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Integration of a Low Cost EEG Headset with The Internet of Thing Framework

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Integration of a Low Cost EEG Headset with The Internet of Thing Framework

Thesis

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for the degree of

MASTER OF SCIENCE

in Computer Engineering

by

Mohammed Hassan Alnemari

Dissertation Committee:
Professor Kwei-Jay Lin, Chair
Professor Pai Chou
Professor Rainer Doemer

2017

DEDICATION

To my loving family...

”Glory to Thee, of knowledge We have none, save what Thou Hast taught us: In truth it is Thou Who art perfect in knowledge and wisdom.” Quran(2:32)

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ABSTRACT OF THE DISSERTATION

Integration of a Low Cost EEG Headset with The Internet of Thing Framework

By

Mohammed Hassan Alnemari

Master of Science in Computer Engineering

University of California, Irvine, 2017

Professor Kwei-Jay Lin, Chair

Over the past years, technology using electroencephalography (EEG) as a means of controlling electronic devices has become more innovative. Today, people are able to measure their own brain waves and patterns outside of medical laboratories. Furthermore, besides analyzing brain signals, these brain signals can be used as a means of controlling everyday electronic devices, which is also know as brain-computer interface. Brain-computer interface along with the "Internet of Things," are growing increasingly popular; more and more people have adapted to utilizing wearables and smart homes. For this thesis, I attempt to explore EEG for an IOT environment, investigate EEG signal, and build a smart applications able to detect different mental tasks using machine learning algorithms. In order to achieve this, this thesis used low cost EEG headset "NeuroSky Mindwave Mobile," Intel Edison and Raspberry Pi 2 as a controller. This thesis uses WuKong IoT framework, in which WuKong application framework provides interoperability of things and Wukong Edge Framework provides reliable streaming support for building intelligence on the edge.

Chapter 1

Introduction

The Internet of Things is increasingly used by normal people. There will be 50 billion Internet of Thing devices by the 2030. More and more people have started to adopt and use the Internet of Thing devices in everyday life. This thesis aims to explore and study the possibility of implementing and using electroencephalography (EEG) as controller in the Internet of Thing environment. Also, this thesis intends to study and integrate the human emotion with the Internet of Things Framework (Wukong).

This chapter introduces what Brain Computer Interface is and discusses the components of the Brain Computer Interface. In addition, this chapter explores some of the techniques used to measure the brain activity. Finally, this chapter discusses this research questions of this thesis.

1.1 Brain Computer Interface(BCI)

Brain Computer Interface is a communication method that depends on the neural activity generated by the brain regardless of peripheral nerves and muscles. The neural activity can be measured using invasive or noninvasive techniques. BCI aims to provide a new channel of output for the brain controlled and adapted by the user [75].

There are many Brain Computer Interface applications that can be implemented, such as applications for disabled people to interact with computational devices, applications for gamers to play games with their thoughts, social applications to capture feelings and emotions, and application for human brain activities [36].

The components of a BCI system include the following:

1. Signal Acquisition

   Measurement of brain activity is recorded using electrodes located on the scalp, or within the brain. The brain signal is amplified to be suitable for processing such as filtering and artifact removing. The signal then is digitized and transmitted to a computer.

2. Feature Extraction

   Feature extraction is analyzing the digital signal and distinguishing the pertinent signal characteristics from extraneous content and representing them in a meaningful form that can be interpreted by computer [67]. The most common feature extracted from brain wave is frequency bands.

3. Pattern Recognition

   Pattern recognition is a branch of machine learning that recognizes the patterns of a signal based on different activities. These patterns are converted into the appropriate commands for the control system.

4. Control System

   The control system consists of the commands that come from the pattern recognition algorithms operating in the external device. Providing the desired function such as motor control, light control, music control, etc. Feedback is provided to the user, which closes the control loop.

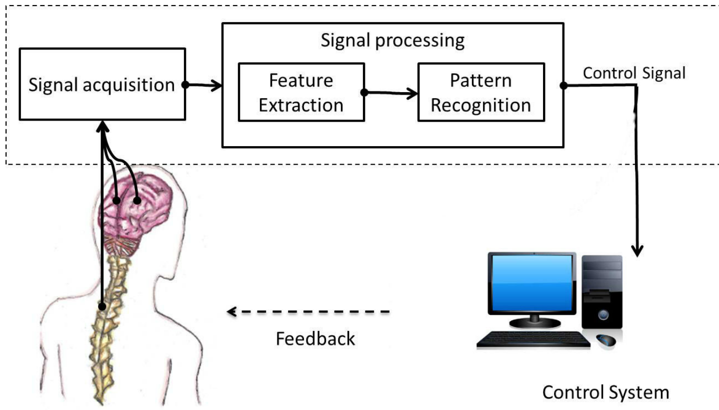


Figure 1.1: Brain Computer Interface Components[60]

1.2 Measuring Brain Activity

There are different methods to measure the activity of the brain; some of these methods are invasive, and some non-invasive. This section shows and explains these different methods.

