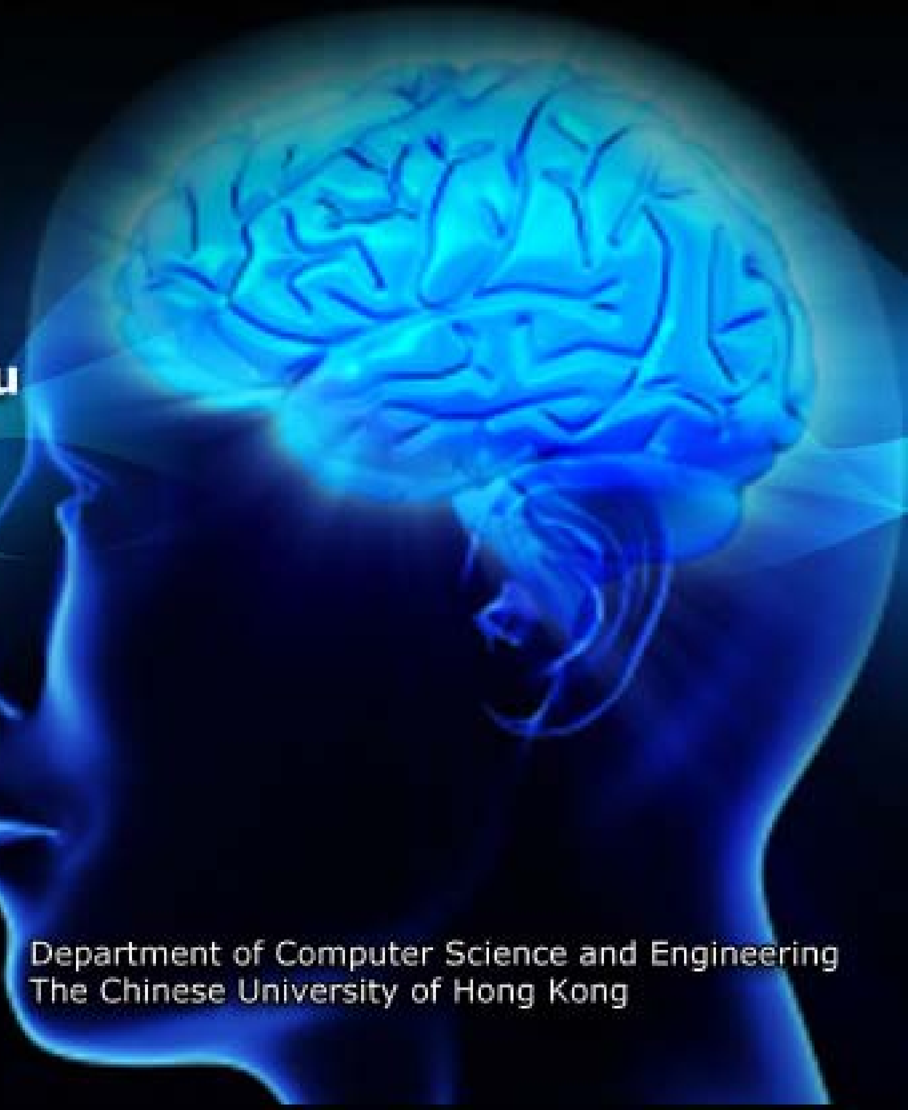
# Unleashing Brain Powers

## A Study on Development of BCI-enhanced Computer Games

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# Abstract

From keyboard and joystick, to Wii-remote and Kinect motion detection, new controllers have always been fuels to bring about new generations of video games. However, when possibilities of motion sensing entertainment are gradually exhausted, one may wonder: what would come next?

We believe Brain-Computer Interface (BCI) might just be a potent candidate.

Our project starts off by studying the consistency and effectiveness of a non-invasive consumer-level BCI, Neurosky Mindset. Afterwards, we attempt to devise a way to improve the BCI control, namely by introducing a way for the users to train themselves to maintain a better control over the brainwave states. In this process, we shall propose our customized algorithm to approximate the attention meter.

Finally, utilizing the modern 3D computer game engine Unreal Engine 3, a complete BCI-enhanced adventure game titled “Psionescape” is developed. The game consists of puzzle elements driven by our newly developed BCI algorithm at the back-end, and this shall further strengthen the belief that BCI-enhanced gaming will be a feasible game genre in the future.

# Contents

# 1 Introduction

## 1.1 Motivation

No one knows what the first digital game was, since it is debatable upon how one defines a “game”. However, one thing is certain - Since the invention of digital games, human has been actively pursuing new kinds of interfaces which enable communication between the games and the players, or at least, enable one-way input from the players to the games.


Figure 1.1-1. For PC games, they started with a keyboard

In personal computers games, keyboard was one of the first interfaces, where early games usually used the arrow keys (e.g. DOOM, a first person shooter game, used ←↑→↓for movement). With the introduction of mouse and trackball as pointing devices, they served as an additional interface when combined with the keyboard, or sometimes control games even without the keyboard.


Figure 1.1-2. A mouse was necessary to play Warcraft II (1995)

Not long after the popularization of the mouse, the game industry evolved to create different controllers to suit different games’ needs.

In the past 10 years, the gaming industry has been a growing multi-billion-dollar business, this shows that the demand of videos games has been growing, and this rocketing demand also attracts a vast investment on new gaming interfaces, such as Dance Pad in PlayStation and Wii controllers in Wii, which furthered feedback to the snowball (i.e. the demand) positively.

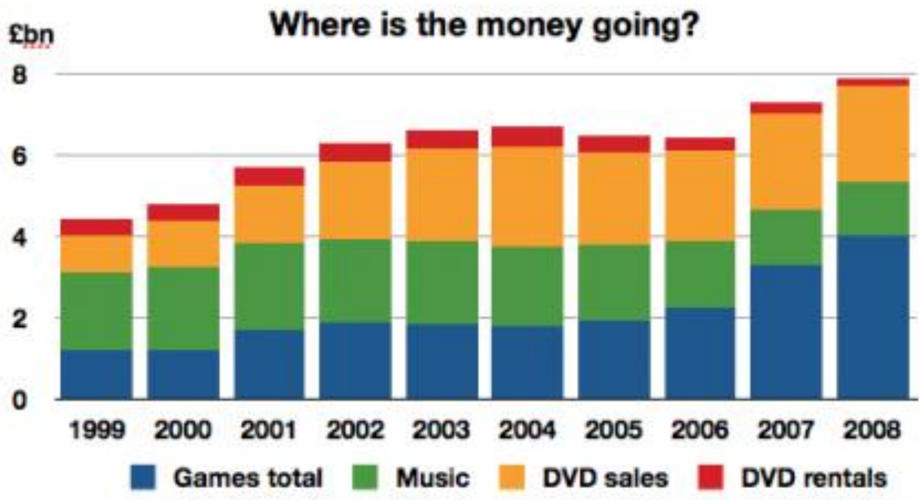



**Figure 1.1-3.** The video game industry has been growing at lightning speed, even exceeding income generated by the music industry.
(Arthur, 2009)

However, while new interfaces for console games (e.g. touch screens for NDS and remote motion sensors for Wii) has been developed, emergence of new gaming interfaces for PC games seem to slow down after the introduction of game pads, and we think a new gaming interface could perhaps give birth to a new genre of games in the big PC games market, where PCs are very widely owned in almost every family in developed countries.

**Figure 1.1-4.** With Microsoft's Kinect, players no longer hold any sensors to play

Following the current trend, we could see that the physical world has almost been captured by interfaces like Microsoft Kinect. Hence one may wonder if anything new would appear in the future gaming world, and what that would be.

Recently, brain computer interfaces for consumer level have been released to the market (See session 2.2.2), making BCI entertainment possible. However, no commercial game has been released onto the market.

Why is that so? Is it because of technical difficulties to utilize the BCI?

We would like to grab that very opportunity by studying the possibility of developing a modern 3D computer game, which can utilize features of BCIs.

# 1.2 Background

## 1.2.1 Research-Level VS Consumer-Level BCIs

Some of the game interfaces, such as keyboards and gamepads, which control games directly, including movement, rotation and inventory controls, are usually of high precision, i.e. you wouldn't see a mouse cursor shivering on the screen or floating in random direction.

Research level BCIs could also read the electroencephalography (EEG) in a relatively accurate manner, allowing recognition of many different actions. For example, the Department of Electronic Engineering of the Chinese University of Hong Kong has been working on a BCI project, where the user could input Chinese characters using one's brain waves alone, but the process requires about 1 minute per word and yields 75% accuracy (Oriental-Daily, 2010). For a game related example, The Department of Neurosurgery of Washington University in St. Louis managed to control a classic game "Space Invader" by moving the space ship left or right (note that only 1D linear movement is allowed), where the shooting behavior is governed by time automatically but not by the BCI. The process time for this kind of in-game operation is shorter, and the player could react to the bullets shot by the aliens on the top of the screen.


**Figure 1.2-1 Research-Level BCI-controlled Space Invader**

(http://www.youtube.com/watch?v=T3-mxhDp-u8&feature=related )

However, consumer-level BCIs are currently not as precise, and are not favorable to be used as direct controls; In addition is the slow recognition speed relative to quick response needed to react to game events (such as shooting a zombie which suddenly popped up in front of the player).

Yet consumer-level BCIs also have their advantages. While a P300 system (the research-level BCI system developed by CUHK mentioned above) may take from 20K to 50K HKD each, consumer-level BCIs are more affordable (cost no more than a few thousand HKDs) by ordinary players. Moreover, they are all very portable and mobile, due to their wireless nature. Another big advantage is the ease to wear the BCI, as they mainly use dry sensors and do not require a very accurate positioning of each electrode (in contrast to research-level BCIs which need to position at least a few dozens of electrodes

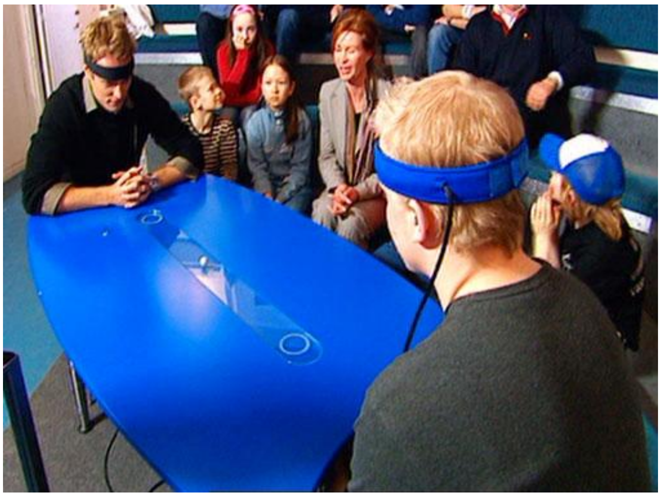


**Figure 1.2-2** Mindball was one of the first consumer-level BCIs

before use). Hereafter, the BCIs we talk about would be consumer-level ones.

### 1.2.2 Brain-Computer Interface Selection

There are vast variety of game-player interfaces in the market, such as Wii-remote and Drum Sticks, but very few of them are intended for personal computer entertainment. However, the consumer level BCIs in the market, up to now, are for that purpose. Therefore connections are easy, usually involving a USB plug-and-play, and those BCIs are usually very light and portable.

Within the ranges of consumer-level BCIs, there are ones with very specific uses.

For instance, 7 years ago, a company called The Interactive Productline which is located in Sweden produced one of the first consumer-level BCIs, named Mindball. A wirelessly controlled ball was place in the middle of a table, the players first attach a BCI onto their forehead, and it will read the EEG of them. As a result, a ball will move from one side to the other player’s side when one of the players’ focuses more intensively onto the ball, and the ball falls off the edge of loser’s side.

However, this kind of BCI did not provide a general use for other application, and is not viable for development of computer software or games.

In March 2007, NeuroSky, a US-based company, released a headset attached with an EEG sensor, which is to be placed onto the user’s forehead. The headset is called Mindset. This should be one of the first BCIs intended for consumer-level computer uses. The single sensor used was a dry one, and is non-invasive (in contrast to medical BCIs which may require insertion of electrodes into the skull for superior accuracy). The device features a decomposition of a whole range of raw brain waves data from the user, including alpha, beta, gamma and theta waves (See Chapter 3 for explanation of brain waves), and also algorithmic values representing “Attention” and “Meditation”, consolidated by the raw brain waves data. “Anxiety” and “Drowsiness” are also supported using particular software. The latest firmware even allows the detection of eye blinks, but the underlying principles are not known.

**Figure 1.2-3** Wireless with a dry sensor - NeuroSky Mindset

A year later, OCZ Technology released the Neural Impulse Actuator (NIA). The NIA is worn by putting it around the user’s forehead, and it is very easy to do so due to the rubber-band-like structure (see Figure 2.2-4). The communication between the NIA and the computer is established by a USB connector (not wireless). There are a total of 3 sensors, which is more than that of Neurosky Mindset. However, the device can only read alpha and beta waves, although there is an overall motor neuron activity (e.g. moving your jaw up can increase its value). Moreover, unlike Neurosky Mindset, there is no processing of raw data, so it is even difficult for developers to tell when the user is in “Attention” state. Yet supposedly, the accurate nature of the 3 sensors may yield more precise brain waves which may be mapped to some keystrokes to play certain games.

**Figure 1.2-5** Easy-to-put-on NIA

The Emotiv EPOC is the latest BCI available came in December 2009. This BCI has 14 electrodes and so far is the BCI with the highest number of electrodes. That is very comparable to medical-level BCIs which usually has 19 electrodes. The vast number of electrodes covers different areas around the head, and thus has a lot of features. Therefore it can detect 12 kinds of movement and rotations (e.g. “up”, “left”, “forward”, “zoom”, “turn clockwise”, “turn left” and “sway right”) as supplemented by detecting motor neuron activities. Similar to Neurosky Mindset, it can detect emotions such as “Excitement”, “Engagement”, “Meditation” and “Frustration”. Moreover, it can detect facial expressions like laughing and clenching. Another feature Emotiv EPOC exclusively demonstrated is the ability to make objects disappear in the demo. In addition to BCI features, it can also measure angular rotation of the head in 2 dimensions (i.e. yaw and pitch, but not roll) as detected by the 2 gyros.

**Figure 1.2-4** Highest number of sensors - Emotiv EPOC

To sum things up, we have prepared a comparison table for the BCIs mentioned above:

| | Mindball | Mindset | OCZ NIA | Emotiv EPOC |
|---|---|---|---|---|
| Released | March 2003 | March 2007 | May 2008 | December 2009 |
| SDK Available | No | Yes | Yes | Yes |
| Connection | Wireless | Wireless | Wired (USB) | Wireless |
| Number of Electrodes | 1 | 1 | 3 | 16 |
| Sensor Type | Dry | Dry | Dry | Saline (Wet) |
| Raw Data Collection | No | Yes | Yes | Yes |
| Attention/Engagement | No | Yes | No | Yes |
| Meditation/Relaxation | No | Yes | No | Yes |
| Anxiety/Frustration | No | Yes | No | Yes |
| Drowsiness | No | Yes | No | Yes |
| Excitement | No | Yes | No | Yes |
| Push | No | No | No | Yes |
| Pull | No | No | No | Yes |
| Lift | No | No | No | Yes |
| Drop | No | No | No | Yes |
| Push Left | No | No | No | Yes |
| Push Right | No | No | No | Yes |
| Rotate Forward | No | No | No | Yes |
| Rotate Backward | No | No | No | Yes |
| Turn Left | No | No | No | Yes |
| Turn Right | No | No | No | Yes |
| Tilt Left | No | No | No | Yes |
| Tilt Right | No | No | No | Yes |
| Disappearance | No | No | No | Yes |
| Facial Expressions | No | No | No | Yes |
| Motor Neurone Activity | No | No | Yes | Yes |
| Playing Music | No | Yes | No | No |
| Head Rotation Detection | No | No | No | Yes |
| Price in USD | $18700.21 | $159.20 | $138.99 | $299.00 |
| Developer Edition | - | (Free SDK) | (Free SDK) | $500.00 |

**Table 1.2-1** Comparison between BCIs as of 28th November 2010

To select the most appropriate BCI for our project, we considered a lot of different features of the above BCIs with weighing.

To begin with, Mindball does not really suit our need because it is of specific use (i.e. for that ball game only), what's more is the terrific price to own one, i.e. $18700.21, which will make it not probable to become a home entertainment trend. Moreover, there is no possible connection for personal computers, and there is no SDK for development, so we cannot use it to build our game.

The OCZ NIA has the lowest price among the 3 remaining candidates, and it employs the use of dry sensors, which makes the user comfortable with putting this on. It enables raw data feedback to the computer / SDK, and that is useful for customized signal processing. A point to note is that the wired nature of the device may be speculated to reduce the comfort of prolonged use because it hinders the user's movement (e.g. for Mindset, you can go grab a cup of coffee without taking it off). The critical reason for not using OCZ NIA is its failure to detect cognitive states (e.g. Attention). In addition, while it may be possible to detect motor activity, it cannot tell the difference between moving one's jaw and moving one's eyebrows, as complained by the users on forums (Kenner, 2009).

