RESEARCH PROJECT IN MECHATRONICS ENGINEERING

A HYBRID SSVEP/MI BASED BCI FOR CONTROLLING AN EXOSKELETON WRIST WITH 1 DEGREE OF FREEDOM

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ABSTRACT

Brain-computer interfaces (BCIs) can transform brain signals of goal-directed mental tasks into desired commands to control external devices without body movement. This report describes a functional design of a novel hybrid BCI system to control an exoskeleton wrist. It aims to create an accurate, precise and fast-response control system integrating Steady-state Visually Evoked Potentials (SSVEP) based and Motor Imagery (MI) based BCIs to assist spinal cord injured patients for rehabilitation. This goal attempts to bridge a gap which was addressed by a deep literature review overseeing the relative designs and their applications.

The preliminary offline experiments totally involving more than 20 test subjects with two different training protocols were designed for both SSVEP and MI subsystems to gain the optimal parameters. These variates were then used to generate the online real-time model to continuously convert user's intents. Subsystem of SSVEP defined the downwards movement and MI assigned the upwards one. Both trigger signals were sent to LabVIEW environment to control the actual motions of the wrist via UDP server/client. The final system achieved the reliable performance of 83.26% accuracy and 15 bit/min information transfer rate. The appropriate improvements for further works to refine the design and increase the commercial value of this field are discussed in the report as well. s

DECLARATION

Student

I ....Yifang Hou.......... hereby declare that:

1. This report is the result of the final year project work carried out by my project partner (see cover page) and I under the guidance of our supervisor (see cover page) in the 2016 academic year at the Mechanical Engineering Department, Faculty of Engineering, the University of Auckland.
2. This report is not the outcome of work done previously.
3. This report is not the outcome of work done in collaboration, except that with a project sponsor as stated in the text.
4. This report is not the same as any report, thesis, conference article or journal paper, or any other publication or unpublished work in any format.

In the case of a continuing project: State clearly what has been developed during the project and what was available from previous years:

Signature: ____________________

Date: 20/9/2016

Supervisor

I confirm that the project work undertaken by this student in the 2016 academic year ~~**is**~~ **is not** (*strikethrough as appropriate*) part of a continuing project, components of which have been completed previously.

Comments, if any:

Signature: ____________________

Date: 20/09/2016

Acknowledgment

Firstly, I would like to express my deep gratitude to my FYP supervisor Professor Shane Xie. He gave me the chance to work through this project and shared his valuable experience and instruction to my partner and I to succeed on this project.

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Thirdly, I would like to express my thanks to my FYP partner Rongze Ma. She is always the best friend and teammate to support the project keep going.

Finally, I would like to say thanks to all the technician who helped improve the experiments setting and all the test subjects invited to support me those evidences of the experiments and design.

Glossary of Terms

Gaze	Where the user is looking
Headset	A set of electrodes intended to connect to a head to measure brain signals
Natural Output	A hormonal or muscular output caused by the brain when intended to do so
Occipital Cortex	A region of the brain that is known as the visual processing center, located at the back of the head.
Offline Test	Testing with pre-recorded data acquired previously.
Online Test	Testing in real time with data acquired from the user.
OpenViBE	An open source software for Brain Computer Interfaces and Real Time Neurosciences
Alpha wave	Brain waves fluctuations in the range of 8 -12 Hz, emerges with relaxation and attenuates with mental exertion
Beta wave	Brain wave fluctuations in the range of 13-30 Hz. Associated with active thinking
Harmonics	Refers to the 2 times frequency. If the fundamental stimulation frequency was at 14 Hz, then the harmonic frequency would be at 28 Hz

Abbreviation

EEG	Electroencephalogram
EMG	Electromyogram
MEG	Magnetoencephalography
ECoG	Electrocorticography
BCI	Brain computer interface
hBCI	Hybrid Brain Computer Interface
MI	Motor Imagery
VEP	Visually Evoked Potential
SSVEP	Steady-state Visually Evoked Potential
SCP	Slow Cortical Potentials
SMR	Sensorimotor Rhythms
ERD	Event Related Desynchronization
ERS	Event-related Synchronization
LFP	Local Field Potentials

DAQ	Data Acquisition
FFT	Fast Fourier transform
CCA	Canonical Correlation Analysis
SNR	Signal to Noise Ratio
ITR	Information transfer rate
CSP	Common Spatial Pattern
BP	Band Power
PSD	Power Spectral Density
AR	Auto-Regression
AAR	Adaptive Auto-Regression
UDP	User Datagram Protocol

ALS	Amyotrophic Lateral Sclerosis
SCI	Spinal Cord Impairment

WHO	World Health Organization
LED	light-emitting diodes
GND	ground
VRPN	Virtual-Reality Peripheral Network
DOF	Degree of Freedom

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1 Introduction

A Brain-computer Interface (BCI) is a communication system that measures central nervous signals which respond to goal-directed mental events and translates them into artificial output. All the converted control messages replace and enhance natural neuromuscular or hormonal outputs [1] and thereby people with physical handicaps or healthy people against using other means of communication can restore the ongoing interactions or controls with external environment via BCIs.

For those people with severe neuromuscular disorders, including amyotrophic lateral sclerosis (ALS), strokes and spinal cord impairment (SCI) which cause motor disabilities, the lost functions can be potentially replaced via establishing BCI system [2]. About 9000 people have brainstem strokes, over 300 people are living with ALS and around 150 people are diagnosed with SCI every year in New Zealand [3-5]. More than one billion people of the world's population have a disability and the World Health Organization (WHO) says that this number grows up with the increase of the population [6]. Those survivors are mostly disabled, thus significant daily support continuous recovery are necessary throughout their life. [3] Because retraining or repairing the connection between the brain and the spinal is the most important goal of rehabilitation for post neurological injury [7], current 2 possible rehabilitation methods, using eyes or other remaining muscular pathways as substitutes to control external devices and introducing EMG for controlling paralyzed muscles, are limited and ineffective.

However, even if a patient suffers from neuromuscular disorders, his brain activities still maintain intactness [8] and the Electrophysiological (EEG) phenomena which reflects the relative activities continuously happen in the spinal cord area [9]. To overcome the obstacles of physical motor disabilities, deciphering people's thoughts can provide a new form of communication. These signals can be quantified by monitoring electric fields via sensors along the scalp to perform as natural inputs of desired mental tasks. Since 1938, people have theorized that EEG of people's intents might provide a novel non-muscular restore function for sending commands to the external world. Therefore, the BCI attracts more and more interests and productive BCI research programs have substantially arisen in recent years along with cheaper high-tech hardware and growing recognition of the needs and potentials of patients [2].

Electrodes will access to the higher-order motor areas located around exposed cerebral cortical surface or within the brain to derive neuronal action potentials including slow cortical potentials (SCP), Visually Evoked Potentials (VEP), P300 potentials and Event Related Desynchronization (ERD) [1]. The proposed programming of BCIs need be carefully designed to select which types of EEG will be recorded to operate the system. The translation of these signals decode the users' wishes in real time and then the system could send the commands to external devices. Therefore, for stable and successful performance, the user and the BCI are required to cooperate continually.

Although many single EEG based BCIs have indicated their high potentials as a new communication channel through multiple applications such as word speller and wheelchair, there are still more possible room to introduce hybrid BCI systems. To improve the lack of reliability and synthesize the benefits, increasing studies focus on this young research field which involves 2 or more brain activity patterns as inputs of a system. However, how to select the proper neural sources for a designed hybrid BCI is critical. The hybrid system should integrate the advantages of 2 or more EEG signals and meliorate the shortages from single EEG based BCIs to improve the performance. Thus, users with severe disabilities are able to control a rehabilitation exoskeleton accurately with higher speed.

As a communication system, there are input, output, translating module and operating protocols [2] to decipher the users' intent. Figure 1 shows the major components and principle interactions of a closed-loop hybrid BCI system to control an exoskeleton wrist with 1 degree of freedom in this project.

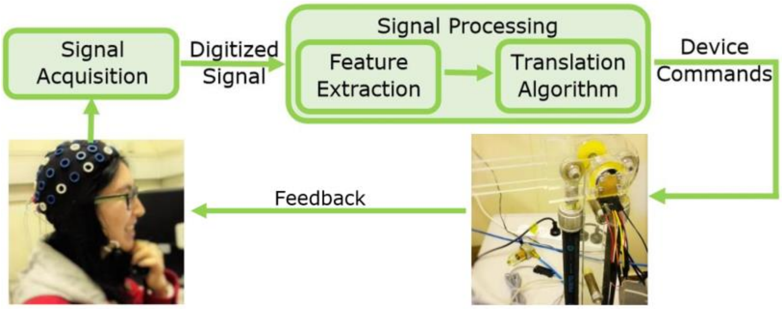

Figure 1: the closed-loop hybrid BCI system controlling the 1DOF exoskeleton wr**ist**

2 Literature Review

To gain a comprehensive understanding of current studies done about hybrid BCI systems and their applications, an in-deep literature review was taken to identify the starting points of this final year project. There were three main fields of researches found about this topic as follows:

- General overview: BCI and signal processing
- Existing paradigms: different types of EEG based BCI
- Rehabilitation application: Brain controlled limb exoskeletons

Meanwhile, it was necessary to figure out the project objectives by recognizing the study interests and potential gaps that are present in the current works done by the University of Auckland.

2.1 BCI General Overview

A BCI system derives EEG signals by electrodes on the scalp and extracts specific EEG features that reflect the user's thoughts. These features, amplitudes of evoked potentials or sensorimotor cortex rhythms [2], are translated into commands to communicate with an external application. Successful operations rely on the good interaction and adaption between user and system. On one hand, the reliable correlation between users' intents and the employed signal patterns must be continuous and stable. And on the other hand the extraction of features should be controllable for users and the translation into machine language must be correctly and efficiently in BCI systems [1].

2.1.1 Choosing signal types and brain areas

Choice of the suitable brain areas from which to record the signals is a crucial question. Different areas may well differ in topographical resolution, frequency content, and technical necessities that may affect their ability to serve as the inputs of BCI system [1].

Figure 2 indicates the range of electrophysiological methods form EEG to Electrocorticography (ECoG) to intercortical recording and indicates the multiple scales of the brain signals available for BCIs [1]. Electrodes to record EEG is located on the scalp. Electrodes to record ECoG is located upon the cortical surface. Arrays of microelectrodes inserting into the cortex are used to record Neuronal action potentials (spikes) or local field potentials (LFPs) [3]. Although the selection of these is usually based on their different advantage and disadvantages, current researches for practical applications mostly prefer to EEG signals due to the non-invasive implementation way.

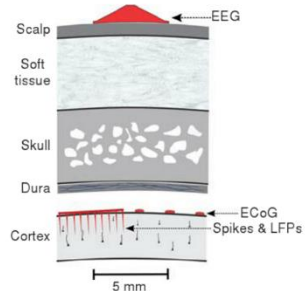

Figure 2: Recording sites for electro-physiological signals used by BCI systems [1].

2.1.2 Signal acquisition

The BCI systems commonly utilize EEG electrodes to non-invasively monitor the desired signal patterns which then are amplified and digitized [2]. Selected electrodes will access to the higher-order specific motor areas located along the scalp [17] shown as Figure 2. This project involves 8 channels within red circles for steady-state VEP (SSVEP) data acquisition (DAQ), 7 channels within orange circles for Motor Imagery (MI) DAQ, GND in green circle and Ear Reference in blue one.

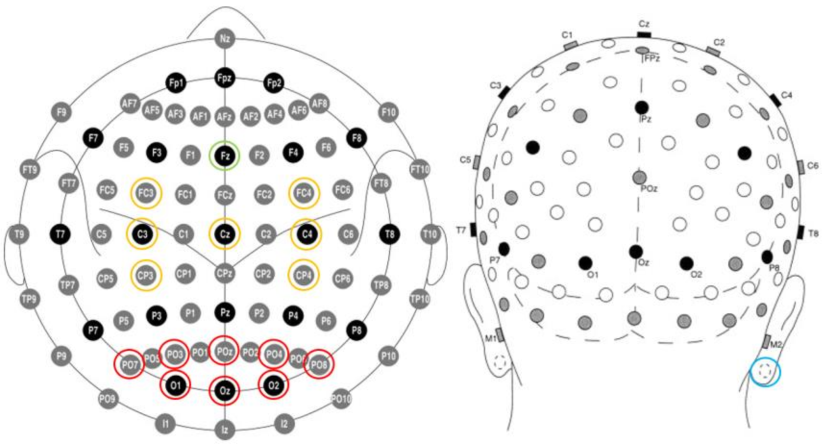

Figure 3: Electrode positions and labels in the 10±20 system [17].

2.1.3 Signal processing

The voltage fluctuations of brain activities are always identified as three different methodologies including steady-state VEP (SSVEP), P300 event related potential (ERP) and event-related desynchronization/synchronization (ERD/ERS) [1, 2, 10-16]. After digitization, these signals are then subjected into several extraction parameters which generally include signal amplitude [18], band power (BP) [19, 20], power spectral density (PSD) [21], auto-regression (AR) & adaptive auto-regression (AAR) [22] and also time-frequency feature which are basically related to specific time-variation information of user’s intents [23]. According to spatial filtering, spectral analysis and other processes, these extracted features are translated to decode the user's messages.

There are several limitations of BCI features consisting of low signal-to-noise ratio, poor stability due to rapid variation, relatively small training set and feature vectors' high dimensionality [23]. To mitigate these problems and improve the performance potentially, BCI should introduce multi-electrode channels, several time segments and as many test subjects as possible [1, 23] and employ more proper patterns both in time-domain and frequency-domain [24, 25].

The next step is translation via linear or nonlinear algorithm. All the analysis methods convert independent extracted features into dependent device control messages that carry out the user's thoughts [1, 2, 23].

2.1.4 Operating Protocol

The protocol defines the system works on/off based on either (dis)continuous communication or triggering command transmission between the system and the user. For instance, designed flickering stimuli evoking SSVEP response, the sequence and speed of interactions and also provided feedback are all able to guide the operations [1, 12, 13].

Most research-type BCI protocols are not completely appropriate for external applications that meet the real-life requirements of people with physical disorders [1, 8, 13]. Because the measurement of communication speed and accuracy is necessary for studies, laboratory BCIs manually tell test subjects what they should think. Contrarily, users operate by themselves in real-life and thereby the evolution from research to application is complicated [2].

2.2 Existing BCI paradigms

Most present studies of phenomena basically serving for BCI design are mentioned only when there is direct relationship with actual BCI applications [2]. Although there are several data logging approaches including EEG, MEG, fMRI, ECoG and NIRS [2, 11, 26-28], EEG signals, the brain activities recorded by placing electrodes outside the scalp, are mostly considered as the input to control the system. The proposed programming of BCIs need be carefully designed to select which neuronal actions will be recorded to avoid the unexpected interrupt between each other [10].

The existing non-invasive BCI systems used mostly can be generally classify into 3 groups including VEPs, P300 evoked potentials and mu and beta rhythms which is always identified as ERD/ERS potentials [1, 11]. A common VEP type system is SSVEP based BCI which depends on muscular control of gaze direction and requires external stimuli [12]. The other 2 groups are usually considered as independent systems which still desire comprehensive confirmation of proper assumptions [2].

2.2.1 SSVEP based BCI

In existing studies, there are many systems based on steady-state visual evoked potentials (SSVEP) in the occipital lobe [1]. These widely used BCIs require a visual stimuli of oscillating light source at a constant frequency, to generate the visual evoked responses as brain activities [29]. The activated SSVEP possesses the same or harmonic frequency as the stimuli [30]. Because of the obvious peaks at multiples of stimuli frequency or its harmonics, feature extraction of the brain signals should introduce a peak detecting algorithm such as band power analysis, canonical correlation analysis or other techniques [1, 12]. An average accuracy of

93.83% and an average information transfer rate of 21.85 bits/min can be achieved by the system [31]. However, the only SSVEP based BCIs is gaze dependent and this could be a hesitation for people who lack reliable gaze control [2]. Enhancement in natural neural responses to perform a task requires continuous attention over prolonged period which may cause lapses in attention. After a long period of staring at the flashing stimuli, visual fatigue also reduces the accuracy of the operations [2, 11, 12, 29-31].

2.2.2 P300 ERP based BCI

The P300 based BCIs measure event related potentials (ERP) with the positive deflection of brain activities which appears about 300 milliseconds after subjects experiencing a relevant stimulus named as the oddball paradigm [1, 2, 32]. The P300-based systems have been broadly validated based on their potential applications for patients. P300 represents a typical and simple reply to a desired choice from the user. As an apparent advantage initial user trainings for systems are normally no more than 5 minutes [13] and the results don't indicate clear shortcomings of accuracy comparing with other experiments that acquire more training data [2, 13, 33, 34]. However, the P300 is a type of relatively noise-sensitive signal, so averaging of the EEG responses caused by flashing stimulus is necessary for BCI design to eliminate the effect of noisy signals. Thereby, the system speed is decreased to a certain extent [2, 35] and thereby an appropriate adaptation via the translation algorithm is important. Another possible situation is that the system changes over time so the current studies are most likely to be short-term [13]. Long-term testing might smoothen P300 due to habituation [2, 33, 36].