1.2.1 Magnetic Resonance Imaging (MRI)

It is a medical imaging technique used to capture high quality pictures of the anatomy and physiological processes of the body. It uses powerful magnet, radio waves, and field gradients to generate images of the body. It is non-invasive, painless and does not use radiation (X-rays). It can provide very detailed high resolution images of a body parts. In particular, it can capture very detailed high resolution images for the brain compared to other imaging techniques such as CT (computed tomography) and X-ray because of its ability to differentiate between soft tissues of the body. However, due to the magnet effects, metallic items are not allowed during the scan which because they limit its applications.

Also, this technique requires an MRI bed to scan a subject, which limits space movement [31]

1.2.2 Functional Magnetic Resonance Imaging(fMRI)

It is a special MRI technology that measures brain activity by detecting changes associated with blood flow. This technique relies on coupled cerebral blood flow and neuronal activation. The blood flow increases in a region when this region is in use. The idea of this technique lies in the amount of oxygenated (Oxy-Hb) and deoxygenated hemoglobin (Deoxy-Hb) (dex) changes in the blood flow during the neural activity. The most common one is Blood Oxygenation Level Dependent fMRI (BOLD-fMRI)which measures the ratio of Oxy-Hb to Deoxy-Hb in order to measure the oxygen consumption of active neurons. It is also invasive and has an excellent spatial resolution compared to EEG, and records signals from all the brain regions. However, this technique has the same limitations of the MRI technique [39, 49].

1.2.3 Magnetoencephalography (MEG)

It is the technique used to measure the magnetic field over the head generated by the electric current in the brain. The most commonly used technology of MEG currently is SQUIDs(Superconducting Quantum Interference Devices). This technique allows capturing MEG of the head efficiently and rapidly. Also, this technique is non-invasive and can be used as complement for other techniques such as EEG and fMRI. Due to the fact that MEG uses magnetic fields,this technique makes less distortion than the electric fields. However, the same restriction applied on fMRI and MRI can be applied to MEG due the to its sensitivity for ferromagnetic [26].

1.2.4 Electroencephalogram (EEG)

An electroencephalogram (EEG) is a method monitoring the electrical activity of the brain using small flat metal discs (electrodes) placed on the scalp. EEG measures voltage fluctuations resulting from brain cells communications via electrical impulse[7]. In Particular when neurons are activated, ions such as Na^+, K^+ and CI^- are pushed through the neuron membrane [16].

EEG is a weak signal and needs to be amplified in order to be displayed or stored on a computer. Two approaches to recording the EEG signal are invasive and non-invasive. In the invasive approach, the electrode is implanted inside the human brain, which requires surgery. In a non-invasive approach, electrodes are placed on the surface of the skull, which have many benefits such as risk free, easy setting, and repeating measurement. In addition, it is more favorable in developing and designing application for normal people. The focus of this thesis will be based on this non-invasive EEG technique .

1.3 Research Questions

1.3.1 Internet of Thing Framework Integration

The first question of this thesis is how to integrate the low-quality cheap EEG headset, which has only one electrode located in forehead, with an Internet of Things framework. In order to do this we have to first build and design the EEGServer which is able to translate EEG signals into commands. Then, we must build an algorithm that construct different patterns from these commands, and these patterns will be used to control different Internet of Things devices. The expected outcome after integration and build, the different EEG pattern is the ability to control Internet of Thing devices such as Light turning on/off, music playing and etc.

1.3.2 Edge Classification

The second question of this thesis is how to build the EEG Edge which is able to classify between eye close and eye open states. In order to answer this question we will use an extension of the Internet of things framework that supports intelligent edge, which is presented in [38]. So, in order to build the EEG Edge we need to extract EEG features for different subjects and build the model that is able to classify between open and close eye states. There are different types of features that could be extracted from EEG raw signal. However, for this application we need only to extract the power spectrum density features. Lastly, we need to define the feature extraction extension which will contain the EEG features and define the execution extension which will contain the classifier model. The expected outcome after the integration will be the ability to classify eye states on the edge.

1.3.3 Emotions Detection and Classification

The third question of this thesis is how to build a model that is able to detect and classify positive and negative emotions. In order to classify the emotions, different factors must be considered, which include participants, stimuli, the temporal window, and EEG features. Different EEG features will be extracted from EEG raw signal and these features include time domain features, frequency domain features, and nonlinear features. Different video clips will be used as stimuli in order to trigger different emotions. The expected outcome will be the ability to classify two different types of emotions, positive and negative emotions.

