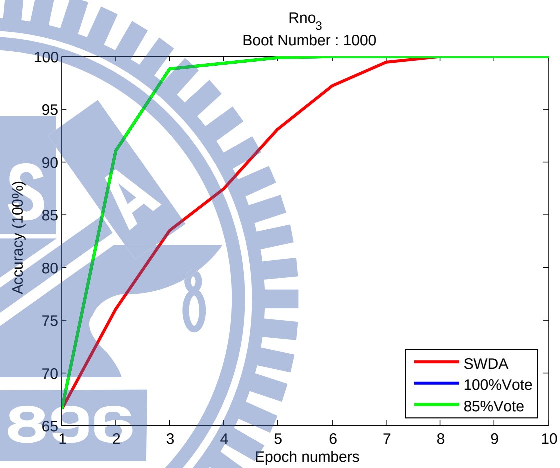
(a) Yes condition



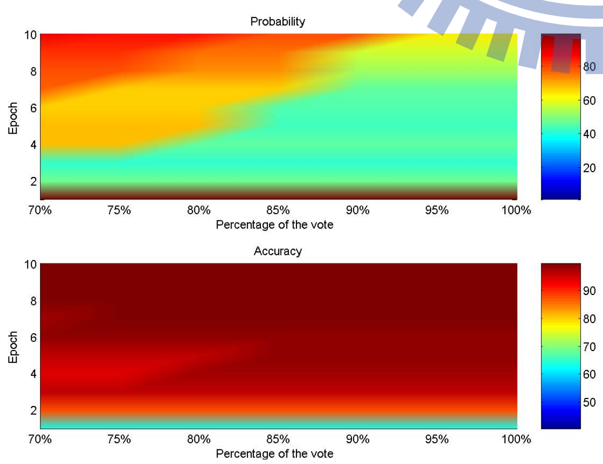
(b) Yes condition



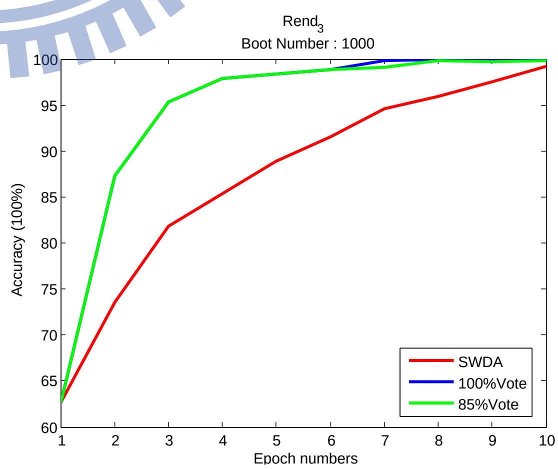
(c) No condition



(d) No condition



(e) End condition



(f) End condition

Figure 4.6: Analysis results in different percentage of votes from Subject 3. Figure a,c and e show the probability of achievement and discriminant accuracy in seven threshold (70, 75, 80, 85, 90, 95, 100 percentage of votes), and the epoch number range from 1 to 10. The colors in the figure are defined in the color bar which show the degree. Figure b, d and f show the comparison of accuracy of the threshold be set to 85%, 100% and only using SWDA.

Online simulation

In this section, we simulate the offline data as a online recorded data. In this procedure, we testing the data trial-by-trial as online recorded until the threshold be reach. Moreover, we evaluate the performance in different threshold setting. Additionally, eighteen datas of each subjects are examined in this procedure.

- The online simulation results of Subject 1 are shown in Figure 4.7. As we expected, the higher the threshold the more data can reach the threshold early. In addition, the result show the good accuracy while the threshold is set above 70%.

- The online simulation results of Subject 2 are shown in Figure 4.8. The growth of the datas number in the 80% threshold which is significantly distinct from the 90% and 100% threshold. Additionally, the best accuracy is presented while the threshold is set above 90%.

- The online simulation results of Subject 3 are shown in Figure 4.9.

  The accuracy are the same by setting the threshod above 70%, and the 83% mean three of the eighteen datas are incorrect.

Bit rate

In this section, we evaluate the performance of each subject by bit rate which decribe in Section 3.4.2,and the maxmum and average information transfer rate are shown in Table 4.1. The information transfer rate in two analysis procedure are evaluated. Futhermore, we show the two transfer rate in bootstrap procedure. First, the result of classifying only by SWDA. Second, the result of classifying by voting in 80% threshold.

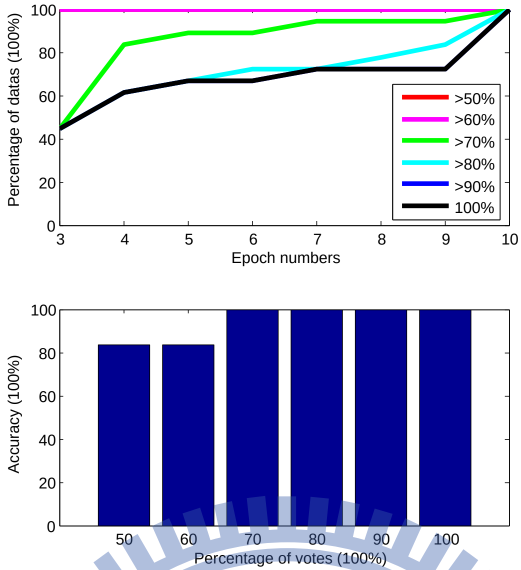


Figure 4.7: Result of online simulation of Subject 1. The upper figure shows the percentage of data which can achieve threshold under the number of trials. The thresholds are set to 50%, 60%, 70%, 80%, 90% and 100%. The bottom figure shows the discriminant accuracy in the six thresholds.