The Emotiv EPOC seems to be very competitive candidate, as it is not only able to detect cognitive states like Neurosky Mindset does, it can also detect motions, which is a very attractive feature for video games. However, while these features are possible thanks to the large number of sensors Emotive EPOC has, saline sensors are employed (not dry). The users may find it troublesome to wet the sensors or their head every time they use it, and it is not just a matter of dropping a few salt solutions onto the sensors but to "make them dripping wet"! Yet even with that, the connection may also be poor. (Emotiv-Administrator, 2010) Moreover, although motion detection is possible, the accuracy is not very high, with some users stating that "it can never follow my thought!" In addition, while there seems to be multiple events to be detected, only a limited number of events can be detected at the same time, and the user needs to explicitly address them, making EPOC not a very suitable candidate. (Emotiv-Administrator, 2010)

While NeuroSky Mindset is not the most accurate BCI (as it only got 1 pea-sized electrode), it still supports a number of detections such as Attention and Meditation. Moreover, it allows a broader range of raw brain waves data, enabling a more potent signal processing to be carried out ourselves. In addition, as a benefit for gaming experience, it is essentially a wireless headset which can play music, this might enhance the gaming experience by providing surrounded sound of better quality than ordinary loudspeakers. Lastly, it has a very low costs compared to other BCIs except NIA, making it more easy to popularize among families as it is more affordable.


**Figure 1.2-6** Some people find it difficult to establish perfect connection

(Notice how the user holds the sensor closely towards the forehead)

However, it also has a drawback (which is also present in other BCIs) – Some people find it difficult to establish perfect connection between the sensor and the users’ head. This will be one of the limitations we would like to address later and perhaps during demonstration.

# 1.3 Game Industry Responses to BCI

The emergence of different BCIs attracted some attention from the gaming industry, with many of the released or potential products relying on the "Attention" state. (See Chapter 3 for reasons)

Figure 1.3-1 MindFlex (Based on Neurosky Mindset)

For example, Mattel Inc released a non-digital game called MindFlex. In this game, the players need to focus to increase their concentration to raise the ball, and lower the ball by lowering the concentration level, and use a knob to move a ball left or right, with the goal of passing the ball through different obstacles. In fact, this game is using a lite version of NeuroSky Mindset's chip (the "Mind Force" chip).

Now here comes a big question:


Figure 1.3-2 NeuroSky's own game - The Adventure of NeuroBoy

## Is there any game-developer-made BCI <u>computer games</u>?

The short answer is: No.

For demonstration purpose, the BCI producers, of course, produced their own game demos.

For example, NeuroSky, the same company which developed the Mindset, built a game called "The

Adventure of NeuroBoy" to demonstrate features of Mindset. The game, which comes free-of-charge with the Mindset, has no story at all, but let the player takes control of a character walking around using WASD keys and use the mouse to select an object for one of the 4 purposes: Attract towards player, Push away from player, Levitate and Ignite, which are governed by the 2 states (i.e. "Attention" and "Meditation").

However, not all hope is lost.

Announced at the 2008 Tokyo Game Show was good news about commercial BCI games. The Japanese game developer Square Enix, which is well-known for its Final Fantasy series, announced the development of the first BCI-enhanced computer game – Judecca. (Fruhlinger, 2008)

Judecca is a first-person shooter game, in which the player is immersed in a world of zombies. The game makes use of NeuroSky Mindset's "Attention" level. Up to now, the announced BCI features are:

1 "After concentrating on a glyph that glows in direct relation to your ability to concentrate, you will open up what's called your "Devil's Eye". Only once you have attained a heightened state of concentration, will you be able to see Judecca's zombies and kill them."
2 "Those who can tweak their concentration levels even further will be able to walk through walls."

If that is not descriptive enough, the below is a screenshot which reflects what happens if the "Attention" / "Concentration" level is high enough in Judecca.

An important point to note is that the game is BCI-enhanced but not directly controlled by it, the movement and shooting still relies on keyboard and mouse. With a global game developing company like Square Enix still not working on more BCI features or direct controls, this leads to our speculation that the current game industry is still remain doubt about the accuracy of consumer level BCIs.

## 1.4 Project Overview


**Figure 1.3-3** Judecca in action, revealing zombies using Concentration level

Chapter 2.2.1 gave us an insight on the current trend of consumer BCIs and also their limitations.

On one hand, we can see that BCIs are rapidly being improved and commercialized. With the lower costs and improving accuracies and features, we predict that in the near future, there will be at least a small to medium sized market for home uses.

On the other hand, we could see there are limitations for current BCIs. The most important part is the difficulties in deciding detected states (e.g. “Meditation”) and movements (e.g. “Move forward and Turn Left”).

Chapter 2.2.2 concludes by stating that the current computer game industry actually is at the beginning of “trying” to develop BCI games. With a large company like Square Enix (a publicly owned multinational company with thousands of employees), they still limit the game with very few BCI features, possibly because of the limited accuracy for direct movement controls.

We speculate that the lack of developers building BCI games is due to:

1) It may be hard to make games which utilize BCI features
2) BCI may just unlock too few in-game features. (e.g. revealing zombies)

Therefore, we would like to see if we can tell a different story by dividing our project into 2 phases, with each phase done within each semester.

Firstly, we will study the NeuroSky Mindset, to see how we could operate it, and how we could get data from it. Moreover, we will try to see if there is any trace of correlation between its claimed states (e.g. "Attention" and "Meditation") and the users' feedbacks.

On the other hand, we will study a game engine, Unreal Engine 3, to see if it is possible to make a BCI-enhanced game (at this stage, we do not plan to build a game "directly controlled" by the BCI, as learnt from lessons of the Judecca). If a modern 3D game engine can be modified to produce BCI-enhanced games, then it would be like owning a factory to developers, and they can make BCI-enhanced games pretty much like how they normally do it.

Moreover, we will study how BCI could help facilitates different game events or features.

For the first phase, we will first make a small demo in Unreal Engine 3 environment to demonstrate that it could actually work to combine BCI and an ordinary game engine. Then proceed to demonstrate the possibility of active controls (See Chapter 4 for details about Active/Passive Controls) using NeuroSky Mindset's eSenses (e.g. "Attention").

For the second phase, we will try to analyze raw brain waves data to see if we could devise our own algorithms to calculate values which represent human emotions, and see if we could improve eSenses or develop other senses (e.g. the state of "Fear"). And on the other hand, investigate the possibility of passive controls by the BCI.

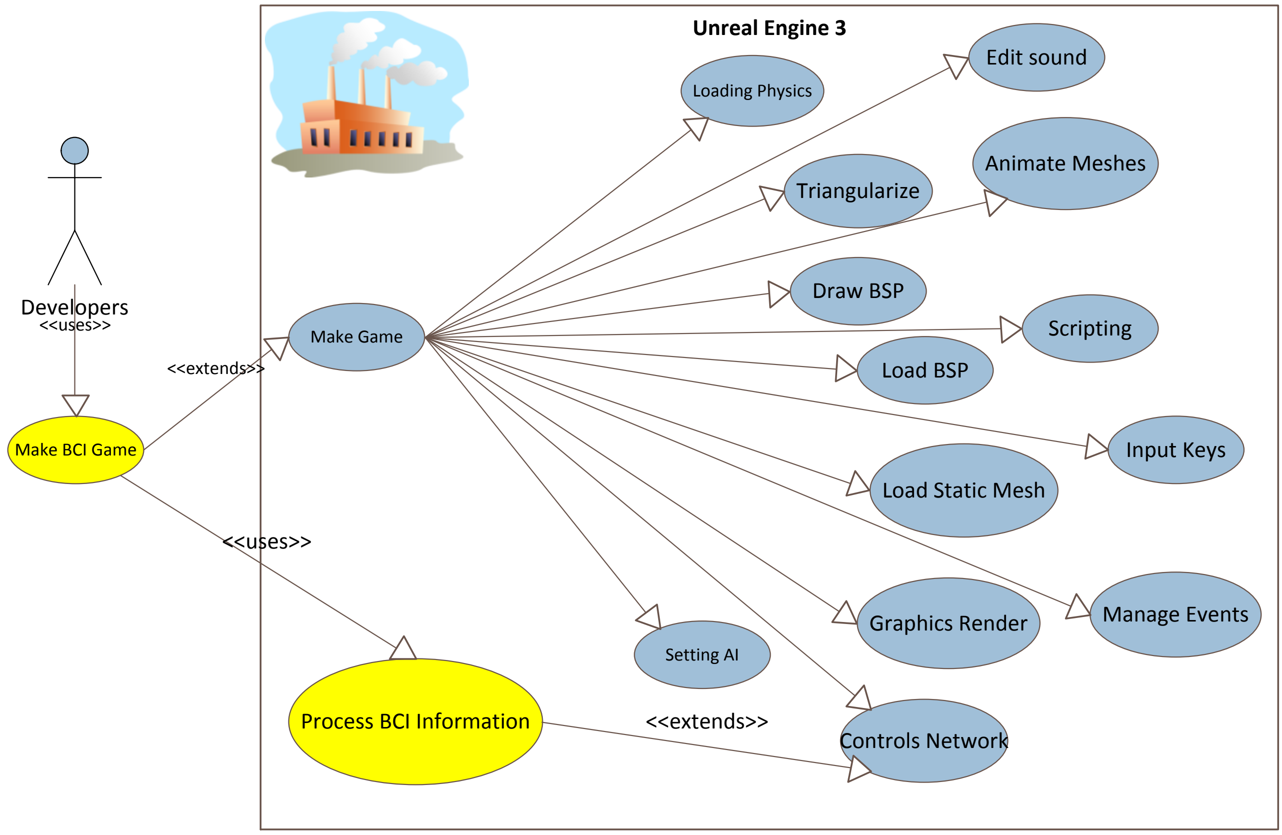
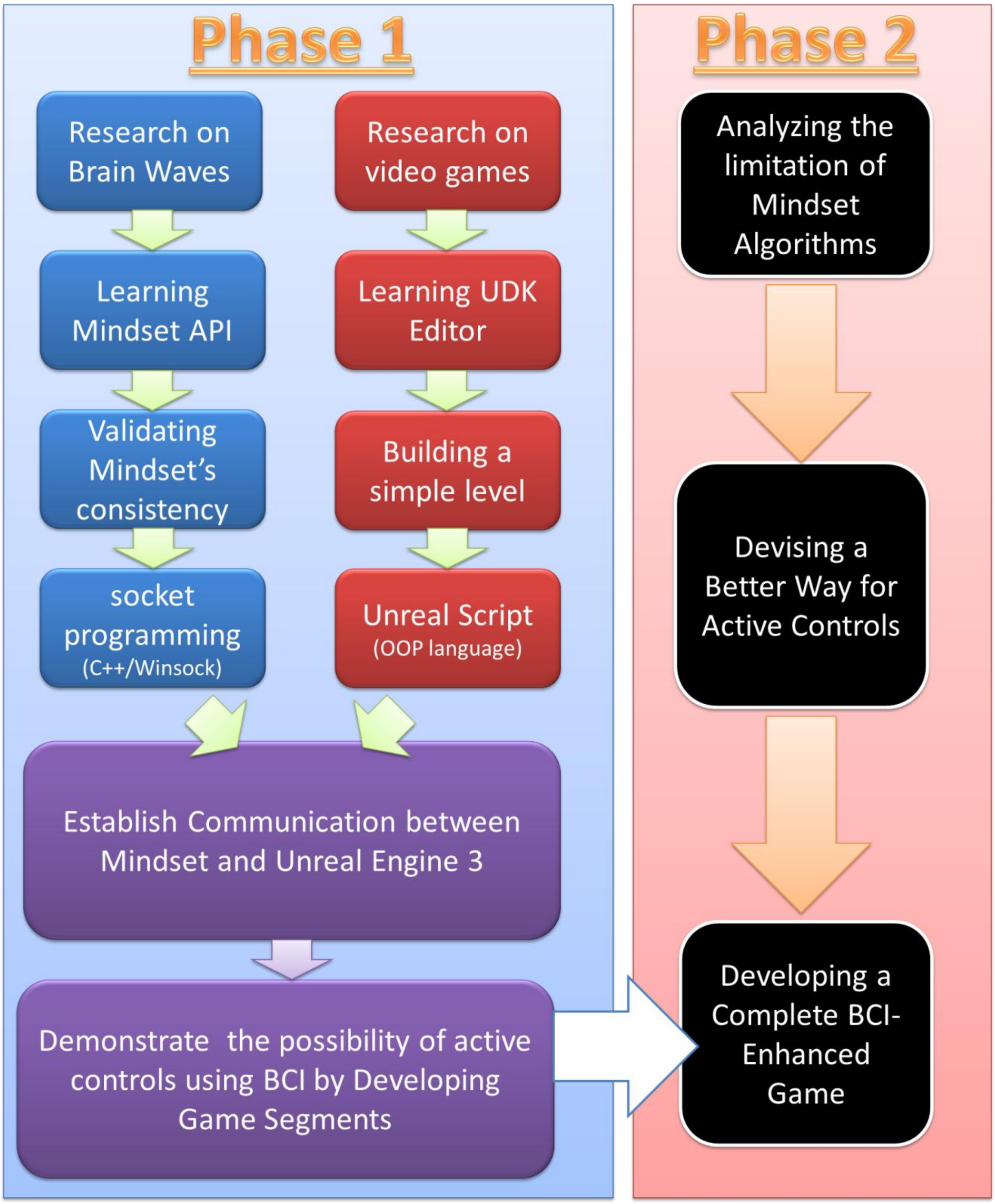



**Figure 1.4-1** Use Case Diagram of Modified Unreal Engine 3

Last but not least, we are looking forward to creating a small-sized BCI-enhanced game by integrating different kinds of controls, and evaluate it to see if the players find it more interesting than non-BCI versions.

(Disclaimer)

Throughout our project, we may use the phrase "BCI-enhanced games". However, by "enhanced" we simply mean the games which are different from those in the current game market in a way that BCI features are absent in present games, we do not attempt to have a bias that "BCI-enhanced" implies an positive impact on the gameplay experience over "ordinary" games. In fact, the question whether games with BCI features would offer a perceived better gameplay experience is exactly what we would like to find out, after developing a small-scaled game featuring some BCI features in the coming semester.



# 2 Studying NeuroSky Mindset

## 2.1 Background

### 2.1.1 Brainwaves

Brainwaves are the records of electrical activity along the scalp produced by the firing of neurons within the brain. Source of brainwave came from neurons. Neurons are electrically charged. When they receive a signal from the neighbor, it releases ions outside the cell. When many ions of like charge repel each other, it will push out its neighbor and form a wave of ions. When the wave of ions reach the scalp, the electrons inside the electrode or the sensory will be pulled or pushed, which forms a voltage, measure such voltage difference between different electrodes or sensory form the brainwaves.

### 2.1.2 What Can Mindset Do

#### Data Collection

Mindset measures the electrical impulses generated by mental activities. This provides a raw unfiltered brainwave measurement. The raw data can be used by researchers and developers to make algorithm to measure mental states. Raw data includes alpha waves, beta waves, gamma waves, delta waves and theta waves.

Mindset also uses algorithm to calculate the mental states, such as attention and meditation which are available as digit input for games and educational applications.

Both raw brainwave data and calculated mental states are updated once per second.