1.3.4 Thesis Structure

Chapter1, "Introduction", introduces Brain Computer interface and its components. Also, this chapter explores different techniques of the brain measuring activities. Finally, this chapter discusses the research questions of this thesis.

Chapter 2, "Background and Related Works", shows the biomedical and system background, and discusses the related works. In this chapter, brain anatomy and brain lobes activity will be discussed. Also, it explains the EEG signal in more details and discusses EEG signal processing and EEG classification. Furthermore, this chapter compare different EEG headsets and why this thesis chooses NeuroSky Mindwave Mobile. This chapter also shows and explains the Internet of Thing Framework (Wukong) along with its architecture. Finally, this chapter discusses the works related to this thesis.

Chapter 3, "Application", discusses different applications that have been built using the NeuroSky Mindwave Mobile headset and the Wukong framework. This chapter shows three different applications: old people assistance application , normal people application to switch light or play music, and finally mind reader office application that has ability to show the status of the person inside his office.

Chapter 4, "Emotions", studies and discusses how to detect the emotions using a low cost EEG headset. In this chapter, a lot of features have been extracted and discussed. In addition, I use machine learning algorithms to build a system that is able to detect positive and negative emotions.

Chapter 5, "Conclusion and Future Works", concludes the thesis, and discusses its limitations. Also, in this chapter I discuss and compare the work presented in this thesis to other related research. Finally, in this chapter hardware and software limitations are discussed.

Chapter 2

Background and Related Works

2.1 Brain Anatomy

The brain is one of the most complex organs in the human body; it consist of 100 billion nerves that communicate through trillion of connections called synapses. The brain is composed of the cerebrum, cerebellum and brainstem [2]. The cerebrum, and cerebellum connect through the brainstem to the spinal cord [2, 3]. Figure(2.1) shows the anatomy of the brain.

- The cerebrum is composed of the left and the right hemispheres, and it is the largest part of the brain [2]. It is responsible for functions such as a touching, vision, hearing, speech, reasoning, learning, emotion, and finding control of movement [2].
- The cerebellum is smaller than the cerebrum and is located under it . It is responsible for functions such as a muscle movement coordination, posture maintained and balance [2].
- The brainstem acts as a relay center connecting the cerebrum and cerebellum to the

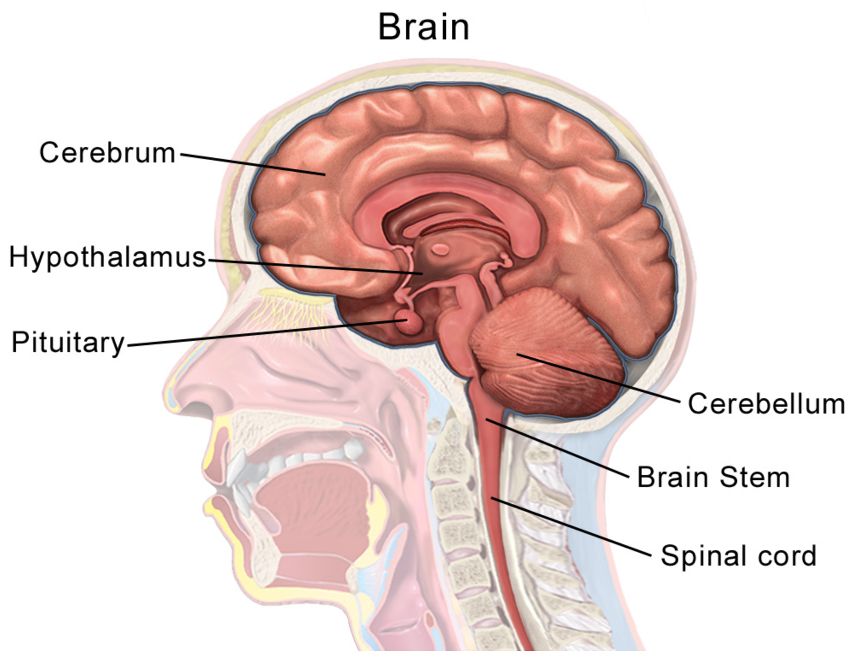


Figure 2.1: The Anatomy of the Brain[9]

spinal cord. It is responsible for atomic functions such as breathing, body temperature, wake and sleep cycles, digestion, sneezing, heart rate and swallowing [2].