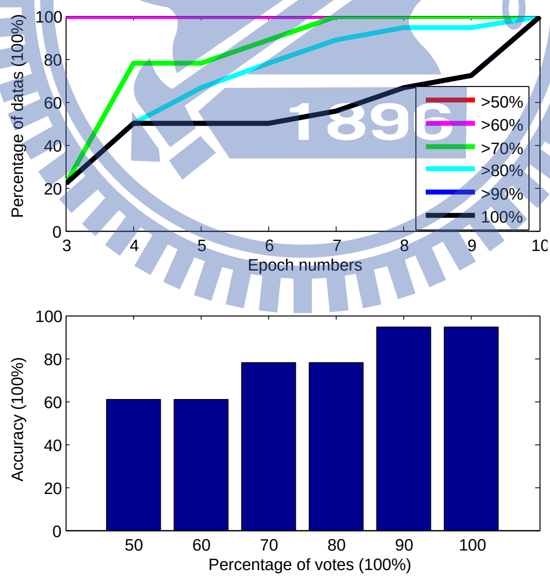
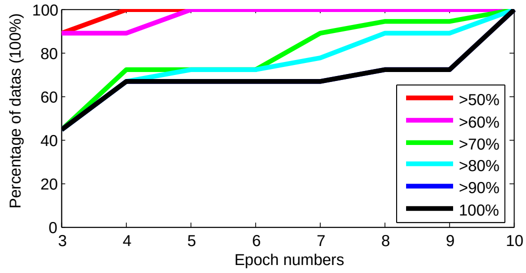


Figure 4.8: Result of online simulation of Subject 2. The upper figure shows the percentage of data which can achieve threshold under the number of trials. The thresholds are set to 50%, 60%, 70%, 80%, 90% and 100%. The bottom figure shows the discriminant accuracy in the six thresholds.



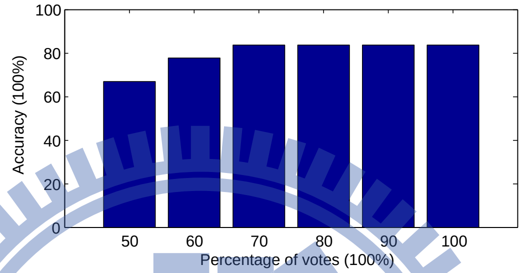


Figure 4.9: Result of online simulation of Subject 3. The upper figure shows the percentage of data which can achieve threshold under the number of trials. The thresholds are set to 50%, 60%, 70%, 80%, 90% and 100%. The bottom figure shows the discriminant accuracy in the six thresholds.

Information transfer rate of offline analysis

		Subject 1	Subject 2	Subject 3
Bootstrap analysis result (SWDA)	Max bit rate/min	7.70 (83.40%)	3.64 (82.10%)	5.74 (76.90%)
	Average bit rate/min	2.45 (66.69%)	1.63 (68.01%)	1.65 (64.98%)
Bootstrap analysis result (80% votes)	Max bit rate/min	7.70 (83.40%)	4.88 (78.40%)	7.09 (97.93%)
	Average bit rate/min	3.24 (84.15%)	2.75 (89.03%)	2.67 (73.82%)
Online simulation (80% votes)	Max bit rate/min	5.28 (100.00%)	5.28 (100.00%)	2.26 (100.00%)

Table 4.1: The maxmum bit rate/min and average bit rate/min of three subjects by the discrimination only SWDA, voting threashold be set to 80% and testing in online simulation procedure.

4.2 Online

Experiment paradigm

The online experiment paradigm is similar to offline experiment paradigm. However, a decision is only made in the online experiment paradigm, and feedback will be shown on the screen after decision making.

4.2.1 Training

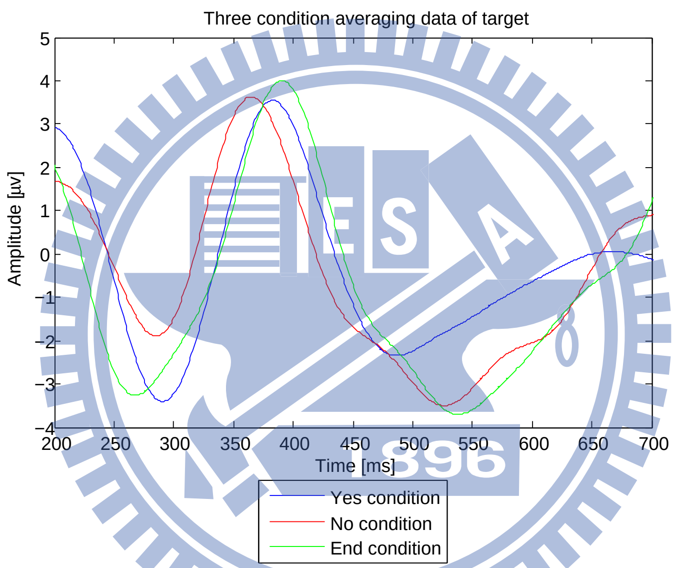


Figure 4.10: Three condition averaging data of target.
Three condition averaging data of target. Ecah line represent different condition P300 response.