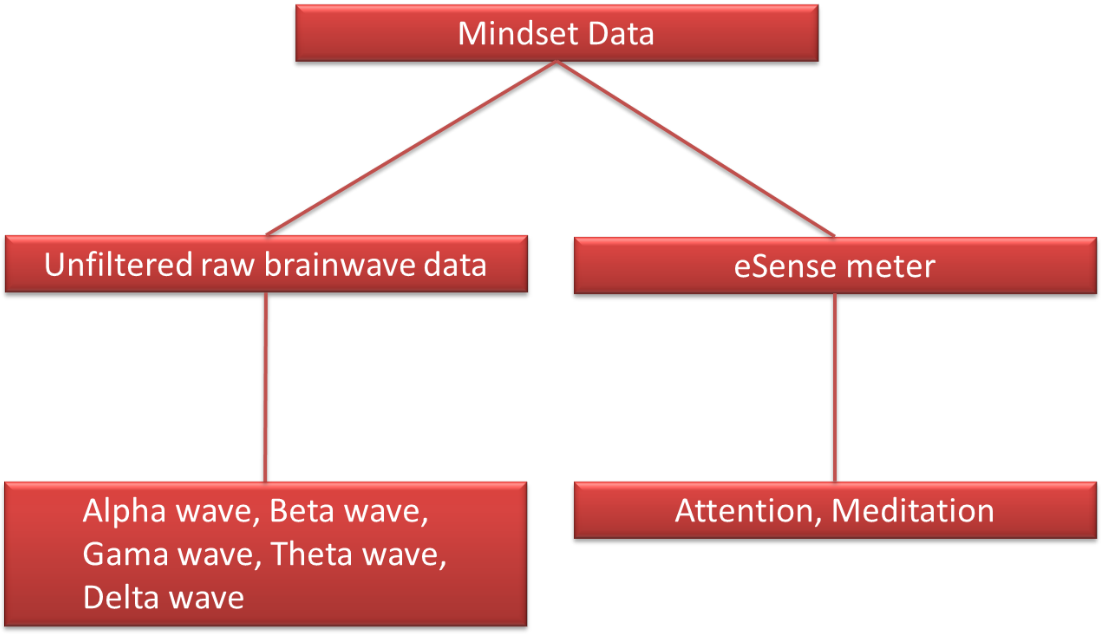



**Figure 2.1-1 Classification of mindset data**

### Mindset SDK

Neurosky provides a Mindset Development Tool (MDT) for developers and researchers to create and publish applications using BCI technology of Mindset. The MDK provides documents, drivers and sample codes for development. Developers can collect Mindset data in different platform (Windows, Mac) and using different language(C, C++, Java).

## 2.1.3 How does Mindset Work

### ThinkGear

Mindset use a technology called ThinkGear to interface wearer's brainwaves. This technology includes the sensor that touches the forehead, the contact and reference points located on the ear pad and the on-board chip that processing all the data. Both eSense Meters and raw data are calculated on the ThinkGear chip. These data are then sent to the computer through Bluetooth.

### eSense

eSense™ is a NeuroSky proprietary algorithm for characterizing mental states. The NeuroSky ThinkGear technology amplifies the raw brainwave signal and removes the ambient noise and muscle movement. The eSense algorithm is then applied to the remaining signal, resulting in the interpreted eSense meter values.

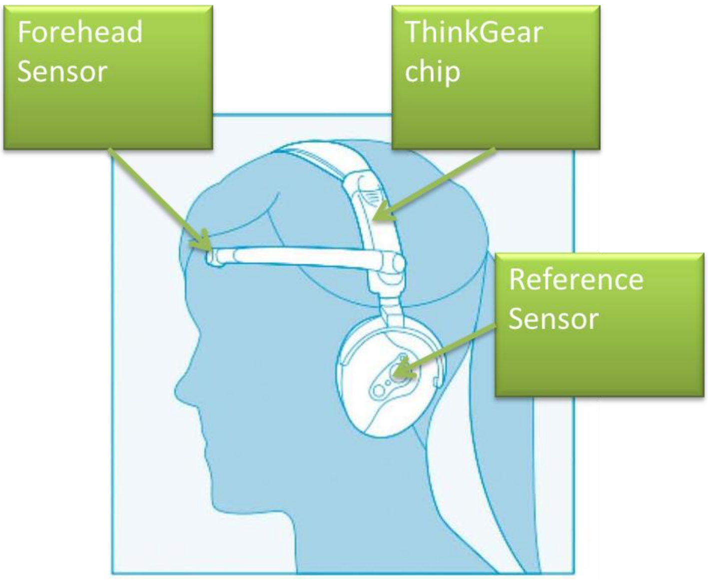



Figure 2.1-2 Key components of Mindset

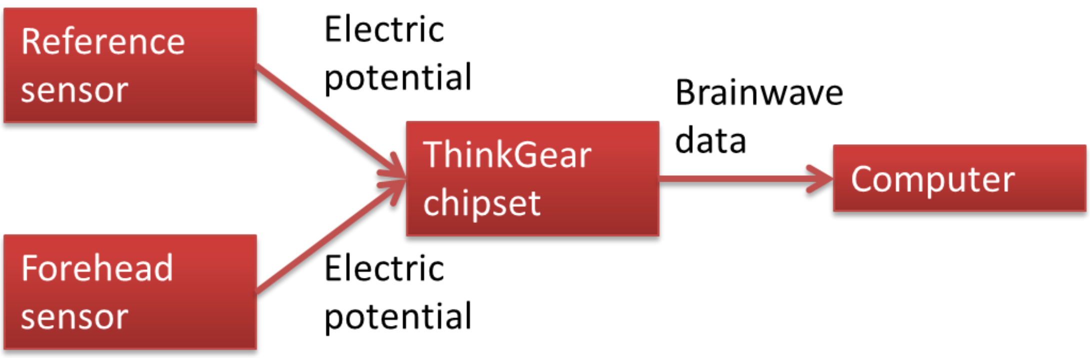



Figure 2.1-3 Data flow diagram from mindset to computer

The data flow of mindset is as follow. First, the forehead sensor and the reference sensor record the electric potential and pass the values to the ThinkGear chipset inside the Mindset. The chipset processes the data and output the raw brainwave data and calculated mental states to the computer.

### 2.1.4 Mindset Structure

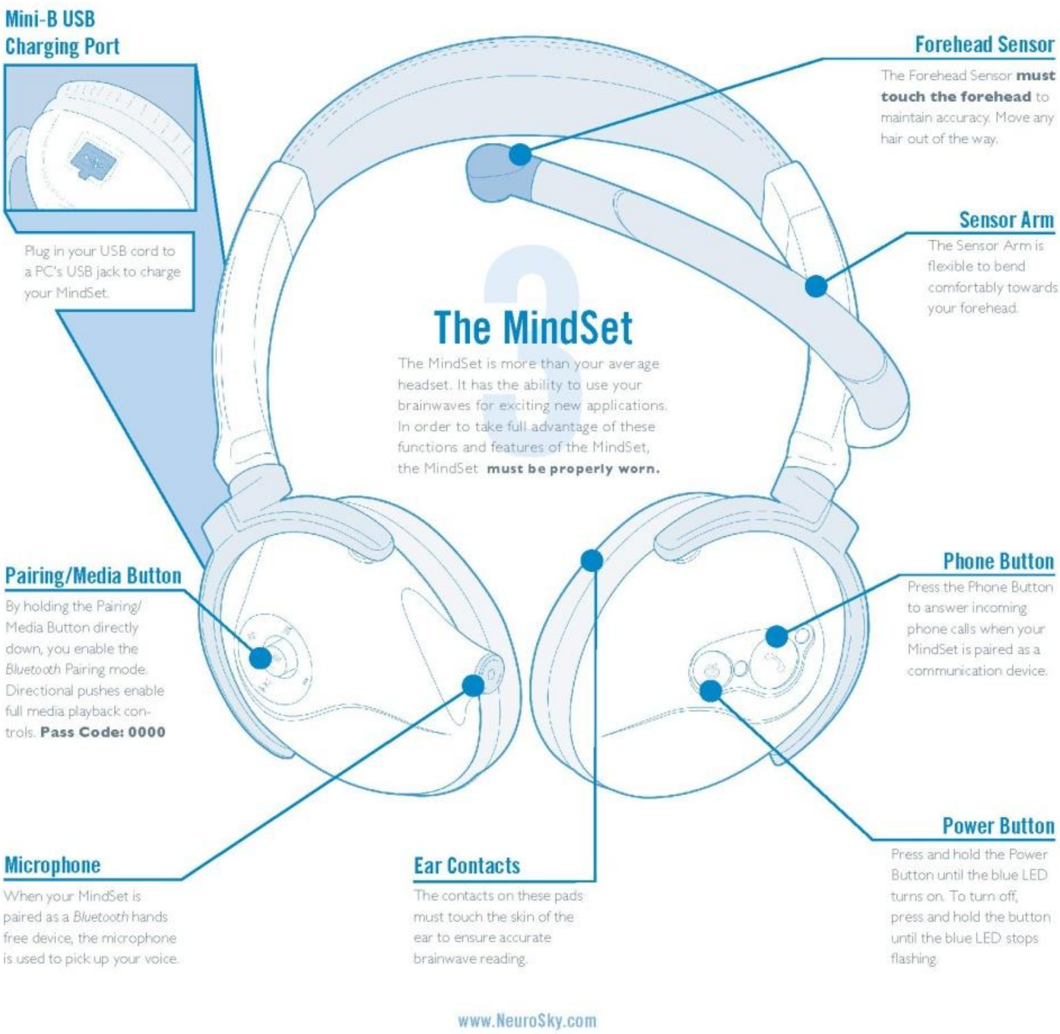



Figure 2.1-4 Complete Mindset components and functions

The Mindset is a head-phone liked BCI. The components of the Mindset include Forehead Sensor, Sensor Arm, Ear Contacts, Microphone, Headphone and different buttons.

### 2.1.5 eSense Meters

The eSense Meter contains two mental states: Attention and Meditation. The meter ranged from 1 to 100. Values between 40 and 60 at any given moment in time are considered "neutral". Values from 60 and 80 is considered "slightly elevated", and may be interpreted as levels being possibly higher than normal. Values from 80 to 100 are considered "elevated", meaning they are strongly indicative of heightened levels of that eSense. Similarly, on the other end of the scale, values between 20 and 40 indicates "reduced" levels of the eSense, while values between 1 and 20 indicates "strongly lowered" levels of the eSense.

Both eSense values are updated once per second.

### Attention eSense

According to the mindset documents, the eSense Attention meter indicates the intensity of a user's level of mental "focus" or "attention", such as that which occurs during intense concentration and directed (but stable) mental activity. Distractions, wandering thoughts, lack of focus, or anxiety may lower the Attention meter levels.

### Meditation eSense

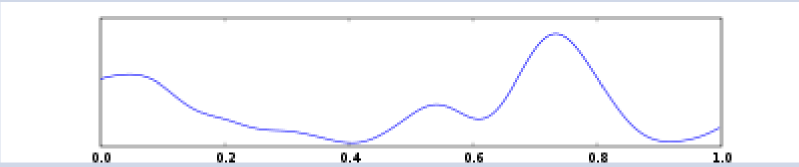
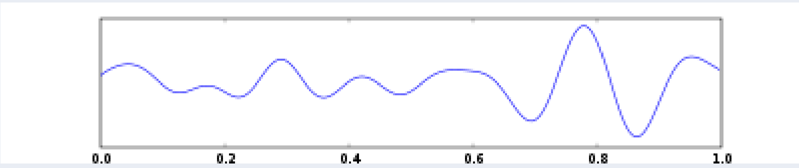
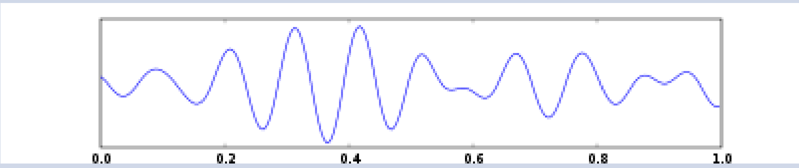
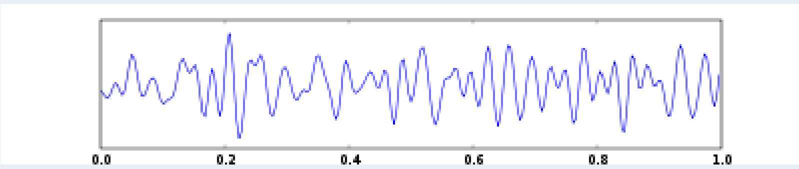
According to the mindset documents, the eSense Meditation meter indicates the level of a user's mental "calmness" or "relaxation". This meter is a measure of mental levels but not physical levels. Simply relaxing all the muscle may not have immediate effect of the eSense meter. Distractions, wandering thoughts, anxiety, agitation, and sensory stimuli may lower the Meditation meter levels.

### 2.1.6 Raw Brainwaves

| Brainwave Type | Frequency range | Mental states and conditions |
|---|---|---|
| Delta | 0.1Hz to 3Hz | Deep, dreamless sleep, non-REM sleep, unconscious |
| Theta | 4Hz to 7Hz | Intuitive, creative, recall, fantasy, imaginary, dream |

| | | |
|---|---|---|
| Alpha | 8Hz to 12Hz | Relaxed, but not drowsy, tranquil, conscious |
| Low Beta | 12Hz to 15Hz | Formerly SMR, relaxed yet focused, integrated |
| Midrange Beta | 16Hz to 20Hz | thinking, aware of self & surroundings |
| High Beta | 21Hz to 30Hz | Alertness, agitation |

**Figure 2.1-5 Table of different brainwave and its information**

| Sample brainwave pictures |
|---|
| Delta waves<br><br> |
| Theta waves<br><br> |
| Alpha waves<br><br> |
| Beta waves<br><br> |
| Gamma waves |

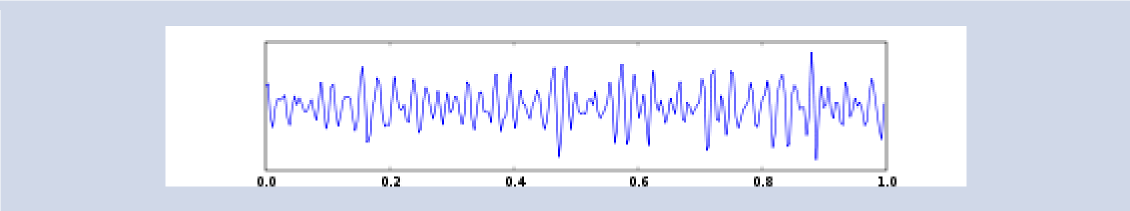



Figure 2.1-6 One second sample of different brainwaves

## 2.2 Experiment on eSense

An experiment is designed to investigate the relation between eSense meter and mental states. eSense meter includes two mental states: attention and meditation. Mental states include: relaxed, bored, concentrated, fear, excited.

### 2.2.1 Hypothesis

The eSense meter can reflect the existence or changes of some mental states.

### 2.2.2 Methodology

We collect the brainwave data of user when watching the movie and use questionnaire to get the feeling of the user watching different part of the movie. Then we will analysis the brainwave data and feeling to see if there is any correlation between mental states and eSense meter.

### VMRPlayer with Mindset

The VMRPlayer uses the Video Mixing Renderer 9 (VMR-9) filter to alpha blend one or two running videos and a static image. We integrate the VMRPlayer with the mindset API so when the user is watching the movie, the VMRPlayer will receive packets from the Mindset and records the brainwave data for future analysis.

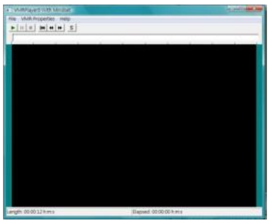


Figure 2.2-1 VMR Player User Interface

## Movie

The movie consists of 4 parts. Each parts of the movie have special features which will affect the mental states of the user.

### Part 1: String Orchestra, Symphony No. 94 in G Major

Description: The movies contain a string orchestra performance of "Symphony No. 94 in G Major". The estimated feeling is relaxed.

Special point: There is a strike of loud sound at time 0:36.

Figure 2.2-2 Video clip of Orchestra performance

### Part 2: cappella sistina - discorso papa Benedetto XVI (Speech of Pope Benedict XVI in Sistine Chapel)

Description: The movies contain contains a fragment of speech by Pope Benedict XVI. The language spoken by Pope Benedict XVI is Italian and there are no subtitles. The estimated feeling is bored.


Figure 2.2-3Video clip of Pope speech

## Part 3: Don't stare at bikini

Description: The movies are separated into two parts. Each part begins with a picture which changes slightly within 10 seconds. Participant will be given 3 attempts to find out the change. After the 3 attempts, the answers will be told and user will watch the picture again. The estimated feeling is concentrated.


Figure 2.2-4 First Picture showing bikini girl

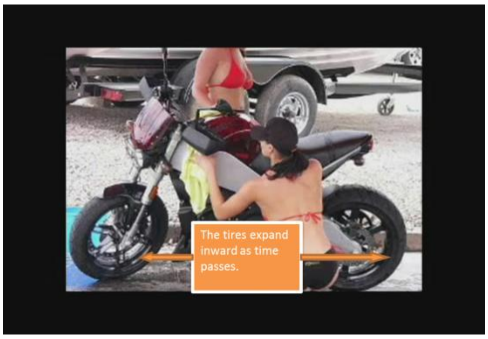



Figure 2.2-5 Second Picture showing bikini girl

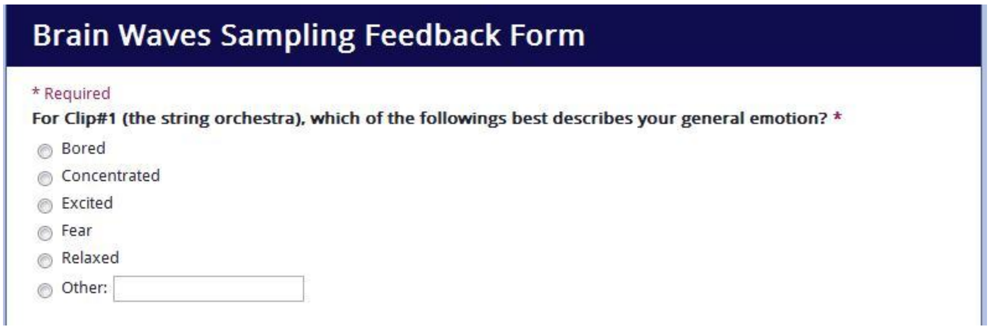
## Part 4: Ghost Pop Up


Figure 2.2-6 Video clip before ghost pop up

Description: Participant is told that the ghost will appear anytime and participant needs to be prepared for the ghost. The general feeling of this part is fear. Special point: There is a ghost appear with loud sound at 5:00.