Right and Left Brain

The brain has two hemispheres which are the right hemisphere and the left hemisphere. These two hemispheres are joined by corpus callosum which is a bundle of fiber responsible for delivering messages from one side to the other [2]. The left hemisphere controls analytic, arithmetic, logic, and writing. The right hemisphere controls creativity, artistic, and musical skills [2, 3]. Figure (2.2) shows the brain hemispheres and the functions of these both hemispheres.

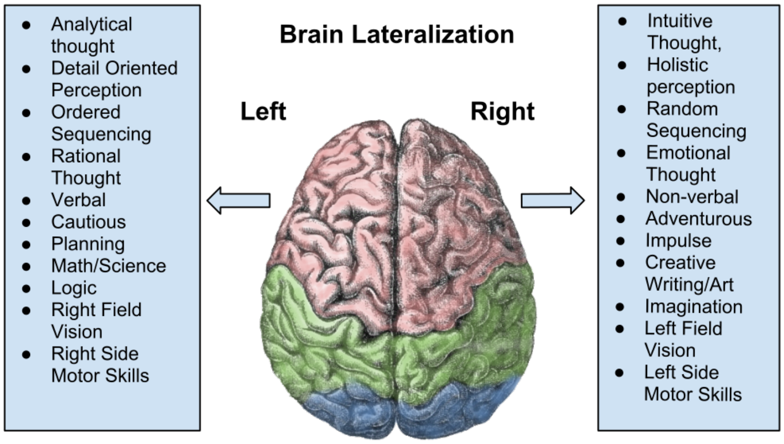


Figure 2.2: Brain Hemispheres[4]

Brain Lobes

Each hemisphere has four lobes: frontal, parietal, temporal and occipital which showing their functions in table 2.1, table 2.2, and table 2.3 respectively. Each lobe is divided to different areas and every area serves very specific functions [2, 3]. For instance, Broca's area is responsible for language processing and speech production [25]. Also, Wernicke's area is responsible for language comprehension and understanding of written and spoken language [23]. Figure (2.3) shows the brain lobes.

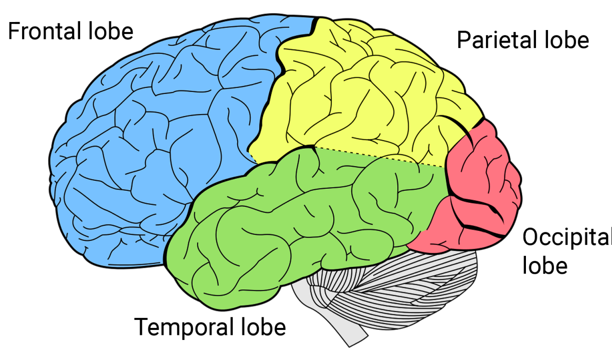


Figure 2.3: Brain Lobes[10]

Table 2.1: Frontal Lobe Functions

Lobes	*functions*
Frontal lobe	• Problem solving , Judgment • Body movement • Concentration , self awareness • Speech : speaking and writing • Behavior , emotions , personality

Table 2.2: Parietal Lobe Functions

Lobes	*functions*
Parietal lobe	• Sensation , Pain • Spatial and visual perception • Language and words interpretation

Table 2.3: Occipital and Temporal Lobes Functions

Lobes	*functions*
Occipital lobe	• Brain visual processing
Temporal lobe	• Language Understating • Memory and Hearing

2.2 EEG Signals

EEG is the electrical activity measurement in the brain. The first measure for EEG was recored by Has Berger in 1924 using galvanometer [52]. Based on the internal brain behavior or external stimulus, EEG varies in amplitude and frequency of the wave [30].

The system contains a EEG headset, and this thesis used "NeuroSky Mindwave Mobile" which is using Bluetooth connection to transfer the EEG signal. The EEG receiver records and receives the EEG signal coming from a EEG headset which is written in Python. I used the Wukong framework to deploy WuClass for the EEG, and WuClass for a controller on Intel Edison and Raspberry Pi. Figure (2.4) shows the system architecture will be used in this thesis.

