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Project Title
An E-Book Viewer with Automatic Page Turning Controlled by Analyzing Brainwave

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Abstract

E-books become increasingly convenient and popular nowadays. However, most e-book viewer applications with traditional computer interface are not accessible for people with severe motor disabilities. This project aims to develop a user-friendly e-book viewer with brain computer interface (BCI) to assist those people to read an e-book.

The BCI system is designed to acquire the EEG data, extract features from the data, classify the data and use the classification result to control the page turning. A customer-grade Electroencephalography (EEG) device called Mindwave Mobile from NeuroSky is used to detect the brainwave data from users. Experiments on blinking, motor imagery, color and eye states have been conducted to find out the best way to analyze a user's mental states recorded by the single dry-contact EEG electrode at Fp1. The final solution is to use the fast Fourier transform (FFT) and a signal quantization method to transform brainwave raw data into feature vectors, classify the data by a linear Support Vector Machine (SVM) model and select blinking and eye states (eyes opening and closing) as the brain control.

This report discusses the design, implement and testing of a BCI system. The result is an e-book viewer application that users can turn pages to the previous and next by keeping eyes closed and open respectively with over 99% accuracy, which can inform the design of BCI applications with the MindWave Mobile that can benefit people with severe motor disabilities.

Acknowledgments

This report about my final year project is to complete my Bachelor of Computer Science at City University of Hong Kong. I would like to thank the Department of Computer Science for offering devices and guidelines on this project. I would also like to express my gratitude to my supervisor, Assistant Professor Howard Leung for giving me valuable suggestions and supporting me throughout the whole project.

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1. Introduction

1.1 Motivation & Problem Significance

At present, people mainly use keyboards and mouse devices to interact with computers. However, these conventional human computer interfaces (HCIs) are not accessible for people with severe motor disabilities. A new communication option, brain computer interface (BCI) technology, has been explored by researchers over the past decades.

BCI is based on neural activity; it does not depend on peripheral nerves and muscles. One main method of this new technology is to record the brain electrical activity from the scalp as electroencephalograph (EEG) [1] and use supervised learning algorithms to recognize the corresponding mental gestures [2]. Thus EEG-based BCI can benefit users with neuromuscular impairments.

Since it has become ubiquitous that people read e-books instead of books in printed form, I am motivated to design a user-friendly e-book viewer system with an EEG-based BCI. A low-cost, mobile EEG device called MindWave Mobile from NeuroSky is used in this project, which is able to report various brainwave data, as presented in Figure 1.1. Classification algorithms can be applied to the EEG samples produced by MindWave Mobile to perform a pattern recognition task, so that the system can recognize a user's commands. Through EEG-based BCI, the e-book reading experience for people with severe motor disabilities can be more natural and comfortable.

Output	**Description**
Signal	Returns poor signal level, 0 is good signal, 200 is off-head state.
Raw Data	Returns raw data values, sampled at 512 Hz.
Delta	The "delta band" of EEG (0.5-2.75Hz).
Theta	The "theta band" of EEG (3.5-6.75Hz).
Alpha 1	The "low alpha" of EEG (7.5-9.25Hz).
Alpha 2	The "high alpha" of EEG (10-11.75Hz).
Beta 1	The "low beta" of EEG (13-16.75Hz).
Beta 2	The "high beta" of EEG (18-29.75Hz).
Gamma 1	The "low gamma" of EEG (31-39.75Hz).
Gamma 2	The "high gamma" of EEG (41-49.75Hz).
Attention	Returns the eSense Attention integer value, between 0 and 100.
Meditation	Returns the eSense Meditation integer value, between 0 and 100.
Blink	Returns an integer value between 0-255, indicating the blink strength.

Figure 1.1: NeuroSky MindWave Mobile Output [3]

1.2 Problem Definition

Although the popularity and availability of e-books are rising, most e-book viewer applications are not usable for people with severe motor impairments, because it is difficult for those people to input commands such as turning pages by keyboards or cursors.

1.3 Project Scope

The project consists of an e-book viewer and an EEG device called MindWave Mobile from NeuroSky. The e-book viewer has both traditional computer interface and brain computer interface, which allows different inputs including the following:

- Traditional computer interface
  - Mouse input
- Brain computer interface (connected to MindWave Mobile)
  - Signal
  - Raw data
  - Brainwave frequency bands
  - Level of attention
  - Level of meditation
  - Blink

The project also consists of a number of functionalities including the following:

- Displaying pdf e-books
- Opening and closing e-books
- Turning pages automatically
- Confirmation for commends

2. Related Work

2.1 Major alternatives of the problem

A major alternative of the problem is to use voice control. For example, an e-book viewer on Windows can use SUITEKeys. The SUITEKeys system is a speech user interface for motor-disabled users to control a virtual keyboard and mouse to input commands. If this system is applied to an e-book viewer, users can turn pages by saying the name of the corresponding key or speaking as if they are transcribing to a person how to perform the same actions with a mouse [4].

Another way to use voice control is to directly speak out the command to the e-book viewer. For instance, users can speak out 'next' or 'previous' to make the viewer turn to the next or previous page correspondingly. Also, an existing iOS mobile application called Voice Control Reader uses auto-scrolling and two voice commands 'play' and 'stop' to control paging (though it cannot turn to the previous page by voice commands)[5].

The alternative is useful for most motor-disabled people but is not suitable for those who also have speech disabilities.

2.2 Current status & limitation

Although many research papers discuss different approaches for processing EEG signals, there are relatively few of them talking about how to design and implement applications using brain computer interface. Most applications described in the papers as well as the available products on the market focus on scientific experiments, neurofeedback training, disease treatments and entertainment. On the one hand, most applications use whole-head multi-channel neuroheadsets such as Emotiv for accuracy, which increases both the cost of the BCI system and time for channel preparation [6]. On the other hand, users usually need to be trained for a long time to adapt to the BCI system.

Rare scientific papers describe BCI based e-book viewer applications but there are still some concern attached to this topic. Two examples are eyeReader and an E-book reader designed by Rejer, I. and Klimek, A.

The eyeReader processes features of the EEG signals acquired from Emotiv EPOC headset to detect the presence and frequency of steady-state visually evoked potentials (SSVEP). And it uses the SSVEP signals as a control signal to turn pages. The eyeReader was only tested three times, on two of the authors, Dunkley, J. and Liu, J. The average detection accuracy is 86.2%.

However, the detecting frequency of control signal (one control signal every ten seconds) is not high [7].

Rejer, I. and Klimek, A. propose an e-book reader based on motor rhythms and motion imaginary strategy. The application detects two mental activity patterns generated when users imagine move their left and right hands respectively. Correspondingly, users can deliver two inputs, activating and changing. The two inputs are used to choose one of several commands in a toolbar. The application was tested by the authors and five other persons. It takes 15 minutes for users to adapt to the interface [8].

3. System Design

Figure 3.1 shows an overview of the main components in the system design. The project is written in .Net development environment of Microsoft Visual Studio 2013, using C# as the programming language. A Dell desktop computer with Windows 8 system has been used as the project computer.