Before online experiment, subjects have to participate in a training session. The session is the same as offline experiment. In this seesion, three run of each stimulus (YES, NO, END) are included. Subjects are asked to focus on specific target that is assigned by experimenter before each run. The three condition averaging data are shown as figure 4.10. Even though the averaging data present the similar P300 response. However, the delay and ampltitude of response are stiil slightly different for three condition. Thus, the three run of data are used to be training data.

4.2.2 Online adaptive strategy

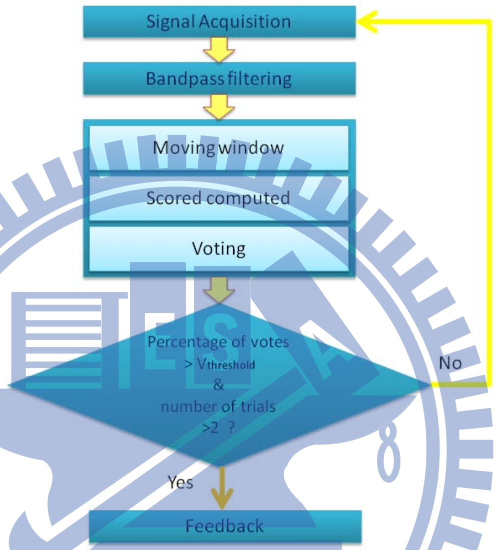


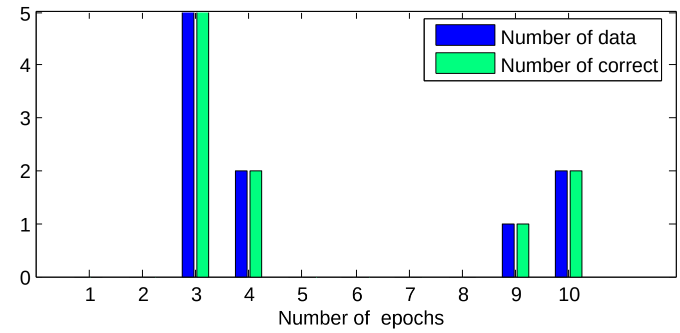
Figure 4.11: Online system flowchart

As Figure 4.11 show, the procedure of our online system is dynamic to stop . At the first step, one trial is recorded and filtered at 1-8hz. Following, all the feature epochs are derived with differnt moving window size according each condition of recorded epochs. In addition, all votes are observed while computing the score of each feature epochs. At the next step, the pecentage of votes according three condition stimulus are used to compare with the preseted threshold. If the percentage over the threshold and over 3 trials are recorded than a dicision is made and the result presented on the screen. Otherwise, the next trial are record until reach the threshold. But the must be made while 10th trial are recorded even though not reached the threshold.

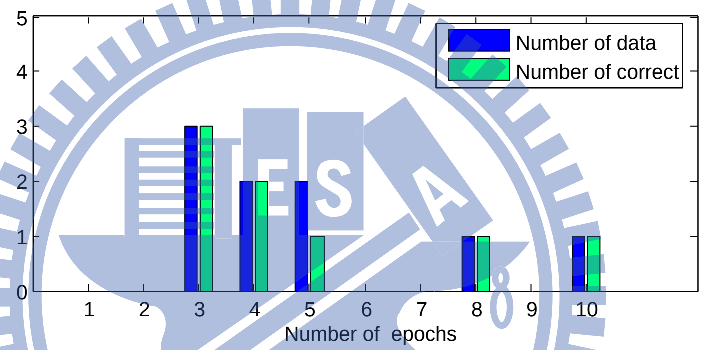
4.2.3 Feedback

While a decision is made, a visual feedback is presented on the screen. The feedback show the answer from subject that the system inferred. Although the feedback is not real time response to the subjects. But it still reflect how much attention subjects pay to the target stimulus and how concentrated subjects are. That can help subjects to pay more attention or to change the mental task for improving the performance of the online system.