### Questionnaire

The questionnaire asks the users their feelings when watching different part of the movie. Participants can select the most suitable word to describe their feelings for each part of the movie.


Brain Waves Sampling Feedback Form

* Required

For Clip#1 (the string orchestra), which of the followings best describes your general emotion? *

- Bored
- Concentrated
- Excited
- Fear
- Relaxed
- Other:

Figure 2.2-7 Brainwaves sampling feedback form

## 2.2.3 Result

There are 18 participants in this experiment,

### Part 1: String Orchestra, Symphony No. 94 in G Major

| | Part 1 |
|---|---|
| Attention | 44.79998 |
| Meditation | 49.83071 |

Figure 2.2-8 Part 1 average eSense Value

| | Attention | Meditation |
|---|---|---|
| Overall | 49.29572 | 53.24579 |
| Part 1 | 44.79998 | 49.83071 |
| Difference between overall values and part 1 values | -4.49573 | -3.41509 |

Figure 2.2-9 Compare overall eSense values and part 1 eSense values

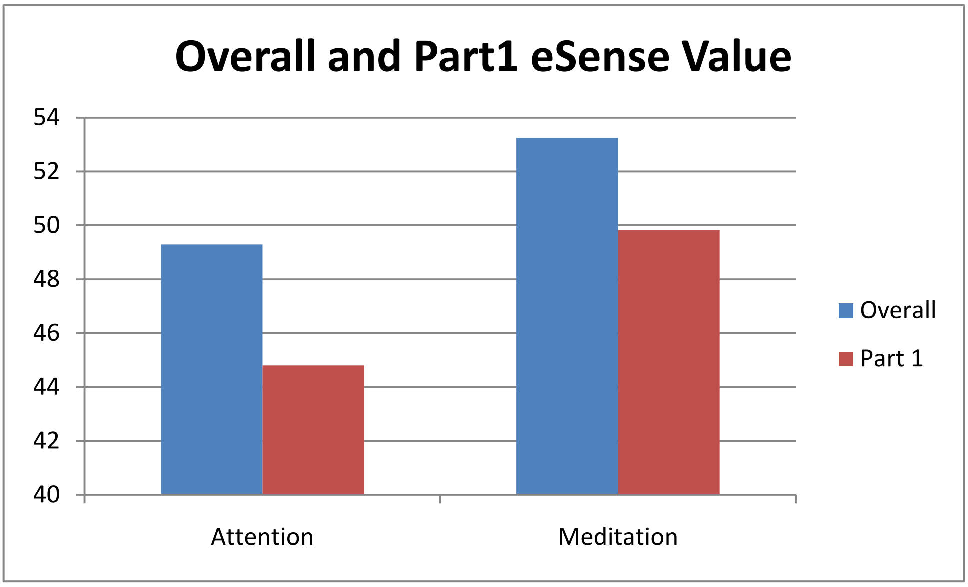



Figure 2.2-10 Overall values and part 1 values

The attention value in part 1 is lower than overall average

### Relaxed Participants

The most common feeling of participants in part 1 is relaxed.

| | Overall |
|---|---|
| Attention | 47.88266 |
| Meditation | 53.2328 |

Figure 2.2-11 Overall eSense values of relaxed participants

| | Part1 |
|---|---|
| Attention | 43.67935 |
| Meditation | 46.75625 |

Figure 2.2-12 Part 1 eSense values of relaxed participants

**While emotion changed from "relaxed" to "excited" after loud sound**

Many people' feeling changes from relaxed to excite after the strike of loud sound.

| | Attention | Meditation |
|---|---|---|
| Before Loud Sound | 45.75841 | 44.45509 |
| After loud sound | 40.40862 | 56.99257 |
| Difference between values before and after loud sound | -5.34979 | 12.53748 |

Figure 2.2-13 Compare eSense values before and after the loud sound

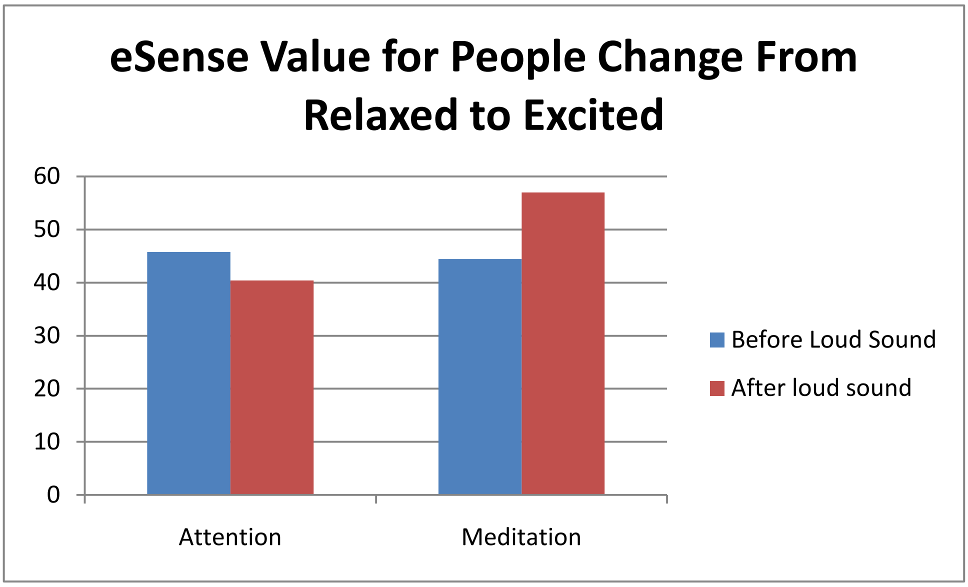



Figure 2.2-14 eSense values before and after the loud sound

The attention value decreases and mediation value increases after the loud sound.

**Conclusion**

When the participants have a feeling of relaxed, the meditation should be higher than normal level. However, in the observation, the meditation is lower than normal value. The meditation does not reflect the relaxed states in this observation.

When the participants ’ mental state changes from relaxed to excited after the loud sound, attention value decreases and meditation value increases. The meditation also does not reflect the change of mental states. One possibility to explain this observation would be: the strike of loud sound does not make the participant excited but help them to relax.

## Part 2: Speech of Pope Benedict XVI in Sistine Chapel

| | Part 2 |
|---|---|
| Attention | 44.19243 |
| Meditation | 55.19941 |

Figure 2.2-15 Part 2 average eSense values

| | Attention | Meditation |
|---|---|---|
| Overall | 49.29572 | 53.24579 |
| Part 2 | 44.19243 | 55.19941 |
| Difference between average values and part 2 values | -5.10329 | 1.953611 |

Figure 2.2-16 Compare overall eSense values and part 2 eSense values

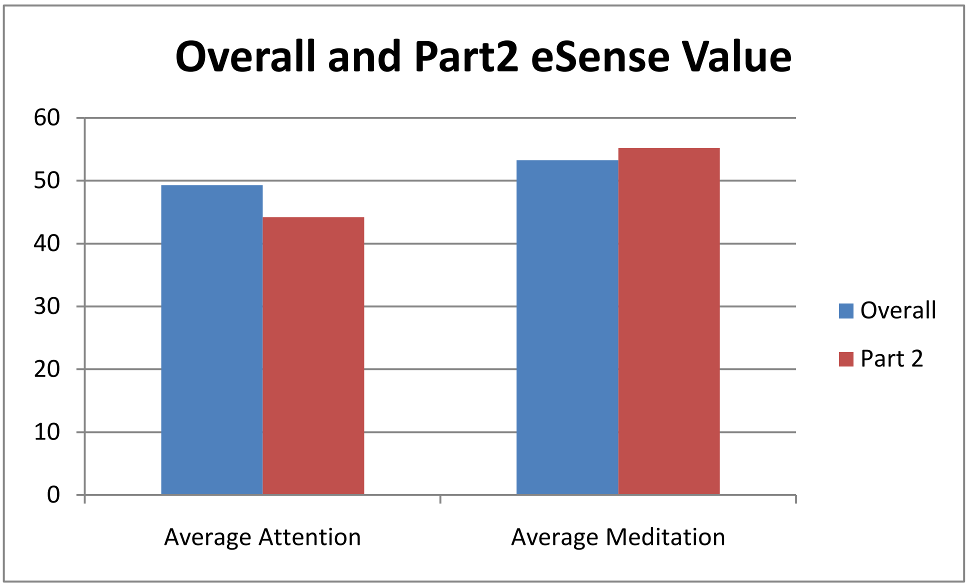



Figure 2.2-17 Overall values and part 2 values

The attention value decreases from first half to second half. The meditation value has no obvious changes.

**Bored Participants**

Most participants feel bored for both first half and second half of the movie.

Compare eSense values between first half and second half for bored participants

| | Attention | Meditation |
|---|---|---|
| First Half | 43.98032 | 55.143 |
| Second Half | 36.59128 | 52.59716 |
| Difference between first half and second | -7.38904 | -2.54584 |

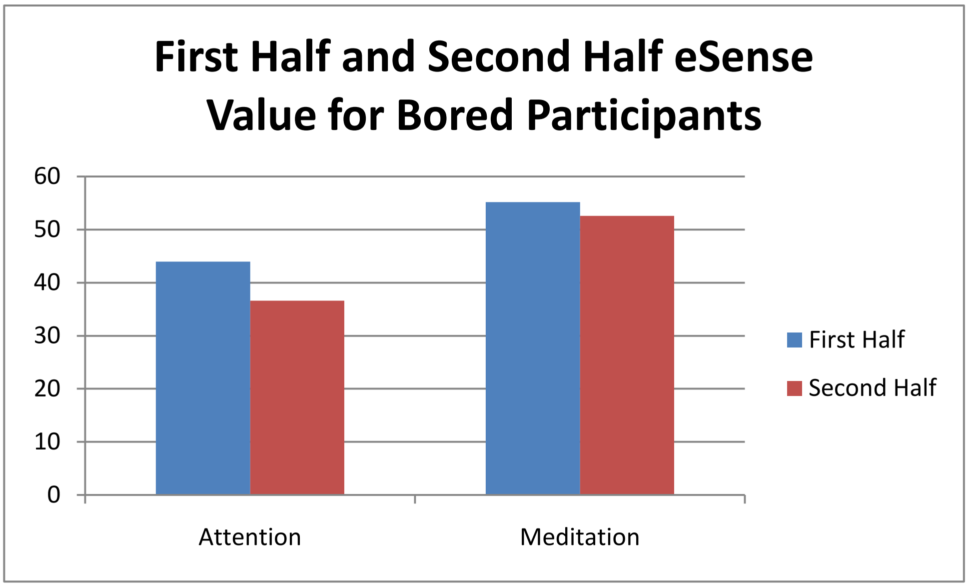



**Figure 2.2-18 First half and second half eSense values of bored participants**

The attention value decreases from first half to second half. The meditation value has no obvious changes.

### Conclusion

When the participants continuously feel bored, there is a decrease in attention. Also, the attention value is lower than normal value for bored participants. There may be some correlations between bored and decrease in attention. One possibility would be the participants lose the focus because they do not understand the Italian that the Pope speaks.

## Part 3: Don't stare at bikini

### Concentrated Participants

| | Attention | Meditation |
|---|---|---|
| Overall | 44.8396 | 54.36843 |
| Question 1 | 40.76725 | 56.93153 |
| Difference between average values and question 1 | -4.07235 | 2.5631 |

Figure 2.2-19 Compare part 3 and overall average eSense values of concentrated participants in question 1

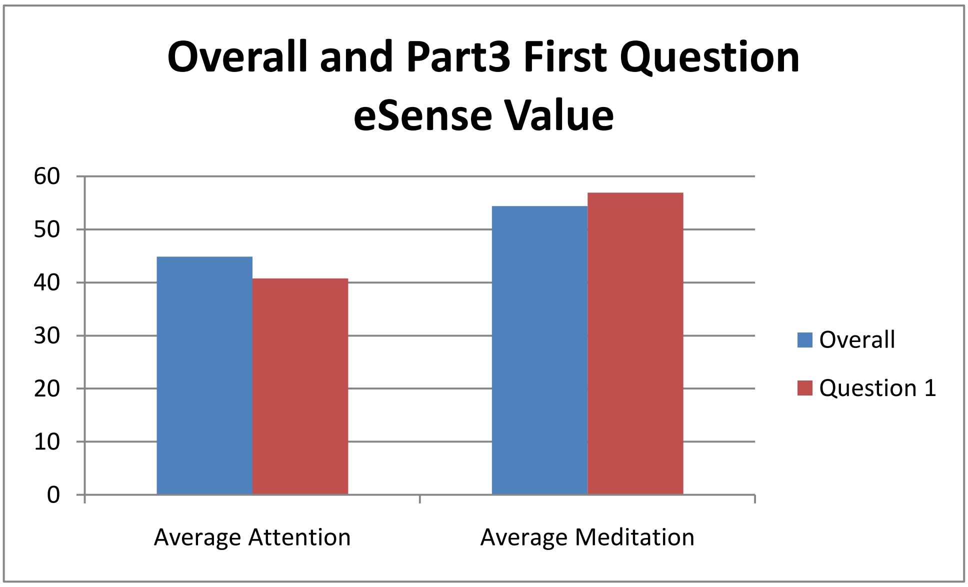



Figure 2.2-20 Overall eSense values and question 1 eSense values

The attention value at question 1 is lower than average value. The mediation value at question 1 is higher than average value.

| | Attention | Meditation |
|---|---|---|
| Overall | 48.59267 | 57.80879 |
| Question 2 | 50.97459 | 56.05645 |
| Difference between average values and question 2 | 2.38192 | -1.75234 |

Figure 2.2-21 Compare part 3 and overall average eSense values of concentrated participants in question 2

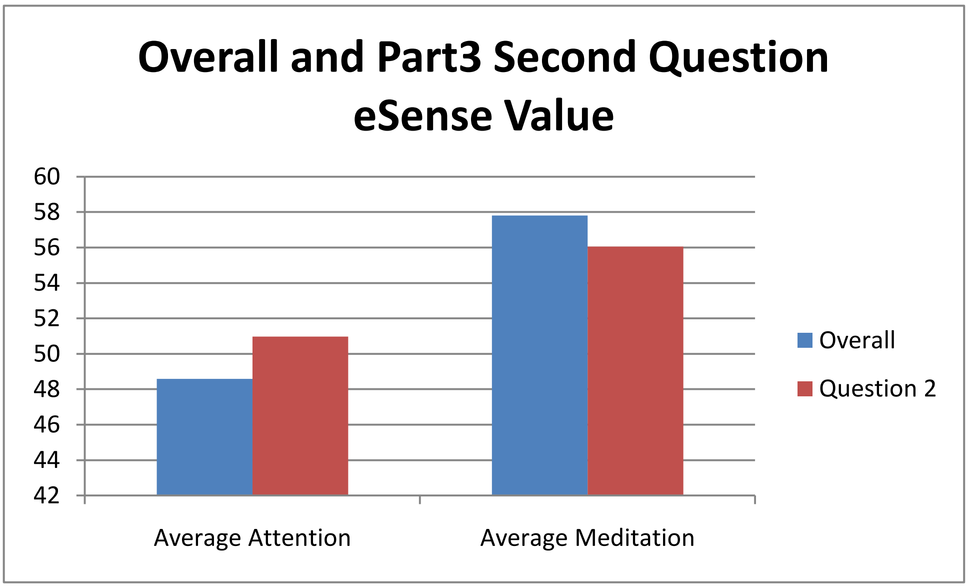



Figure 2.2-22 Overall eSense values and question 2 eSense values

The attention value at question 2 is higher than average value. The mediation value at question 2 is lower than average value.

| | Attention | Meditation |
|---|---|---|
| Overall | 56.67004 | 55.79628 |
| Answer 1 | 58.65714 | 52.41048 |
| Difference between average values and answer 1 | 1.9871 | -3.3858 |