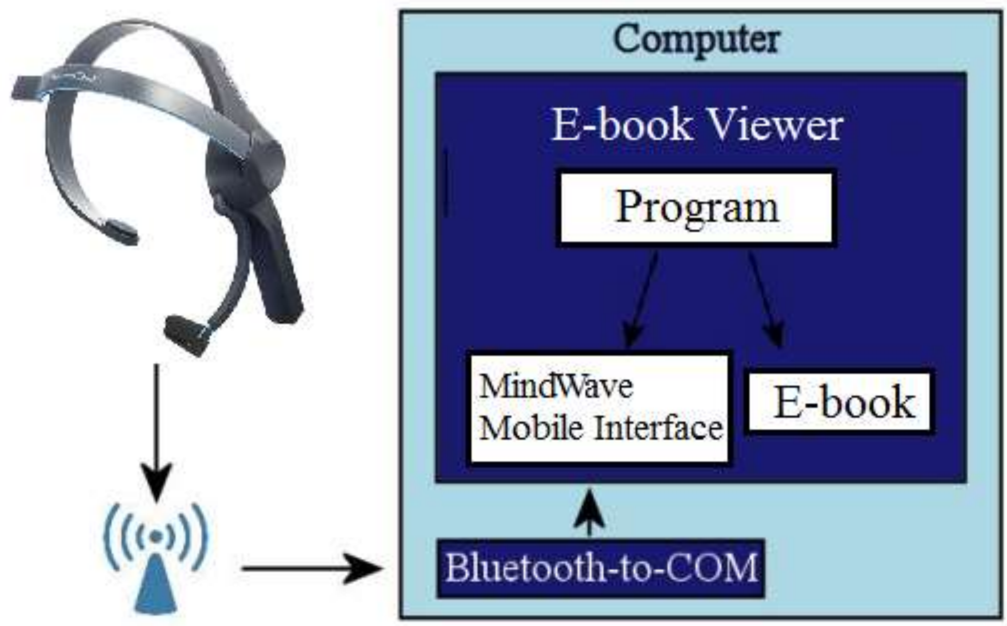
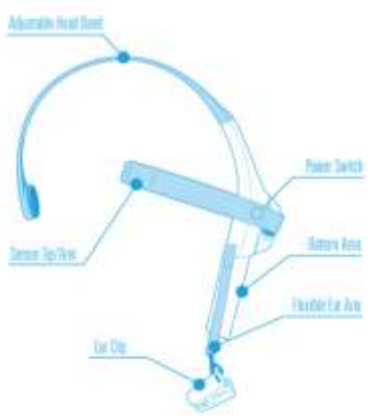


Figure 3.1: System design: component overview. NeuroSky MindWave Mobile and the computer program main parts.



NeuroSky MindWave Mobile: an EEG device consists of ThinkGear technology. The ThinkGear includes a sensor that should be put on and touch the forehead, the contact and reference points in the ear clip, and the on-board chip that processes all data [3]. The chip can calculate the raw brainwaves, brainwave frequency bands and the level of attention and meditation as Figure 1.1.

Figure 3.2: MindWave Mobile HeadSet

MindWave Mobile Interface: NeuroSky provides libraries for many platforms and programming languages, which require Bluetooth communication to connect the computer and the MindWave Mobile. In this project, the ThinkGear SDK for .Net API is used. It can detect and handle device's connection and disconnection, and output the raw data at 512Hz, blink strength when it detects blinking and other data such as frequency bands, attention and meditation at 1Hz.

Bluetooth: an additional Bluetooth adapter is needed for this project. It is used to convert the Bluetooth connection to a COM-port, so as to connect the device and the program.

Program with Brain Control Interface: the program written in C# uses a graphical user interface with brain control. This program has two modes: reading mode and experiment mode. A user can open and read the pdf e-book by mouse device in both modes. In the experiment mode, it can record EEG brainwave data from the MindWave Mobile as JSON files for experimental use. In the reading mode, the program can execute the actions by analyzing the real-time brainwave data from the MindWave Mobile. In order to find significant mental activity patterns, I performed multiple mental experiments, which will be covered in Chapter 4. Detailed interface design will be discussed in Chapter 5.

4. Experiments

4.1 Blinking

Since the MindWave Mobile can generate the blink strength whenever a blink occurs and has a high detection accuracy of blinking, the program was designed to use eye blinks to trigger the turning page commands to reduce the interference during reading.

According to a study on blink rate patterns in normal subjects conducted in [9], the mean blink rate for normal people was 17 blinks/min at rest, 26 blinks/min during conversation and 4.5 blinks/min while reading. Another study in [10] shows that the mean blink rate for reading from a computer screen was 14.9 blinks/min. However, the eye blink rate varies a lot between individuals, ranging from 2.8-48 blinks/min. People who have 'frequent' eye blink activity would blink more than 20 per minute [11]. I recorded the eye blinks for 5-min reading on the screen using this program and the blink rate was around 19.2 blinks/min. In summary, I assumed a user would blink 20 times in one minute when reading on this application, i.e., between each blink is an interval of 3 seconds.

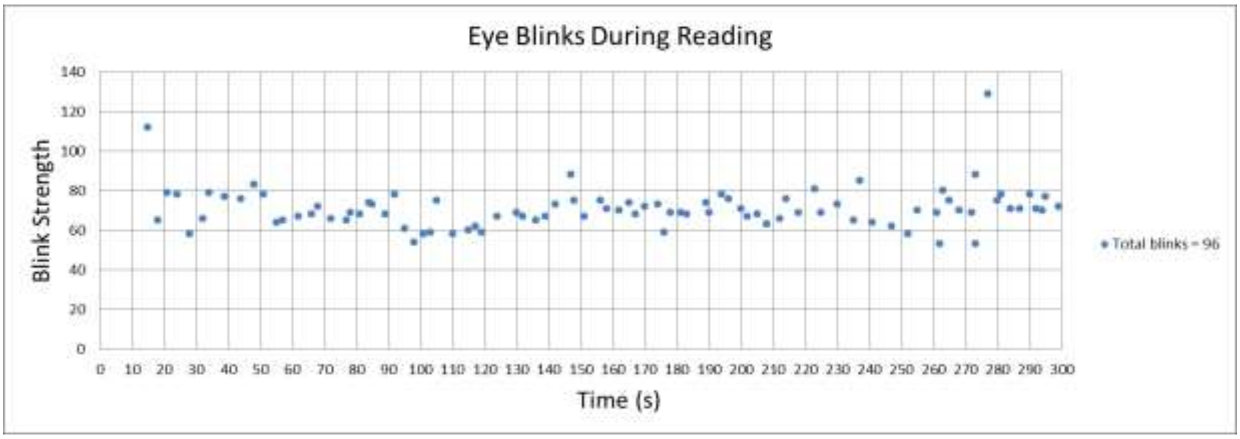


Figure 4.1: Eye blinks in 5-min reading on this application.

In addition, the blink strength of eye blinks in the 5-min reading record was mainly less than 80 while it was easy for me to intentionally blink at strength larger than 80. Since the duration of a single blink is between 100-400ms [12], it is enough for a user to intentionally blink twice in 2 seconds. Considering the user experience during reading, the system should avoid false positive detection of blinking to the greatest extent but could allow missing trigger detection. Therefore, to handle the tradeoff between the false positive rate and the false negative rate, the program was designed to allow users to turn pages only when they blink at least twice at strength > 80 in 2 seconds. To validate this design, I conducted another 5-min reading experiment (natural blinking) and 100 trigger experiments (intentional blinking). The false positive rate was 0 and the false negative rate was 77%, which could meet the design requirements.

Actual Class / Predicted Class	Trigger +	Not trigger -	Total
Trigger +	77	0	77
Not trigger -	23	95	118
Total	100	95	195

Figure 4.2: Testing results on the trigger design.