2.2.3 ERD/ERS based BCI

BCIs based on SSVEP requirement for training, but external stimuli are necessary. On the other hand, ERD/ERS of sensorimotor rhythms (SMR) based BCIs require extensive training rather than external stimuli [1, 2, 10-12, 16]. One particular signal of this type is motor imagery (MI) which obtains self-paced control [1].

The relative strategies in need of body motion imagination from subjects may be intuitive, natural signals to control systems [10, 13]. Either motions or imagination of motions result in changing of sensorimotor rhythms in subjects' parietal lobe by MI based BCIs [2, 19]. The benefit of MI based BCIs is no requirement of external stimuli to generate EEG commands, although sometimes, BCIs need some external stimulus to get feedback [1, 23, 37]. Compared with the SSVEP or ERP based BCIs, much more amount of training is necessary to attain adequate control and build an accurate model of imagery. Thus MI based BCIs are normally considered as complex and difficult systems. And high demandingness of attention for imagination may encounter greater problems than other systems [1, 10, 17, 38].

2.2.4 Hybrid BCI

To utilize the benefits of each conventional BCI types and help people who lack of some abilities to effectively control the certain BCI overcome their own shortcomings, the combinations of two or more BCI systems called hybrid BCIs are essential for the design [1, 2, 11, 16, 39-41]. Thus the hybrid BCIs are more likely to address illiteracy and improve accuracy, minimize the response time, rise the information transfer rate [1, 11, 16]. Moreover, another non-BCI based system such as eye-tracking system or electromyogram (EMG)-based system is able to combine with EEG based BCI as well. To minimize the variables of evaluation, the combinations discussed in this report only consist of two pure BCIs.

Meanwhile, hybrid BCIs (hBCIs) can be classified as simultaneous or sequential processing based on different structure of combinations. Figure 4 shows a basic block diagram of both types of hybrid BCIs. Type A is the simultaneous processing which both input features are processed at the same time, and sequential processing, type B refers to one feature maintains higher priority to be processed than the second one. In sequential structure, the first system mostly acts as a switch [49] which determine the process of the second BCI. For this task, one of the appropriate options is most likely to be SSVEP which has high classification accuracy, fast information transfer rate and no need of training.

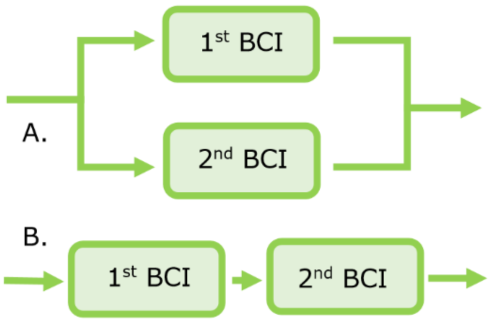

Figure 4: Two structures of hybrid BCIs.

Generally, it is not reasonable and likely that all kinds of brain imaging approaches can be combined together. The required situation of technology limits the possibility of some combination [1], hence careful selection of hybrid BCIs is important to attain simple controls for subjects [31]. Meanwhile, the design of hybrid BCIs need focus on the applications and targets which systems are aimed at. The types of hybrid systems can be identified via combined BCI models, connection algorithms and inputs signals [11].

A. Review of different hybrid BCIs

The different types of hybrid BCI systems and the summary of their important features which are reviewed in this paper are shown in table below.

Table 1: A comparison of several different BCI hybrid systems

Paper #	Hybrid BCI type	System organization	Improvement	Number of subjects	Classification
[32]	SSVEP, P300	simultaneous	Promised achievements of high IFT rate and high accuracy	12	LDA
[42]	SSVEP, P300	sequential	Improved information transfer rate	10	FLDA and BLDA
[40]	SSVEP, MI	sequential	False positive rate was reduced	6	FLDA
[43]	SSVEP, MI	sequential	Improved IFT rate and signal accuracy	3	FFT, LDA
[44]	ERD, EOG	simultaneous	More flexible system with subjects control state in a passive way	4	LDA, CSP

B. SSVEP/P300 hybrid BCI

A new hybrid BCI paradigm combining two EEG patterns, P300 and SSVEP are introduced to compare them with a pure BCIs [32]. Experimental results demonstrated that the performance of this system was significantly improved relative to the normal hybrid BCIs using SSVEP features. The new paradigms could affect BCI applications by improving performance for some users. [42]

C. SSVEP/MI hybrid BCI

In order to get better understanding of the hybrid based on SSVEP and motor imagery BCI, the task and was applied in three different conditions: ERD BCI, SSVEP BCI, and ERD/SSVEP hybrid BCI [43]. During the ERD BCI experiments, two arrows appeared on the screen. Left appearing means subjects were instructed to imagine opening and closing their left hand. For the right one, subjects imagined opening/closing the corresponding hand.

During the SSVEP experiments, all the subjects were required to gaze at either left (8Hz) or right (13Hz) LED depending on which arrow appeared. In the hybrid one, when the left arrow showing, subjects kept imagining the left hand opening/closing while gazed at the left LED simultaneously.

Results indicated the average accuracy of 74.8% for ERD, 76.9% for SSVEP, and 81.0% for hybrid. Good performance was achieved by this hybrid system [40, 43].

D. EEG/EOG hybrid BCI

The research designed a novel EEG/EOG-based hybrid BCI system and an online-target selection experiment. The gaze orientation was extracted as EOG signals, treated as target selection procedure, while the MI system tasks were detected via EEG signals. Once detecting the ERD, the current gaze direction corresponded would be triggered to remain more flexibility and voluntariness [45]. However, due to longer detecting time of ERD rather than EOG, the response time was increased. The EOG measured the relative eye movements with low accuracy of the absolute gaze orientation. This hybrid BCI thus might not perform as expected. [45]

2.3 BCI applications for controlling exoskeletons

The useful application of BCI system is crucial to its efficacy and to its potential clinical and commercial achievement, otherwise this area is only an interesting laboratory endeavour without any practical value [2].

Many disabled patients already choose assistive applications which commonly provides an accessible interface with commercial devices. Instead of standard physical interfaces such as joysticks or mouse, BCIs might be designed for disabled users in mind to serve as a general-purpose interface to operate existing limb exoskeletons more conveniently [2, 8, 46, 47] and promote patients' contribution to excite the corticospinal channels and allow the remodelling of injured brain [7]. The exoskeleton receives the BCI's output commands which then are converted into useful actions, thus integrating the BCI and application together into a powerful assistive device with higher commercial value [1].

2.4 Conclusion and gaps in work done in UOA

It was important to identify the gaps in literature and the work done about the BCI researches at the University of Auckland. Following the deep review, the current researches start attaching importance to hybrid BCI system to potentially improve the performance including accuracy and system response time. And thereby, the assistive devices might be more convenient for patients with severe neuromuscular disabilities to communicate with external environment or even remodel the motor functions. Hybrid BCIs have been used in more and more fields to develop our real life.

Overseeing all these relative studies can address gaps and then develop the appropriate objectives upon the work done at the university. SSVEP is currently the predominant neural pattern of BCI the BCI team is currently exploring. A major concern for PhD students is the researches on the design of word speller application and analysis methods about this signal to achieve better accuracy and higher signal-to-noise ratio (SNR). The previous BCI fourth year project back in 2012 focused on using a commercial EEG package, Emotiv EPOC, to create a brain controlled wheel chair [48] which combined intelligent auto control algorithms, EEG signal analysis and EMG techniques to simplify the navigation of a robot passing across an obstacle. Last year, two students developed a better signal processing paradigm by integration of both SSVEP and focus patterns and thus the information transfer rate (ITR) and accuracy were both enhanced [31].

All these previous designs required more than one channel to control 1 or 2 dimensional applications by singular EEG based BCI. However, the prior works didn't attempt to combine 2 or more types of EEG features to mitigate the interruption between multiple channels of any singular systems. There were also large number of projects done about the rehabilitation exoskeleton by PhDs or other part four students. To ease the experience of users with motor disabilities, these applications should replace the physical controllers such as joysticks with conjunction of the BCI controlling interfaces. According to stimulating the paralyzed muscles via integrating with an upper limb exoskeleton, the BCI system restores the lost brain functions to achieve the rehabilitation processing.

Thus the major gaps were identified as follows:

- A hybrid design of BCI system based on both SSVEP and MI signals which is more applicable, reliable and fast-response than the singular EEG based BCI.
- Adjustable combination between the BCI system with rehabilitation exoskeleton without involving the peripheral neural and muscular pathways to allow disabled patients to control devices directly by means of brain activities.

3 Project objectives

After addressing the potential interests and gaps in literature, the ultimate practical objective is to operate devices that provide communication or control capacities to people with physical impairments. This mainly focuses on hybrid system design and application. The current designs all have multiple channels of dimensional control via a singular EEG based BCI. For example, the last year project created a SSVEP based BCI with 4 different flickering frequencies to control a robot move towards 4 directions. However, SSVEP is not a stable brain activity with relatively low SNR and the more frequencies required the more interruption of classification between channels might happen. It can also help overcome the shortages of each system including the critical dependence of gazing ability in SSVEP and indeterminate imagination in MI. MI responses without external stimulus needed, thus the visual fatigue caused by SSVEP part can be minimized. And also this area requires most interests for people to remodel the lost motor functions of injured brains, Therefore, hybrid BCI may assign less frequencies with operational meanings by introducing another kind of EEG signal, MI, to divide the desired tasks.

Due to the critical requirement of long-term training and complex signal processing analysis of MI, it's difficult to classify the imagination of different areas from non-trained subjects within one semester. This new hybrid system is good to start with a simple artificial wrist with only 2 directions (1DOF) controlled by SSVEP and MI towards up and down respectively. The BCI with both single-channel sections aims to achieve robust enhancement on accuracy, ITR and SNR.

To design a reliable system, the parameters of each sub-system are crucial to the final performance. A set of offline experiments are necessary to figure out optimal key values under both singular EEG based BCIs.

The project mainly contains following 3 parts:

- Offline experiments
- Online BCI system design
- Connection with exoskeleton wrist

4 Software and hardware description

Figure 5 shows the current BCI system installed in the university lab. There is a main computer, desktop 1being used for most BCI experiments and having all the g.tec software and licenses for running the g.tec hardware.

In this project, Matlab 2015 Pro. (64 bit) and its Simulink module were the most important software platform to support the final design of hybrid BCI system and connect with the Labview 2015 which was used for exoskeleton control. The Simulink online system models were based on the analysis methods of MinimumEnergy and BandPower which were blocks given by g.RTanalyze (64 bit) software.

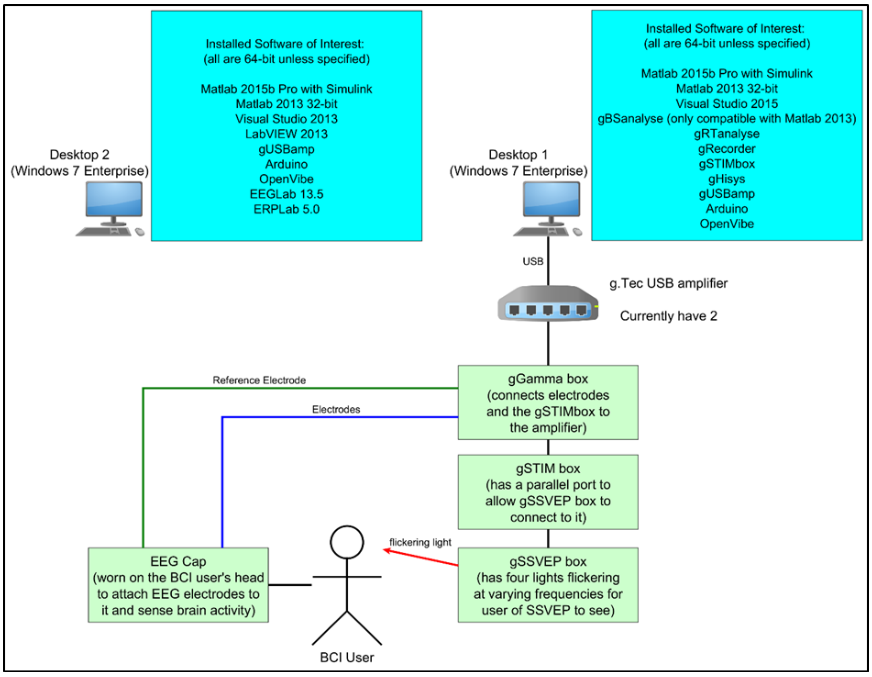

Figure 5: Current BCI system block diagram.

For the offline experiments, g.Recoder (32 bit) was used for data acquisition and then the recoded data was sent to the analysis matlab script on Matlab 2013 (32 bit). Arduino code was also involved to create the paradigm procedure for offline SSVEP testing and control the frequencies of LEDs. This setup will be talked in the later offline SSVEP section.

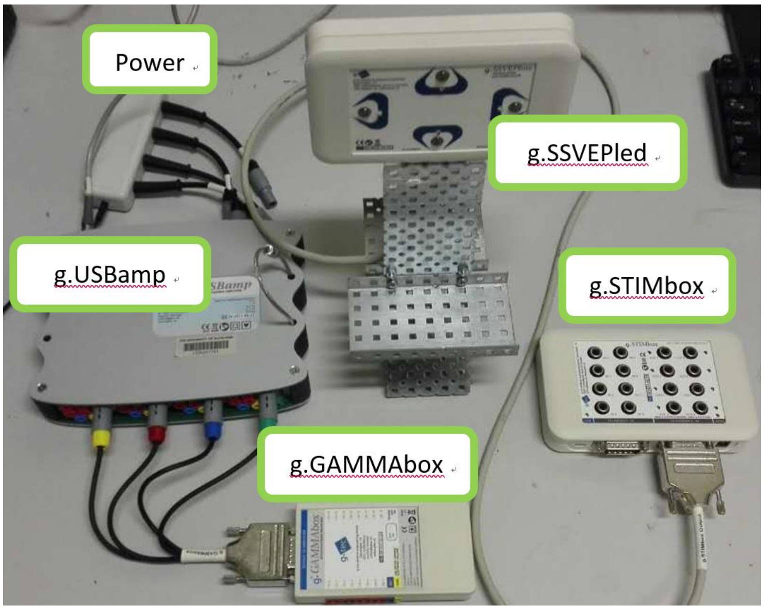

Figure 6: Setup of hardware for EEG DAQ and stimulation.

The hardware products shown in the above figure 6 for DAQ and stimulation were all from the g.tect company. The g.EEGcap with 65 electrode positions was provided to use with g.GAMMAsys active electrode system to detect the subjects' real-time SSVEP [51]. In terms of the electrodes, there must be at least one electrode, one ground electrode and a reference electrode present in order to be able to acquire an EEG signal from the BCI user's head. The current maximum number of electrodes allowed to connect simultaneously for any given time is 16. 8 or 7 Ag/AgCl electrodes for each sub-system were attached subjects' scalps along the occipital lobe area (O1, O2, Oz, PO3, PO4, PO7, PO8 and POz for SSVEP and FC3, C3, CP3, Cz, FC4, C4 and CP4 for MI), which were mentioned in section 2.1.2. The ground and reference electrodes were located at Fz and M2 respectively. The g.GAMMAbox, the driver/interface box supplied the power for maximum 16 active electrodes and was connected with g.USBamp by a connector cable. The g.USBamp is a bio-signal amplitude with good performance and the relating acquisition system connected with a PC for later feature extraction [51]. The online SSVEP system also required a g.STIMbox to provide the stimuli with a parallel port to guide the user following the designed paradigm from Simulink model.

The next important part is the setup of the exoskeleton wrist, the external application of designed hybrid BCI system. Its 1DOF movement performed by 2 air muscles is monitored and recorded by the angle sensor AS5048 which needs calibration before initializing the system. The MyRIO board is a real-time embedded evaluation device used to develop applications and integrate the angle sensor and two pairs of pneumatic controllers based on LABVIEW 2015. All the primary and secondary connection are shown in Appendix A.2. Powered by a 24V power source, the pneumatic controllers regulate the inlets and outlets of both air muscle to control the dimension and speed of movement via T type joints. MyRIO continuously accepts the output sent from BCI module to realize the uninterrupted control from user's intents. An air compressor was used for air supply.