**Figure 2.2-23 Compare part 3 and overall average eSense values of concentrated participants in answer 1**

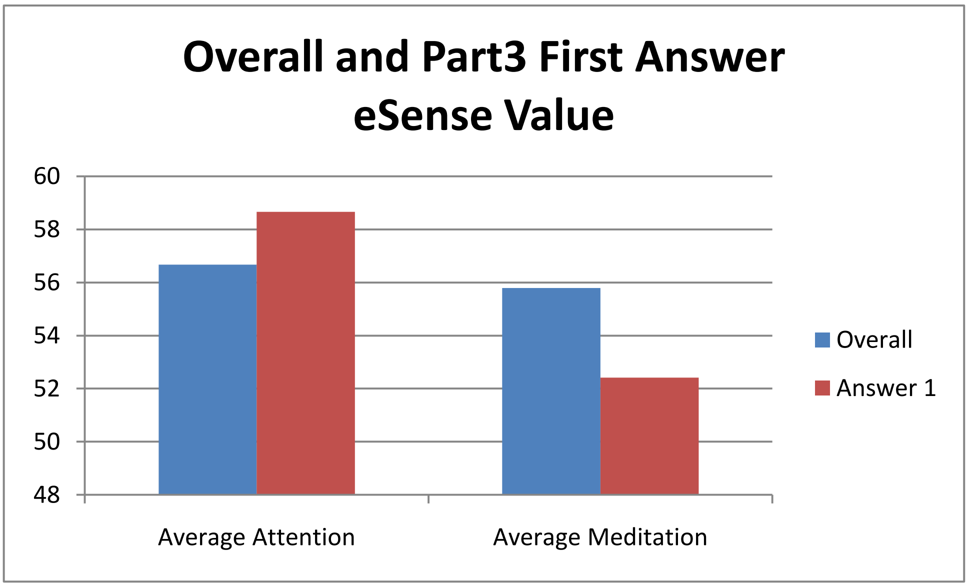



**Figure 2.2-24 Overall eSense values and answer 1 eSense values**

The attention value at answer 1 is higher than average value. The mediation value at answer 1 is lower than average value.

| | Attention | Meditation |
|---|---|---|
| Overall | 50.41634 | 53.7065 |
| Answer 2 | 54.8775 | 52.63166 |
| Difference between average values and answer 2 | 4.46116 | -1.07484 |

Figure 2.2-25 Compare part 3 and overall average eSense values of concentrated participants in answer 2

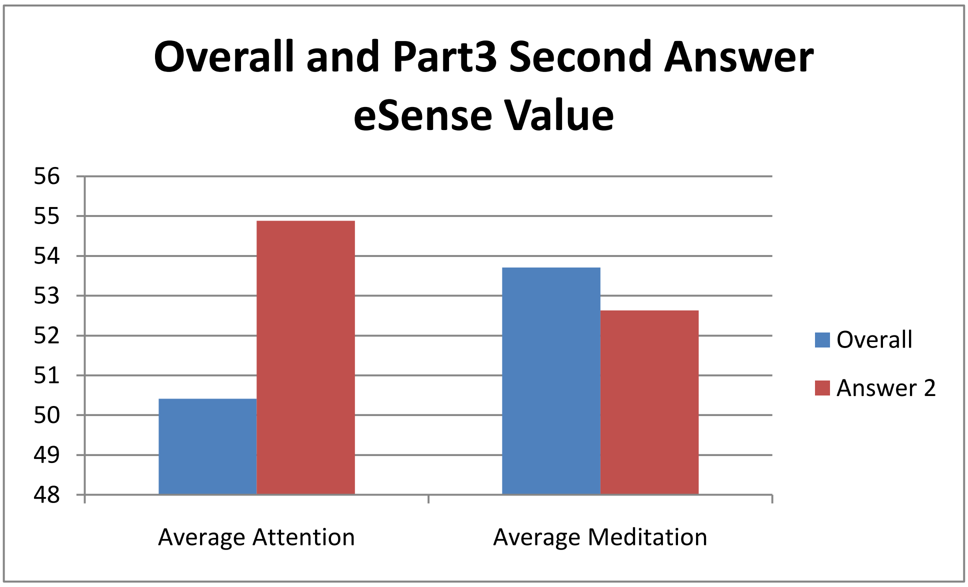



Figure 2.2-26 Overall eSense values and answer 2 eSense values

The attention value at answer 2 is higher than average value. The mediation value at answer 2 is lower than average value.

| | Question 1 | Question 2 | Answer 1 | Answer 2 |
|---|---|---|---|---|
| **Overall Attention** | Q1 < Overall | Q2 > Overall | A1 > Overall | A2 > Overall |
| **Overall Meditation** | Q1 > Overall | Q2 < Overall | A1 < Overall | A2 < Overall |

Figure 2.2-27 Compare of eSense values for each part with overall value

### Conclusion

Some participants are concentrated at question 1, question 2, and answer 1 and answer 2. For attention at question 2, answer 1 and answer 2. The attention is higher than the overall average value which the feeling of concentrated.

The attention value of participant is lower than overall average value but the feeling of participants are concentrated. This error may be caused by participants not fully understand the question when they watch the movie.

For meditation value of each part, it is lower than overall values. The decrease in meditation may cause by bikini girl. Participants become less calm.

## Part 4: Ghost Pop Up

| | Average |
|---|---|
| Attention | 57.95749 |
| Meditation | 51.58219 |

Figure 2.2-28 Part 4 average attention and mediation

| | Attention | Meditation |
|---|---|---|
| Overall average | 49.29572 | 53.24579 |
| Part 4 average | 57.95749 | 51.58219 |
| Difference | 8.661778 | -1.66361 |

Figure 2.2-29 Compare overall average values and part 4 average values

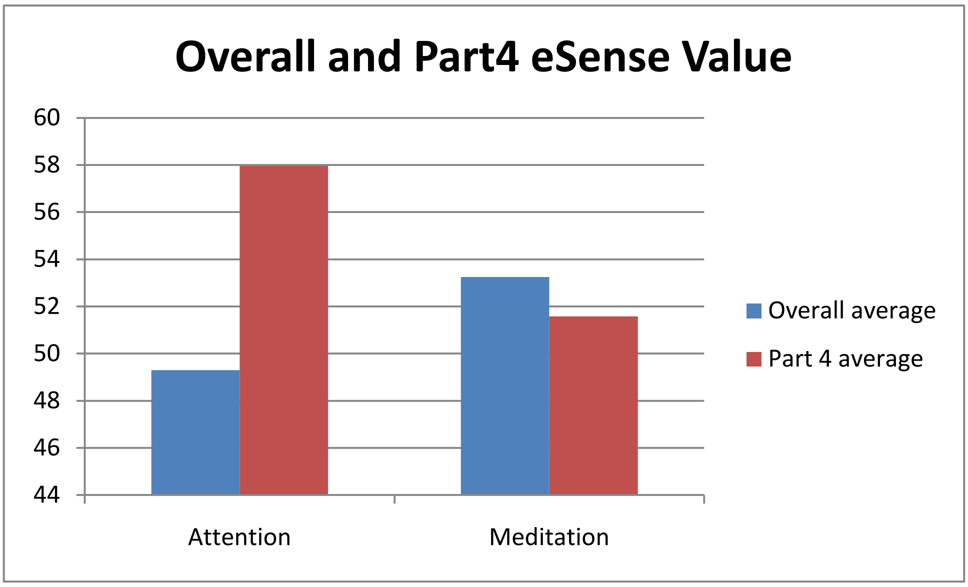



Figure 2.2-30 Compare the overall average values and part 4 average values

The attention value in part 4 is higher than average value. The mediation value at part 4 is slightly lower than average value.

**Compare attention and meditation values before and after the ghost appears**

The most common feelings of the participants change from concentrated to fear.

| | Attention | Meditation |
|---|---|---|
| Before Ghost appear | 59.18367 | 52.84439 |
| After Ghost appear | 53.51871 | 50.38266 |
| Difference | -5.66496 | -2.46173 |

Figure 2.2-31 Compare average values before and after the ghost appear for participants' feeling changes from concentrated to fear

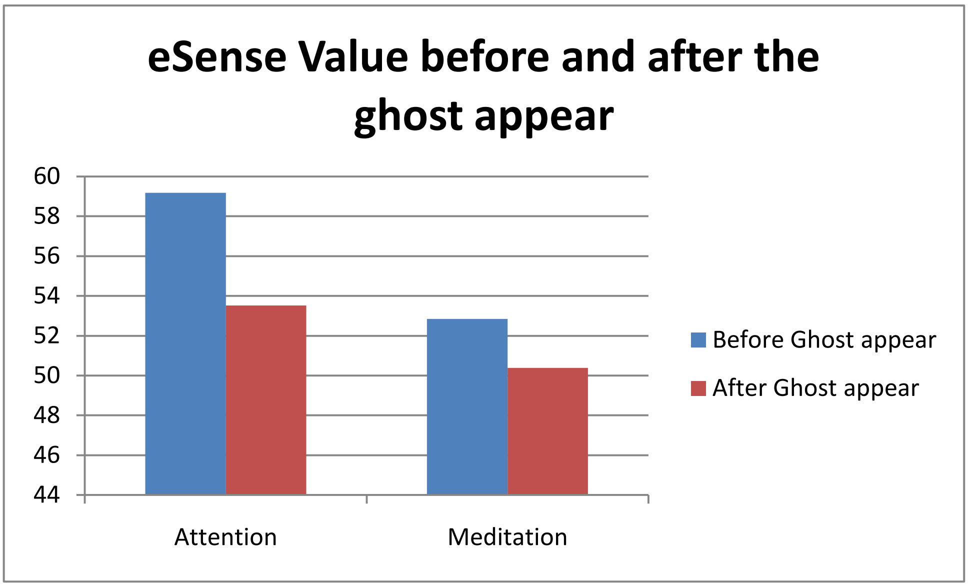



Figure 2.2-32 Compare the average values before and after ghost appear

The attention value and the mediation value decrease after the ghost appears.

**Conclusion**

In this movie, the participants are told that there will be a ghost appears and to be prepared for the ghost. The attention is higher than normal value. The high attention value supports that the high concentration of the participants since they are aware about the ghost. The decrease in meditation value after the ghost appears support that the participants are less calm because they feel fear.

### 2.2.4 Conclusion for result and data analysis

The attention and meditation values usually can reflect the changes or existence in mental states.

The attention can correlate to the mental state concentrated. When the participants are concentrated, there is usually an increase in attention value (Part 3 conclusion). When the participants are affected by outside environment (strike of loud sound in part 1and ghost appear in part 4), there is usually a decrease in attention value (Part 1 and part 4). It reflects the focus of the participants decrease.

Attention can also correlate with mental states boring. There is an obvious decrease in attention when participants are bored (Part 2 conclusion). It can be explained as people become less focus when they are bored.

The relation between meditation value and different mental states are not conclusive. The change in meditation is lower than average value even the participants feel relaxed (Part 1 conclusion). The reason may be the meditation is not measuring the physical relax but the mental relax which is difficult for the participants to identify. However, there are observations which show an decrease in meditation when they are fear (Part 4 conclusion) or change in meditation value after special point (Part 1 loud sound and Part 3 bikini girl).

To conclude, the attention value shows a correlation with concentration and boring while the correlation between meditation value and relaxation are not conclusive and need further investigation.

# 3 Brainwave Classifier

## 3.1 Introduction

Brainwave Classifier is an active brainwave control trainer that can classify the brainwave data within a sliding window to different types according to their brainwave pattern. This tool instantly shows the current brainwave states (types) of the user brainwave. The objective to develop this tool is to create an active control brainwave trainer. By using the instant feedback from the Brainwave Classifier, user will train himself/herself maintaining in different brainwaves states (types) or changing from one state to another. This tool shows the possibility of active control using brainwaves.

In this part, the working flow of Brainwave Classifier, brainwave pattern of the three brainwave types, the algorithm used in the Brainwave Classifier and the training result of Brainwave Classifier will be presented.

## 3.2 Working flow of Brainwave Classifier

The Brainwave Classifier has two stages, the calibration stage and classifying stage. The program first enters the calibration stage and followed by the classifying stage.

### 3.2.1 Calibration Stage

In the calibration state, user brainwave data will be collected. These data will be used to calculate the value of the peak. In calculate the values of the peak, k-mean clustering algorithm is used. The period of calibration stage is 2 minutes.

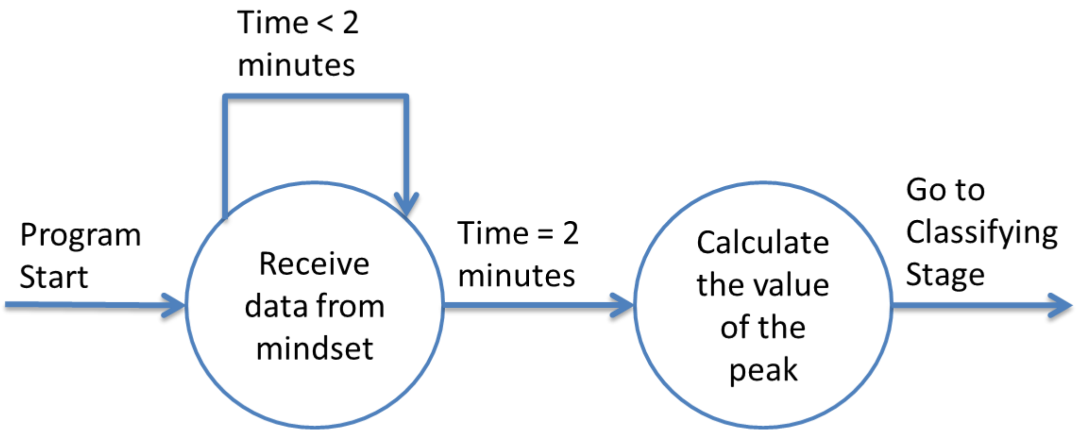



Figure 3.2-1 Program Flow in Calibration Stage

### 3.2.2 Classifying Stage

In the classifying stage, the program will plot a line chart showing the brainwave data of the latest 15 seconds using a sliding window. The program will calculate the current brainwave type using the latest brainwave data. The resultant brainwave type is showed using color in the chart.

| Brainwave Type | Color of line chart |
|---|---|
| 1 | Red |
| 2 | Yellow |
| 3 | Blue |

Figure 3.2-2 Color of different brainwave

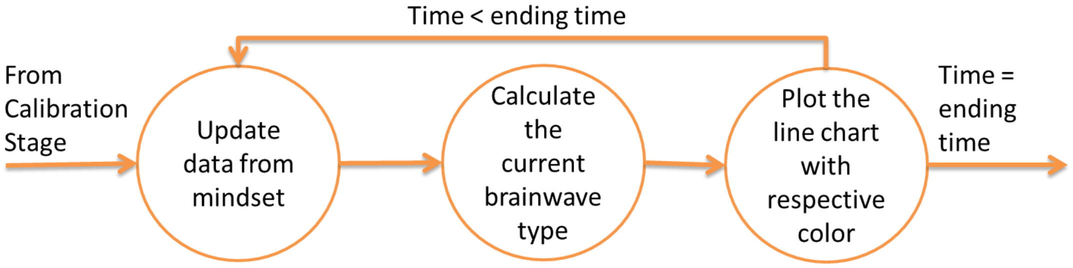



Figure 3.2-3 State Diagram showing the working flow of Brainwave Classifier

In the calibration stage, Brainwave Classifier will first record user brainwave data for 2 minutes.

Then, the data collected will be used to determine the peak of brainwaves using k-mean clustering algorithm.

Then it enters the classifying stage, the Brainwave Classifier will use the latest data (past 15 seconds brainwave data) to calculate the brainwave type. The Brainwave Classifier will update the brainwave type regularly and show the results in the output windows.

## 3.3 Brainwave Types

Three Brainwave types are defined according to their patterns. Type1 brainwaves mean within the window, there is more than one peak. Type 2 brainwaves mean that within the sliding windows, there is only one peak. Type 3 brainwaves mean that within the sliding windows, there are no peaks.

| Brainwaves | Features |
|---|---|
| **Type 1** | More than one peaks |
| **Type 2** | One peak |
| **Type 3** | No peaks |

Figure 3.3-1 Features of different brainwave types

### 3.3.1 Type 1

Brainwaves are classified as type 1 when there is more than one peak within the window. This brainwave pattern means there are great variations in the brainwave data. User showing more type 1 brainwave should have active mental activities.