4.2 Tasks

As long as the program successfully triggers the turning page commands, it needs to decide the command: turn page to the previous or to the next. Therefore different tasks were designed to explore two distinguished mental states which could be classified by supervised learning algorithms. According to the 10-20 electrode placement system (Figure 4.1), the Neurosky MindWave Mobile electrode (the forehead sensor) is placed at Fp1. Due to the real-time property and reading function of the e-book viewer application, three group of tasks related to Fp1 are selected.

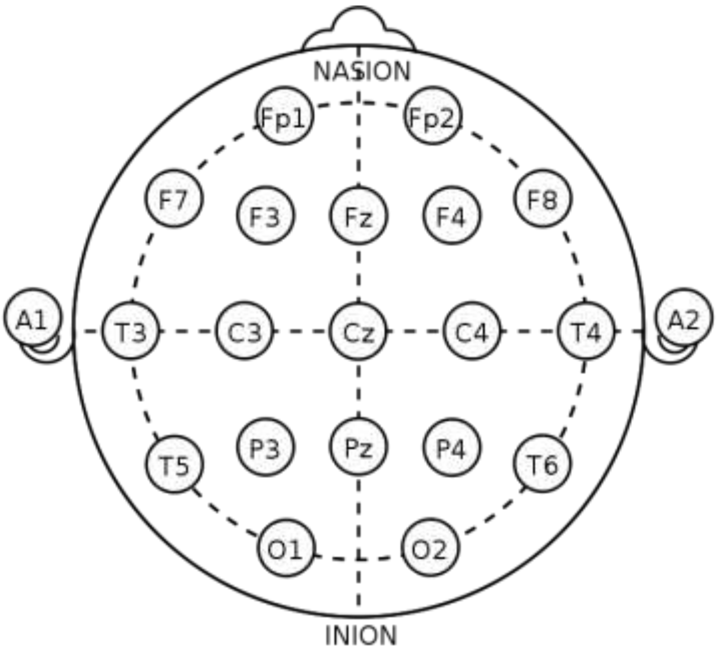


Figure 4.3: The International 10-20 electrode placement system.

Motor imagery of hand movements (left hand and right hand): Subjects imagine moving their left or right hand in their minds without actually moving corresponding hand. Past studies showed that the accuracies obtained from forehead electrodes can be equivalent to those from electrodes placed at sensorimotor area [6].

Color stimuli (red and blue): Subjects stare at a red or blue rectangle. It was shown in [13] that the power densities of the alpha band as measured by EEG at Fp1were greater when the subjects looked at red paper than looking at blue paper.

Eye states (open and closed): Subjects open or close their eyes. Eyes opening shows a negative deflection at Fp1 while eyes closing results in a positive deflection at Fp1 [14].

To avoid excessive electrooculography (EOG) and electromyography (EMG) artifacts (EOG artifacts are generated mainly by blinking and rolling of the eyes and EMG artifacts are related to movement of head and body) [15], subjects need to keep gaze steady on a point (except for eyes closing experiments) and try not to blink eyes and move any part of their body. Therefore, when performing the tasks in the motor imagery group and the eyes opening task, subjects would be instructed to keep their gaze fixed on the sentence in the pop up confirmation window (Figure 4.4); in the experiments of color stimuli, subjects should stare at the center of the corresponding color rectangle (Figure 4.5).

Figure 4.4: Interface in the experiment mode for motor imagery and eyes opening tasks.

Figure 4.5: Interface in the experiment mode for color stimuli tasks.

4.3 Brainwave Data

I conducted the experiments with the NeuroSky MindWave Mobile in a sitting position in a quiet and closed room setting and performed 20 trials for each of the six tasks and each trial lasted 10 seconds. The EEG samples consisting of raw data, frequency bands, attention and meditation were recorded every 0.5 second as JSON files and stored in the corresponding task folder using the e-book viewer program in the experiment mode. Therefore, each task consisted of 20*10*2 = 400 brainwave samples and each group consists of 800 samples. Since the raw data was sampled at 512 Hz from the MindWave Mobile, each sample consisted of 256 raw data values. Other data was sampled at 1Hz so that the two samples generated in the same second shared the same values of frequency bands, attention and meditation.

4.4 Feature extraction

The raw data of each sample was converted into a two-sided power spectrum using ALGLIB's fast Fourier transform (FFT) and transformed into a single-sided power spectrum containing 256/2 = 128 data points by discarding the second half of the power spectrum array. To optimize both the accuracy and the computing time of the classifier, I adopted a signal quantization method proposed from [16]: average K adjacent power spectra into a single bin and scale each bin by logarithm with base 10. The number of bins B determines the feature size, which can be adjusted.

To achieve the best result of classification, different values of K (the number of power spectra to be averaged) and B (the number of bins) have been tried. Larger K means the power would be assigned to the correct frequency more accurately while generating each sample for command prediction takes longer time (0.25K). Considering both the accuracy after averaging and the real-time testing time, K = {2, 4} was tried. As for B, although the majority of the EEG signals used in BCI research fall in the range of 1-40 Hz, it is possible that the data outsides the frequency range may be useful for classification [16]. Therefore B could be in the interval (1, 128). $B = \{x | x = 10n, n \in N, n < 13\}$ was tried. In each task group, 800/K data with feature size of B was trained.

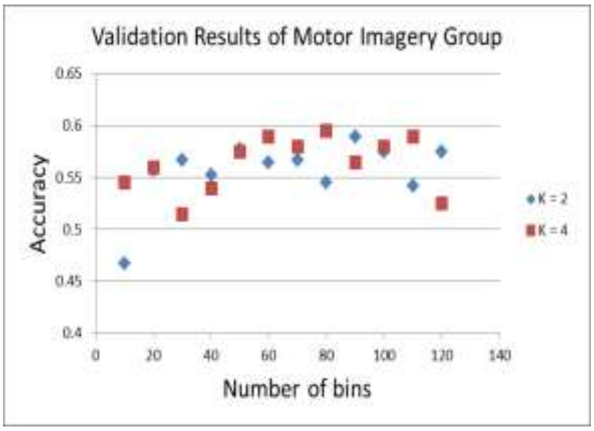
4.5 Classification model

There are mainly five categories of classifiers in BCI design, including linear classifiers, neural networks, nonlinear Bayesian classifiers, nearest neighbor classifiers and combinations of classifiers [2]. Among the linear classifiers, Support Vector Machine (SVM) is frequently used to classify EEG signals because it can deal with feature vectors of high dimensionality and noise and outliers with a high speed and accuracy. A linear SVM from Accord.Net was used in this project. The parameter C of the classifier was selected by grid-search with 5-fold cross-validation.

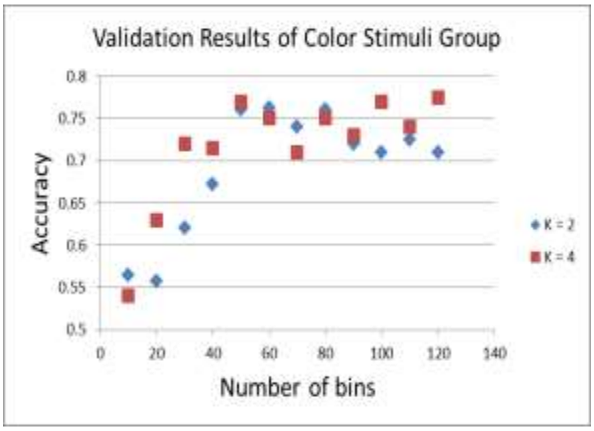
4.6 Training results

Figure 4.6 shows that with the same number of bins, lager number of power spectra to be averaged K results in a higher accuracy for all three groups. However, only eye states group shows a significant difference between the validation results with K = 2 and K = 4. The value of B also affects the validation results. The accuracy of eye states group with K = 2 reaches the peak when B = 50. Except for this, the accuracy tends to increase when B < 60 and remains relatively stable when B >= 60.