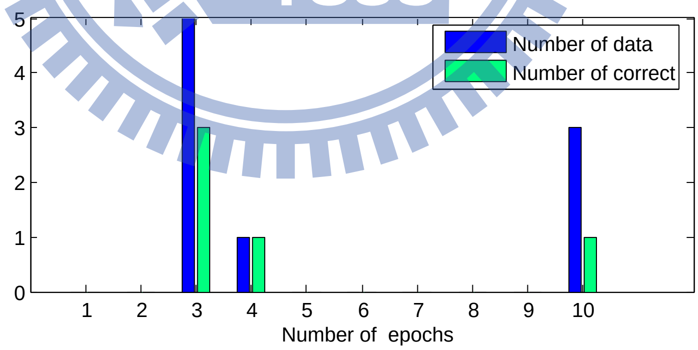
4.2.4 Experiment result



(a) Subject 1

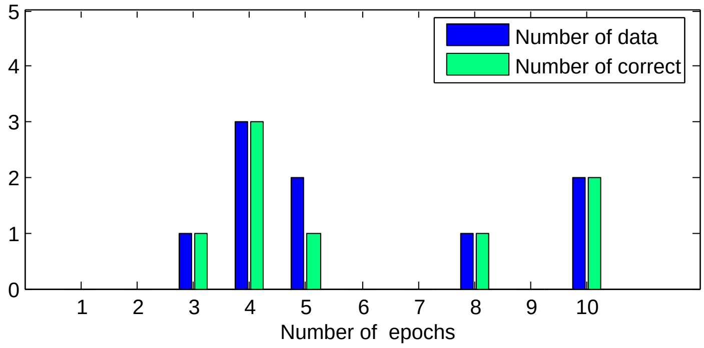


(b) Subject 2

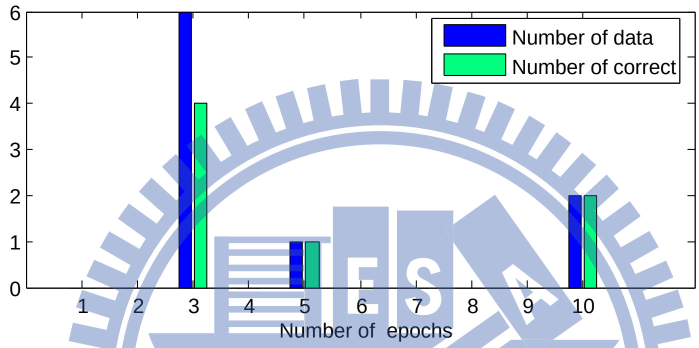


(c) Subject 3

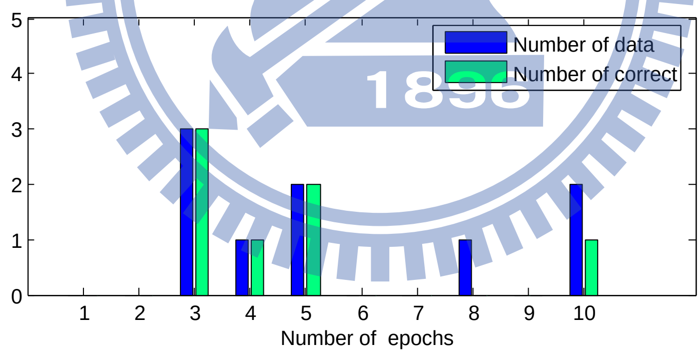
Figure 4.12: The online testing results. The blue bar represent the number of runs achieve the threshold in how many trials be recored. The green bar represent the number of correct runs while archieving the threshold.



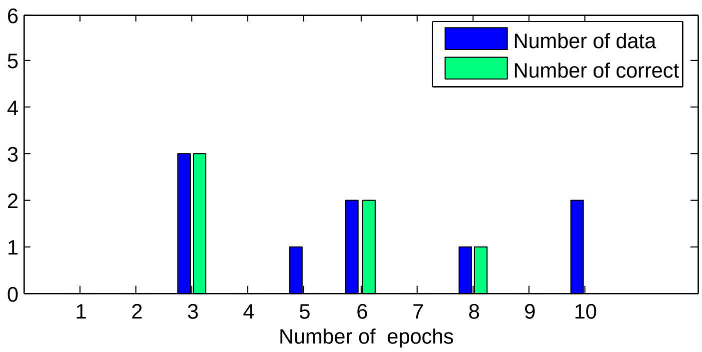
(a) Subject 4



(b) Subject 5



(c) Subject 6



(d) Subject 7

Figure 4.13: The online testing results. The blue bar represent the number of runs achieve the threshold in how many trials be recored. The green bar represent the number of correct runs while archieving the threshold.

Information transfer rate of online testing						
Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7
5.28	5.28	3.96	5.28	3	5.28	5.28

Table 4.2: The maxmum bit rate/min in online testing by setting the threashold to 80%.

4.3 Summary

Offline analysis

- Setting the higher threshold of votes leads to high accuracy with low probability of achievement, or vice versa. Through the analysis result, we can select a suitable threshold which can maintain high accuracy and reasonable probability of achievement.
- The classification accuracy is significantly improved by setting the voting threshold.
- In online simulation, the communication rate are speeded up. Take Subject 1 for example, the accuracy is high enough while setting the threshod greater than 70%. Over 90% data achieve the threshold before the tenth trial.

Online testing

- In online testing, the accuracy of three subjects are higher then 89%(eight correct and one incorrect) accuracy. Furthermore, the accuracy of five subjects are higher then 78% (seven correct and two incorrect). We believe the voting method has its effectiveness and stability.

Chapter 5

Disscusion

In this chapter, we will discuss the performance of differenct adaptiv method, and give the discussions of the comparison between our system and Seller's system.