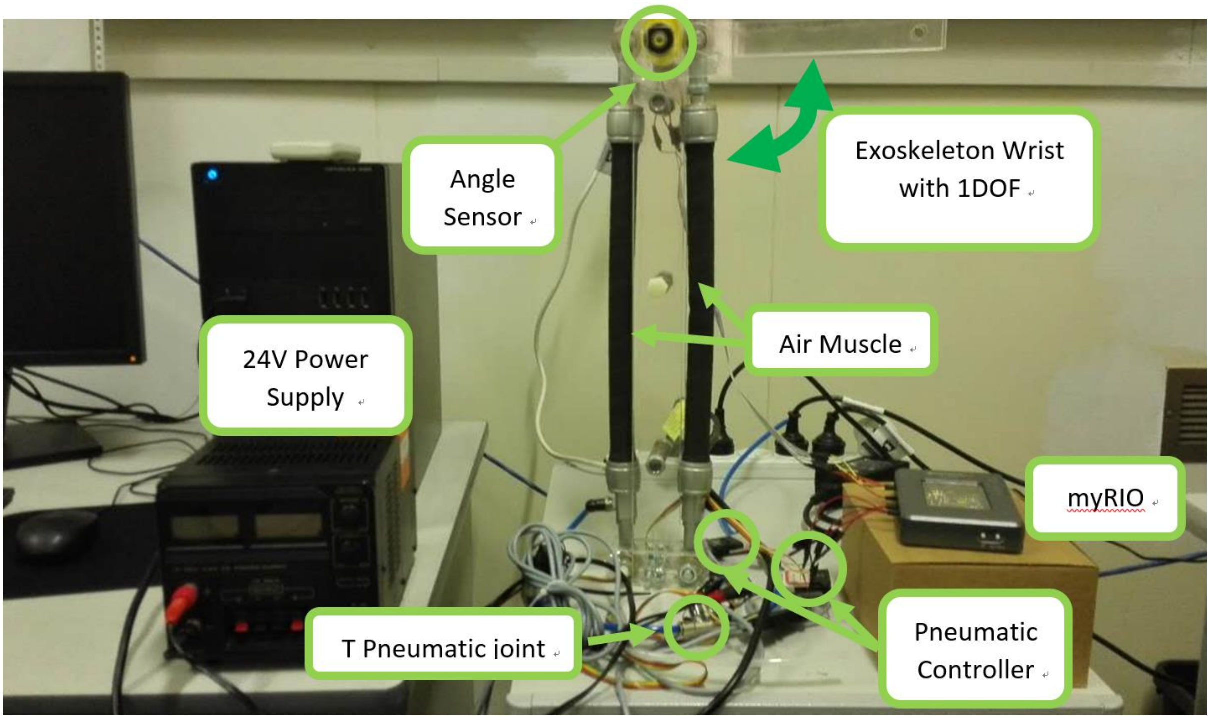

Figure 7: Exoskeleton Wrist setup.

5 Offline Experiments

As a hybrid BCI combining SSVEP and MI, it is not necessary to create a multi-channel SSVEP system to control several motion directions of external devices. The possibility of interference between different frequencies and their harmonics was considerably eliminated during the process. In this project, to design an accurate and fast-response system, an optimal flickering frequency should be figured out as the control input. Although those frequencies above 20Hz could buffer the visual stress after long-period gazing at the flickering lights, they might also cause the decrease in amplitude of responses and SNR [50]. On the other hand, frequencies between 10Hz to 15Hz are able to achieve a higher voltage amplitude with fast-response rate which also avoids the visual fatigue due to less operating time in need.

Following the literature, the difficulties in MI system is to get the obvious and stable response from non-trained test subjects to show the difference between imagination and thinking nothing. It was also not necessary to figure out the imagination from which part of areas but to get better performance, the experiments were designed to guide the users' intents to control the system. Considering about the difficulty of imagination and analysis, the test subjects for SSVEP were 18 people and only 8 subjects were invited for MI.

5.1 SSVEP offline

A set of offline experiments were designed and carried out to understand the key parameters of SSVEP section in depth. Repetition of DAQ and offline training were used to refine the parameters if necessary.

5.1.1 Methodology of offline SSVEP testing

A. Subjects

A total of 18 right-handed test subjects (10 males and 8 females aged from 20 to 35 years) with no history of neurological, psychiatric or other serious vitia were recruited for the section. Every participant had normal or relatively normal vision. All the subjects following the designed SSVEP Data Acquisition Procedure (shown in Appendix G) took part into the offline testing. Based on different eyesight conditions and eye dominance, the experiments were designed slightly different to compare serval variables in SSVEP BCIs. Details of the experimental procedures were explained to each participant and informed consent was given by everyone.

B. Stimuli and apparatus

SSVEP subsystem requires a visual stimuli of oscillating light source at a constant frequency, to generate the visual evoked responses as brain activities. There was an existing light-emitting diodes (LED) board designed by last-year students. 4 flashing frequencies (10, 11, 12 and 13 Hz) of top-right-corner LED array were set up as the sequence shown in Data Acquisition Procedure. Between each frequency and each trial, 3sec rest with short-beep warning tone was introduced to avoid visual fatigue. The lights and beeps were coded in Sparkfun RedBoard by Arduino (shown in Appendix A.1). All the subjects underwent the same first two sessions with both eyes open. 9 of the subjects experienced a third session which required them covering their dominant eyes (8 left and 10 right) with their hands to test the brain signals and a fourth session covering the other one. For those who don’t have good eyesight (1 long sight and 13 short sight), there was one more session to take off the glasses as a contrast to figure out the influence of glasses. All sessions contained one-minute closing eye stage as the testing baseline.

The 4*4 LED array with a dimension of 2cm*2cm was set at the same height as the subjects’ eye level and had a distance of 80cm perpendicular to the subjects shown in figure 8.

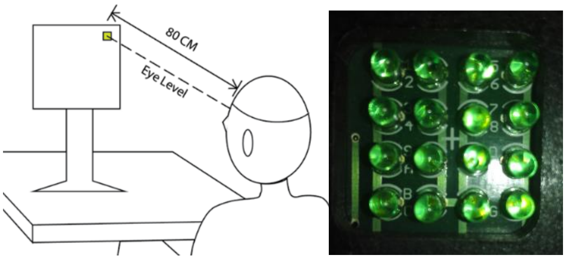

Figure 8: The basic paradigm of system setup and the LED array used as stimuli.

To capture EEG signals, data acquisition (DAQ) stage involved a system of equipment, including an EEG based cap, signal processing filters, analogue-to-digital converters and amplifiers (detailed graphs shown in Appendix A.1). As mentioned in section 2.1.2, the 8-electrodes was attached subjects’ scalps with the location mentioned in section 2.1.2 (fig.3). During the experiments, each participant sat in a comfortable chair and was asked not to move his or her body and to concentrate on the flickering lights. The environment was relative quiet but bright.

C. Signal Acquisition

BCI signal processing step requires digital filtering, data-independent spatial filters and data dependent spatial filters [1]. SSVEP signals from the electrode pair of Oz-POz were recorded by g.Recoder which supported DAQ devices mentioned before and could provide comfortable configuration and system setup (Shown in Appendix C). The bandpass Butterworth filter (with 0.5Hz low pass and 30Hz high pass cut-off frequency) was applied to all the channels before sampling and the sampling rate was 256Hz. The digital filters and settled sensitivity (-100 to

100) were able to help get more accurate frequency response with higher SNR. All the signals and parameters displayed were stored to disk, and later reviewed in the offline mode [52] (UI shown in Appendix C). The samples used for extraction required approximate 4 secs for the system to settle down.

D. Algorithm

The recorded SSVEPs from each channel were digitized and segmented and could be easily converted from time-domain signals to frequency-domain signals by using Fast Fourier Transform (FFT) [55].

The MATLAB script (shown in Appendix D) was used for developing the FFT algorithms. The translated spectra basically told the response strength and tolerance of the testing stimuli. The harmonics of all the four target frequencies in range of 20-27Hz from the amplitude spectra were used as feature vectors in signal classification [55]. In this project, their negative effects could be considerably ignored. Figure shown below indicates the amplitude spectra of all 8 different channels of SSVEP from one subject at 10Hz. The subject was right-eye dominance which induced obvious higher responses in left-hand side channels (O_1, PO_7 and PO_3).

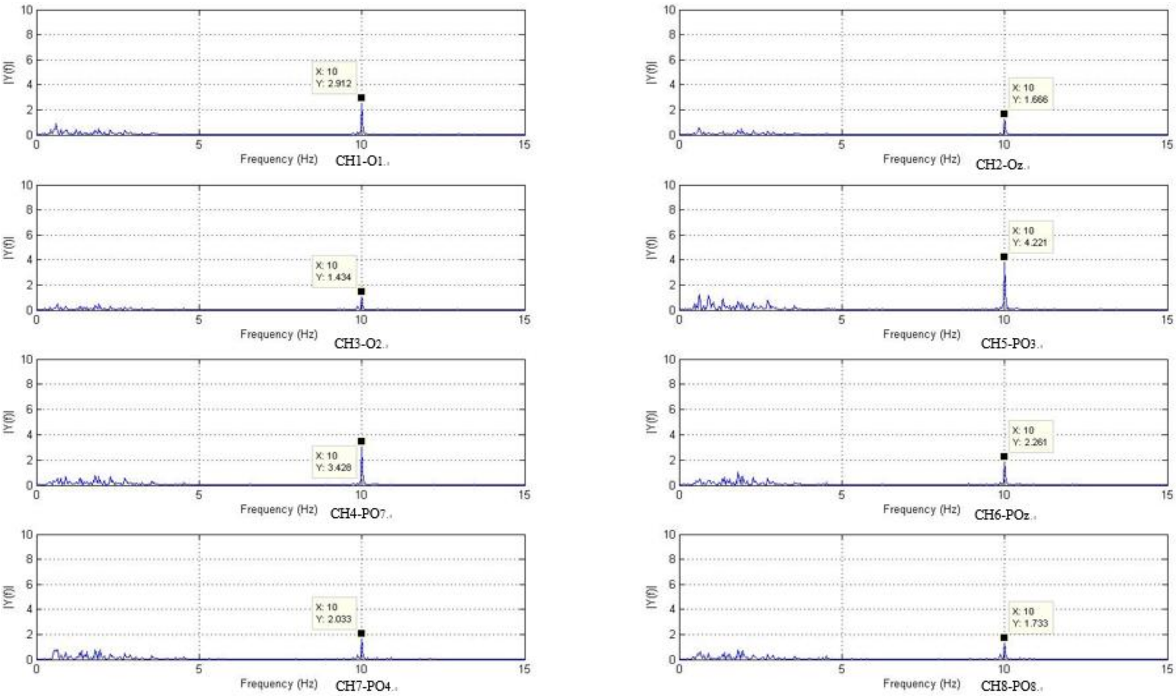

Figure 9: one subject's frequency responses of analyzed data at 10Hz in session 1 plotted by Matlab

E. Results

After applying FFT, Matlab was used to sum up and average all the noise frequency within 2 resolutions. To estimate the designed BCI system, Signal to Noise Ratio (SNR) is usually used to judge the signal quality, and is calculated the equation [53]:

$$\mathrm{SNR}_{dB} = 10 \times log_{10}(\frac{P_{signal}}{P_{noise}})$$

The total analysis of system was realized by the student T-test and summarized.

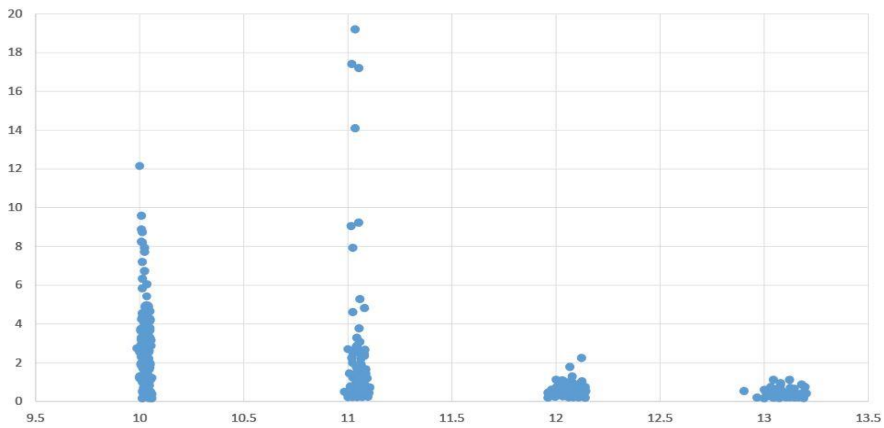

Figure 10: distribution of the peak values under different flickering frequency.

- The figure shown above directly indicates distribution of the peak value under each frequency. To mitigate the tolerance and achieve larger median amplitude and SNR, 10Hz should be selected as the input of hBCI with 81.24% confidence.
- Considering about the eye dominance, most subjects obtained more obvious react on the associated hemisphere (e.g. Left-eye dominance correlated with right brain). Meanwhile, after covering the dominant eye, the subjects always got the worst result in all the sessions. Thus the hypothesis for eye dominance was consistent with 66.67% confidence (12 subjects in 18). Thus, the channel selection can be adjusted by different users' condition in future testing.
- For the eyesight condition part, the power of short/long sight or taking off glasses didn't specify a certain relationship with the results. The passive properties of SSVEP activities might be the reason. There was a similar result gotten by Lim and etc. [56] that the stimulation in their paradigm triggered on during eye closing and the response was still good enough to actuate the word speller.

5.2 MI offline

Motor Imagery is a brand new area in the university thereby the sufficient experiments are necessary to build the full grasp of it and finalize the online system design.

5.1.1 Methodology of offline MI testing

A. Subjects

Totally 8 right-handed test subjects (5 males and 3 females aged from 20 to 25) with no history of serious physical defects were invited for MI offline experiments. MI is a type of active self-paced EEG signal without external stimuli. Following the literature, the training experience influences in the result of testing greatly. Only 2 participants had already gotten training sessions for more than one month and the others were the first time to go through the MI system. All the subjects followed the designed MI Data Acquisition Procedure (shown in Appendix H) and wrote down their reflection after the testing. 4 different variates in MI BCIs were evaluated according to the experiments including different locations of channels, closing/opening eyes, the duration and the intensity of imagination whether caused any difference on the results. Details of the experimental procedures were explained to each participant and informed consent was given by everyone. The reflection of experiments was also required for test subjects.

B. Signal Acquisition

As mentioned in section 2.1.2, the electrode pair of FC3-PC4 were utilized to record the MI signals by g.Recoder. The configuration of amplifier and software maintained the same values with the setting of SSVEP. The MI system also needed 4 secs to be settled down as initialisation. Any slight actual movement would involve significant noise into testing so the test subjects must keep an “absolute rest” during the DAQ.

C. Algorithm

The band-power estimation method was introduced to extract the MI patterns from offline raw data and this algorithm was developed throughout the MATLAB script (shown in Appendix I). The power spectral density (PSD) described the distribution of signal power into frequency components which generally consisted of alpha band (8-12Hz) and beta band (13-30Hz) [1, 9, 19, 20]. Both actual movements and imagination could evoke the peak responses among these areas. The estimation of PSD using the Yule-Walker algorithm to train an AR model which generate the PSD from its response. The extracted feature ranging the whole band (8-30Hz) then was applied with the log-transform which converted the data into time domain and the This can help tester easily figure out the response of each action following the desired sequence.

The translated spectra basically were squared to enlarge the difference between imagination of relaxation. This treatment might introduce some unexpected noise which then was smoothed by the median filter. The MI sub-system only needed a single channel output which exempt the classification of right/left-hand side and thereby it allowed the imagination of whole body motion which generated more obvious amplitude as output. Figure 11 shows the responses of session3 from a non-trained subject. There wasn’t any clear difference among 7 channels.

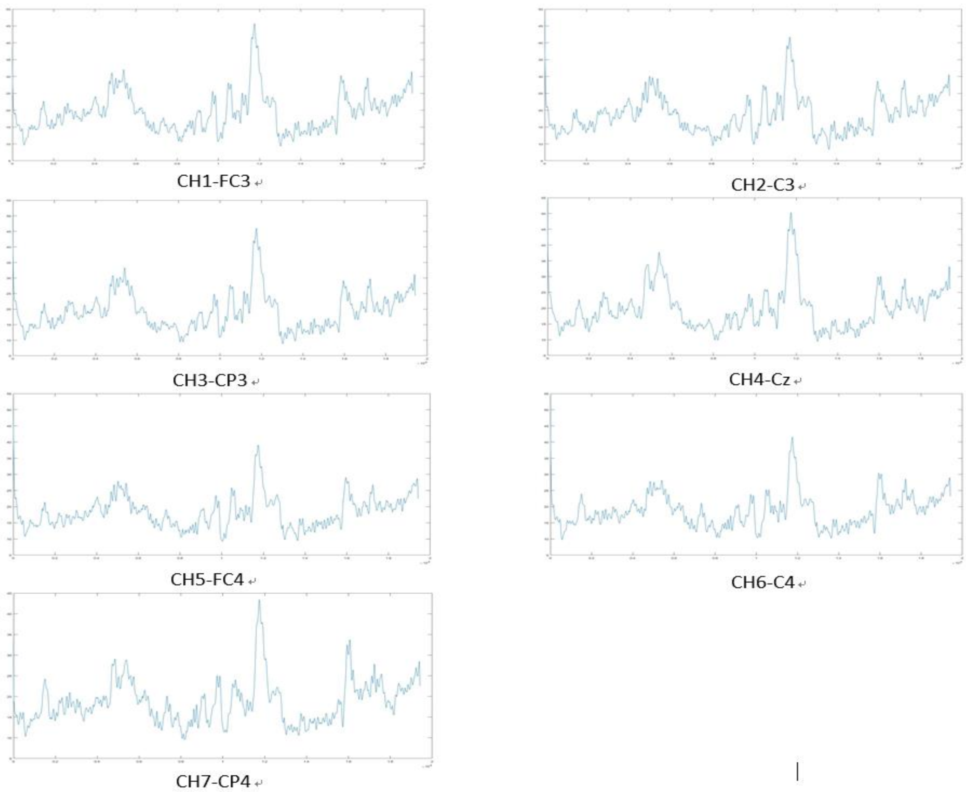

Figure 11: one subject's responses of 15sec duration of imagination plotted by Matlab

D. Results

MI system is a type of active system and tremendously depends on the current condition of test subject. The processed results analyzed and summarized as follows:

- The electrode system with 7 channels had an even distribution along the scalp. However, the subject's intent of imagination was full-body movement which couldn't lead any bias between left and right cerebral hemispheres.
- Three different durations including 5sec, 10sec, 15sec of imagination were tested. Only 2 subjects responded well to 5sec, 2 for 15sec and almost all subjects got good response with 10sec imagining especially for 4 of them. The trigger of actions was instructed manually which might introduce some tolerance into time measurement and it was really difficult for subjects to switch between 2 statuses within only 5sec. Some literatures discussed subject would lose attention due to mental fatigue during the long period of imagination [2, 10, 19]. This might explain why amplitude of most subjects' response decrease as time goes on and only few people got success in 15sec imagination.
- There was 81.4% confidence that imagination of larger movement range can attain analyzed data with more distinct contrast between relaxation and imagination.
- The performance of experiments to compare closing with opening eyes didn't show any appropriate result. This parameter really varies with each individual.
- The training of imagination relatively affected the results of MI system. Most non-trained subjects got worse performance due to unfamiliarity of this task. There were 2 people without any training but still getting good responses. In their feedback of experiments, they described that the imaginations of movements were critical detailed and vivid. Thus, longer training could guide people to create more details in their imagination to achieve higher amplitude of signals.