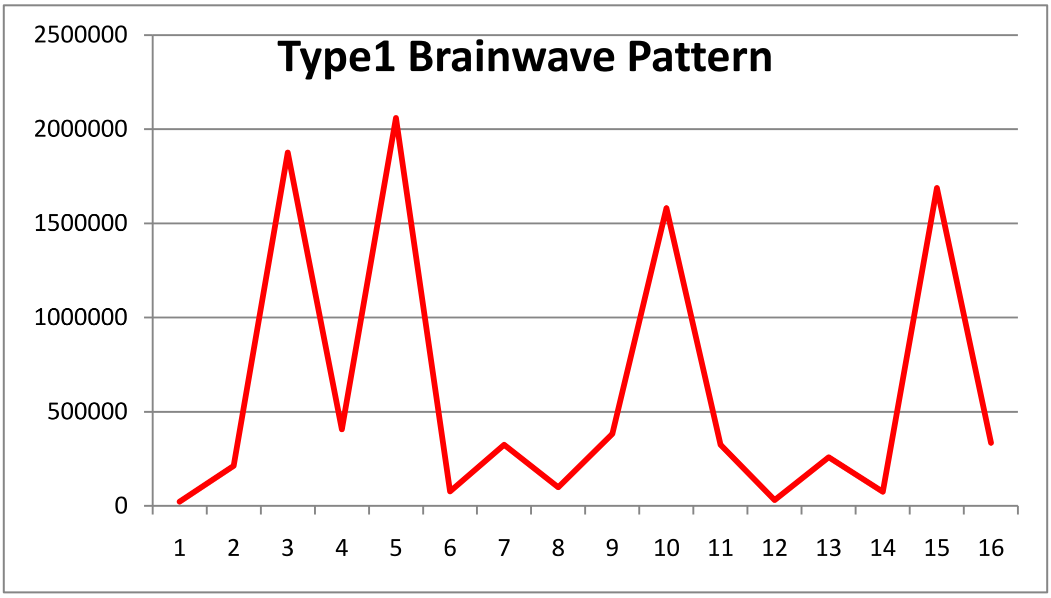



Figure 3.3-2 Sample Type 1 brainwave pattern (window size = 15 data points)

### 3.3.2 Type 2

Brainwaves are classified as type 2 when there is exactly one peak within the window. This brainwave pattern is the transition state between type 1 and type 3 brainwaves. User showing this brainwave type means the user mental activities is not stable and varies between type 1 and type 3.

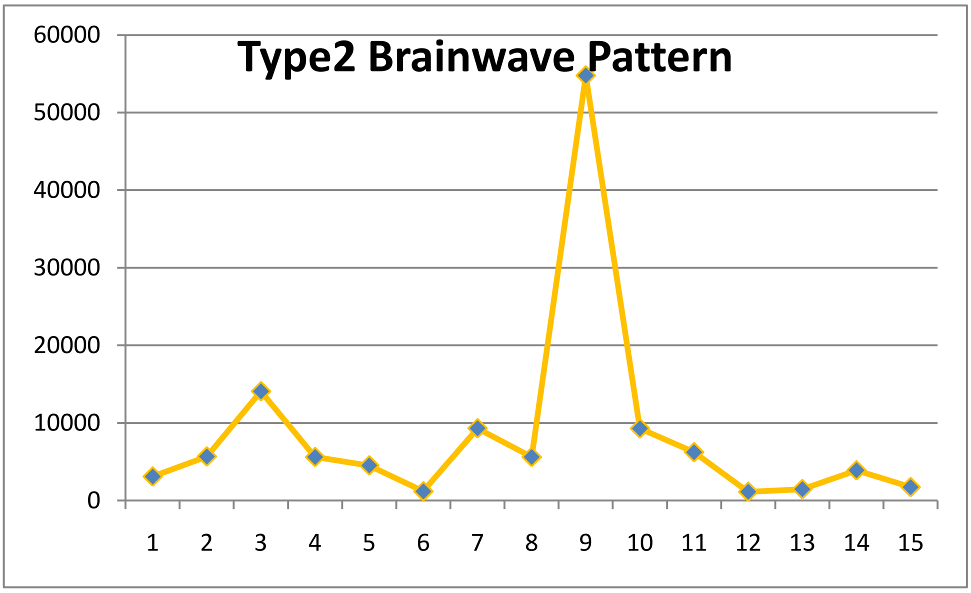



Figure 3.3-3 Sample Type 2 brainwave pattern (window size = 15 data points)

### 3.3.3 Type 3

Brainwaves are classified as type 3 when there are no peaks within the window. This brainwave pattern means there are small variations in the brainwave data. User showing more type 3 brainwaves should have less active mental activities.

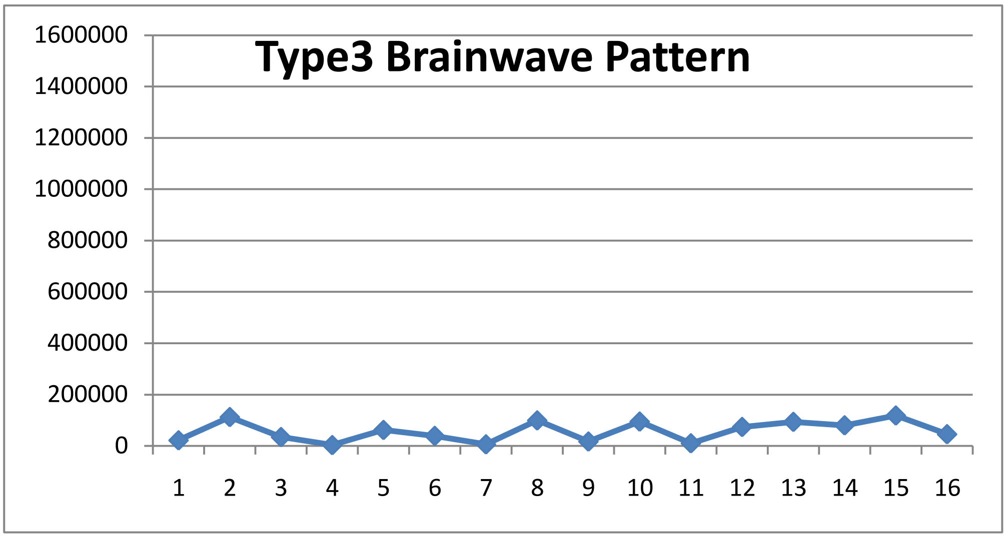



**Figure 3.3-4 Sample Type 3 brainwave pattern (window size = 15 data points)**

# 3.4 Algorithm

## 3.4.1 K-mean clustering

K-mean clustering algorithm is used in the calibration stage. It is used to calculate the value of the peak. When we classify the brainwave, we need to know the value of the peak so we can identify the pattern of the brainwave data.

We use k-mean clustering algorithm to cluster the brainwave data into three clusters. We use the value of the center in the middle cluster as the lowest value of a peak.

The k-mean clustering is defined as:

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), where each observation is a *d*-dimensional real vector, *k*-means clustering aims to partition the *n* observations into *k* sets ($k \leq n$)$\mathbf{S}$ = {$S_1$, $S_2$, …, $S_k$} so as to minimize the within-cluster sum of squares (WCSS):

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \left\| \mathbf{x}_j - \boldsymbol{\mu}_i \right\|^2$$

where $\boldsymbol{\mu}_i$ is the mean of points in $S_i$.

## Initiation

K-mean algorithm begin with choose the cluster center. In Brainwave Classifier, three data points are randomly chosen as the center of three clusters.

## Assignment step

The assignment step will them assign each data point to the closest cluster.

$$S_i^{(t)} = \left\{ \mathbf{x}_j : \left\| \mathbf{x}_j - \mathbf{m}_i^{(t)} \right\| \le \left\| \mathbf{x}_j - \mathbf{m}_{i^*}^{(t)} \right\| \text{ for all } i^* = 1, \ldots, k \right\}$$

## Updating step

The updating step will calculate a new center for each cluster.

$$\mathbf{m}_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j$$

The assignment step and updating step are repeated until the terminating requirement is reached.

## Termination

K-mean clustering terminated when the assignments no longer changed.

Use of k-mean clustering in Brainwave Classifier

After k-mean clustering, the center of the second cluster will be used as a cut off line. The data point above this value will be considered as a peak and the data point below this value will be non-peak.

### 3.4.2 Sliding Window

Sliding window is used in the classifying stage. Only the latest value of the brainwave is used to calculate the current brainwave type. In the Brainwave Classifier, the window size is 15 seconds.

Time t (seconds)

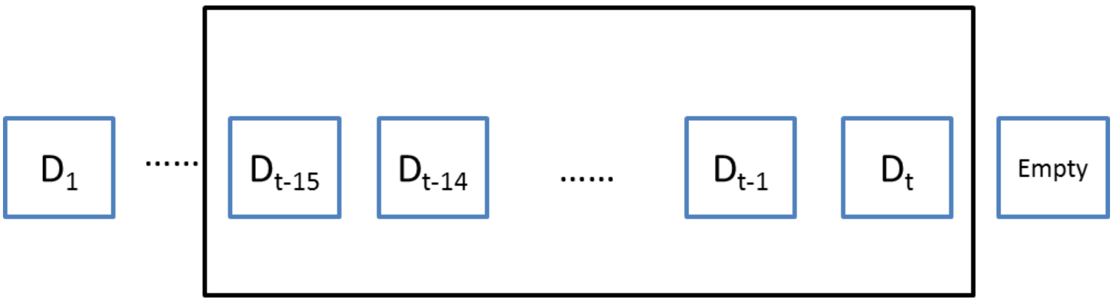



**Figure 3.4-1 Sliding Window at Time t**

Time t+1 (seconds)

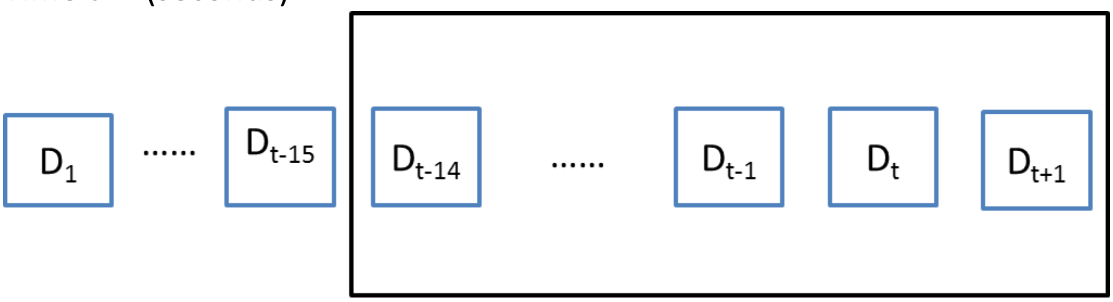



**Figure 3.4-2 Sliding Window at Time t+1**

Every time the Brainwave Classifier collects a new data from Mindset. The sliding window shifts right to use updated data to calculate the new brainwave type.

### 3.4.3 Calculating the Brainwave Type

#### Count the Peak

Since the difference between the Type 1, Type 2 and Type 3 brainwave types are the number of peaks in the sliding windows. The method to classify the brainwave type is to count the number of peaks. Using the peak value calculated from the k-mean algorithm, every data point is classified as above peak value or below peak. The number of peaks can be counted by scanning through these data once.

#### Majority

There are 8 channels of brainwave data. To make the output of the brainwave classifier more user-friendly, an overall brainwave type is returned by majority vote.

In tie-breaking situation, type2 brainwave has a higher priority than type3 brainwaves and a type 3 brainwave has a higher priority than type1 brainwave.

## 3.5 User Interface

### 3.5.1 Overall View

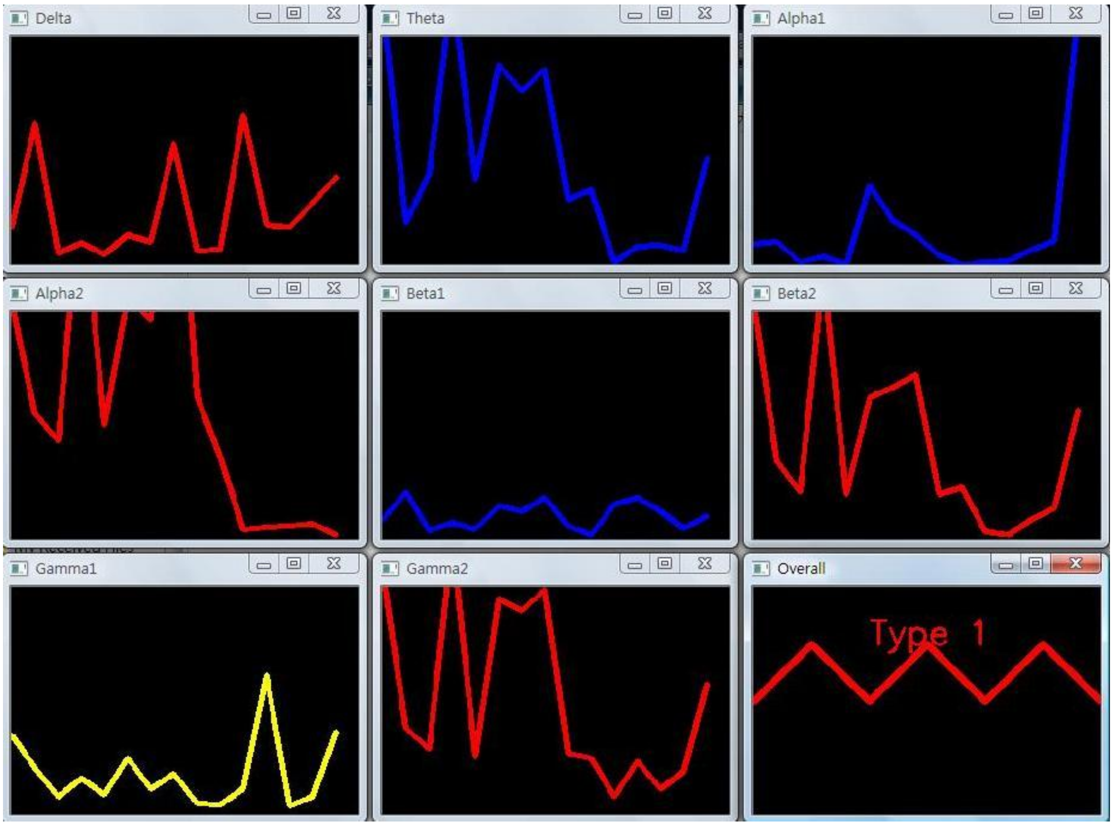



Figure 3.5-1 The whole picture of the Brainwave Classifier

The user interface are created using OpenCV.

The window at the bottom right corner is the overall brainwave window. The overall brainwave window presents the overall brainwave type by the color and simple graph.

The other eight windows are the individual brainwave windows which represent different frequent brainwave. The individual windows present the brainwave type by color and show the exact brainwave pattern by line chart.

### 3.5.2 Individual Channel and Overall Channel

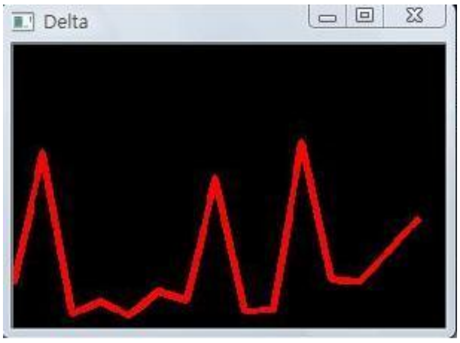



Figure 3.5-2 Channel with type 1 Brainwave

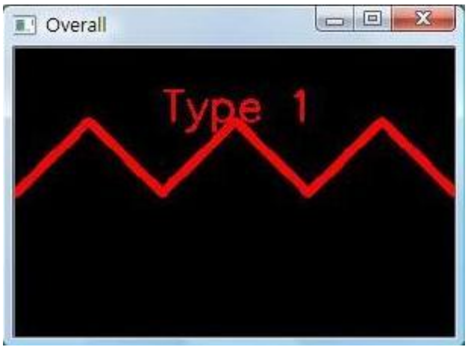



Figure 3.5-3 Overall Channel with type 1 brainwave

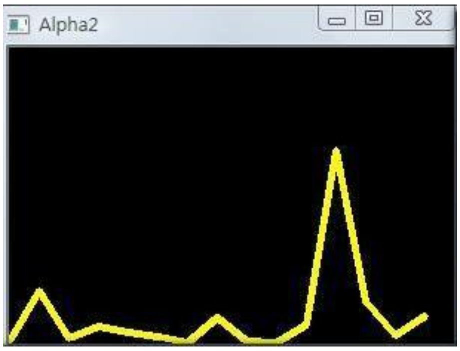



Figure 3.5-4 Channel with Type 2 Brainwave

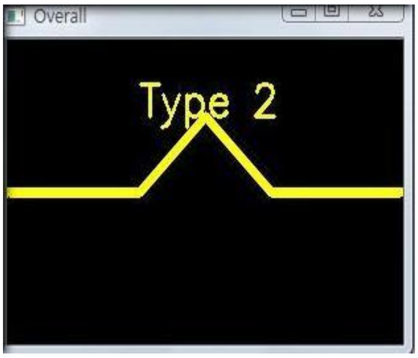



Figure 3.5-5Overall Channel with type 2 brainwave

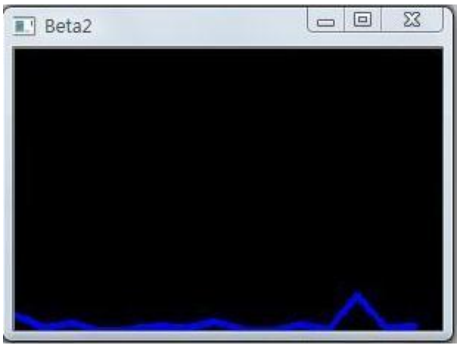



Figure 3.5-6 Channel with type 3 Brainwave

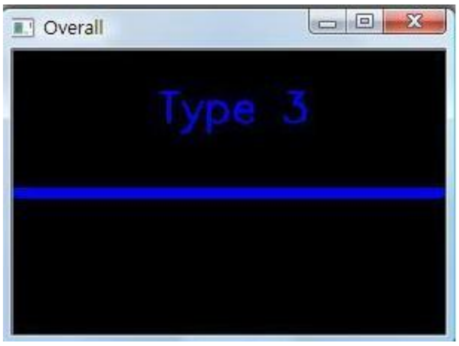



Figure 3.5-7 Overall Channel with type 3 brainwave

## 3.6 Personal Training

As long term users of Brainwave Classifier, we fully train ourselves and are able to control the brainwave states. The controls include keeping a specific brainwave type or changing between different brainwave types. We found that we can use brainwave pressure or image different music to control different type brainwave.