Feature selection

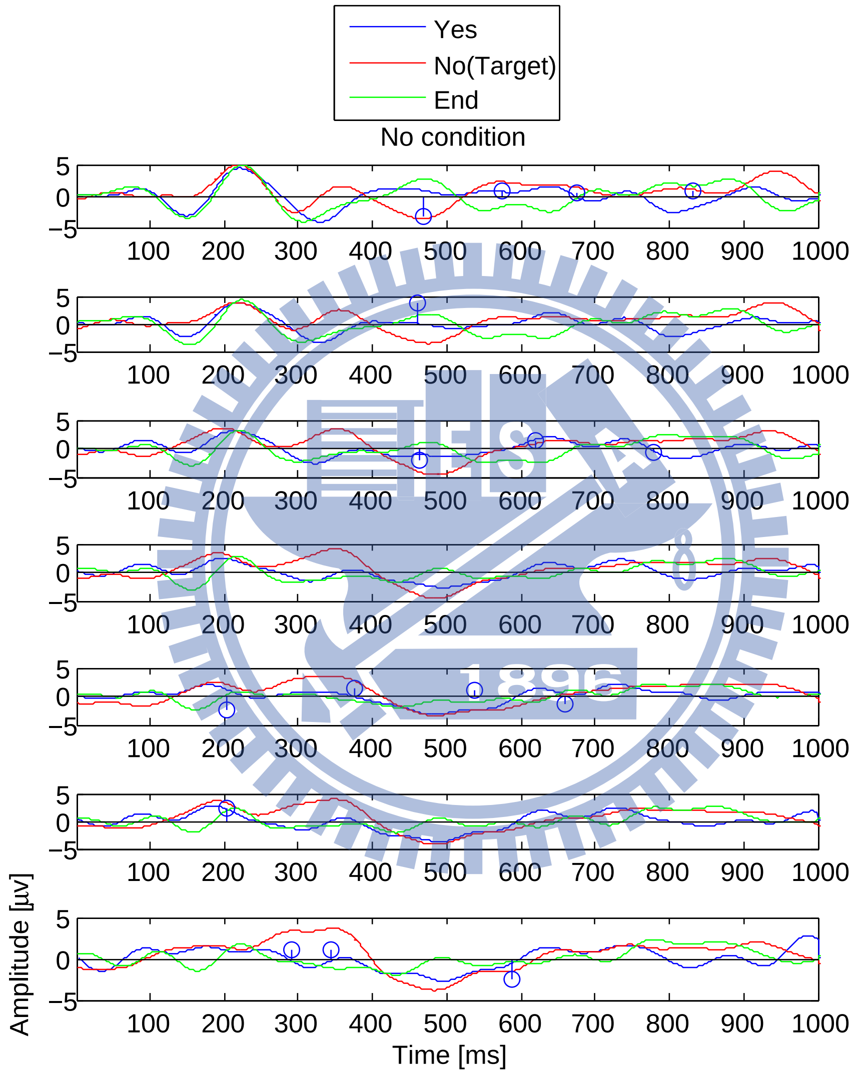
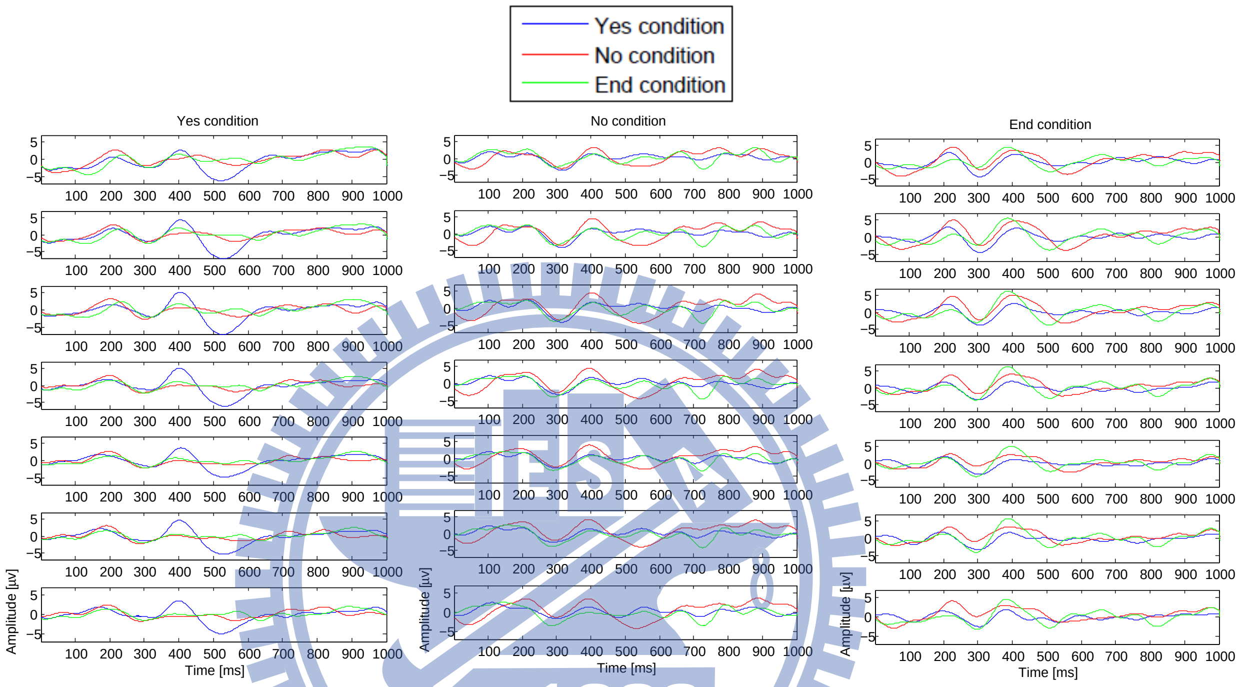


Figure 5.1: The feature points are selected by SWDA. The stem mean feature point, and up stem mean positive weighting, down stem mean the negitive weighting.