6 Online hybrid BCI system design

Based on the full grasp from offline experiments of both SSVEP and MI system, the online systems were then designed using the optimal key parameters found out before. All the online models were built on Simulink embedded in Matlab 2015b Pro. Both processing method blocks and hardware models such as g.USBamp for SSVEP and MI were existing blocks in g.RTanalyze software.

This section took the largest time because of the unreliable hardware and software platform. All the products in the lab were already out-of-date and the company would never produce them again. This means if the hardware or software suddenly crashed, there would no backup equipment to keep the project going on. During the design, more than ten times of uninstallation and reinstallation of the computer were taken to attempt to fix the problems. The finalized hybrid BCI integrated with the artificial wrist has already worked up to now. However, there is still possibility that the DAQ or other parts of apparatus suddenly goes wrong. After discussion and application, PhD students in the lab had already reported the problems and ordered a brand new set of hardware and analysis software which will help the future work dramatically.

6.1 Singular SSVEP based online BCI

The figure 12 shows the complete Simulink model of online SSVEP based BCI. The structure can be mainly divided into 5 parts: signal generation, signal acquisition, signal processing and control algorithms.

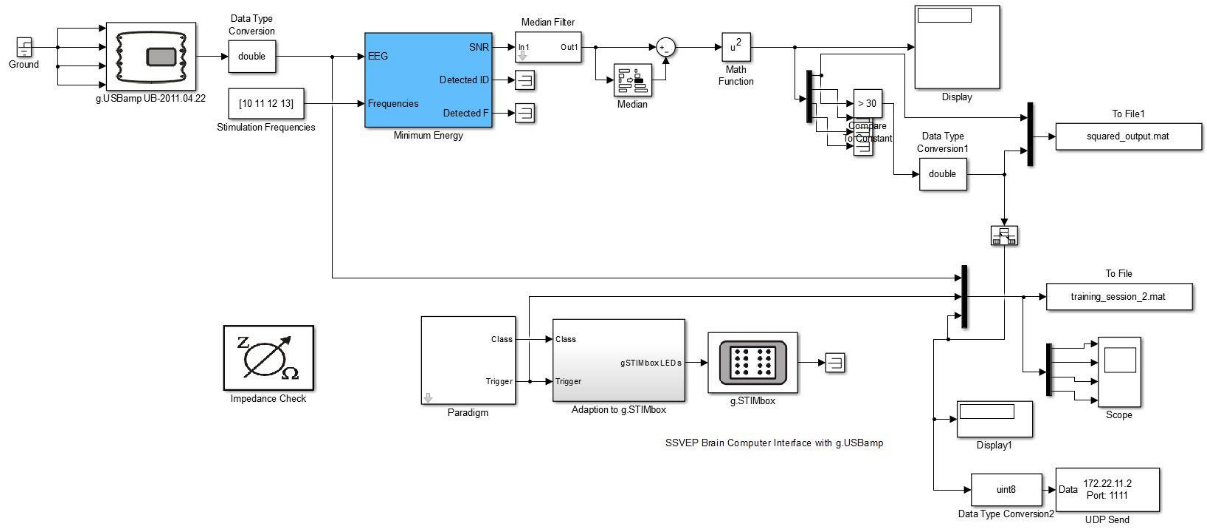

Figure 12: online SSVEP based BCI system.

6.1.1 Signal Generation

Instead of using LED board controlled by Arduino, g.SSVEPled and g.STIMbox created the 10Hz flickering lights following the paradigm. This paradigm was set with 3 trials per session and 20sec per trial including 10sec rest and it only used for the singular SSVEP system to help evaluate the performance. The structure of an adaption block (shown in appendix B) assigned the port number and triggering time to the g.STIMbox Users focused on the lights for 1 min and their raw data was then sent to be recorded. Figure 13 indicate the simple block diagram of SSVEP generation.

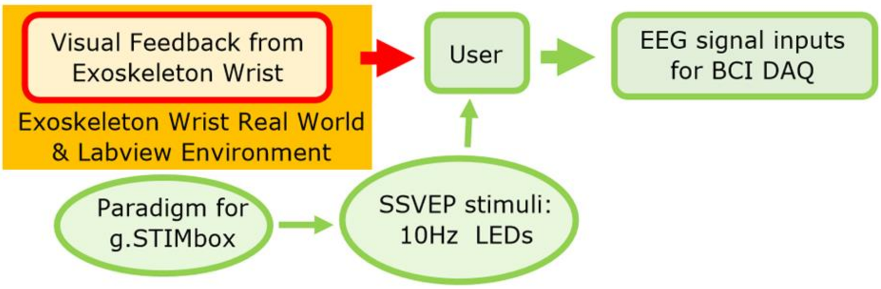

Figure 13: Signal generation of SSVEP BCI

6.1.2 Signal Acquisition

The online SSVEP DAQ section had same structure as both offline systems. The g.USBamp block in Simulink needed careful configuration (shown in Appendix C) otherwise the system will not be able to derive the related responses. Apparently, online MI would have this stage as well thus the block diagram shown below won't be talked in 6.2 section again.

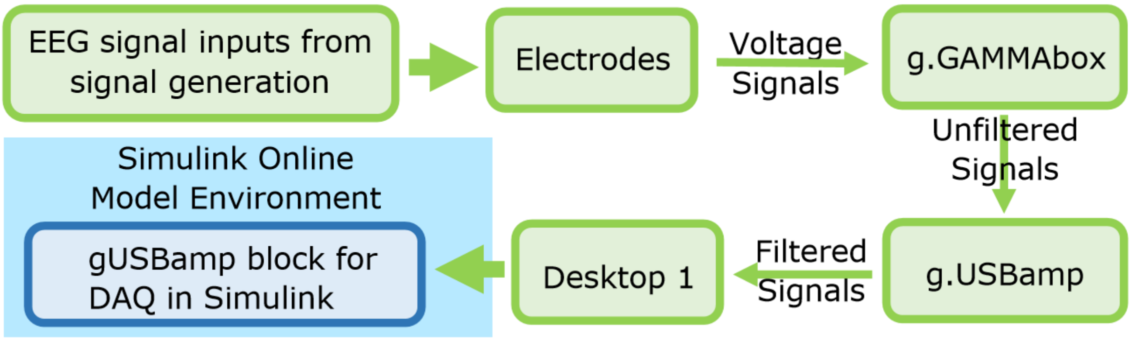

Figure 14: Signal acquisition of both MI & SSVEP singular based BCI

6.1.3 Signal Processing

According to literature review, many studies said that FFT was not a highly reliable approach to extract the desired patterns in real-time model [12, 21, 56]. In all existing analysis method from g.RTanalyze, only Minimum Energy Combination widely contributes on SSVEP signal processing. The method is to conjoin all signals from arbitrary number of the electrodes together and then cancel the nuisance signals potentially [57] and then the stimulus frequency corresponding to the max power is obtained. The only hesitation of minimum Energy is that it usually yield lower SNR and larger 2^{nd} harmonic components of stimulus frequency [58]. However, the system only requires 10Hz to control one direction, thus, no possible interruption from its harmonies would happen. The configuration of this block sets the buffer length with 768 samples, re-estimation in period of 0.2sec, only one harmonics and 7 order of AR model.

We then apply median filter to the extracted data in order to smooth out some unwanted noise. Square operation is also taken to enlarge the difference and helps us to find out a reliable threshold to control the exoskeleton wrist.

6.1.4 Control Algorithms

The simple comparator judges the previous value from processing step with the threshold to define the current condition of user's intent. If it is true, the output "1" means user is looking at the 10Hz LED and he or she wants to control the artificial wrist moving downwards. Otherwise, the yielding output is zero.

6.1.5 UDP Server

The UDP server then transmit the final trigger output into LabVIEW environment to control the device's movements. The remote address depends on the property of myRIO board rather than the computer. Figure 15 shows the configuration in detail.

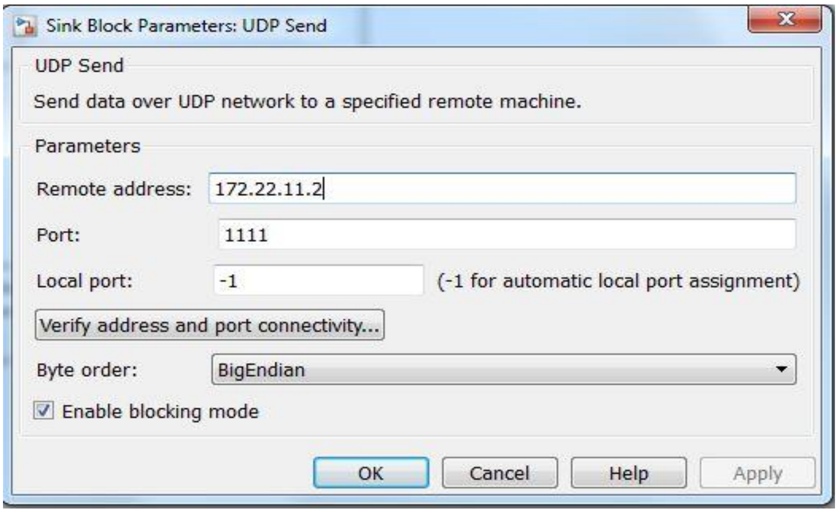

Figure 15: The configuration of UDP server.

6.2 Singular MI based online BCI

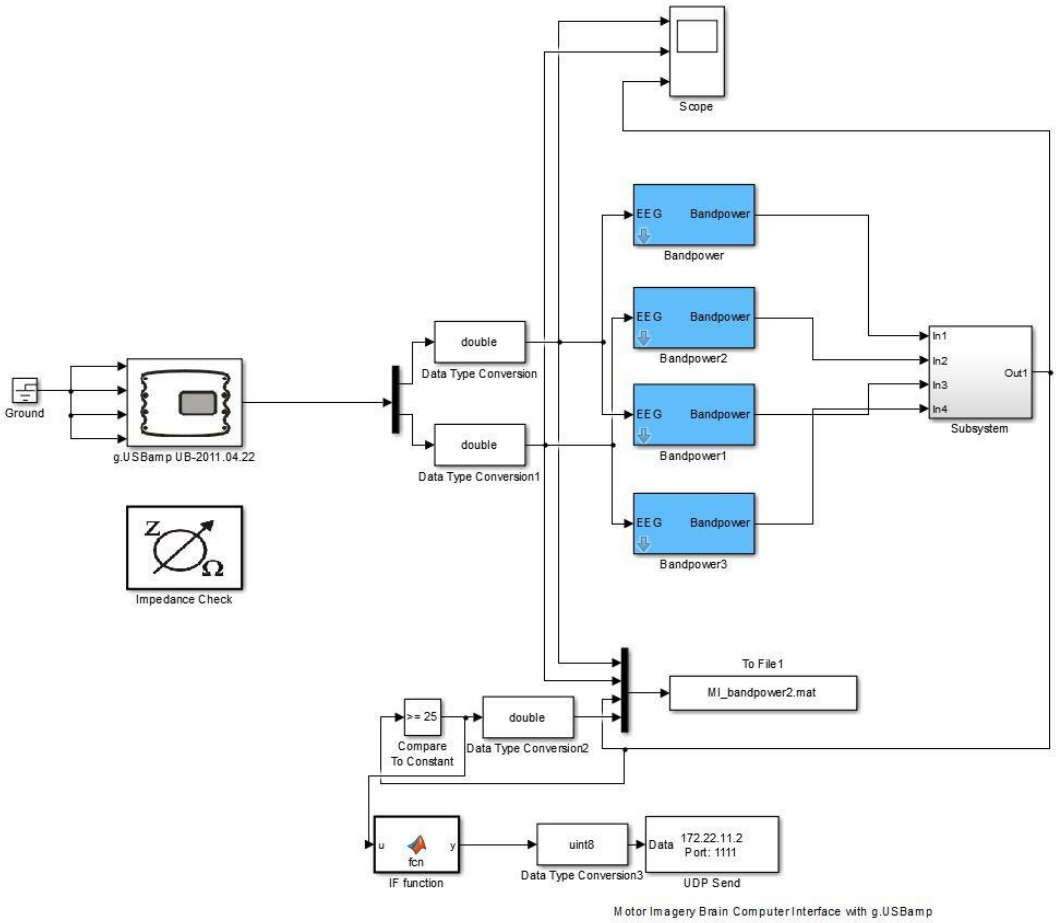

Figure 16: Online MI based BCI.

The online MI based BCI only have electrodes of C3 and C4 because the offline experiments indicates that the difference caused by location is not influential. The Simulink model is shown as figure 16 which still utilize Bandpower as analysis method.

6.2.1 Signal Generation

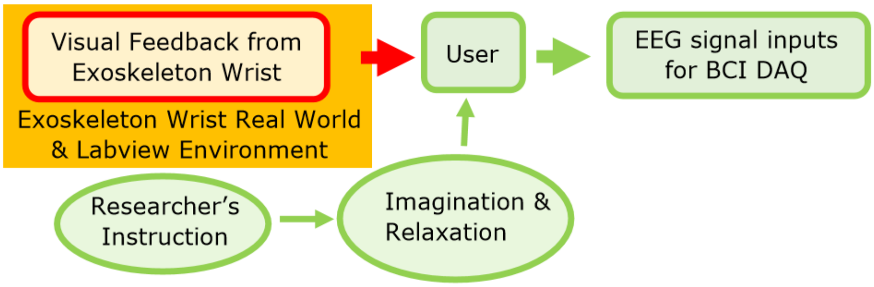

Figure 17: Signal generation for MI based BCI

The only difference between two generations of sub-systems is that test subjects can follow the voice prompt to guide their thoughts without any external stimulus. Hence the experiments' paradigm of MI system changed. There would be some tolerance due to the manual instruction. Meanwhile, both singular online systems have the same DAQ part, so it won't be mentioned here again.

6.2.2 Signal Processing

Unlike the PSD based band power in offline BCI, this method is band pass filtering with a Butterworth IIR filter. It is likely to directly apply a band-pass filter to the input raw signal and aim to damp out frequencies outside for both alpha (8-12Hz) and beta (12-30Hz). The resulting extracted feature presumably remains only the selected frequency [19]. The order of this IIR filter was 5 and window length contained 128 samples. The log-transform converted the signals into frequency domain again. With one more median filter with length of 10 samples smoothing the noise, it then estimated the energy in these bands by squaring the magnitude directly and timed specific weight values for 2 channels (2 bands each) for significant discrepancy.

6.2.3 Control Algorithms

There was a comparable logic in the MI system. The yielding output of it is 2, which is achieved by a simple "if" clause. Then this signal was sent to the UDP server in the same way as the SSVEP based BCI.

6.3 hybrid SSVEP/MI based BCI

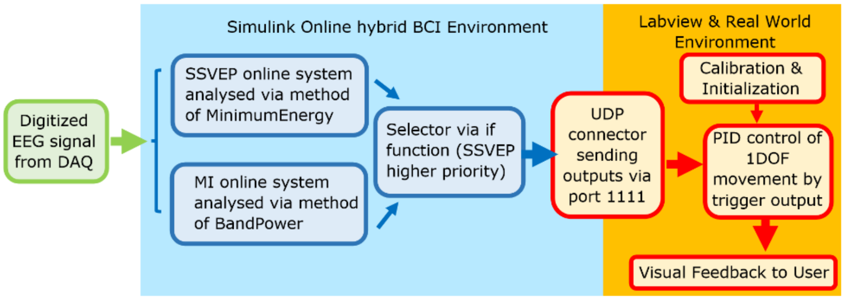

Figure 18: Block diagram of hybrid SSVEP/MI based BCI

The structure of hybrid SSVEP/MI based BCI is shown as figure 18 which simply integrates two subsystems together with only one g.USBamp block including a total number of 10 electrodes (8 for SSVEP, 2 for MI) for EEG DAQ.