The following parts are going to demonstrate how well we can control our brainwave using Brainwave Classifier.

### 3.6.1 Keeping Type 1

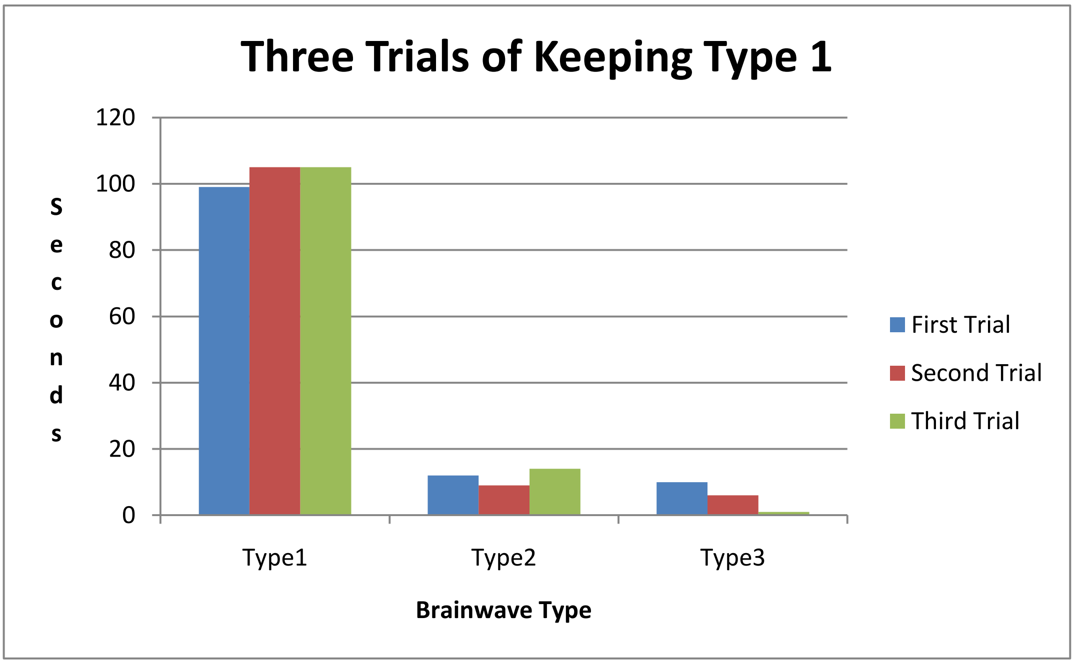



Figure 3.6-1 Bar chart showing keeping type 1 time

We use the brainwave for three times and each trial longs for 2 minutes. In each trial, we are going to keep our brainwave at type 1. The results show that we are able to maintain our brainwave states at type 1 most of the time. We can hold the type 3 brainwave pattern for about 100 seconds out of 120 seconds.

### 3.6.2 Keeping Type 3

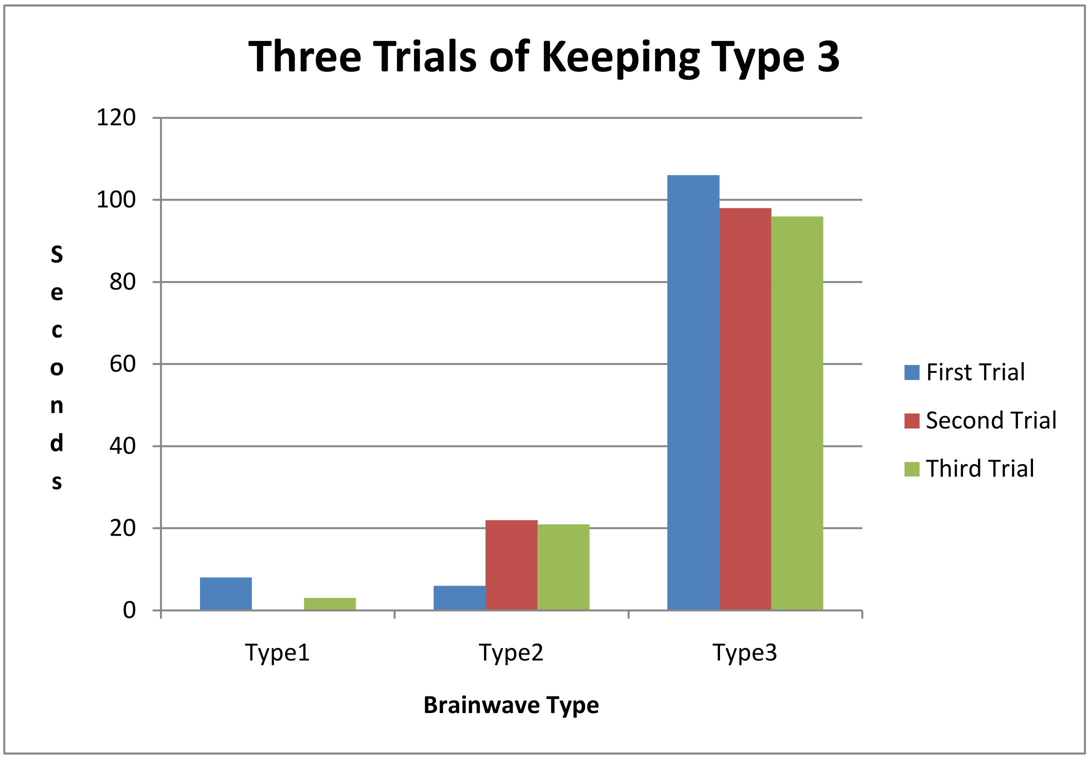



Figure 3.6-2 Bar chart showing keeping type 3 time

We use the brainwave for three times and each trial longs for 2 minutes. In each trial, we are going to keep our brainwave at type 3. The results show that we are able to maintain our brainwave states at type 3 most of the time. We can hold the type 3 brainwave pattern for about 100 seconds out of 120 seconds.

### 3.6.3 Oscillating between type 1 and type 3

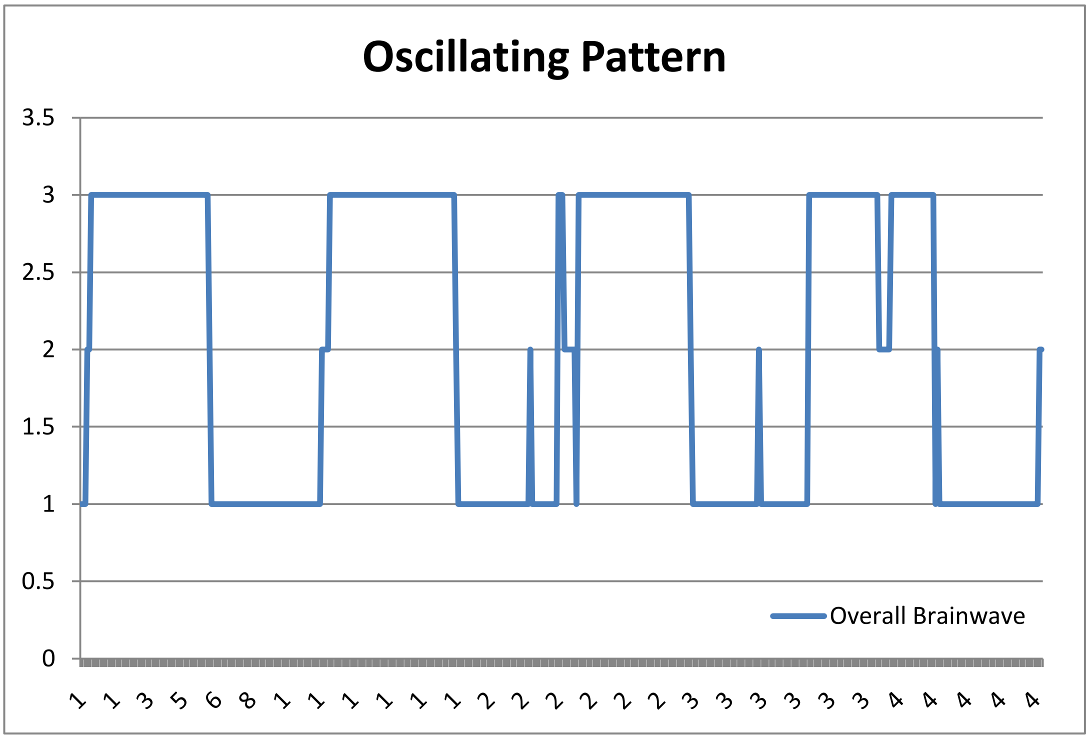



Figure 3.6-3 Line chart showing the oscillating pattern produced

This personal testing lasts for 10 minutes. We try to maintain the brainwave type3 and then change to type1 after 1 minute. We change our brainwave type to one another once per minute.

The pattern on the line chart shows that for most of the time, the brainwave types 1 and type 3 are maintainable. We can maintain our brainwave type for at least 1 minute and we can change the brainwave types from one another within 5 to 10 seconds.

This shows that we can completely control type1 and type3 brainwaves.

## 3.7 Experiment on Brainwave Classifier

We would like to investigate whether non-experienced user are able to use Brainwave Classifier to train themselves.

### 3.7.1 Objective

The objective of this experiment is to show that Brainwave Classifier help some people training their brainwave.

### 3.7.2 Methodology

Users will have 15 minutes to use the Brainwave Classifier. They will use the Brainwave Classifier to train their brainwaves, trying to control the brainwave types.

After the training, user will be asked to maintain type 1 and type 3 brainwaves for 2 minutes as much as possible. By compare the time that they can maintain at type 1 and type 3, it may show that users can control their brainwave in some degree.

### 3.7.3 Result

Nine participants have do the experiment and all of them are male.

## Overall Result

Keeping Type 1

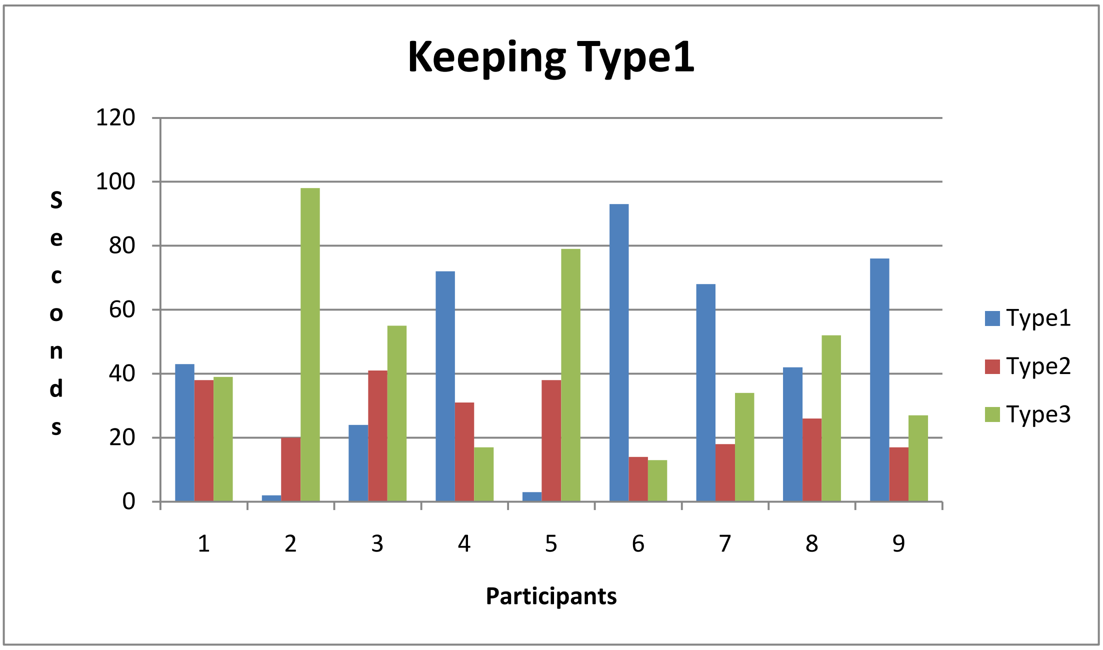



Figure 3.7-1 Bar chart showing result in Keeping Type 1 Brainwave

For keeping type1 experiment, the participants are asked to keep the type 1 brainwave (pattern with more than one peak) as long as they can within two minutes.

The result shows that 5 participants have maintain longer type 1 brainwave than type2 and type 3 while the remaining 4 participants have more type3 brainwave than type1 brainwave.

Keeping Type 3

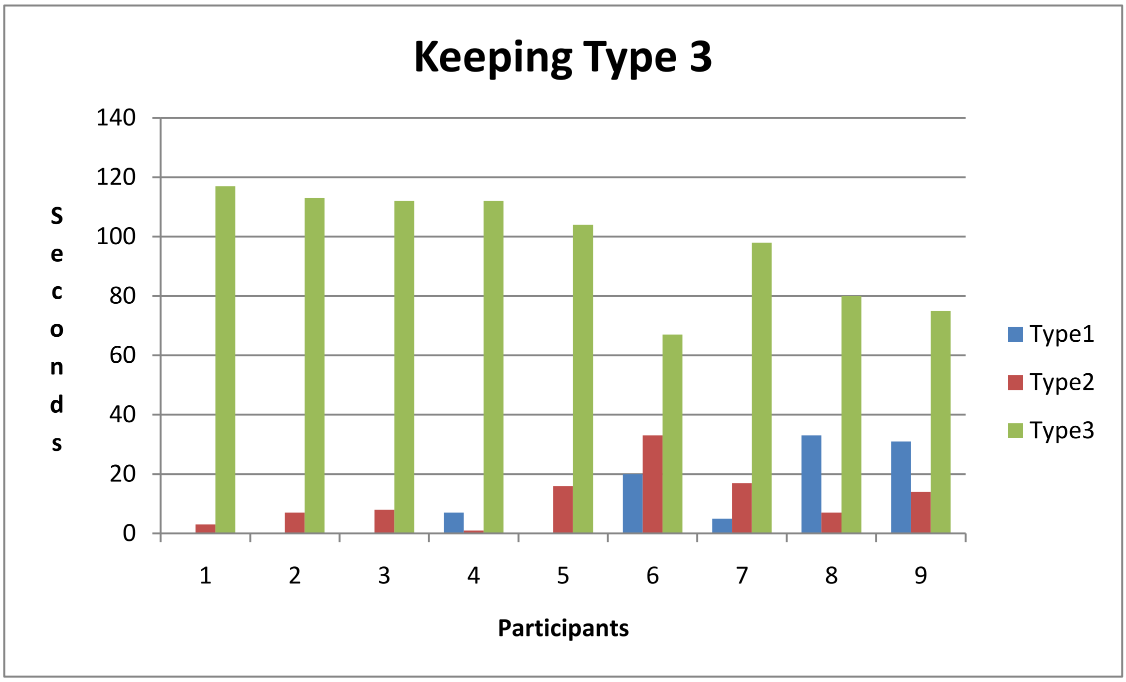



Figure 3.7-2 Bar chart showing result in Keeping Type 3 Brainwave

For keeping type3 experiment, the participants are asked to keep the type 3 brainwave (pattern with more than one peak) as long as they can within two minutes.

The result shows that all participants can maintain longer type3 brainwave than type1 and type2. Some participants can even keeping type3 brainwave for more than 100 seconds out of 2 minutes.

This results show that type3 brainwave is more easier to control than type1, since all participants are able to control type3 brainwave while only half of the participants are able to control type1 brainwave.