We use SWDA to select the feature points from three condition training data. Figure 5 shows that the feature points are commonly locating in seven channels. Futhremore, most of the feature points locate in the 200 ms to 600 ms. That is the time duration of P300 and N400. The experiment result are similar as our expectancy.

Three target condition comparison



(a) Yes target condition (b) No target condition (c) End target condition

Figure 5.2: The averaging data in three target condition. Each figure show the averaging data in seven channel while subjet pay attention to different stimulus.

In this section, we compare the averaging data while the subject pay attention to different stimulus.

In our experiment, while the specific stimulus which is called target is shown on the screen, subjects are asked to do mental counting and do not react to another stimulus. Thus, the P300 response will be elicited while the target is presented. In Figure 5.2, we can see the different P300 response in different target conditions. In our study, mental counting is the way to confirm that the subject actually focuses on the target stimulus. Before the experiments, we also test three different ways such as tapping, noting, and mental counting to help the subject focus on the target. The result shows the P300 response is elicited while subjects do the three tasks. It also proves that P300 response is elicited while subject pay attention on the target stimulus.

Adaptive method comparison

In this section, we compare another thresholding technique with our voting mehod. We also compare the performance of each method.

In the past study of P300 BCI system, most of them focused on improvement of the discriminant accuracy with fixed number of stimulus, but payed less attention to the adaptability of online BCI system. An thresholding technique that is able to dynamically adapt to stop has been described by Serby. In the Serby's system, the threshold is designed based on the classfier score, and it significantly improves the speed of communication rate in online system. However, the performance of Serby's classifier without thresholding technique is worse than the performance of SWDA perform by Donchin [5]. Therefore, we believe that designing the threshold based on the score computed by SWDA may improve the performance of the system. Thus, we test the thresholding technique based on the scores computed by SWDA, the scores could be regarded as the standard of reliability. The result is shown in Figure 5.4(a). Another idea decribed in Section 3.3 is using sequential results as the temporal features which can be seen as the standard of reliability. In addition, we also use temproal features to vote, and the tesing result are shown in Figure 5.4(b). Furthermore, the testing result of our voting method which uses the same data are shown in Figure 5.3. From the result, we find the voting method has the best performance. The result of score-based thresholding technique shows high classification accuracy by large threshold but has very low probability of achievement. Moreover, the probability of achievement by using sequential result to vote is similar to the voting by moving window, but using sequential result has worse classification accuracy. In the score-based thresholding technique, although the score is a good classification standard, it has the less information than the voting which uses the temporal feautures. In another technique, using the sequential result as the temporal feautes has disadvantage, because the influence of early recorded trials are larger. Thus, we prove that the voting method proposed is a better way to implement adaptability.

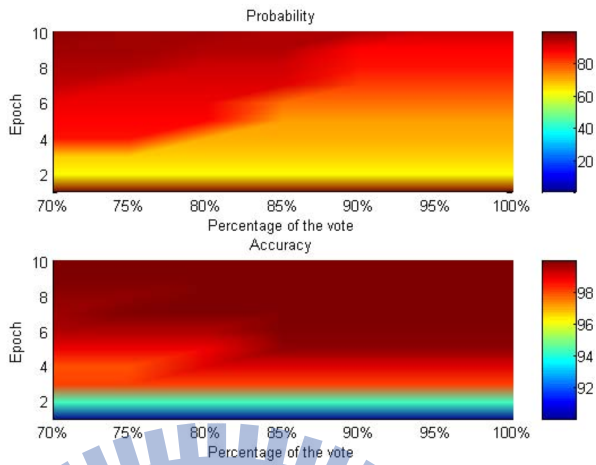
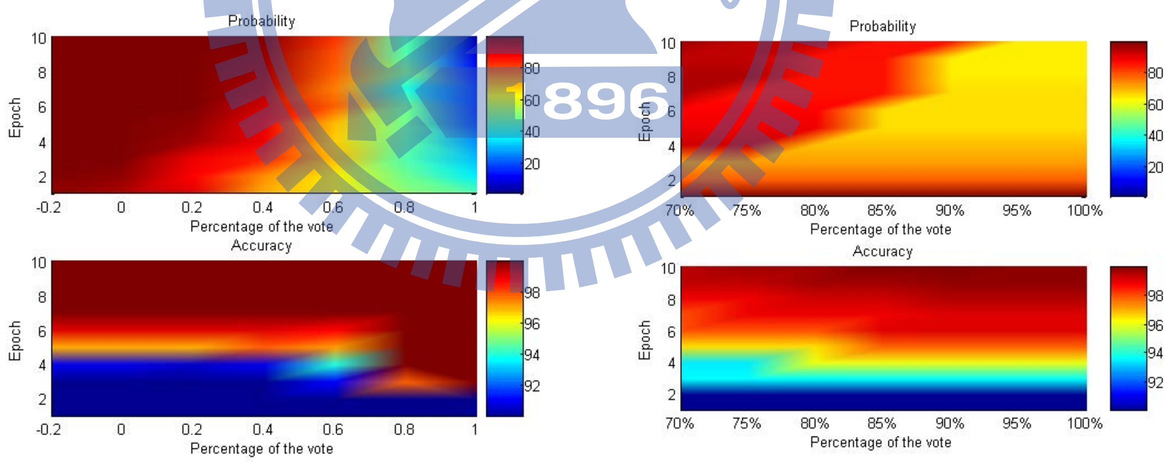