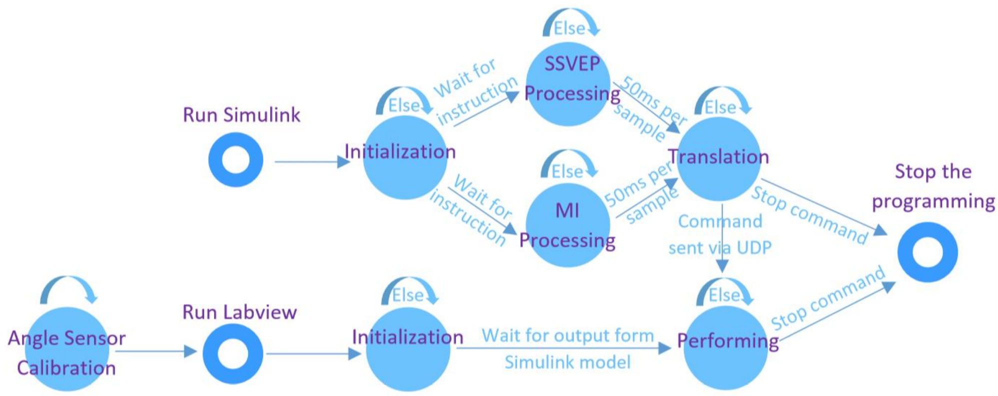

Figure 19: Finite state machine of hybrid BCI

The finite state machine shown above generally describe the working pathway of this complete system. At the beginning of operation, a calibration of angle sensor is necessary to set the zero point. After pressing the start button of both Simulink and Labview models, initialization status desires about 20sec to settle down the system

This hybrid BCI continuously acquires user's intents and extracted by two subgroups simultaneously to figure out which type EEG is implemented by user at the present and send their Boolean value to comparator. In the next stage, the "if" clause is used to judge the conditions. If both responses attain a positive value, SSVEP has a higher priority to be sent to the Labview environment due to higher accuracy of SSVEP offline performance.

The continuous output of Simulink is then digitized by about 50ms sampling rate to set aside some time for air muscle complete the fixed step length 0.2 degree. If the trigger value is 1, the wrist goes downwards and if the value shows 2, it will go upwards. Otherwise, the beam of wrist maintains the same position during triggering off. This control algorithm allows people continuously control the wrist in two directions. After the instructor stop the programme, the wrist will automatically return the initial position.

7 Exoskeleton Wrist Application

7.1 Communication with Simulink

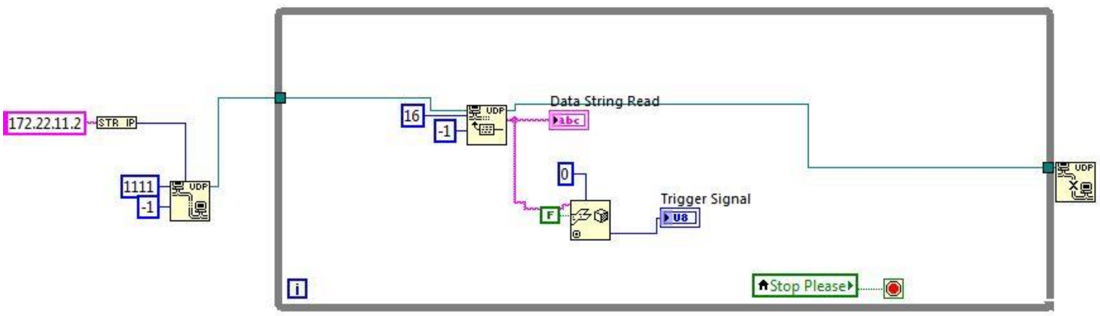

Figure 20: UDP client in Labview

The above figure shows how the Labview code receives the data from Simulink. The waveform diagram named Trigger Signal shows the changes of user's intents. This while loop is embedded in the main code after initialization. The trigger signal is then sent to the actuator which is shown in figure 21 to control the actual movements by PID controller.

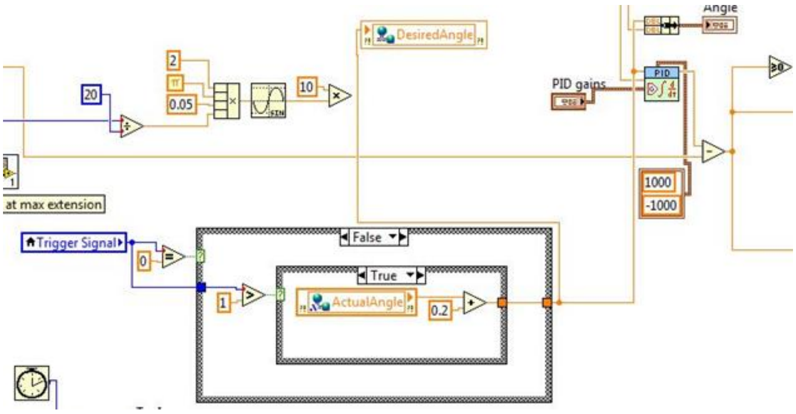

Figure 21: Actuator in Labview to define the direction and length of movements

7.2 Angle Sensor

Calibration of the angle sensor is another important part to operate the exoskeleton wrist.

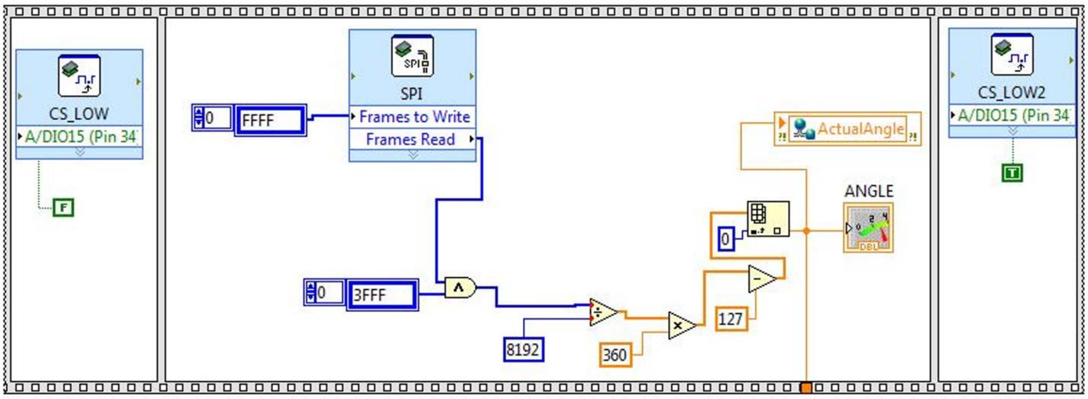

Figure 22: Calibration of Angle Sensor

The number of 127 is the current tolerance which is also necessary to be changed in main code before every initialisation of the device to achieve a zero-point position.

7.3 Weakness of Device

The current wrist has some defect in its mechanical design thus it keeps making loud and annoying noise which has a strong impact on subject's imagination. Meanwhile, the air supply for air muscles is a compressor machine and it also create noise to make the lab environment worse. For most subjects, how to decrease the liveness of their brain activities during the testing is the crucial problem.

8 Performance Analysis of Online system

The online SSVEP system achieved a critical high amplitude of response along with almost zero noise existing. The figure 23 indicates the clear edges between focusing on the flickering lights or having a relaxation. The accuracy of online singular SSVEP system gain an average value of 98.17% and the delay is about 2.5 sec.

The second subsystem, MI BCI, got a lower threshold at about 60 after bandpower analysis shown in figure 24. The 3.5 sec delay of response might be due to the subject had no training before. And without the connection of exoskeleton wrists' noise, its accuracy is 99.04%.

However, this result only comes from the 2 subjects with more than 1 month of training while others could not to tell there was a stable MI features encode the user's intents.

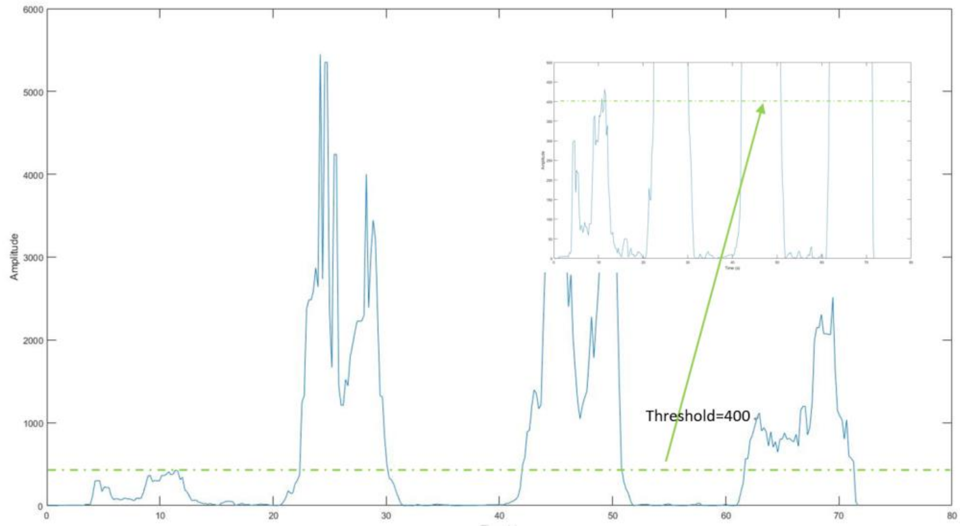

Figure 23: one subject's response of online SSVEP based BCI with threshold value of 400.

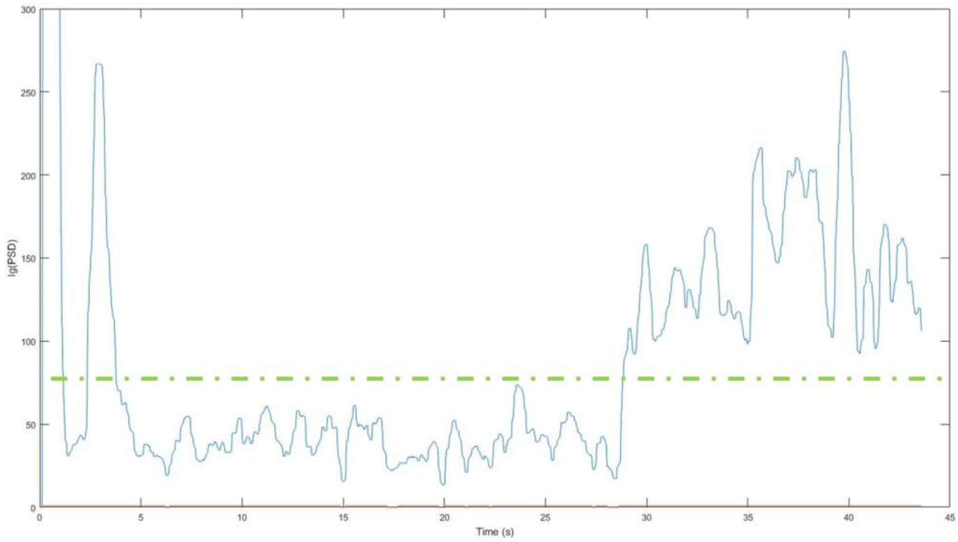

Figure 24: one subject's response of online MI based BCI with threshold value of 60.

And the finalized hybrid BCI achieved an accuracy of 83.26% which is lower than both subsystems. This decrease might because when user do the SSVEP experiments, strong attention of eyes is necessary to achieve and the visual fatigue or fast eye blinking could introduce the voltage fluctuations in MI area. The slightly interrupt between two types of EEG signals during the control of artificial wrist is reasonable.

The connection with application device is considered as an important part to achieve a great response time of the BCI. This performance is judged by Information Transfer Rate (ITR), a common standard which measured in bits per minute [59]:

$$\text{ITR} = \left(\frac{60}{T}\right) \times \{log_2(N) + P \times log_2(P) + (1-P) \times log_2[\frac{1-P}{N-1}]\},$$

Where T is the time taken per action of application device, N is the number of possible choices and P is the probability of selecting the correct output, also known as the accuracy.

Thus, SSVEP online system has a rate of 24 bit/min, MI online system has a rate of 17.143

bit/min, and hybrid BCI system gets the value of 15 bit/min. The existing Labview code of device is the main part to slow down the rate because air muscle requires many wait clock to complete the smooth motion of wrist. The system can continuously receive the control signals, thereby the slow motion might become an advantage for user to adjust the proper angle for rehabilitation.

8.1 Improvement for online design

After integration of two subsystems, the accuracy and ITR has a minor drop which actually can be eliminated by the more DAQ electrodes, updated hardware, longer training and better processing approaches for both types of EEG. A few of studies utilized some complex analysis methods and improved filters to accomplish to avoid the interrupt via the good distinction and classification of two or more kinds of EEG signals.

Adaption in translation algorithm is another area should be considered. A BCI that possesses a first level that adjusts to a new user only initially and never again will be likely to make the performance unstable. EEG usually varies with those variations related to time such as immediate environment, fatigue, illness and other possible factors. To reduce those impacts, a good translation algorithm should be designed to adjust to user's current condition.

9 Conclusion

Overall, the main goals of this FYP have already been realized by the successful design of hybrid SSVEP/MI based BCI and good communication between the hybrid interface with the existing exoskeleton wrist for rehabilitation application. These targets addressed the gaps and interests in literature and also the work done by the university. The design of MI system breaks the limitation of works in the university that only focused on the SSVEP part which may be difficult to attract more potential users. The success of online system design develops the practical skills in programming and analysis works bridges a gap of statistic knowledge. The performance analysis has already proved that the designed hybrid system is reliable to control the exoskeleton wrist. Thus, the summary of key points in this project is shown as follows:

- The full understanding of this project was built by a deep literature review to find out the gaps and interests. There were some researches that integrated the BCI system with rehabilitation applications. However, only few of them attempted to utilize the hybrid BCI and current works done by UOA had a gap in studies of MI based BCI.
- A set of offline experiments contribute on a deep understanding of several key parameters during the design of singular SSVEP or MI based BCI.
- The communication between Simulink and Labview extends the applications of BCI system and replace the physical controller thereby those patients with critical neuromuscular disabilities might be attract by this convenient and accurate system.
- The hybrid EEG based BCI for rehabilitation applications exploit the new field in the university, thus the further cooperation and development are possible to be carried out.
- EEG signals vary with individual. Some subjects had better performance on one part of the hybrid BCI than the other. Whatever hybrids people are developing, the results are unpredictable because everyone is different and some people perform better in some BCIs. Thus a hybrid BCI is difficult to implement for everyone.

10 Future work

10.1 Critical Problems in BCI lab

- Some of the hardware involved in the BCI setup is outdated and will require and upgrade. The critical pieces of hardware that needs to be replaced soon are the electrodes. Electrodes are becoming worn and are larger than the ones used in the current market. Hybrid BCIs may be difficult with the current electrodes and there are currently smaller electrodes out in the market which offer a better spatial resolution. Currently the company no longer continue making or selling, and replacing them will become more and more difficult.
- Even for short experiments require a long procedure to setup and cleaning electrodes make it not only time consuming for the researcher, it also affects the test subject as well, and this happens for every time an experiment needs to be performed. Dry electrodes may be a solution to this problem.
- All the software installed on the computer has compatibility issues and general issues with certain versions of software and as a result programs suddenly crash or throw errors and some features of software cannot be used.

To solve all those and some other minor problem, PhD students have already reported the current situation of the BCI lab and applied a complete new set of hardware and software. It will be greatly helpful for them and next year Part IV students to develop better hybrid BCI.

10.2 Improvements

- Based on the analyzed results, earlier session always gained the better performance. As mentioned before, long-time period gazing at flickering lights caused visual fatigue. And in the designed experiment procedure, 10Hz was always the first tested frequency, it might be the reason why it became an optimal selection. For the further improvement, the sequence of these target frequency should also be considered in the design of experiments.
- The LED board was designed last year and it wasn't quite suitable for this project. In the hBCI, a smaller board with central location of LED array could be implemented on the artificial wrist.
- The current manual instruction which might leads to time delay for MI experiments is not reliable. Both imagination and relaxation of this part are difficult for people without training, especially when the application device creates loud and annoying noise to distract the attention. Other exoskeletons with linear actuators rather than air muscle could be considered to connect.
- In feedbacks most of subjects reflected that they felt sleepy and blurring after several sessions and also distracted sometimes by surrounding noise or display screen. Dimly-lit and soundproof background is necessary for the further experiments.
- Users with disabilities are likely to attend even more variation such as illness, fatigue and etc. Thus, BCI systems should be tested in more number of users, and the test subjects should have some users with neuromuscular disabilities. Each user can be tested more than 1 time for DAQ over substantial periods. To analyze the performance, more appropriate and comprehensive statistical tests are necessary.