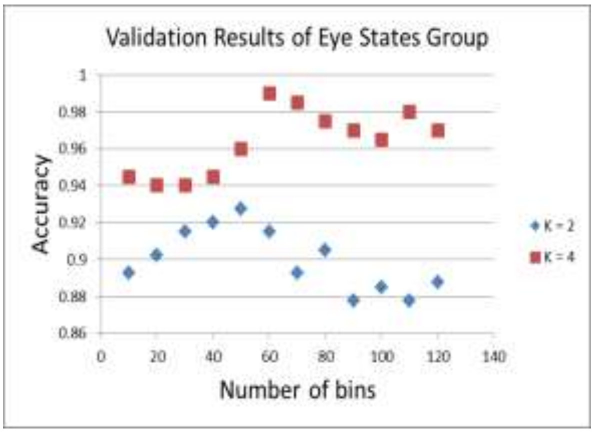
According to the overall results, training data from motor imagery group cannot achieve accuracy significantly higher than a random choice (50%). It is highly probable that there is no connection between brainwave data received from a single electrode at Fp1 and motor imagery of left and right hand. The accuracy can reach above 70% for the color stimuli group, which means red and blue colors are likely to cause different brainwaves at Fp1 that can be classified by SVM. The eye states group has the best validation results: the accuracy of eye states group with K = 4 reaches above 96% when B >=60. Since training with feature vectors of a smaller size requires a shorter training time, B = 60 was selected.



(a)



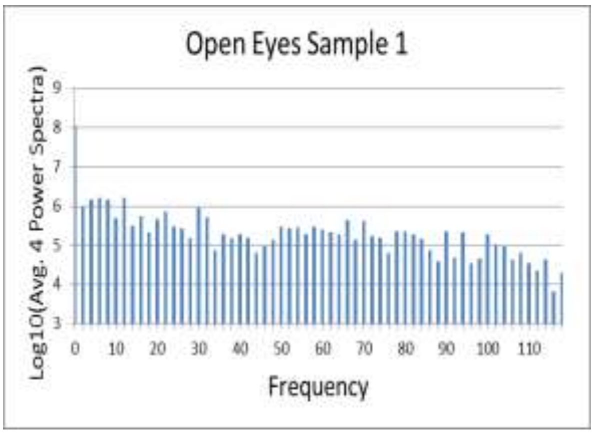
(b)



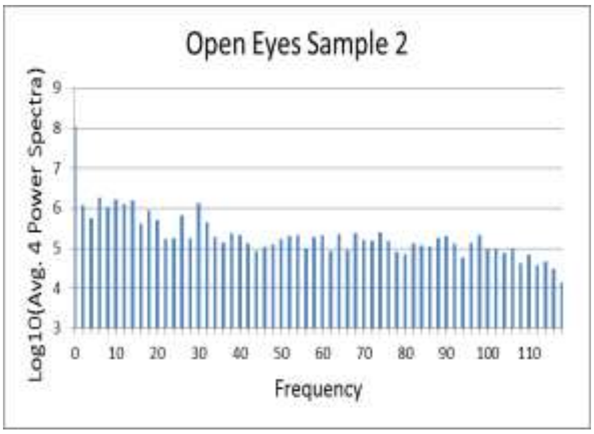
(c)

Figure 4.6: Validation results of three experiment groups. Figure (a), (b) and (c) show the mean validation accuracy of 5-fold cross-validation using experimental data from motor imagery group, color stimuli group and eye states group respectively with parameter K = {2, 4} and B = {x| x = 10n, n ∈N, n < 13}.

Based on the above analysis, the feature extraction method with K = 4 and B = 60 was applied to the eye states training data. From Figure 4.7, it was clear that the processed EEG data of open eyes task was different from that of closed eyes. Compared to the eyes open state, the power spectra was generally higher when closing eyes, especially at the frequency <= 10Hz. Therefore the EEG data of different eye states could be correctly classified by SVM and eye states could be used to indicate turning-page commands. It is necessary to conduct more experiments on eye states and test on the data using the SVM classifier trained with 800/4 = 200 data of 60 features.



(a)



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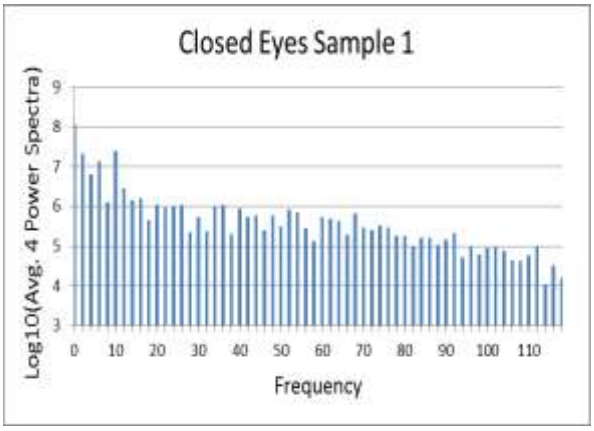

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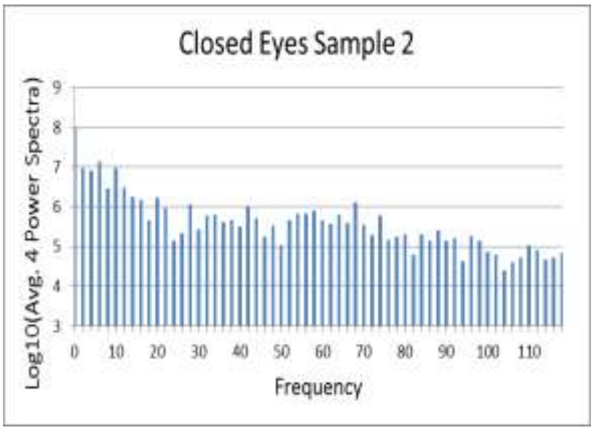

(d)

Figure 4.7: 4 training samples from the eye states group. Each sample is generated by scaling 4 power spectra with 60 bins by logarithm 10.

4.7 Testing results

I performed another 20 trials for each task in the eye states group and each trial took 10 seconds. Therefore each class had 20*10*2 = 400 data samples. Using the feature extraction method with K = 4 and B = 60, each class had 400/4 = 100 testing feature vectors. Figure 4.5 shows the testing results using the trained linear SVM classifier. The overall accuracy is (100 + 97) / 200 = 98.5 %, which is similar to the validation accuracy. The true positive rate is 100 % while the true negative rate is 97/100 = 97 %. Since turning page to the next is a more frequent command, eye opening is used as the command to turn to the next page while eye closing is for the previous page.

Actual Class / Predicted Class	Open +	Closed -	Total
Open +	100	3	103
Closed -	0	97	97
Total	100	100	200

Figure 4.5: Testing results using the trained linear SVM classifier.

5. System Implementation & Detailed Interface Design

The pdf viewer application consists of a toolbar, a pdf display panel and a page number panel. The toolbar includes four buttons (‘Open’, ‘Previous’, ‘Next’ and ‘Settings’) in the default mode (reading mode) and two more buttons (‘Start’ and ‘Stop’) in the experiment mode. Next to the buttons, two text blocks indicate the headset status and signal quality respectively. When running the pdf viewer, a sample pdf is directly shown in the interface. The page number panel shows the current page and the total page. The interface supports both traditional computer interface and brain computer interface.