Figure 5.3: The probability and accuracy which using votes as the standard of reliability.



(a) Score based

(b) Sequential result based

Figure 5.4: Figure(a) show the achieve probability and accuracy which using socre as the standard of reliability. Figure (b) show the achieve probability and accuracy which using the sequential results as the standard of reliability.

Performance comparison

The best information transfer rate of Seller's system is shown in Table 5.2. Moreover, in our work, the best information transfer rate of three subjects in offline analysis are 7.7 (83.4%), 3.64 (82.1 %) and 5.74 (76.9%), and in online testing are 5.28 (100%), 5.28 (100%), 3.96 (100%). Furthermore, we also test the three-choice system and four-choice system on the same subject. The comparisons of performance between three and four choice system are shown in Table 5.1. We can see that the information transfer rate of four-choice system is actually improved by voting. Moreover, the performance of three-choice system is better than four-choice system. Thus, we believe that our system significantly improve the performance in two ways. First, even though the probability of the target stimulus in three-choice paradigm is larger than the probability of the target stimulus in four-choice, the results show that the P300 response still can be reliably elicited by the three-choice paradigm. Second, the stimulus duration is shorter in our system. These two factors largely influence the performances. In addition, most answers to questions or choices in daily life are binary. Thus, we believe that the three-choice system is more practical and more efficient.

Information transfer rate of offline analysis

		Subject 1 (Three choice)	Subject 1 (Four choice)
Bootstrap analysis result (SWDA)	Max bit rate/min	7.70 (83.40%)	2.37 (81.5%)
	Average bit rate/min	2.45 (66.69%)	0.93 (66.5%)
Bootstrap analysis result (80% votes)	Max bit rate/min	7.70 (83.40%)	4.32 (89.95%)
	Average bit rate/min	3.24 (84.15%)	1.94 (74.34%)
Online simulation (80% votes)	Max bit rate/min	5.28 (100.00%)	5.00 (100.00%)

Table 5.1: The comparison of information transfer rate between three choice system and four choice system. The maxmum bit rate/min and average bit rate/min of subjects 1 by the discrimination only SWDA, voting threashold be set to 80% and testing in online simulation procedure.

Information transfer rate of Seller's study

		Subject 1	Subject 2	Subject 3
Non-ALS	Max bit rate/min	1.80 (97.00%)	1.04 (82.10%)	0.74 (73.20%)
ALS	Max bit rate/min	0.97 (79.60%)	0.74 (73.2%)	0.43 (61.60%)

Table 5.2: The best information transfer rate in Sellller's study. [16]

Chapter 6

Conclusions

In this thesis, we focus on a BCI system using P300 ERP, and design a three-choice pradigm in the BCI system. Futhermore, we use the voting streategy to develop an adaptive and effencient online BCI system. In the following parts, we will discuss the significance in each component.

In experiments, we confirm that the three-choice paradigm used to lead the P300-based BCI is more efficient than four-choice paradigm. Moreover, we prove that a pratical BCI system can be implemented by a simple interface, and don't require complex tasks.

In offline analysis, we combine SWDA and movining window to produce temporal features which is the vote, and compute the percentage of votes. Thus, we can regard the percentage of votes as the standard of reliability; if the percentage of votes is high, the degree of reliability is high, or vice versa. By way of bootstraping procedure, the percentage of votes as the standard of reliability can be proved to have high discriminating accuracy. Moreover, the online simulation result can prove that this technique of this system can efficiently adapt to subjects, and also adapt to each run of experiments performed by the same subject. Futhermore, in virtue of observing the offline analysis result we can select the suitable threshold based on each subject, thus making the BCI system more flexible. We also prove that using moving window to establish a standard of reliability can yield better performance and more feasibility than using the score or squential results.

In online testing, automatically adapting to stop actually speed up the online communication rate with high discrimination accuracy. The three subjects recruited to participate the offline system have good performance. Two of them also have the expected good performance in online testing. However, we find the other one have poor performances in online testing. With the self-report of the subject the poor performance is due to the lost of concentration during the experiments. In order to solve this problem, using different mental tasks may be helpful to subjects who lose concentration during the experiment. Or, we could set the higher threshold with reduced communication rate.