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Appendix A Hardware Setup

A.1 Offline SSVEP Experiments Setup

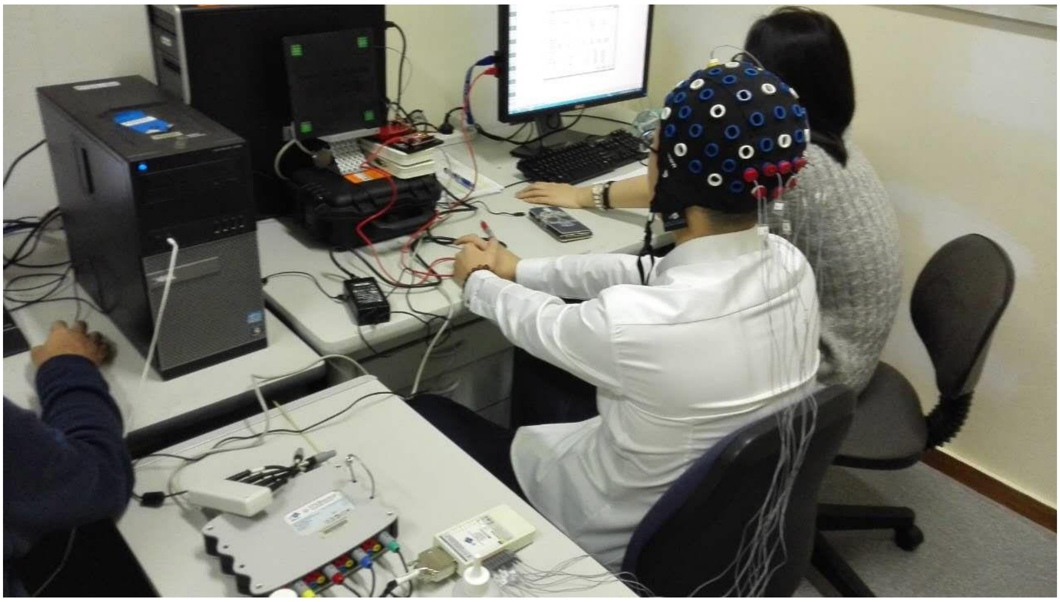

Figure A 1: Setup of offline SSVEP

Figure A 2: gUSBamp

Figure A 3: Electrodes

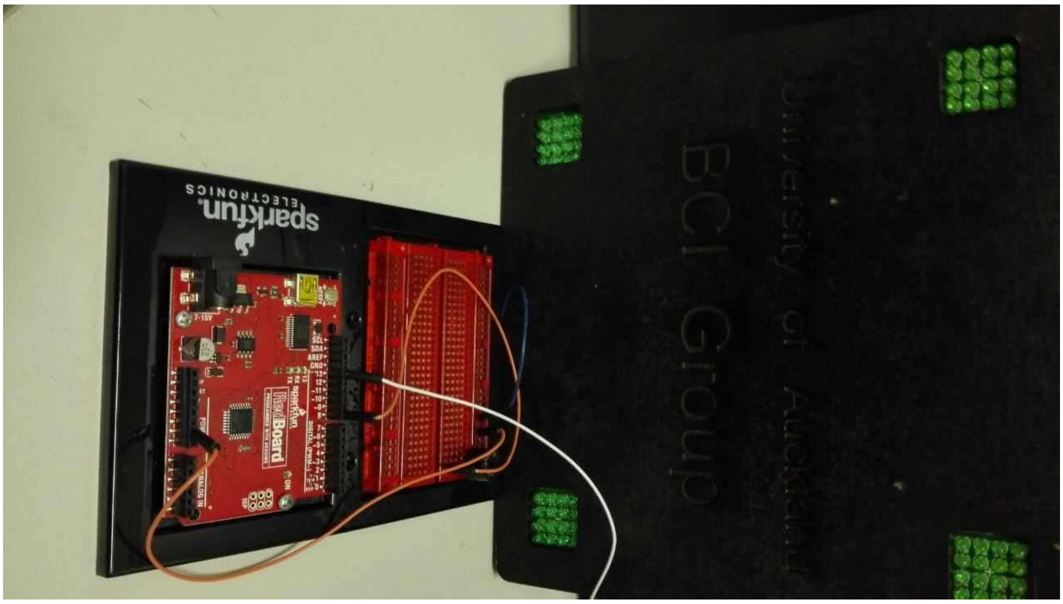

Figure A 4: LED and Arduino Board Setup

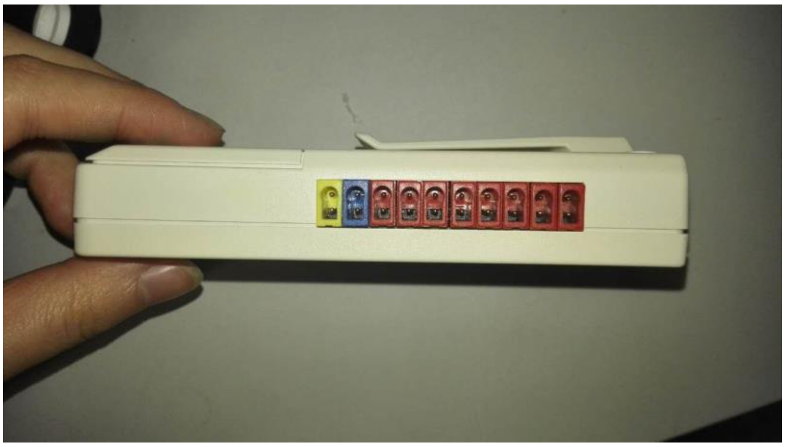

Figure A 5: gGAMMAbox

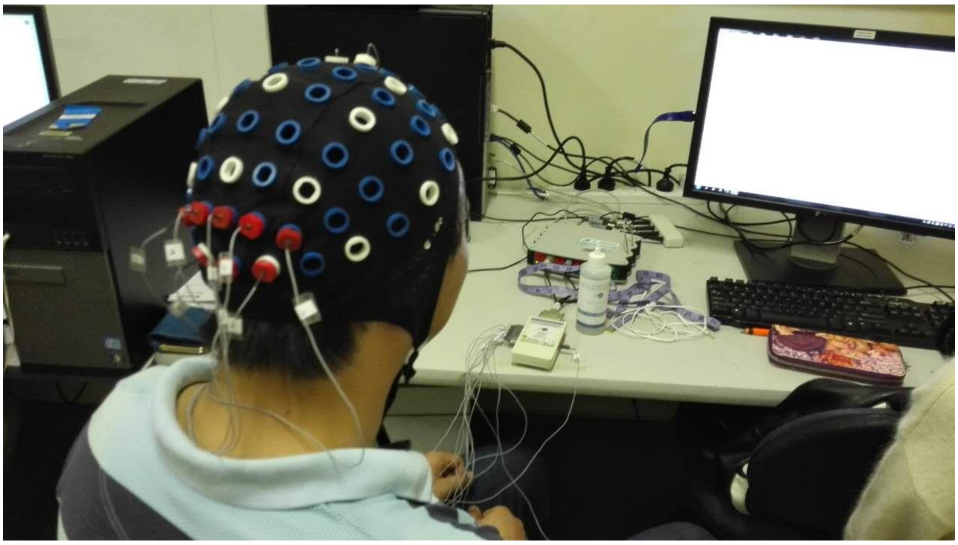

Figure A 6: 8 electrodes system for SSVEP

A.2 Online Exoskeleton Wrist Setup

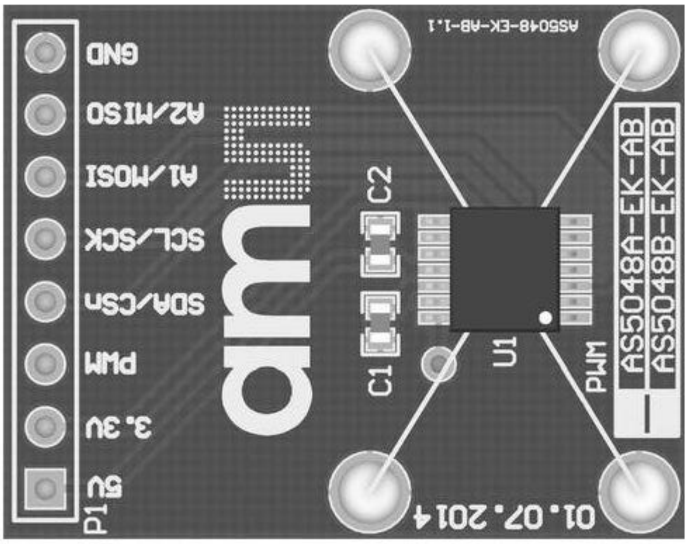

Figure A 7: Angle Sensor AS5048

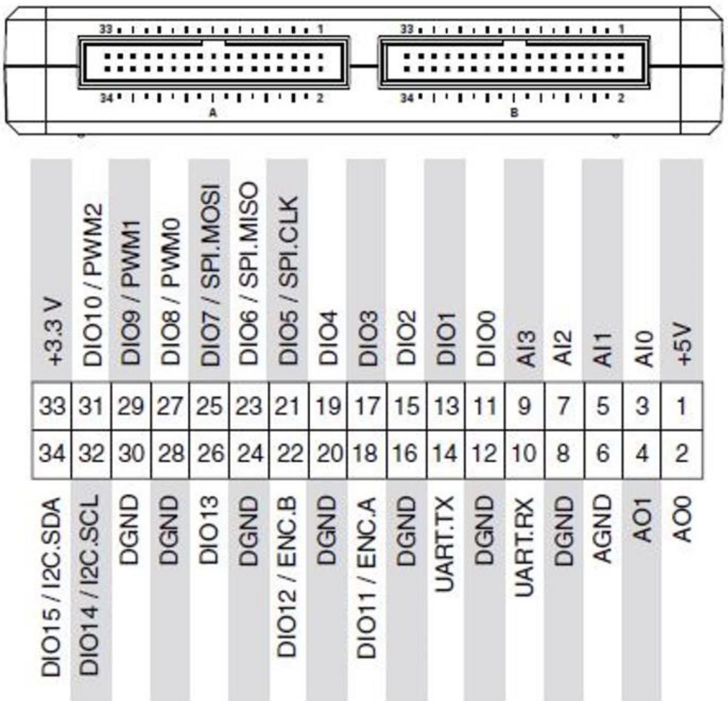

Figure A 8：Primary/Secondary Signals on MXP Connectors A and B

Figure A 9: 24V power supply

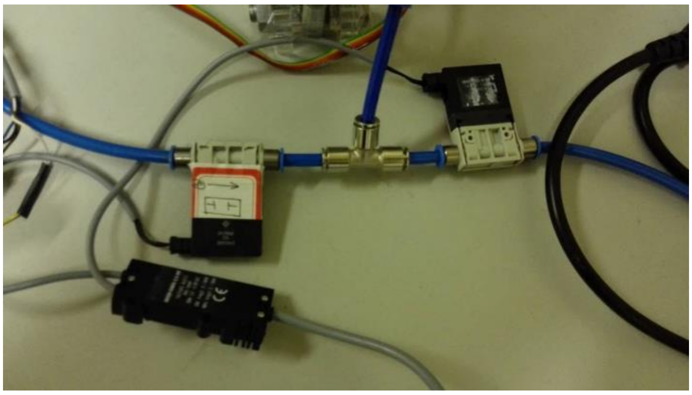

Figure A 10: Pneumatic controller and inlet/outlet pipes

Figure A 11: myRIO board

Appendix B Configuration and User Interface of Analysis Software

B.1 Online SSVEP

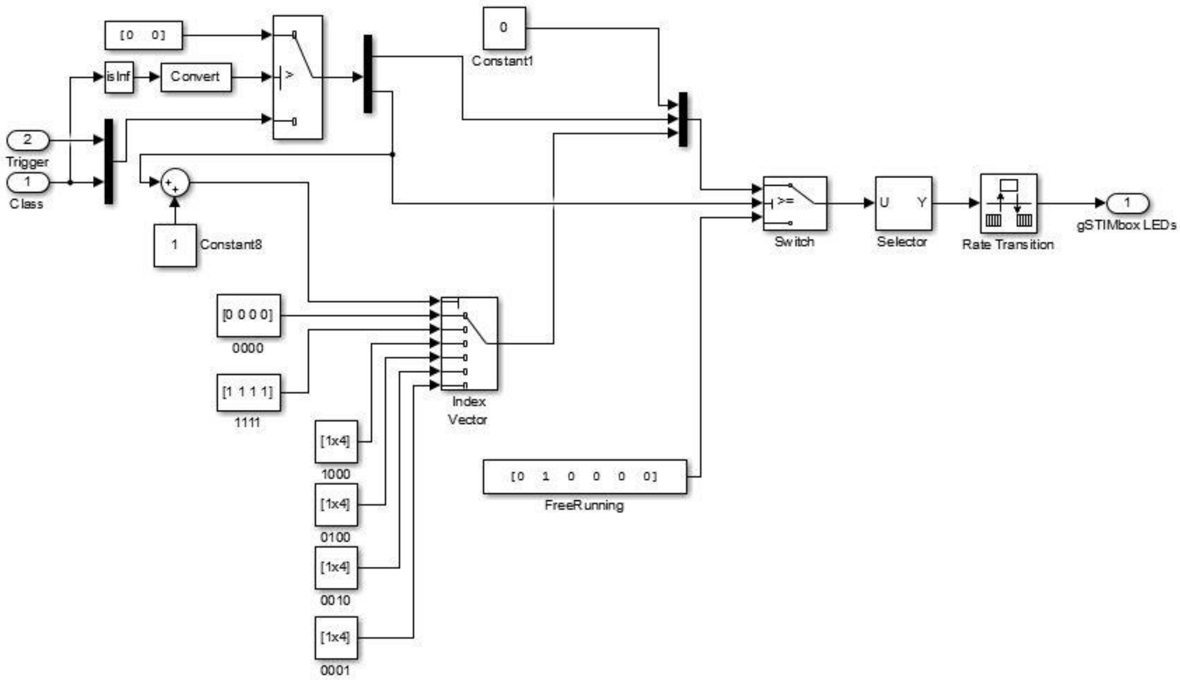

Figure B 1: Adaption to g.STIMbox for Online SSVEP system

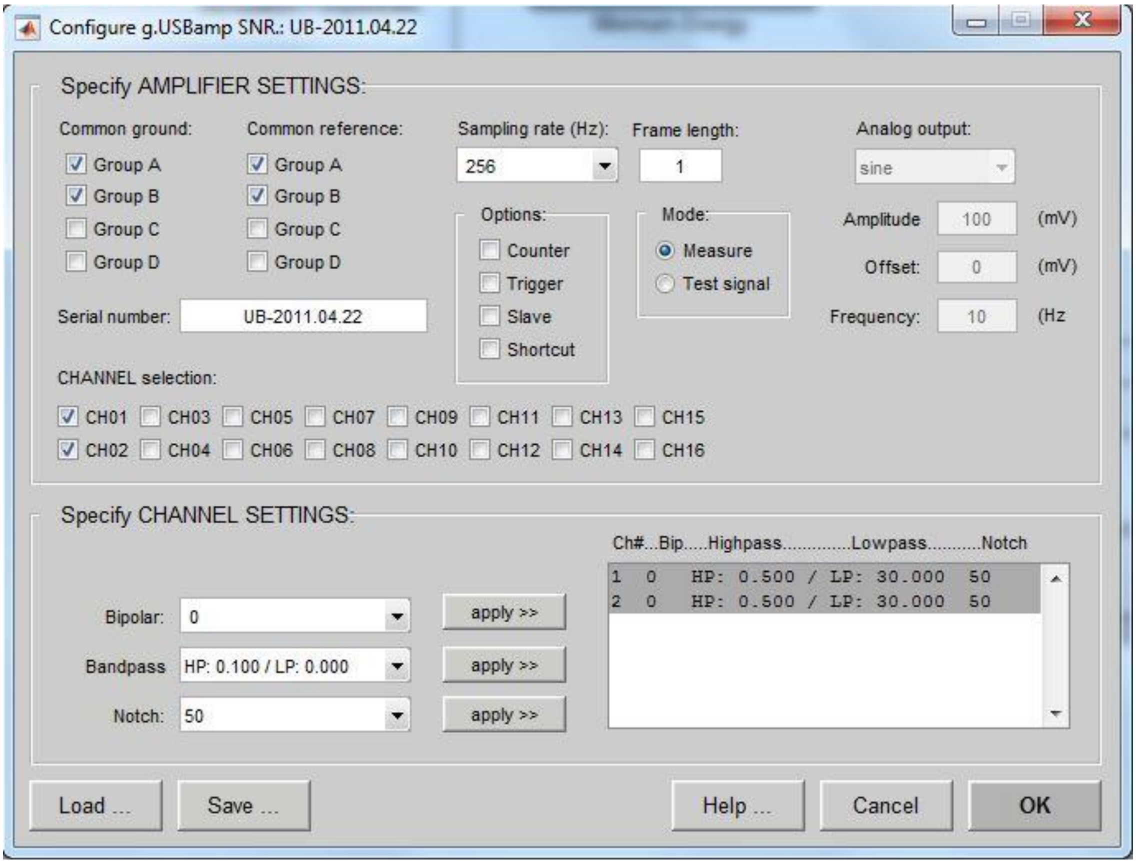

Figure B 2: Configuration of gUSBamp in Online SSVEP

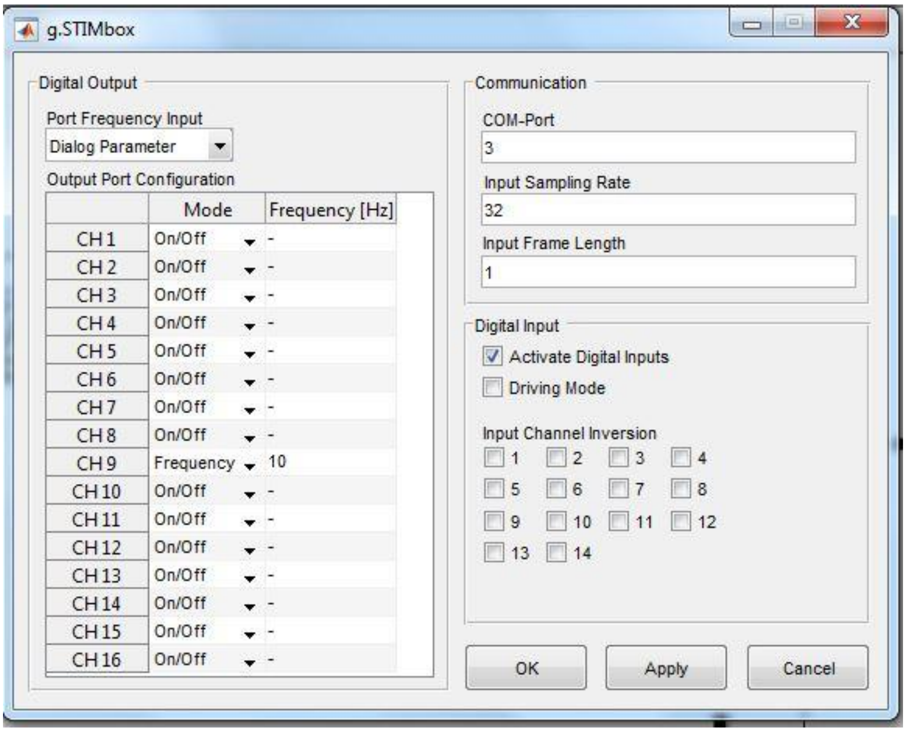

Figure B 3: Configuration of g.STIMbox

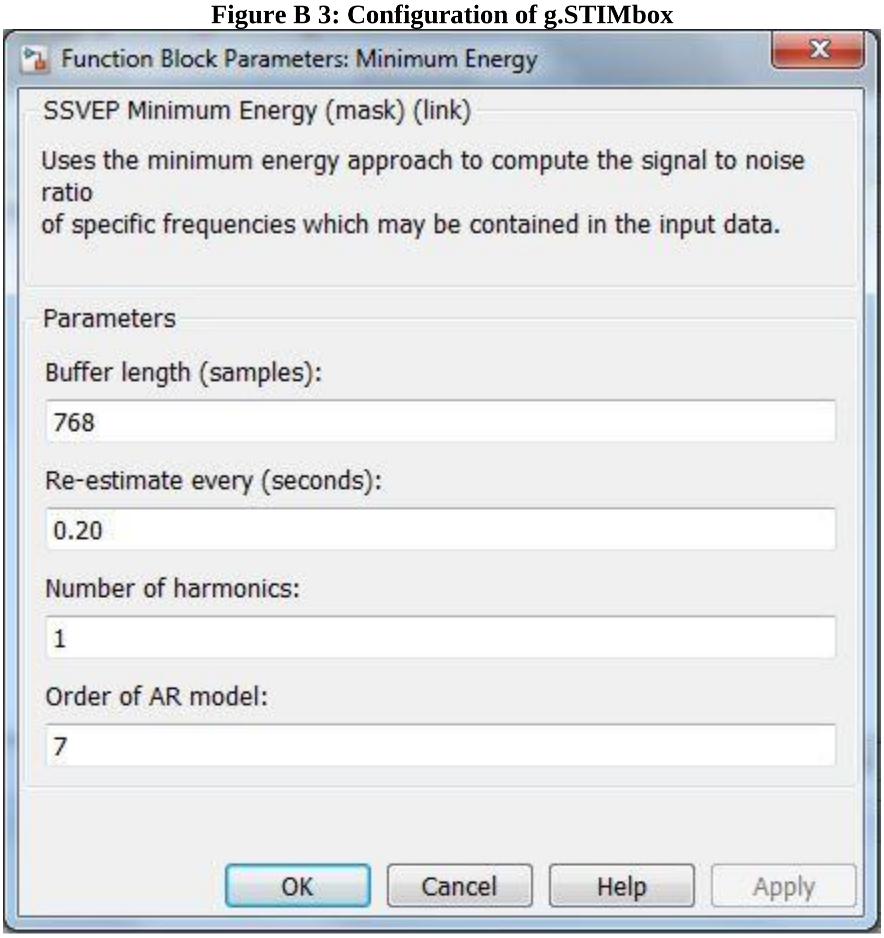

Figure B 4: Configuration of MinimumEnergy

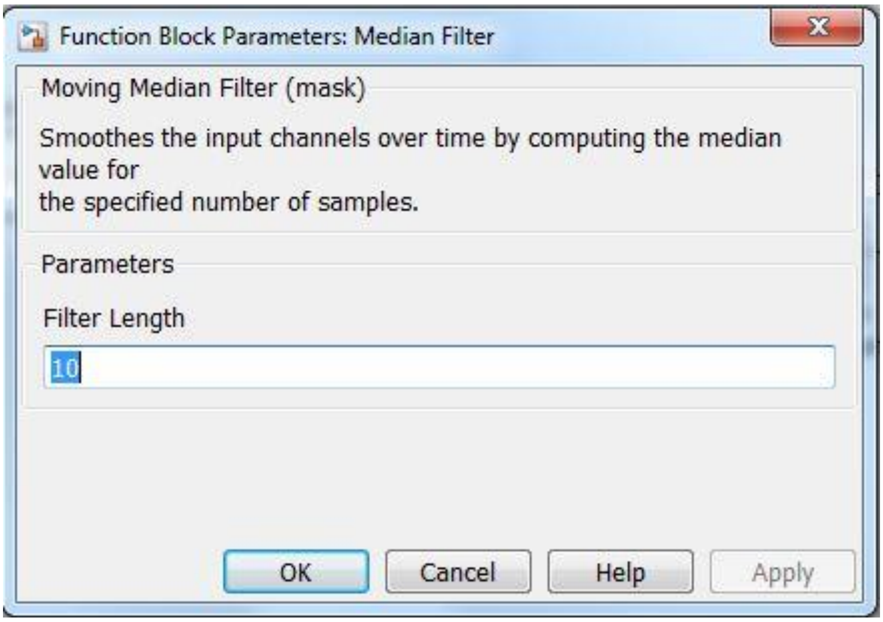

Figure B 5: Configuration of Median Filter

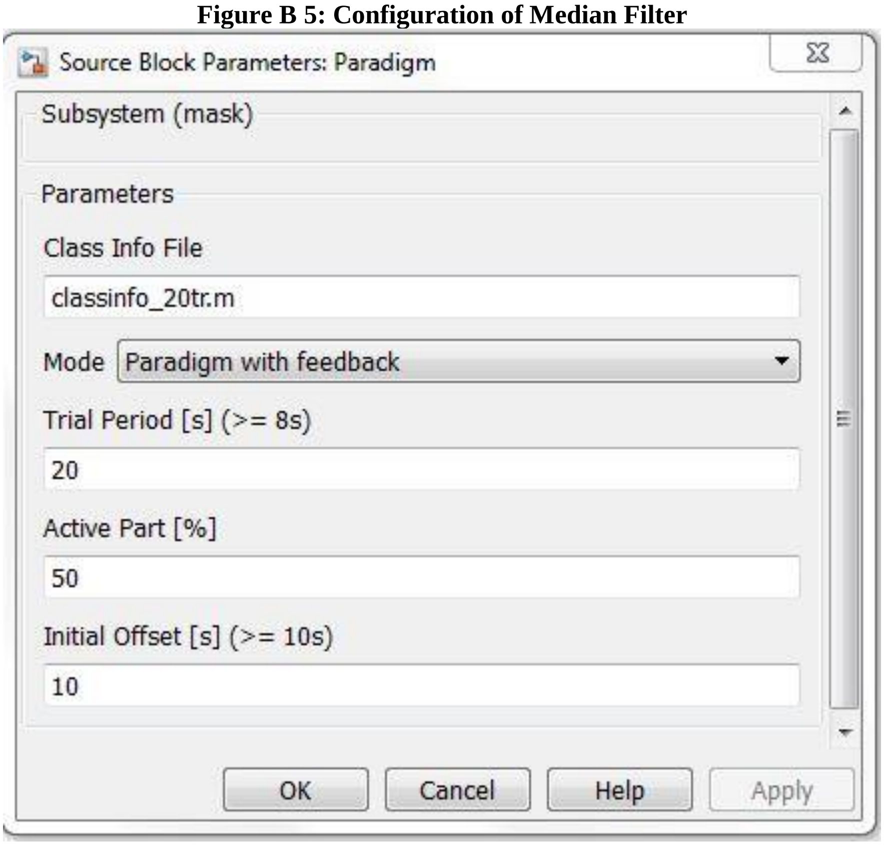

Figure B 6: Configuration of Paradigm

B.1 Online MI based BCI

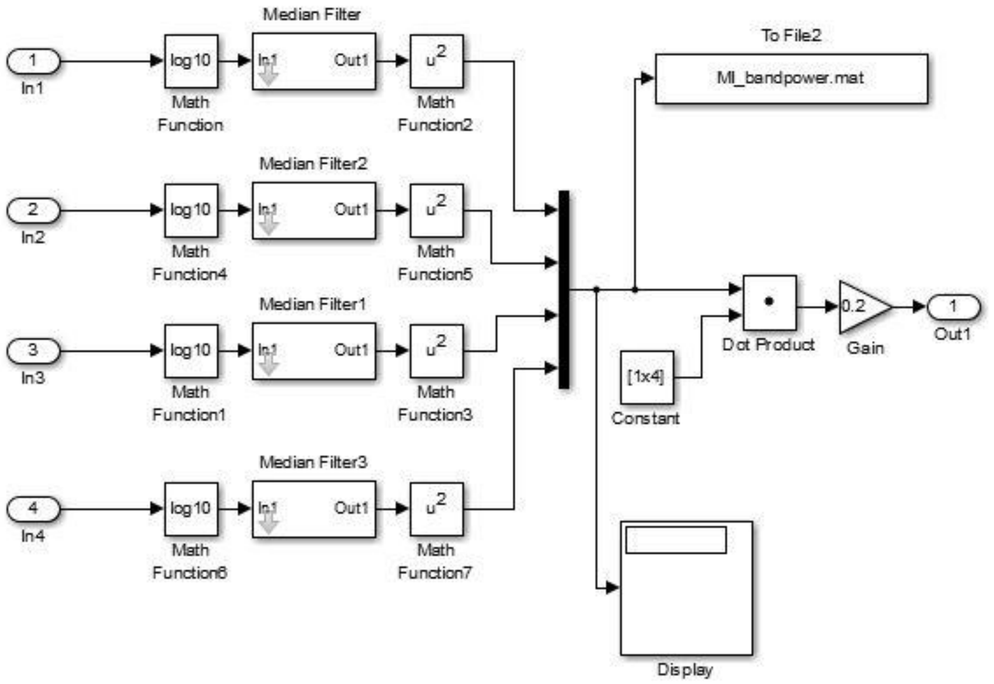

Figure B 7: MI Online Translation Algorithm

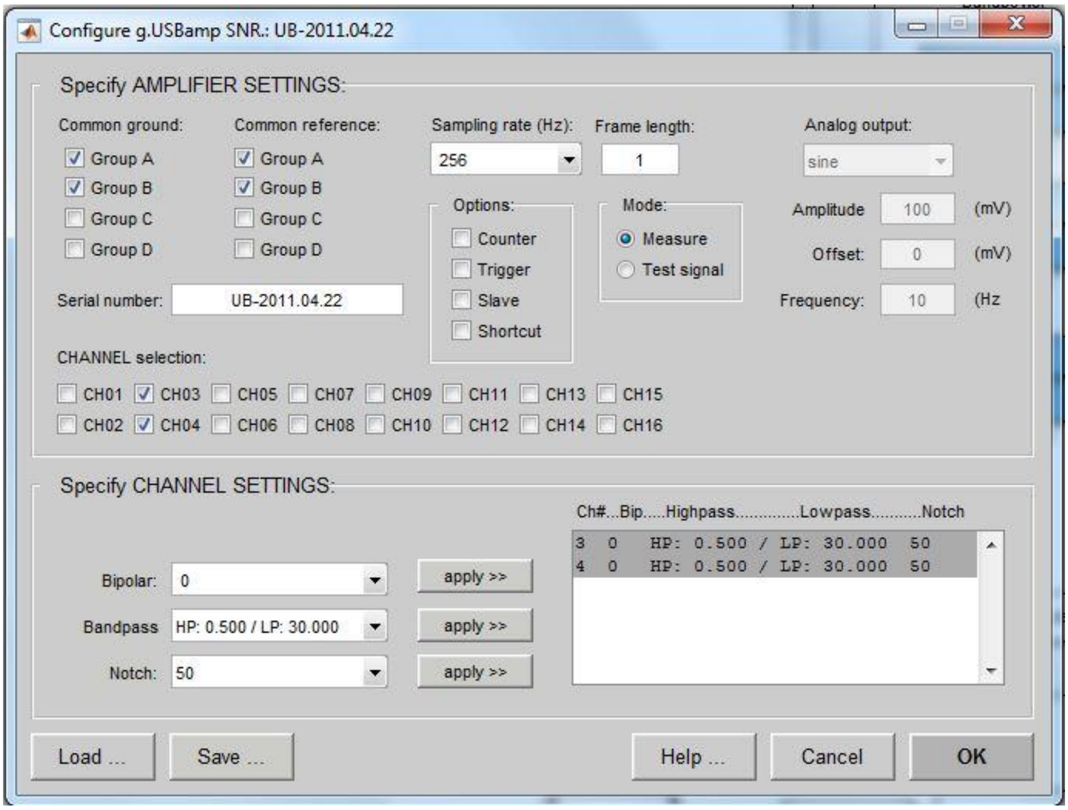

Figure B 8: Configuration of g.USBamp for online MI BCI

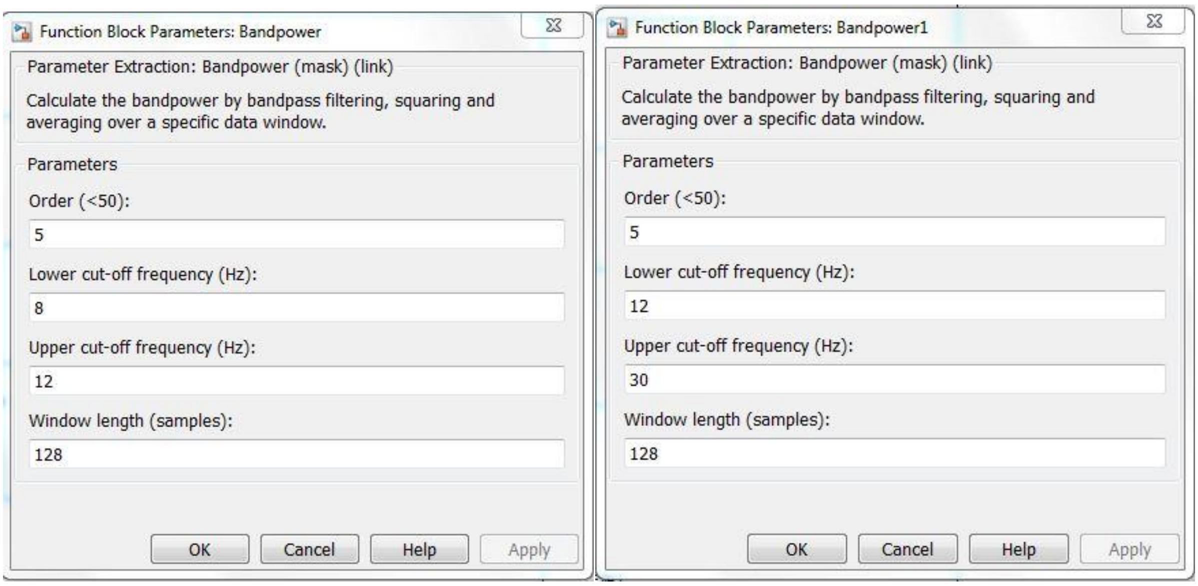

Figure B 9: Configuration of Bandpower in alpha & beta band respectively

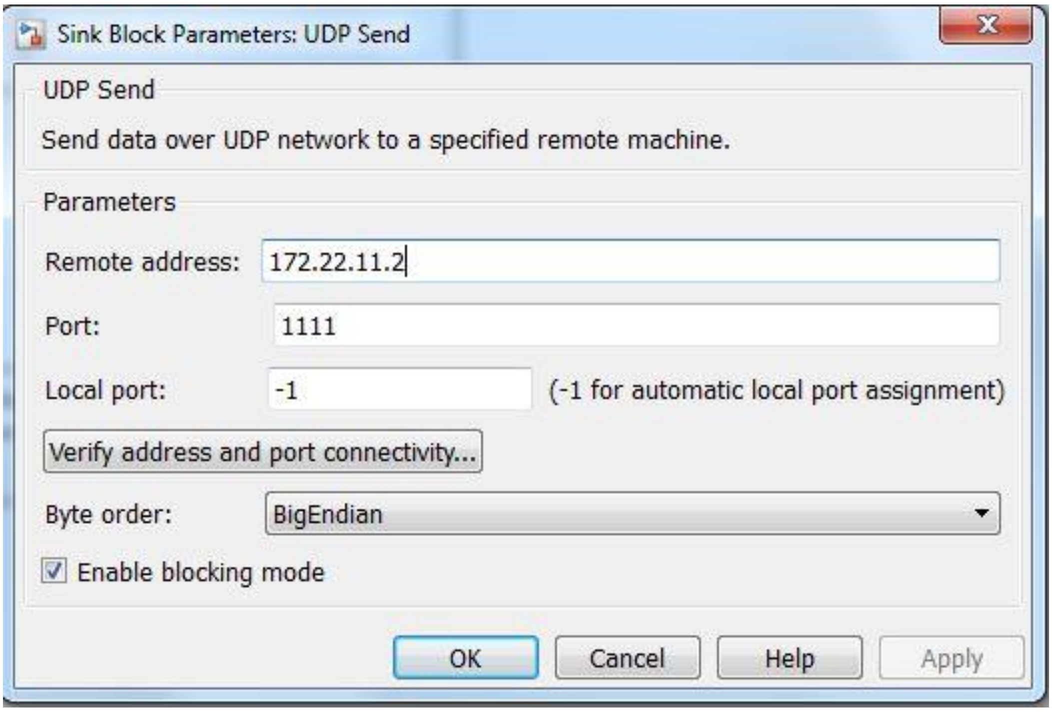

Figure B 10: UDP server in Simulink

Appendix C Offline Configuration of g.Recorder

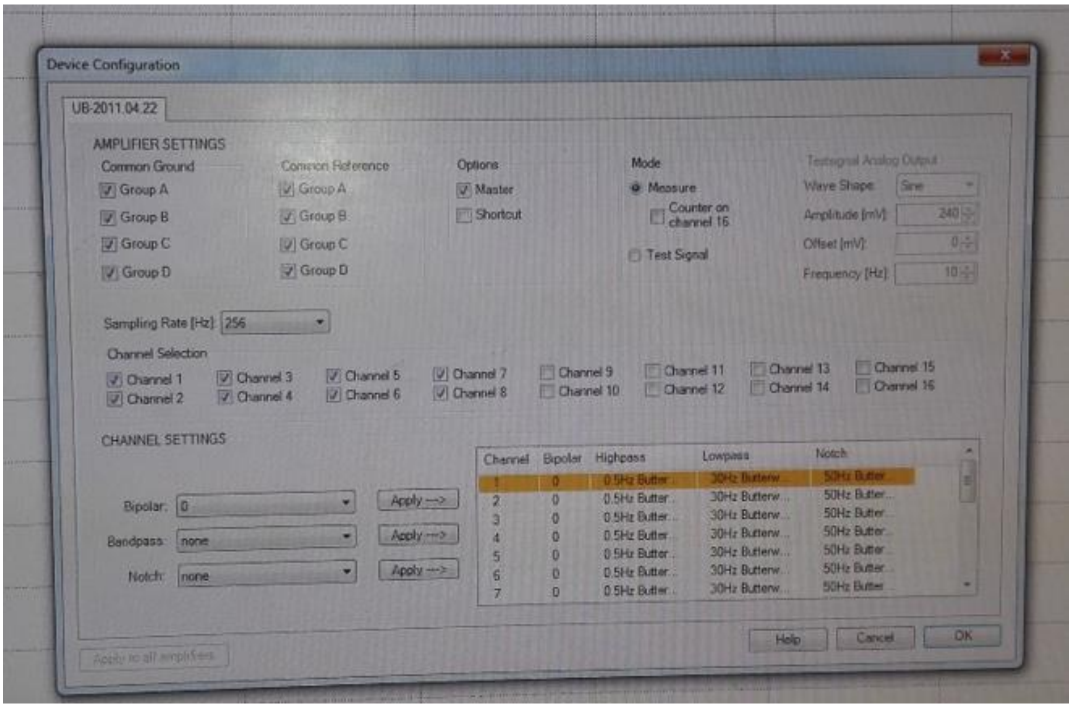

Figure B 11: bandpass filter for pre-processing

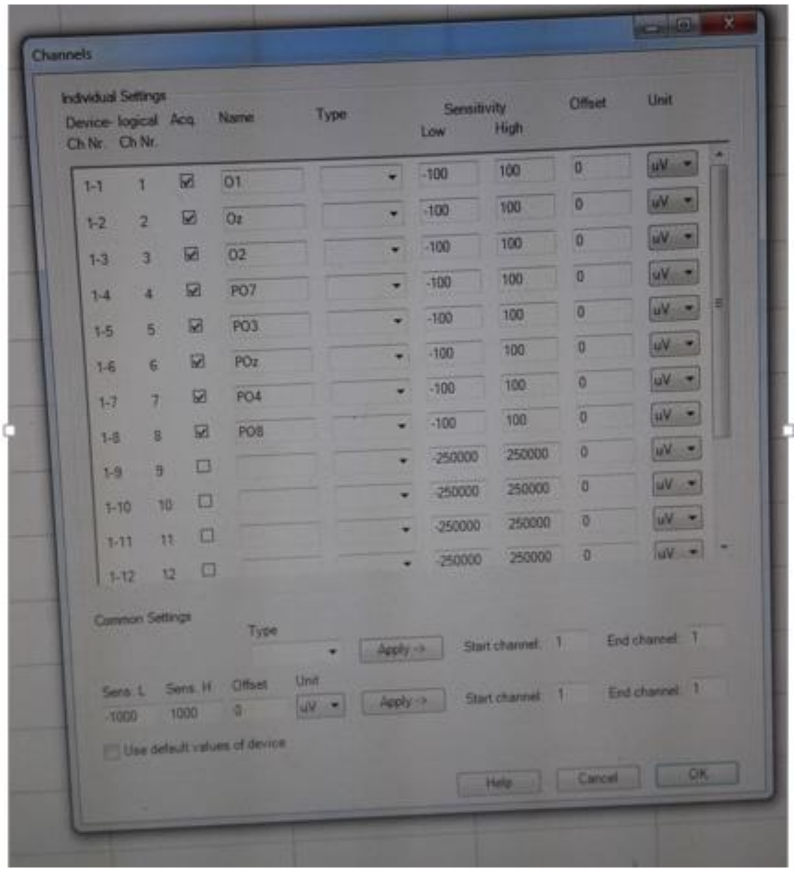

Figure B 12: sensitivity and channel selection

Appendix D Matlab Code for FFT analysis under 10Hz

```
% FFT of One Channel
M = h5read('session12016.06.30_12.10.24.hdf5','/RawData/Samples');
%M=load('test1.mat');

Fs = 256;               % Sampling frequency
                      %Number of samples, L = 9186
figure (1);
for i=1:8

y = M(i,15872:17664);
L = length(y);
NFFT = 2^nextpow2(L);   % Number of points on the fft, Nfft= 16384
Y1 = fft(y,NFFT)/L;    % cal fft and Discard Half of Points
frequency = Fs/2*linspace(0,1,NFFT/2+1); % linspace(0,1,3);x as a vector of
3 linearly spaced values between 0 and 1
amplitude = 2*abs(Y1(1:NFFT/2+1));
power = (abs(Y1(1:NFFT/2+1)).^2);

subplot(4,2,i)
plot(frequency,power);
axis ([0 15 0 5]);

xlabel('Frequency (Hz)')
ylabel('|Y(f)|')
grid on
end
```

```
figure (2);
for i=1:8

y = M(i,27648:29440);
L = length(y);
NFFT = 2^nextpow2(L);   % Number of points on the fft, Nfft= 16384
Y1 = fft(y,NFFT)/L;    % cal fft and Discard Half of Points
frequency = Fs/2*linspace(0,1,NFFT/2+1); % linspace(0,1,3);x as a vector of 3 linearly spaced values between 0 and 1
amplitude = 2*abs(Y1(1:NFFT/2+1));
power = (abs(Y1(1:NFFT/2+1)).^2);

subplot(4,2,i)
plot(frequency,power);
axis ([0 15 0 5]);

xlabel('Frequency (Hz)')
ylabel('|Y(f)|')
grid on
end

figure (3);
for i=1:8

y = M(i,39424:41216);
L = length(y);
NFFT = 2^nextpow2(L);   % Number of points on the fft, Nfft= 16384
Y1 = fft(y,NFFT)/L;    % cal fft and Discard Half of Points
```

```
frequency = Fs/2*linspace(0,1,NFFT/2+1); % linspace(0,1,3);x as a vector of
3 linearly spaced values between 0 and 1

amplitude = 2*abs(Y1(1:NFFT/2+1));

power = (abs(Y1(1:NFFT/2+1)).^2);


subplot(4,2,i)

plot(frequency,power);

axis ([0 15 0 5]);


xlabel('Frequency (Hz)')

ylabel('|Y(f)|')

grid on

end



figure (4);

for i=1:8


y1 = M(i,15872:17664);

y2 = M(i,27648:29440);

y3 = M(i,39424:41216);

y = [y1,y2,y3];