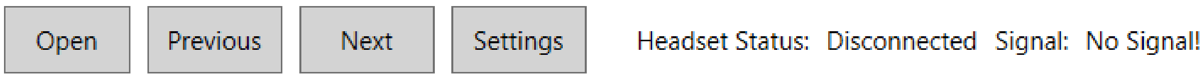

Figure 5.1: The toolbar in the default mode.

5.1 Traditional computer interface

Users can use mouse devices to click ‘Open’, ‘Previous’, ‘Next’ to open new pdf file, turn to previous page and next page correspondingly.

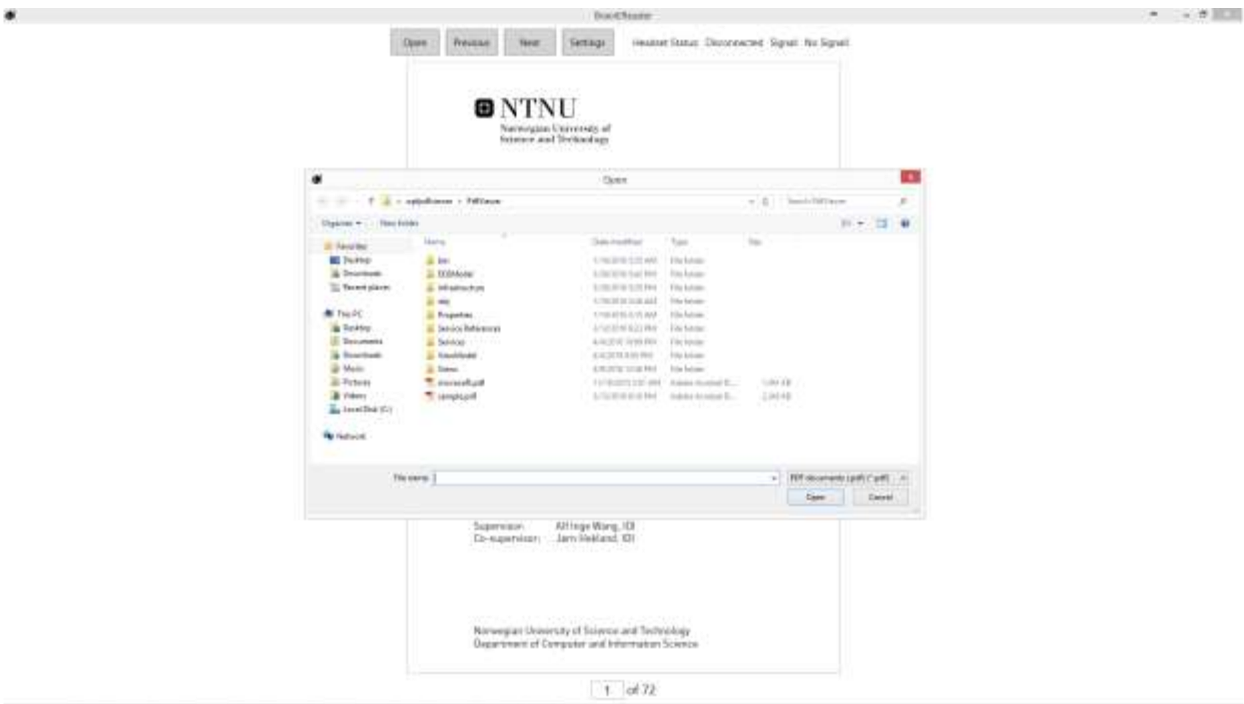

Figure 5.2: The interface after clicking the ‘Open’ button.

The ‘Settings’ button is used to switch mode and set whether to display the confirmation window and play the audio notification when users want to turn pages with brain control. However, the settings can only be modified in the traditional computer interface. Details on settings will be discussed in next section.

5.2 Brain computer interface

5.2.1 Headset Status & Signal Level

The interface will indicate the status of the Mindwave Mobile headset, including ‘Disconnected’ and ‘Connected’. The default status is ‘Disconnected’. The program will search for the device immediately after it starts. The status and the signal level will be ‘Disconnected’ and ‘No signal’ respectively until the program successfully finds the headset. If it is connected, the status and will become ‘Connected,’ and ‘No signal’ will also change to the current signal level - ‘Poor’ or ‘Good.’ Since blinking is only calculated if signal level is less than 51, the signal will be ‘Good’ if the signal value is less than 51. Otherwise, the signal will show ‘Poor’ and the interface will pop up an information window with instructions about how to adjust the headset as Figure 5.3. If the headset is suddenly disconnected, the headset status and the signal level will again be ‘Disconnected’ and ‘No signal’ respectively. The poor signal information window will disappear and the program will keep searching for the headset.

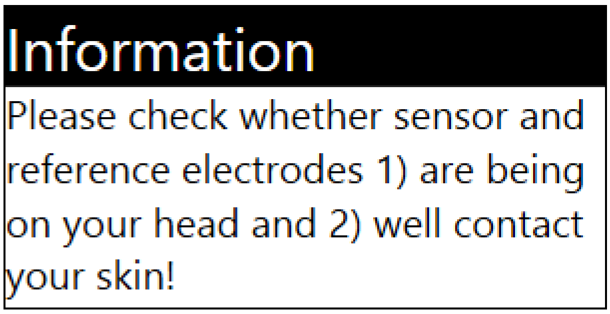

Figure 5.3: The pop up information window when the signal is poor.

Once the signal becomes ‘Good’, the interface will read the EEG data from the headset. The system will either record the data for experimental use in the experiment mode or analyze the data to recognize commands in the reading mode.

5.2.2 Experiment Mode

Since the default mode is reading mode, a user needs to change settings to turn on the experiment mode. Once the radio button ‘Experiment Mode’ is checked, the path configuration will show. A user can change the name of the task and the class. For example, if the task is ‘eye_states’ and the class is ‘1’, then the EEG sample files will be saved under the directory ‘exp\eye_states\1’. The name of a newly created EEG sample file is the same as the number of files in the directory, i.e., the EEG sample is named as ‘0’ when the folder is empty and the second one is ‘1’. Figure 5.5 shows how the EEG samples are stored.

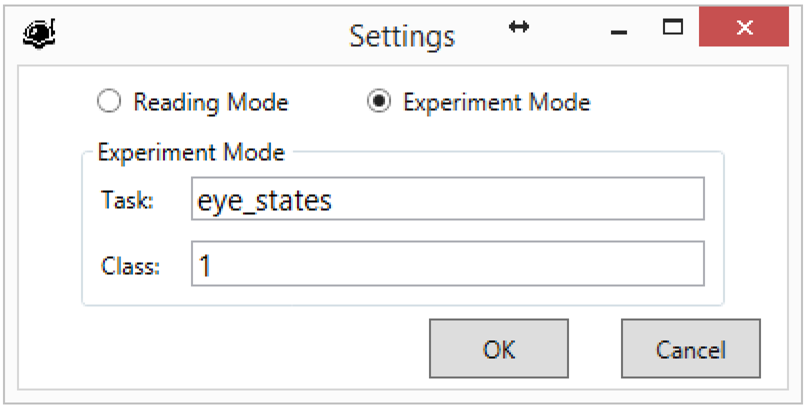

Figure 5.4: The pop up settings window when the experiment mode is checked.