## Successful Users of Keeping Type 1

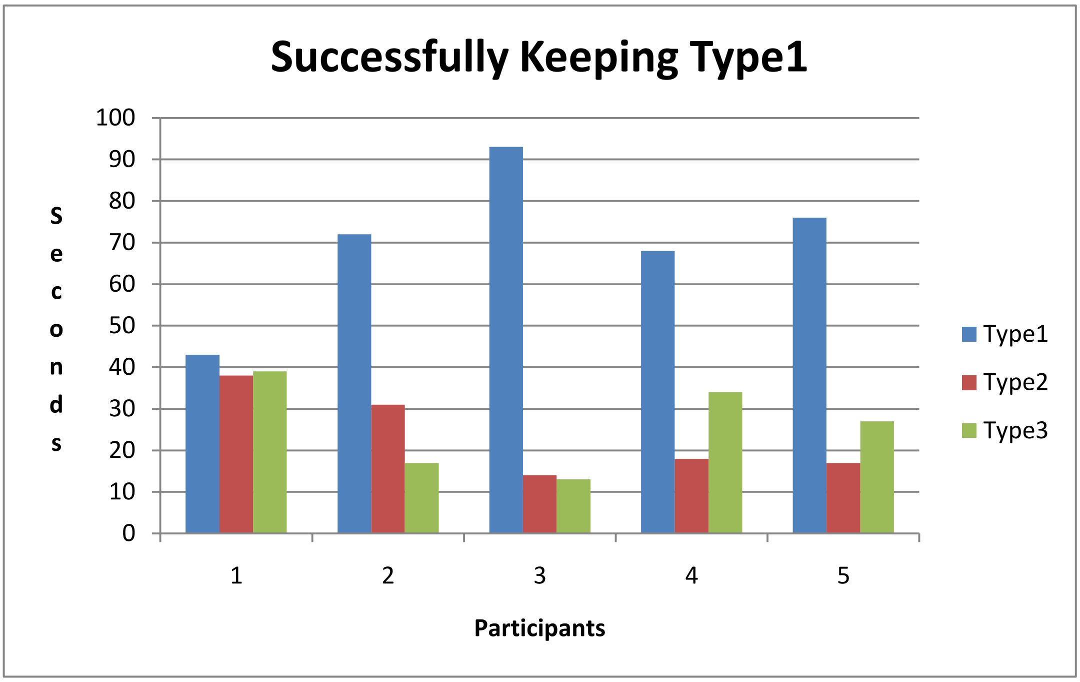



Figure 3.7-3 Bar chart showing data of those who can control Type 1

If we only consider the successful user in keeping type1, we find that the performance in keeping type 1 is not as good as keeping type 3.

This results show that keeping type1 is more difficult than keeping type3. The time that keeping type3 is about 100 seconds but the time that keeping type1 is only about 70 seconds. Moreover, only half of the participants can successfully control type1 brainwave while all participants can control type3 brainwave.

To conclude, keeping type1 brainwave seems more difficult and needs more training when comparing to type3 brainwave.

**Compare Keeping 1 and Keeping 3**

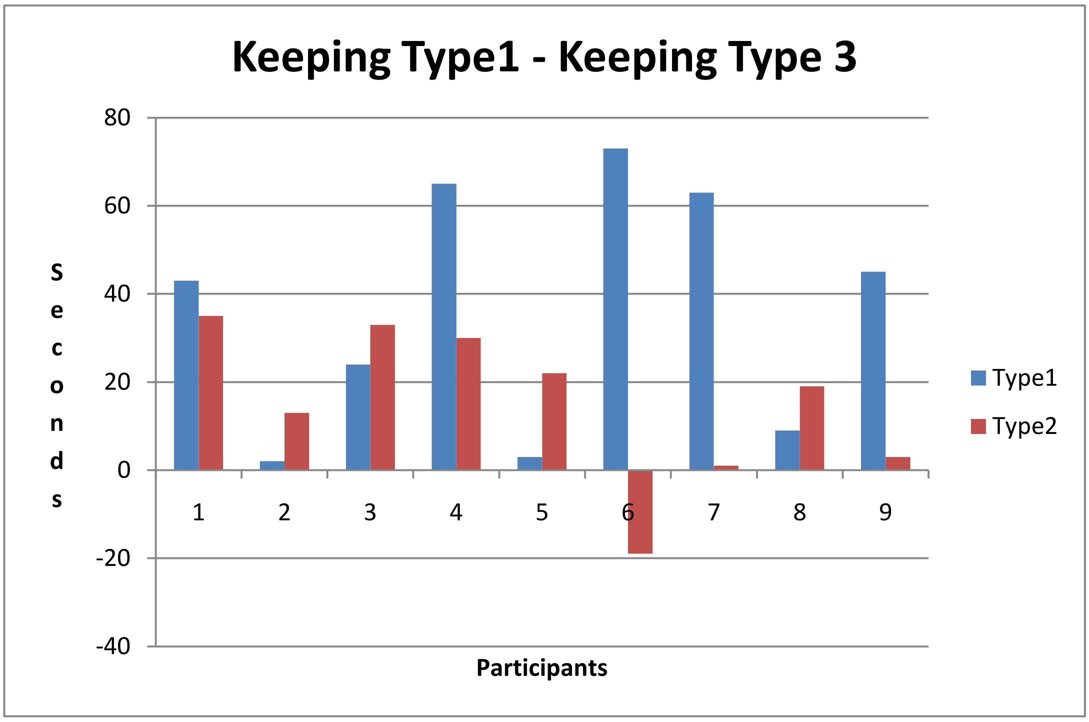



Figure 3.7-4 Bar chart showing difference between Keeping Type 1 and Keeping Type 3

We compare the brainwave data in experiment of keeping type1 and experiment of keeping type3.The chart above is produced by time in keeping type1 minus time in keeping type3. We find that their generally more type1 and type2 in keeping type1 experiment than keeping type3 experiment.

Although not all participants can maintain longer time in type1 than type3, they are able to produce more type1 and type2 brainwave when they try to produce type1 brainwave. It means the participants can control the brainwave in some degree using Brainwave Classifier.

To conclude, Brainwave Classifier is quite successful. Most participants can control their brainwave in some degree.

## 3.8 Control Method

### 3.8.1 Keeping Type 1

Keeping type1 brainwave is relatively difficult when comparing to keeping type3 brainwave. Different participants have different ways to maintain their type1 brainwave. The method includes, image some music, small muscle movement, concentrate on surroundings people or scene, and increase the brain pressure.

Keeping type1 brainwave is more difficult than keeping type3. Only half of the participants can show significant control on type1. For those successful participants, 5 to 10 minutes are needed to achieve some degree of control.

### 3.8.2 Keeping Type 3

Keeping type3 brainwave is relatively easy when comparing to keeping type1 brainwave. Most people are able to maintain type3 brainwave when they keep themselves at resting state or keeping very calm, not making large muscle movement.

Keeping type3 brainwave is quite easy to control. Most participants are able to achieve maintain type3 brainwave within several minutes.

## 3.9 Summary

In this semester, we develop Brainwave Classifier, which act as a brainwave trainer. With some training, we are able to control our brainwave to use the Brainwave Classifier with high accurate. We are able to maintain about 100 seconds out of 120 seconds for both type1 and type3. We are also able to change quickly from type1 and type3 and vice versa.

We also examine this tool with normal users; we find that they can also control their brainwave in some degrees. In the experiment, we found that type1 brainwave is more difficult to control than type3 brainwave. On the other hand, keeping type1 brainwave does not have any general method while keeping type3 can generally be achieved by keeping calm or at rest.

To conclude, Brainwave Classifier can help the user to train their brainwave. In the experiment, participants only use the Mindset for about 15 minutes but they already show some degree of control on brainwave. As experienced users of Brainwave Classifier, we even show an excellent control of brainwave with high accuracy.

# 4 Training Method

## 4.1 Introduction

From the development of Brainwave Classifier, we conclude a training method for users to learn and identify their ways to control the brainwaves. This training method provides a working flow for user to follow and discover their brainwave pattern.

## 4.2 Training Flow

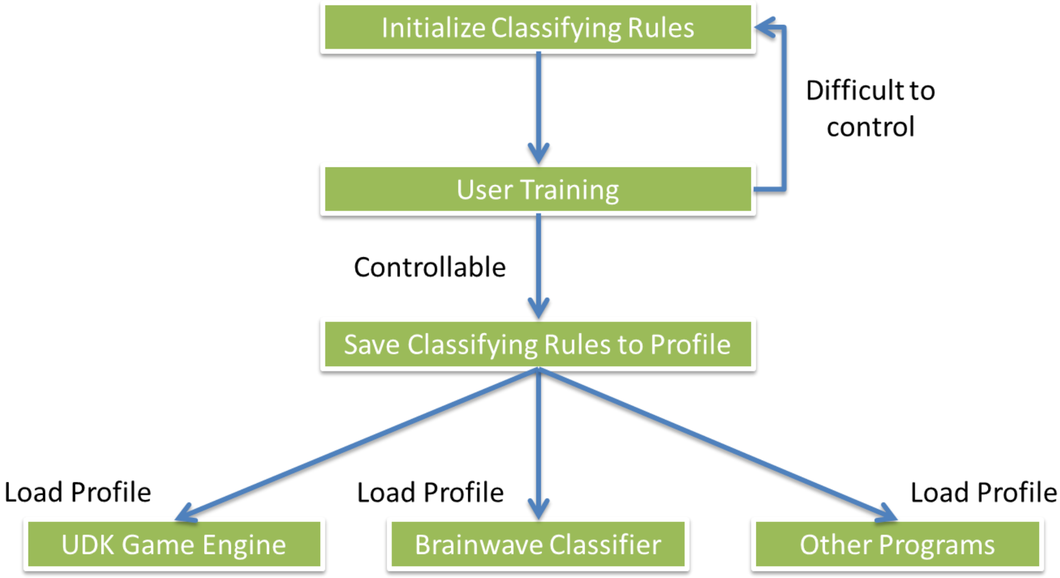



Figure 4.2-1 Training flow using Brainwave Classifier

The users can discover a controllable brainwave pattern by following the working flow below:

First, the user first initializes the rules to classifying brainwaves, for example, number of brainwave types and brainwave pattern of each brainwave type. Then the users use the brainwave classifier and train themselves to control these brainwave types.

If users feel difficult to control the defined brainwave types, they can modify the brainwave classifying rules of each type. If users feel the current brainwave patterns are controllable, a personal profile that contains the brainwave classifying rules and relevant data is created.

Using this profile, different programs can read the personal profile and classify the user brainwave using the brainwave classifying rules that are most suitable to the user.

## 4.3 Personal Profile

Personal profile is universal to all Mindset program. Mindset program will read the personal profile and use the brainwave classifying rules in the profile. The main advantage of using a personal profile is user does not need to learn new method to control their brainwave for different programs.

Possible Profile Format:

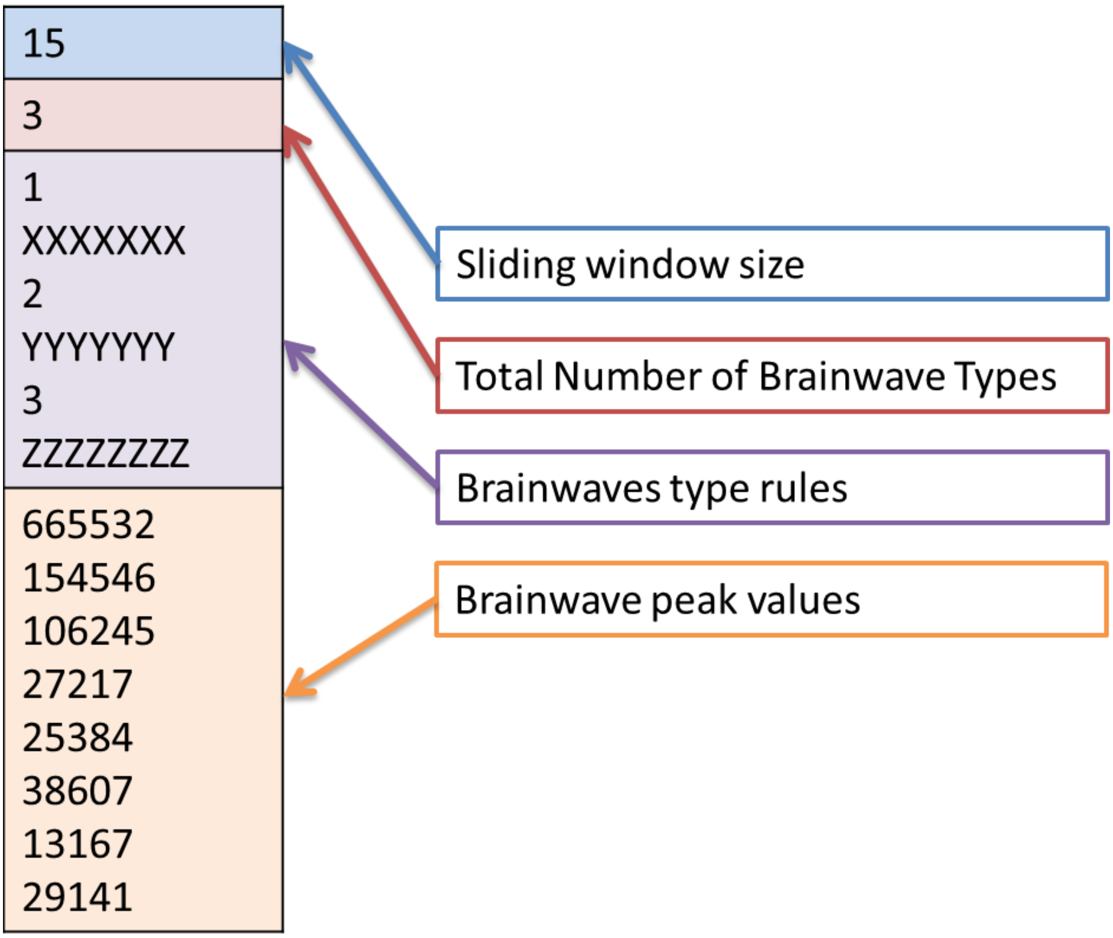



Figure 4.3-1 Possible Profile Format

## 4.4 Summary

This training method is a new idea in controlling brainwave. It suggests an idea of personal profile to help user easier to control their brainwave.

# 5 Conclusion

This project has introduced a brainwave training tool, Brainwave Classifier, an experiment based on this tool and its results and a new training method discovered from the experience of using Brainwave Classifier.

Brainwave Classifier is a active control trainer that helps the user to train his/her brainwave. The Brainwave Classifier classifies the brainwave pattern within the sliding windows into three types. This tool provides an instant feedback on brainwave which helps the user to learn how to change or maintain different brainwave states.

The k-mean clustering algorithm and sliding window are some techniques used in the Brainwave Classifier. OpenCV is used to create a user-friendly interface.

As we are experienced user of Brainwave Classifier, we are able control different brainwave type with high accuracy. The personal testing shows we are able to control type1 and type3 and we are able to smoothly change from one state to another.

An experiment on Brainwave Classifier is carried out. Most participants show good control on type3 brainwave and some participants show some degree of control on type1 brainwave. The result of the experiment shows that the Brainwave Classifier is quite reliable as the user only has limited time to use it.

The new training method is a working flow that user can follow and train their brainwave. It also brings an idea of personal profile.

The development of Brainwave Classifier is quite successful. The experiment shows people can control their brainwave in some degree. It also helps to conclude a new brainwave training method.

# 6 Limitations & Difficulties

## 6.1 Poor Signal

The Poor Signal from Mindset is how poor the signal measured by Mindset. The value ranges from 0 to 200. A non-zero value means the existence of noise contamination. Poor signals may be caused by a number of different things, such as, poor contact of sensor, excessive motion of user, excessive environmental electrostatic noise.

In this semester, we still cannot figure out a complete way to get rid of poor signal. However, we find that the poor signal will come out less frequently if the Mindset are tightly attached on the user' head and the user does not have very large body movement.

Since our experiment in this semester do not rely on any special points, we analysis a longer period of time to see if the user can control the brainwave. The effect of poor signal on the experiment is not significant.

## 6.2 Curve Matching

In this semester, we have tried to use some curve matching method, such as compare area under curve, using Frechet distance, to find repeated pattern or find similar curve. However, the result in using those methods to analysis the brainwave pattern is not successful. There are not significant findings when we use these methods. Therefore, results of using curve matching technique in analysis brainwave are not presented in this report.

## 6.3 Passive Control

In the last semester, a passive control is one of our targets to be achieved in this semester. However, we face several problems in developing a passive control. First, a large amount of data is needed and analysis on these data is difficult. We lack a proper algorithm in BCI to produce new algorithms for passive control.

Therefore, before develop the passive control; we decide to test different algorithms by develop a simple active control, which is Brainwave Classifier. After developing the Brainwave Classifier, we find that it is very successful and may help develop an active control trainer. Therefore, we shift our BCI development from passive control to an active control trainer.

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