L = length(y);

NFFT = 2^nextpow2(L);   % Number of points on the fft, Nfft= 16384

Y1 = fft(y,NFFT)/L;    % cal fft and Discard Half of Points

frequency = Fs/2*linspace(0,1,NFFT/2+1); % linspace(0,1,3);x as a vector of
3 linearly spaced values between 0 and 1

amplitude = 2*abs(Y1(1:NFFT/2+1));

power = (abs(Y1(1:NFFT/2+1)).^2);
```

```
subplot(4,2,i)
plot(frequency,power);
axis ([0 15 0 5]);

xlabel('Frequency (Hz)')
ylabel('|Y(f)|')
grid on
end

% %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Nsamps = length(y);
% Do Fourier Transform
% Y1= abs(fft(y));            %Retain Magnitude
% Y1 = Y1(1:L/2);               %Discard Half of Points
% f = Fs*(0:L/2-1)/L;           %Prepare freq data for plot
% %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Appendix E Arduino Code for LED and Beep tone

```
/*
  Blink
  Turns on an LED on for one second, then off for one second, repeatedly.

  Most Arduinos have an on-board LED you can control. On the Uno and
  Leonardo, it is attached to digital pin 13. If you're unsure what
  pin the on-board LED is connected to on your Arduino model, check
  the documentation at http://www.arduino.cc

  This example code is in the public domain.

  modified 8 May 2014
  by Scott Fitzgerald
 */



// the setup function runs once when you press reset or power the board
void setup() {
  // initialize digital pin 13 as an output.
  pinMode(13, OUTPUT);//LED output
  pinMode(8, OUTPUT);//BEEP output
}

// the loop function runs over and over again forever
void loop() {

  tone(8, 1000, 1000); //long beep 1sec
```

```
  delay(1000);


  digitalWrite(13,LOW); //close eyes for 1min
  delay(57000);


  for (int trial = 0; trial < 3; trial++){ //3 trials per session




  for (int beep = 0; beep < 3; beep++){ //beep 3sec
    tone(8, 1000, 100);
    delay(900);
    digitalWrite(8,LOW);
  }


  for (int light = 0; light < 71; light++){ //7secs,10HZ, total 71 counts
    digitalWrite(13, HIGH);                  //the gap between 2 blinks is
100ms total, 50 for high(light on),50 for low(light off)
    delay(50);
    digitalWrite(13, LOW);
    delay(50);
  }
  digitalWrite(13,LOW);
//  delay(2700);


    for ( int beep = 0; beep < 3; beep++){ //beep 3sec for rest
    tone(8, 1000, 100);
    delay(900);
    digitalWrite(8,LOW);
  }
```

```
 for (int light = 0; light < 78; light++){ //7secs,11HZ, total 78 counts
    digitalWrite(13, HIGH);                   //the gap between 2 blinks is 90.9090909090909ms total, 45.4545454545 for high(light on),45.4545454545 for low(light off)
    delay(45.4545454545);
    digitalWrite(13, LOW);
    delay(45.454545454545);
  }
  digitalWrite(13,LOW);
  //delay(2700);


    for ( int beep = 0; beep < 3; beep++){
    tone(8, 1000, 100);
    delay(900);
    digitalWrite(8,LOW);
  }
   for (int light = 0; light < 85; light++){  //7secs,12HZ, total 85 counts
    digitalWrite(13, HIGH);
    delay(41.66666666666667);
    digitalWrite(13, LOW);
    delay(41.6666666666667);
  }
  digitalWrite(13,LOW);
  //delay(27000)
    for ( int beep = 0; beep < 3; beep++){
    tone(8, 1000, 100);
    delay(900);
    digitalWrite(8,LOW);
```

```
  }
 for (int light = 0; light < 92; light++){  //7secs,13HZ, total 92 counts
    digitalWrite(13, HIGH);
    delay(38.46153846);
    digitalWrite(13, LOW);
    delay(38.46153846);
  }
  digitalWrite(13,LOW);

for ( int beep = 0; beep < 3; beep++){//the rest for different trial is 10sec
    tone(8, 1000, 100);
    delay(900);
    digitalWrite(8,LOW);
  }
  delay(4000);


  }
  tone(8, 1000, 1000);    //the rest for different session is 1min
  delay(1000);
  digitalWrite(8,LOW);
  delay(59000);
}
```

Appendix F the log note of one subject

Date: 30/6/2016 12pm-12:30m

Test Subject: Gloria Hou (right eye dominant), good sight

Channels: CH1-O1,CH2-Oz,CH3-O2,CH4-PO7, CH5-PO3, CH6-POz, CH7-PO4 , CH8-PO8

Test Procedure(ed2) written in Word Document.

LED is about 2cm*2cm and almost perpendicular to the table.

LED and eye distance 80cm