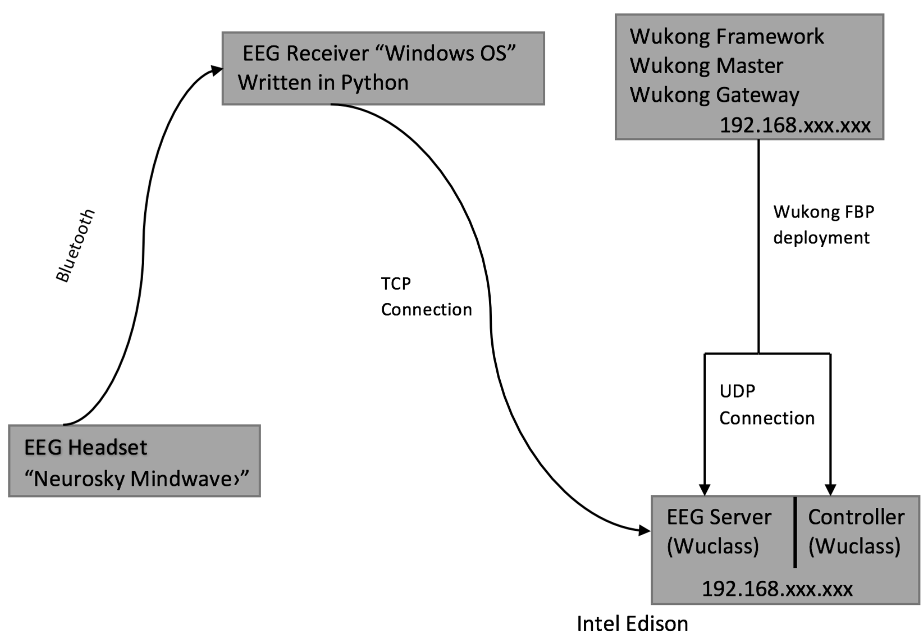


Figure 2.4: System Architecture

2.2.1 Electrodes Placement

There are different system placements of electrodes on the scalp. There is the 10/20 system which has 21 electrodes, the system 10/10 system which has 81 electrodes, and the 10/5 system which has 300 electrodes. This thesis discuss the 10/20 system, because it is mostly used by clinics and research [44].

The 10/20 System

The numbers 10 and 20 in the 10/20 system refer to the distance between adjacent electrodes, which is 10% or 20% of the total front back or right-left distance of the skull. The 10/20 system has in total 21 electrodes. There are two landmarks to positioning the EEG electrodes, the nasion which is the area between the eyes above the nose bridge, and the inion which is the skull lowest point from the back of the head as shown in the figure (2.5) [44].

Table 2.4: Electrodes Lobes

Electorde	*Lobe*
F	Frontal
T	Temporal
C	Central
P	Partial
O	Occipital
A	Earlobe

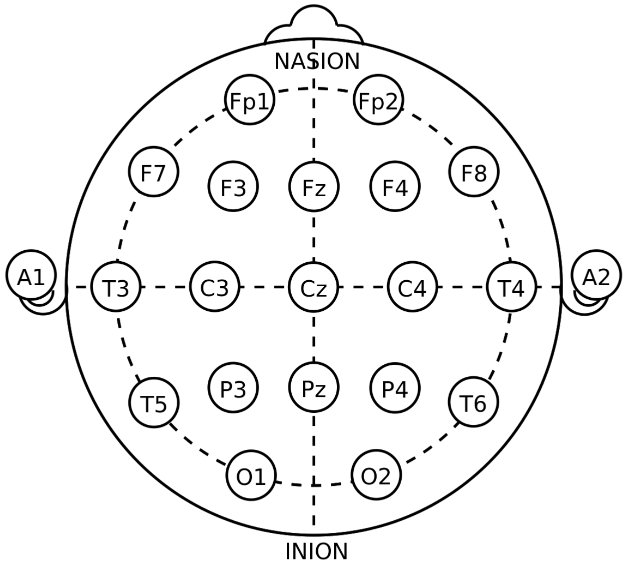


Figure 2.5: System 10-20

2.2.2 EEG Frequency

1. Delta band (1 — 4 Hz)

   The slowest and l Delta waves primarily exist between 1Hz and 4Hz. The are also known as deep sleep waves, since they are most prevalent when the human body is in a state of deep meditation or relaxation as well as deep sleep. During this period waves, the body is undergoing a process of healing and regeneration from the previous day's activities [62]. Figure (2.6) shows the delta band.

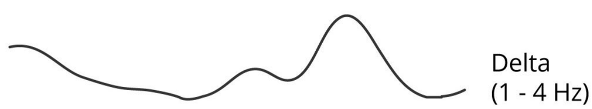
   

   Figure 2.6: Delta Band

2. Theta band (4 — 7 Hz)

   Theta waves are mostly generated around 4Hz to 7Hz range. These waves are associated with light meditation as well as sleep. When an increasing number of theta waves are generated, the brain is in a "dream-mode" state. In this state, humans experience the Rapid Eye Movement (REM) sleep. Studies report that the frontal theta waves are correlated with information processing, learning, and memory recall [62]. Figure (2.7) shows the theta band.