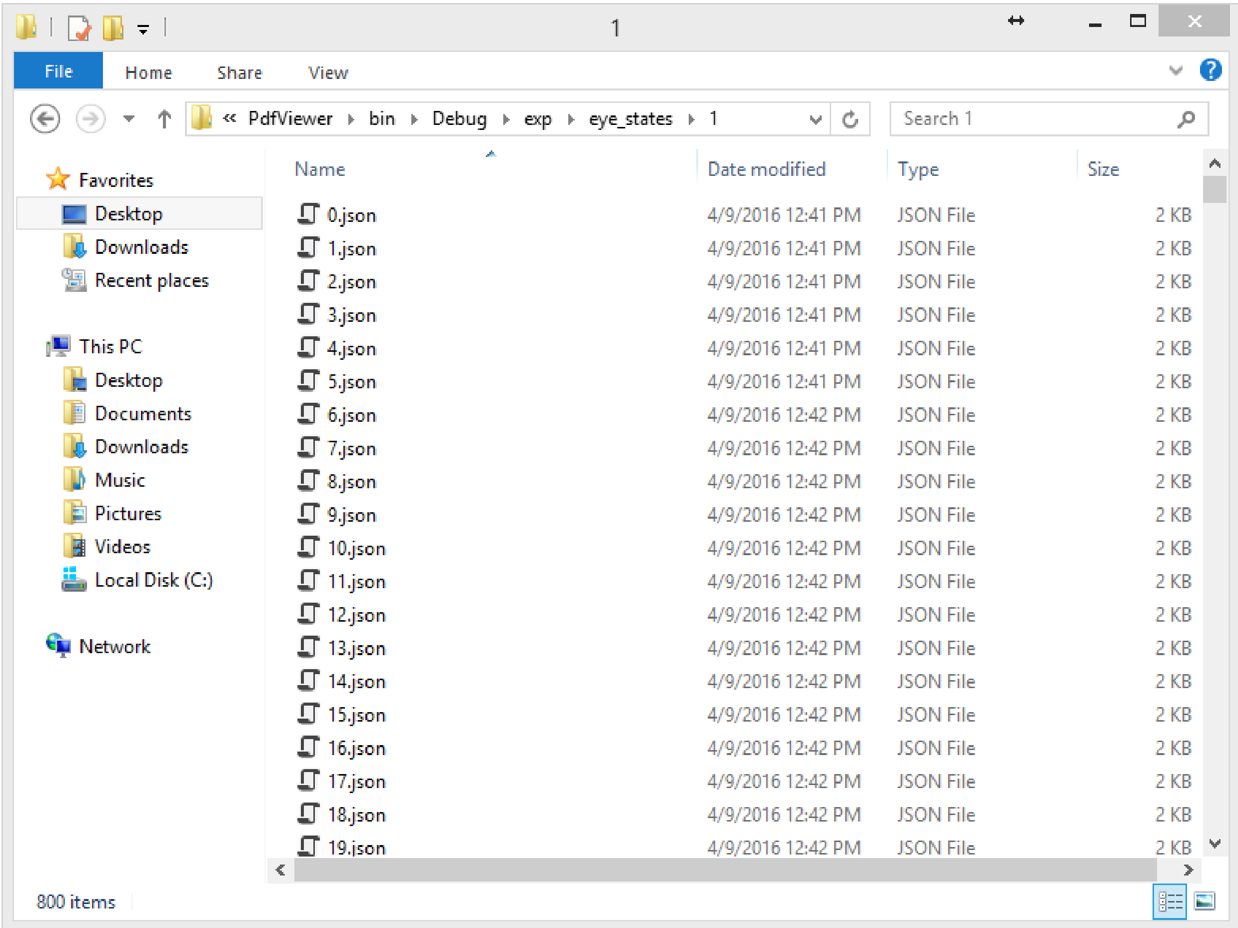

Figure 5.5: The recorded 20 EEG sample files in 10 seconds under the directory 'exp\eye_states\1'.

When the experiment mode is on, the 'Start' and 'Stop' button will show. After clicking the 'Start' button, an experiment will start and an information window will pop up (Figure 5.6). The EEG data will be recorded as described in Chapter 4. After 10 seconds, the 'Stop' button will show pressed effect () to indicate the end of the experiment and the information window will disappear. A user can repeat performing experiments by re-clicking the 'Start' button.

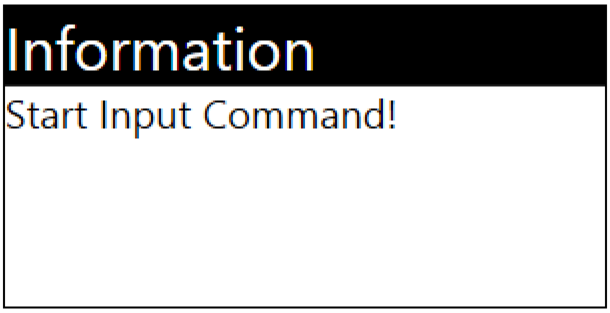

Figure 5.6: The pop up information window when an experiment starts.

5.2.3 Reading Mode

Based on the analysis in Chapter 4, a user needs to blink at least twice at strength >= 80 in 2 seconds to trigger the turning page command. Once the system detects the trigger signal, a window as Figure 5.6 will pop up to inform the user to input command. The user could keep eyes closed (class = 1) or open (class = 2) to turn to the previous (command = 1) or next (command = 2) page respectively. Figure 5.7 shows the whole process of brainwave analysis.

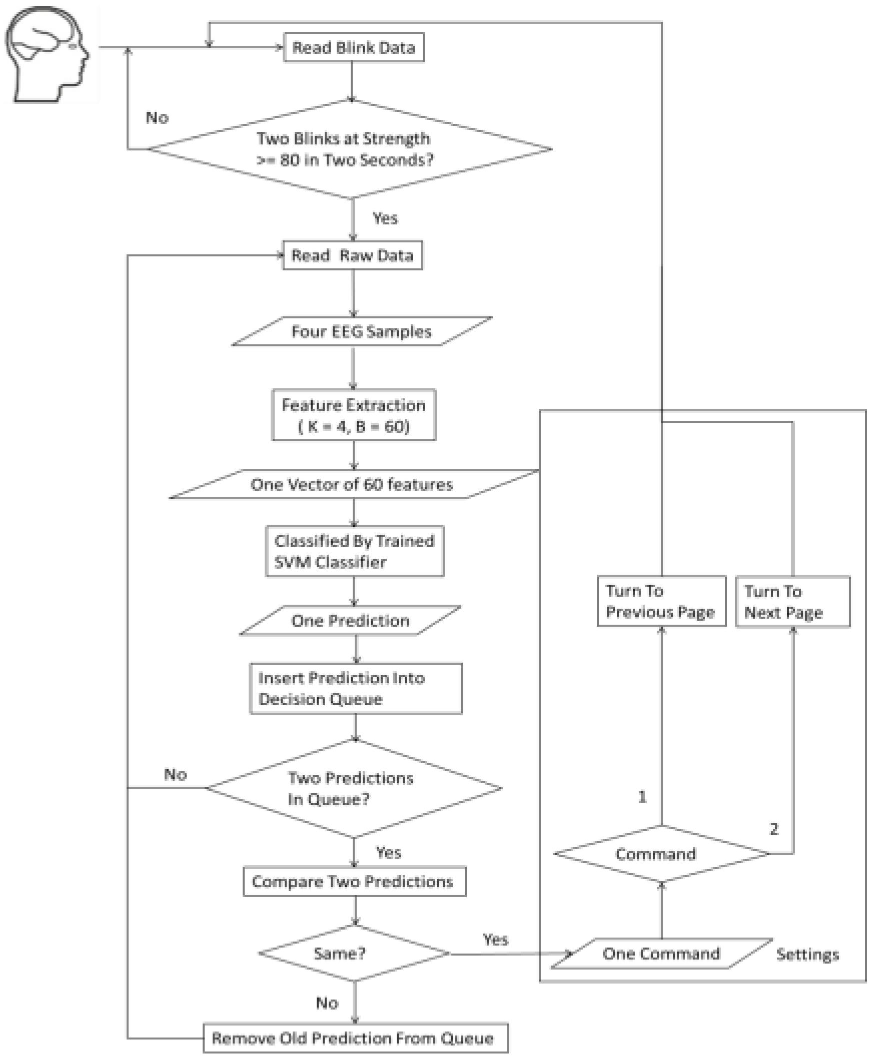

Figure 5.7: The whole process of brainwave analysis.