In this system, although the paradigm duration is longer, we lack the main disadvantages existing in other proposed BCI systems such as speller or motor-based BCI. For instance, Speller has the disadvantage that subjects have to do more eye movements. Also, the motor-based BCI has longer training time and requires subjects' initial training. In conclusion, our system has the few eye movements to reduce subject's burden, and requieres no subjects' initial training.In this regard, it is more pratical for a BCI system.

Bibliography

[1] J. D. Bayliss. Use of the evoked potential p3 component for control in a virtual apartment. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 11(2):113–116, 2003.

[2] Niels Birbaumer. slow cortical potentials: Plasticity, operant control, and behavioral effects. *Neuroscientist*, 5(2):74–78, 1999.

[3] Eric H. Chudler. The ”10-20 system” of electrode placement. *Http://faculty.washington.edu/chudler/1020.html*, 2000.

[4] E. Courchesne. Changes in p3 waves with event repetition: long-term effects on scalp distribution and amplitude. *Electroencephalogr Clin Neurophysiol*, 45(6):754–66, 1978. Courchesne, E Research Support, U.S. Gov't, P.H.S. Netherlands Electroencephalography and clinical neurophysiology Electroencephalogr Clin Neurophysiol. 1978 Dec;45(6):754-66.

[5] E. Donchin, K. M. Spencer, and R. Wijesinghe. The mental prosthesis: assessing the speed of a p300-based brain-computer interface. *Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Neural Systems and Rehabilitation]*, 8(2):174–179, 2000. 7.8 chars/min. Similar paradigm to the original P300 matrix speller.

[6] Norman Draper. and Harry Smith. Applied regression analysis (2nd ed.): New york: Wiley. 1981.

[7] L. A. Farwell and E. Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr Clin Neurophysiol*, 70(6):510–523, 1988.

[8] Galen F. Hagen, James R. Gatherwright, Brian A. Lopez, and John Polich. P3a from visual stimuli: Task difficulty effects. *International Journal of Psychophysiology*, 59(1):8–14, 2006. doi: DOI: 10.1016/j.ijpsycho.2005.08.003.

[9] D. J. Krusienski, E. W. Sellers, F. Cabestaing, S. Bayoudh, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw. A comparison of classification techniques for the p300 speller. *J Neural Eng*, 3(4):299–305, 2006. Krusienski, Dean J Sellers, Eric W Cabestaing, Francois Bayoudh, Sabri McFarland, Dennis J Vaughan, Theresa M Wolpaw, Jonathan R Comparative Study England Journal of neural engineering J Neural Eng. 2006 Dec;3(4):299-305. Epub 2006 Oct 26.

[10] Tomas Hruby Marsalek and Petr. Event-related potentials - the p3 wave. *Acta Neurobiologiae Experimentalis*, 63(1):55–63, 2003.

[11] G. R. Muller-Putz and G. Pfurtscheller. Control of an electrical prosthesis with an ssvep-based bci. *Biomedical Engineering, IEEE Transactions on*, 55(1):361–364, 2008.

[12] G. Pfurtscheller, R. Leeb, C. Keinrath, D. Friedman, C. Neuper, C. Guger, and M. Slater. Walking from thought. *Brain Res*, 1071(1):145–152, 2006.

[13] G. Pfurtscheller and F. H. Lopes da Silva. Event-related eeg/meg synchronization and desynchronization: basic principles. *Clin Neurophysiol*, 110(11):1842–1857, 1999.

[14] F. Piccione, F. Giorgi, P. Tonin, K. Priftis, S. Giove, S. Silvoni, G. Palmas, and F. Beverina. P300-based brain computer interface: reliability and performance in healthy and paralysed participants. *Clin Neurophysiol*, 117(3):531–537, 2006.

[15] Brice Rebsamen, Etienne Burdet, Cuntai Guan, Haihong Zhang, Chee Leong Teo, Qiang Zeng, Christian Laugier, and Marcelo H. Ang Jr. Controlling a wheelchair indoors using thought. *IEEE Intelligent Systems*, 22(2):18–24, 2007. 1251919.

[16] E. W. Sellers and E. Donchin. A p300-based brain-computer interface: initial tests by als patients. *Clin Neurophysiol*, 117(3):538–548, 2006.

[17] H. Serby, E. Yom-Tov, and G. F. Inbar. An improved p300-based brain-computer interface. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 13(1):89–98, 2005.

[18] KC Squires, C Wickens, NK Squires, and E Donchin. The effect of stimulus sequence on the waveform of the cortical event-related potential. *Science*, 193(4258):1142–1146, 1976.

[19] Erich Sutter. The brain response interface: communication through visually-induced electrical brain responses. *J. Microcomput. Appl.*, 15(1):31–45, 1992.

[20] Samuel Sutton, Margery Braren, Joseph Zubin, and E. R. John. Evoked-potential correlates of stimulus uncertainty. *Science*, 150(3700):1187–1188, 1965.

[21] T.Hinterberger., J. M. Houtkooper., and B. Kotchoubey. Effects of feedback control on slow cortical potentials and random events. *The Parapshchological Association Convention*, 2004.

[22] Jonathan R. Wolpaw, Niels Birbaumer, Dennis J. McFarland, Gert Pfurtscheller, and Theresa M. Vaughan. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 113(6):767–791, 2002. doi: DOI: 10.1016/S1388-2457(02)00057-3.