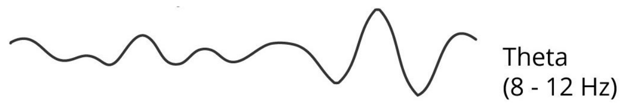


Figure 2.7: Theta Band

3. Alpha band (8 — 12 Hz)

   Alpha waves exist mostly at range 8Hz to 12Hz. The Alpha waves are known as the deep relaxation waves; they depict the resting state of the brain. These waves are dominant during a period of daydreaming or meditation. Alpha waves effect imagination, visualization, learning, memory, and concentration. Studies also report that alpha waves are correlated with reflecting sensory, motor and memory functions [62]. Figure (2.8) shows the alpha band.

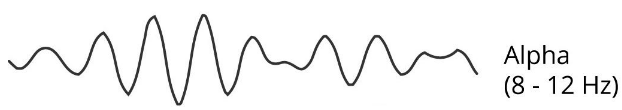


Figure 2.8: Alpha Band

4. Beta band (12 — 25 Hz)

   Beta waves exist mostly at 12Hz to 25Hz. These waves are associated with a person's consciousness and alertness. These waves are most prevalent when we are wide awake or alert,engaged in some form of mental activity such as problem solving or decision making [62].Figure (2.9) shows the beta band.

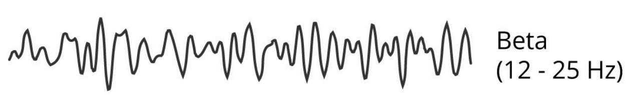


Figure 2.9: Beta Band

5. Gamma band (> 25 Hz)

   Gamma waves are the fastest and along with beta waves, are most prevalent when the person is alert and awake. These waves are associated with cognition, information processing, attention span, and memory. It is speculated that the gamma waves can also denote a person's 'higher virtues', altruism, love, and spiritual emergence [62].Figure (2.10) shows the gamma band.

Figure 2.10: Gamma Band

2.2.3 EEG Signal Analysis

1. Preprocessing

   EEG signal is weak signal and needs to be amplified in order to be brought to a suitable range for preprocessing .

   - Artifact/Noise removal

     EEG signal often captured unwanted signals either coming from physiological artifacts and non-physiological artifacts. Physical artifacts such as muscle movements artifacts know as Electromyography (EMG), and eye movement artifacts are called Electrooculography artifacts (EOG). Also, other artifacts come from the cardiac activity which known as Electrocardiogram (ECG). Non-physiological artifacts come from interferences from electrical equipment and cables in the surrounding environment. Standard filters such as high pass filter are used to remove low frequency, and low pass filter to remove high frequency from EEG signals [34]. Also other advanced filters are used such as Finite impulse response (FIR), Infinite impulse response (IIR), Principle Components Analysis (PCA), Independent Component Analysis (ICA), and Empirical Mode Decompositions (EMD) [76]. This phase of preprocessing EEG signal aims to increase the signal to noise ration and enhance the quality of EEG information in the signal.

- Segmentation

  Due to the nature of EEG signal which is non-stationary signal, its values can vary from one point to another. Segmentation of EEG signal can allows searching for a sequence. Also, segmentation is very necessary in order to apply feature extraction and classification. Segmentation of EEG can be vary from one second to several minutes based on the desired application [19].

2. Features Extraction

   A great variety of the EEG features that can be extracted vary from simple features such as mean or standard deviation to complex features in time, frequency domain, or non-linear features. The most common features are Power Spectral Density (PSD) values, Auto Regressive (AR) parameters, and time domain features such as Zero crossing (ZC), Mean absolute value (MAV), Slope sign change (SSC) and Waveform Length (WL) [50].

3. Classification

   There are different algorithms used to classify different mental states of EEG signals. Different applications require different algorithms and different modification. The classification algorithms can be supervised or unsupervised based on the desired application. Supervised algorithm vary from simple algorithms like linear classifier and Naive Bayes classifier to more complex classifiers such as support vector machine or neural networks [50].

2.3 EEG Preprocessing

2.3.1 Fourier Analysis

It is decomposition of a periodic signal x(t) in term of infinite sum of sines and cosines. Fourier series is presented in formula (3.1) :

$$x(t) = \frac{1}{2} * a_0 + \sum_{k=1}^{\infty} (a_n \cos(\omega kt) + b_n \sin(\omega kt)) \tag{2.1}$$

$x(t) \rightarrow$ an integrable signal on an interval [0,T] and is periodic with period T.

$t \rightarrow$ it is time variable.