To reduce the false detection of a command, the system uses voting strategy to determine the command from predictions. Since generating one prediction takes 2 seconds (four 0.5-sec EEG samples), collecting N predictions for voting needs 2N seconds. To optimize the system response time and guarantee the true positive rate, only two predictions are required for the final decision. If two consecutive classification results are the same, the system will generate a corresponding command. Otherwise the system will repeat reading and classifying EEG samples until one command is generated.

The 'Settings' rectangle in Figure 5.7 means that the system's response to the user's command varies according to the settings. It is designed to accommodate the needs of both the novice and experienced users.

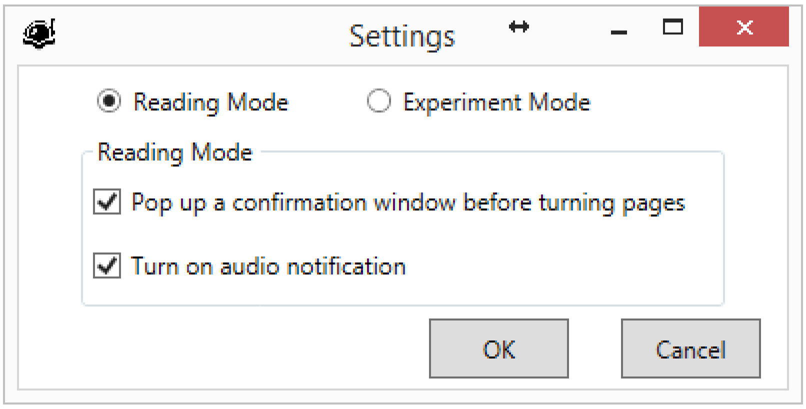

Figure 5.8: The pop up settings window when the reading mode is checked.

The default setting is that the system will pop up a confirmation window before turning pages (i.e., a user needs to confirm before the page turning) and play audio to inform the command. For example, a user wants to turn to the next page (command = 2) and keeps eyes open after seeing the information window as Figure 5.6 in the default setting. But the program gets two same classification results equal to 1 and generates a 'Previous' command. The system will pop up a confirmation window as Figure 5.9 and play an audio 'Do you want to turn to the previous page'. To cancel the wrong command, the user can blink once in 3 seconds after the audio is finished. The time duration is designed based on the blink rate as mentioned in Chapter 4, and is also a tradeoff between reaction time and waiting time. The confirmation window will indicate the time by 3 countdowns. On the other hand, if the system generates the right command and displays the confirmation window with text 'Turn to the NEXT page', the user needs to keep no blinking in 3 seconds. Using blinking to cancel a command instead of confirming is to prevent the fatigue caused by frequent blinks. The default setting is suitable for the beginners.

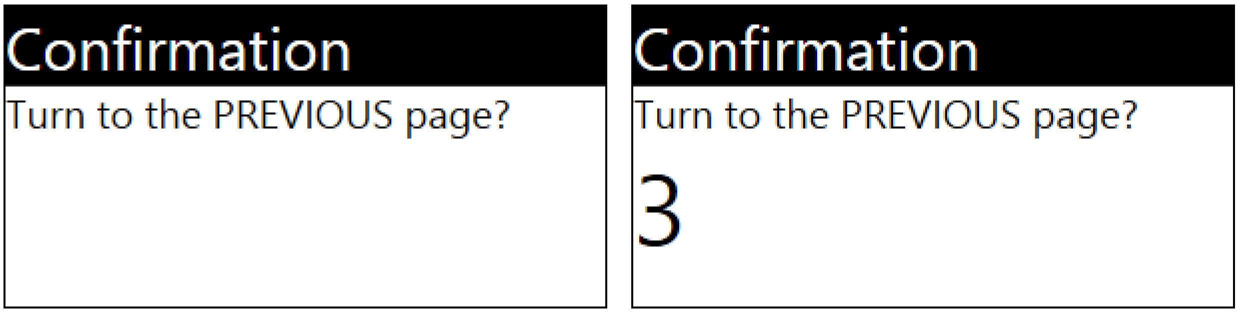

Figure 5.9: The confirmation window of turning page to the previous.

An experienced user is likely to prefer no confirmation. For example, if a user chooses audio notification but no confirmation, when the system successfully recognizes a command, it will execute the command immediately and inform the user by playing the audio 'turn to the previous (next) page'. Other system responses related to the confirmation window and audio notification are illustrated in in Figure 5.10.