Session 1&2: normal

Session 3: cover right eye

Session 4: cover left eye, during 1:20-1:27, Channel 5 lose connection

Feedback of the test:

- the earlier trial could lead better result becuz the views were clear without any blurring
- long period of focusing on the flashing lights make eyes tried, thus no sensitive responses based on different freqs
- after one minute closing eye, should not open eyes just at the third beep, eyes need one to two senconds to get used to the bright views
- the rest between each trials should become longer rather than just 3 sec
- the sequence of different freq may also be a problem to get lower response for 12 and 13Hz

Appendix G SSVEP BCI Data Acquisition Procedure

1. Preparation:

- Distance between the LED stimuli and the test subject: 80 cm
- Height of the person when sitting on the chair should be recorded
- Stimuli size should be recorded
- Frequency of the stimuli should be recorded
- Channals Oz, O1, O2, POz, PO3, PO4, PO7, PO8, F1

2. Session 1:

    - trial 1
        - 1 min eye-closed
    - trial 2 (starts at 58s)
        - 3s Rest 7s 10Hz 3s Rest 7s 11Hz 3s Rest 7s 12Hz 3s Rest 7s 13Hz 3s Rest
        - Rest 4s
        - Repeat above steps for 3 times

4. Repeat Session 1 for 3 times

5. Session 4:

    - Same as session 1 but with the dominant eye covered

Note:

- After reset the Arduino board there's a 2s delay before the subject hearing the long beep sound
- Total time taken for one session is 3 min 21 sec
- There is a 1 sec in advance after each trial
- Let the test subject write down their thoughts about the experiments such as any discomfort etc.

Appendix H Motor Imagery BCI Data Acquisition Procedure

1. Preparation:

- Speed of the hand movement should be settled, 4 motions/s
- Ways to imagine should be settled, generally divided into placid imagination of hand movement and strenuous imagination of whole body movement
- Test subject should be told to think about nothing during the relax
- Channels: C3, C4, Cz, FC3, FC4, PC3, PC4, Oz.
- The instructions of all actions are given by researchers.

2. Session 1:

   10 sec relax -> 5 sec strenuous imaginations -> 10 sec relax -> 5 sec strenuous imaginations -> 10 sec relax -> 5 sec strenuous imaginations

   Session 2:

   10 sec relax -> 10 sec strenuous imaginations -> 10 sec relax -> 10 sec strenuous imaginations -> 10 sec relax -> 10 sec strenuous imaginations

   Session 3:

   10 sec relax -> 15 sec strenuous imaginations -> 10 sec relax -> 15 sec strenuous imaginations -> 10 sec relax -> 15 sec strenuous imaginations

   Session 4:

   10 sec relax -> 15 sec placid imaginations -> 10 sec relax -> 15 sec strenuous imaginations -> 10 sec relax -> 15 sec placid imaginations -> 10 sec relax -> 15 sec strenuous imaginations

   Session 5:

   10 sec relax -> 15 sec close eye imaginations -> 10 sec relax -> 15 sec open eye imaginations -> 10 sec relax -> 15 sec close eye imaginations -> 10 sec relax -> 15 sec open eye imaginations

Note:

- There is a half min rest between each session.
- Total time taken is about 8.5 min

- Let the test subject write down their thoughts about the experiments such as any discomfort, any movements that they found hard to achieve etc.

Appendix I Bandpower Matlab Script

```
Fs=256;                                   % sampling rate
t_length=10;                               % data length (7 s)

sti_f=[10];              % stimulus frequencies 10, 11, 12, 13 Hz
n_sti=length(sti_f);                      % number of stimulus frequencies

ws=256;
count=0;
y = h5read('SESSION62016.09.10_15.08.29.hdf5','/RawData/Samples');

for dd=1:length(y)-ws       % data number= recorded data-moving window
length
    temp=y(2,dd:dd+ws-1);
    [psdx,freq] = pwelch_power(temp);
    index=find(freq>8 & freq<30);
    pp=sum(psdx(index));
    count=count+1;
    bandpowerv(count)=pp;
end
bandlog=log(bandpowerv);
bandmedian = smooth(bandlog,100);
band2=power(bandmedian,2);
```