$\omega \rightarrow$ it is angular frequency which is presented this formula $\omega = \frac{2\pi}{T}$

a_0, a_n , b_n $\rightarrow$ are Fourier coefficients which are presented in formulas (2.2) ,(2.3).

$$a_n = \frac{2}{T} \int_0^T x(t) \cos(\omega kt) dt, k = 0, 1, 2, 3, ..., N. \tag{2.2}$$

$$b_n = \frac{2}{T} \int_0^T x(t) \sin(\omega kt) dt, k = 0, 1, 2, 3, ..., N. \tag{2.3}$$

From Euler's formula (2.4), Fourier series can be presented as (2.5).

$$e^{jt} = \cos t + \sin t \tag{2.4}$$

$$x(t) = \sum_{k=-\infty}^{k=\infty} (c_n).e^{j\omega kt}. \tag{2.5}$$

Where $c_n = \frac{1}{T}\int_0^T (x(t)e^{-j\omega kt}dt$.

Continuous Fourier Transform used to transform a signal from time domain to frequency domain. The Continuous Fourier Transform presented in formula (2.6)

$$F(\xi) = \int_{-\infty}^{\infty} x(t)e^{-2\pi j\xi}dt. \tag{2.6}$$

transform between frequency and time domain formula (2.7) used to do this transformation.

$$x(t) = \int_{-\infty}^{\infty} F(\xi)e^{2\pi tj\xi}d\xi. \tag{2.7}$$

The Continuous Fourier transform (CFT) can represented by Discrete Fourier Transform(DTF) if the signal is periodic , band limited and sampled at Nyquist frequency or higher . Discrete Fourier Transform (DFT) formula shown in (2.8)[54] which produce N-Periodic sequence X_0,X_1,X_2,X_3,.....X_{N-1} from N complex numbers in time domain x_0,x_1,x_2,x_3,.....x_{N-1}.

$$X_k = \sum_{n=0}^{N-1} x_n e^{\frac{-2j\pi kn}{N}} \tag{2.8}$$

Inverse Discrete Fourier Transform(IDTF) is data transformation between frequency domain and time domain shown in formula (2.9).

$$x_n = \frac{1}{N}\sum_{K=0}^{N-1} X_K e^{\frac{2j\pi kn}{N}} \tag{2.9}$$

The limitation of applying Discrete Fourier transform on EEG signal its complexity which is $O(N^2)$. So, to apply Discrete Fourier Transform and Inverse Discrete Fourier Transform on EEG , this thesis used different algorithm to apply Fourier Transform. This algorithm known as Fast Fourier Transform (FFT) and its Inverse (IFFT) which used divide- -and-conquer approach to apply Discrete Fourier Transform [27]. This algorithm divides the of size K transform to transform of size K_1 and K_2. Discrete Fourier Transform divided into smaller part of Discrete Fourier Transform, one for the odd values , and another for even values. From the symmetric property show in formula (2.10), half of computations need to be performed for each sub-problem with reapplying this approach of divide and conquer the complexity will scale at $O(N \log N)$ [27].

$$X_k = \sum_{n=0}^{N/2-1} x_{2n} e^{\frac{-2j\pi k(2n)}{N}} + \sum_{n=0}^{N/2-1} x_{2n+1} e^{\frac{-2j\pi k(2n+1)}{N}} \tag{2.10}$$

$$X_k = \sum_{n=0}^{N/2-1} x_{2n} e^{\frac{-2j\pi k(2n)}{N/2}} + e^{\frac{-2j\pi kn}{N}} \sum_{n=0}^{N/2-1} x_{2n+1} \cdot e^{\frac{-2j\pi kn}{N/2}} \tag{2.11}$$

2.4 EEG Features

,There are different type of EEG features extracted, these features are Power Spectrum Density [18],Petrosian Fractal Dimension [17, 18],Detrended Fluctuation Analysis [18], Fisher Information [55, 18], Approximation Entropy [59], Sample Entropy [64], Spectacular Entropy [40], Autoregressive [56] , Waveform Length [33], Zero Crossing [33], Sign Slope [33].

- Power Spectrum Density (PSD) Features and extract these different bins

$$H(x) = -\sum_{f=0}^{f=f_s/2} PSD(f)\log_2[PSD(f)]$$

(δ , θ , α , β , γ), Square of (δ , θ , α , β , γ), Power of (δ , θ , α , β , γ)

- Petrosian Fractal Dimension of a time series (PFD)

$$PFD(X) = \frac{\log(N)}{\log(N) + \log(\frac{N}{N+0.4N_\delta})}$$

- Detrended fluctuation analysis (DFA)

$$F(n) = \left[\frac{1}{N}\sum_{t=1}^{N}(X_t - Y_t)^2\right]^{\frac{1}{2}}$$

- Fisher information

$$I(\theta) = \mathrm{E}\left[\left(\frac{\partial}{\partial\theta}\log f(X;\theta)\right)^2 \middle| \theta\right] = \int \left(\frac{\partial}{\partial\theta}\log f(x;\theta)\right)^2 f(x;\theta)\,\mathrm{d}x\,,$$