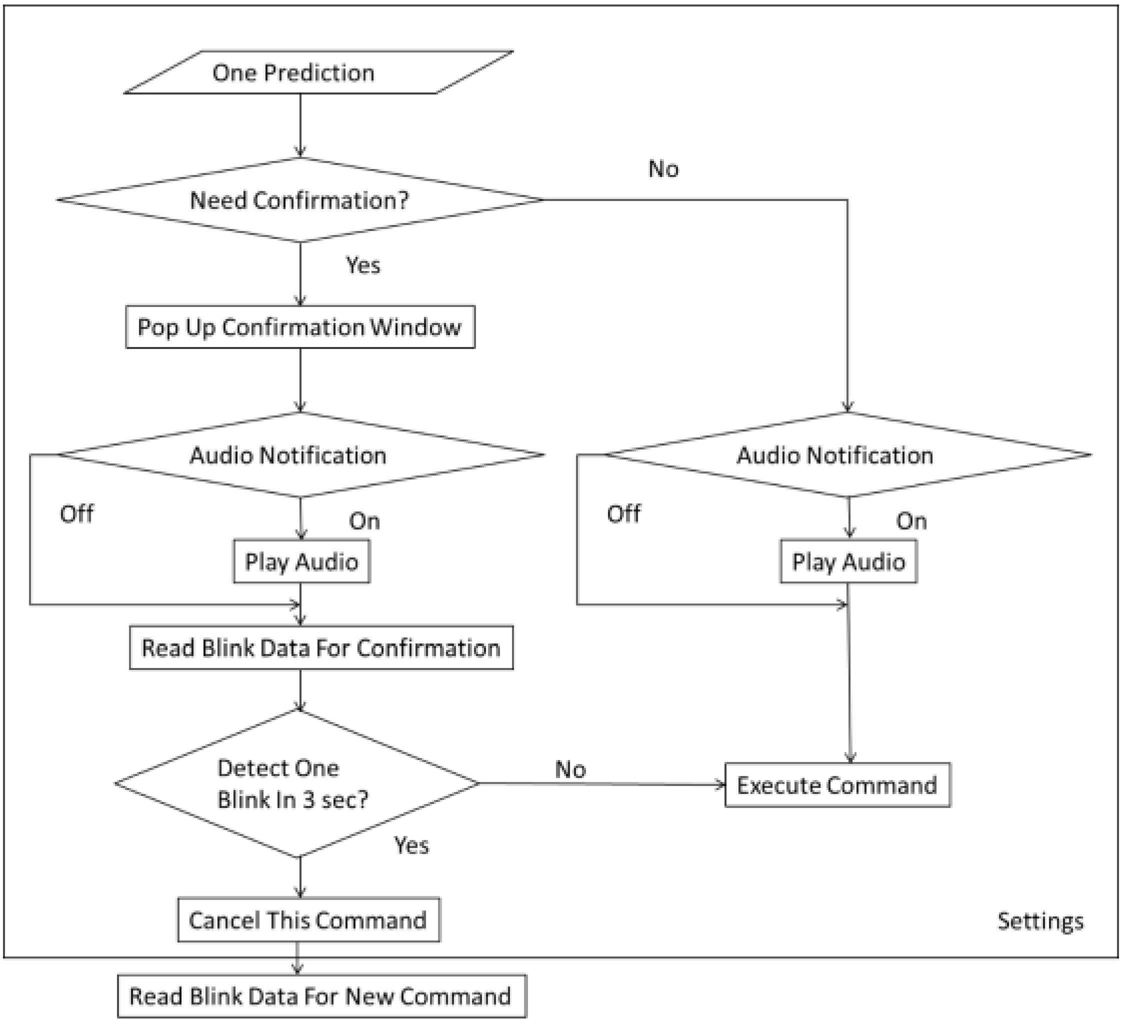

Figure 5.10: The system response of different settings.

6. System Testing

I performed 40 turning page tests on the final system: 20 for turning to the previous page and 20 for the next. All the 40 commands were executed successfully. The testing accuracy was 100%. In details, 42 predictions were generated for 20 'Next' command and 47 predictions were generated for 20 'Previous' command. Each successful 'Next' and 'Previous' command toke 4.2 seconds and 4.7 seconds on average respectively.

Actual Class / Predicted Class	Open/Next +	Closed/Previous -	Total
Open/Next +	41	7	48
Closed/Previous -	1	40	41
Total	42	47	89

Figure 6.1: Testing results on the final system.

7. Conclusions & Future Work

In this report, I designed and implemented a BCI application with a single-channel, mobile and low-cost EEG device. I used blinks and eye states as the control signal, FFT and a signal quantization method as the feature extraction method and a linear SVM as the classifier. The result was that this BCI could allow me to turn a page using brain control with 100% accuracy in less than 5 seconds. This real-time e-book viewer application with BCI is very easy to use and requires no pre-training, which is promising for developing more BCI applications that can benefit disabled people using a simple and cheap EEG device.

The challenges in this project were to find out which mental state detected by a single electrode at Fp1 could be easy to distinguish and which features of the brainwave data were significant for classification. Three groups of mental states and many feature extraction methods have been tried. Except for extracting features from raw brainwave data described in this report, I have also spent a lot of time to use SVM to classify data with the processed frequency bands and values of attention and meditation from the MindWave Mobile. However, the results turned out that the given frequency bands and attention and meditation were not good features to distinguish two tasks. Thus I turned to work on the raw data and finally found an effective method to extract usable features after experiencing many failures and reading plenty of related paper work.

However, all the data for training and testing in this project was from myself. Taking individual difference into consideration, this application may not work well for other individuals. Therefore, to validate this system, more experiments conducted by other people can be done in the future. In addition, using blinks and eye states as the control signal would cause the tiredness of eye using. Another shortcoming is that users need to close eyes to turn to the previous page. Users cannot know what happens with closed eyes so that I used audio notification in this project. More tasks can be designed and examined to find a better way of control and further improve the practicality of this application.

8. References

[1] Wolpaw, J. R., Birbaumer, N., Heetderks, W. J., McFarland, D. J., Peckham, P H., Schalk, G., Donchin, E., Quatrano, L. A., Robinson, C. J., and Vaughan, T. M., 2000b, Brain-computer interface technology: A review of the first international meeting, *IEEE Trans. Rehabil.* Eng. 8(2): 164-173.

[2] Lotte, F., Congedo, M., Lecuyer, A., Lamarche, F., & Arnaldi, B., (2007). "A review of classification algorithms for EEG-based brain-computer interfaces," *Journal of Neural Engineering*, vol.4, pp.R1-R13.

[3] NeuroSky. (2015). *User Guide*. Retrive from http://www.neurosky.com/.

[4] Manaris,B., McCauley,R., MacGyvers,V. (2001, May). An Intelligent Interface for Keyboard and Mouse Control--Providing Full Access to PC Functionality via Speech, *Proceedings of 14th International Florida AI Research Symposium (FLAIRS-01)*, Key West, FL, pp. 182-188.

[5] Mavek, H., & Matej V. (2015). Voice Control Reader. Retrieved from http://www.vcreader.com/.

[6] Ge S, Wang R, Yu D (2014) Classification of Four-Class Motor Imagery Employing Single-Channel Electroencephalography. P*LoS ONE* 9(6): e98019. doi:10.1371/journal.pone.0098019

[7] Liu, J., Ransohoff, W., Dunkley, J., Kwasa, J., Welshon, D., Mahoney, M., Lefkowitz, J. (n.d.). EyeReader: SSVEP-based BCI. Retrieved from http://neuro.embs.org/.

[8] Rejer, I., & Klimek, A. (n.d.). (2015). E-book Reader Application Driven by Commands Provided by a Brain-Computer Interface Based on Motor Imagery Paradigm. *Advances in Intelligent Systems and Computing Soft Computing in Computer and Information Science*, pp. 95-105.

[9] Bentivoglio, A., Bressman, S., Cassetta, E., Carretta, D., Tonali, P., & Albanese, A. (n.d.). Analysis of blink rate patterns in normal subjects. *Movement Disorders Mov Disord.*, 1028-1034.

[10] Chu, C. A., Rosenfield, M., & Portello, J. K. (2014). Blink patterns: reading from a computer screen versus hard copy. *Optometry & Vision Science*, 91(3), 297-302.

[11] Doughty, M. J., & Naase, T. (2006). Further Analysis of the Human Spontaneous Eye Blink Rate by a Cluster Analysis-Based Approach to Categorize Individuals With 'Normal'

Versus 'Frequent' Eye Blink Activity. *Eye & Contact Lens: Science & Clinical Practice*, 32(6), 294-299. doi:10.1097/01.icl.0000224359.32709.4d

[12] Average duration of a single eye blink - BioNumbers. (n.d.). (2016). Retrieved from

http://bionumbers.hms.harvard.edu/bionumber.aspx?&id=100706&ver=0

[13] Yoto, A., Katsuura, T., Iwanga, K., & Shimomura, Y. (2007). Effects of object color stimuli on human brain activities in perception and attention referred to EEG alpha band response. *Journal of Physiological Anthropology*, vol. 26, pp. 373-379.

[14] Kropotov, I. D. (2009). *Quantitative EEG, event-related potentials and neurotherapy*. pp.142

[15] Fatourechi, M., Bashashati, A., Ward, R. K., & Birch, G. E. (2007). EMG and EOG artifacts in brain computer interface systems: A survey. *Clinical Neurophysiology*, 118(3), pp. 480-494.

[16] Merrill, N., Maillart, T., Johnson, B., & Chuang, J. (2015). Improving Physiological Signal Classification Using Logarithmic Quantization and a Progressive Calibration Technique. *Proceedings of the 2nd International Conference on Physiological Computing Systems.*