- Approximate Entropy

$$\Phi^m(r) = (N-m+1)^{-1}\sum_{i=1}^{N-m+1}\log(C_i^m(r))$$

$$\mathrm{ApEn} = \Phi^m(r) - \Phi^{m+1}(r).$$

- Sample Entropy

$$SampEn = -\log\frac{A}{B}$$

A = number of template vector pairs having $d[X_{m+1}(i), X_{m+1}(j)] < r$ of length $m+1$

B = number of template vector pairs having $d[X_m(i), X_m(j)] < r$ of length m

- Spectacular Entropy .

$$H(x) = -\sum_{f=0}^{f=f_s/2} PSD(f) log_2[PSD(f)]$$

- Autoregressive

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

- Waveform Length

$$WL = \sum_{n=1}^{N-1} |X_{n-1} - X_n|$$

- Zero Crossing

$$ZC = \sum_{n=1}^{N-1} [sgn(x \times x_{n+1}) \cap |x_n - x_{n+1}| \geqslant threshold]$$

- Sign Slope

$$SSC = \sum_{n=2}^{N-1} [f[(x_n - x_{n-1}) \times (x_n - x_{n-1})]]$$

2.5 EEG Classification

2.5.1 Ensemble Classifiers

Ensemble Classifiers are learning algorithms which construct a predictive model by integrating multiple different models. Ensemble classifiers improve prediction performance. There are different types of ensemble methods which are boosting ,bagging and stacking. Boosting methods such as Ada-Boost involve a committee of weak learners evolving over time. Bagging (bootstrap aggregation) methods such as random forest involve a committee of trees, each of which cast vote for the predicted class. Finally, stacking combines different fitted models in order to improve the overall prediction performance [32].

Adaptive Boosting:

This is an algorithm using weak or simple classifiers like linear classifiers to construct a strong classifier and is able to classify very complex data. Random Forests obtain the class from each tree, and the classification will be drawn using a majority vote.

$$f(x) = \sum_{t=1}^{T} \alpha_t h_t(x) \tag{2.12}$$

$h_t(x) \rightarrow$ Weak classifier or simple liner classifier.

$H(x) = sign((f(x)) \rightarrow$ Strong of final classifier .

Figure (2.11) shows Adaptive Boosting Classifier which is using many simple classifiers to construct a strong classifier.

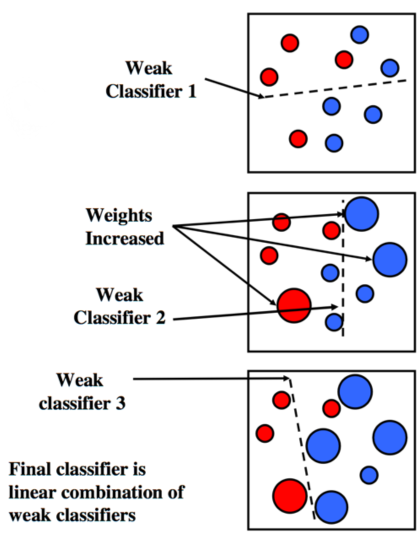


Figure 2.11: Adaptive Boosting Classifier [5]

Random Forest:

This is an algorithm using diverse models on different random samples of the original data. The samples are drawn with replacement [50]. Figure (2.12) shows the random forest classifier.

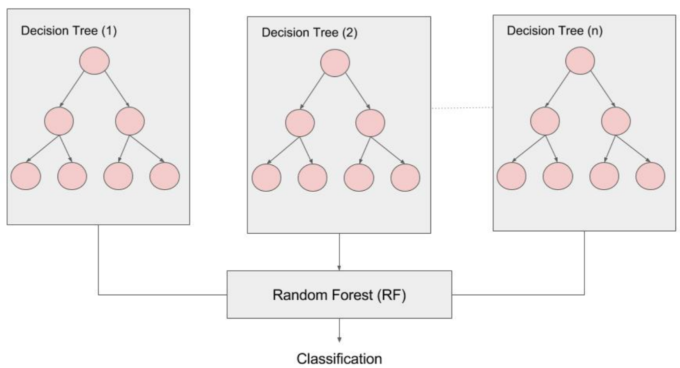


Figure 2.12: Random Forest Classifier

2.5.2 Linear and Nonlinear Classifiers

The classification decision in linear classifiers is constructed based on a linear combination of features. On the other hand, the classification decision in nonlinear classifiers is constructed based on a nonlinear combination of features.

Decision Tree

This is a commonly used algorithm in which every branch is an outcome testing each non-leaf node, and every leaf holds a class label. Every node shows the most informative feature among other features, and this can be calculated by using information gain (entropy)[50]. Figure (2.13) shows decision tree classifier.

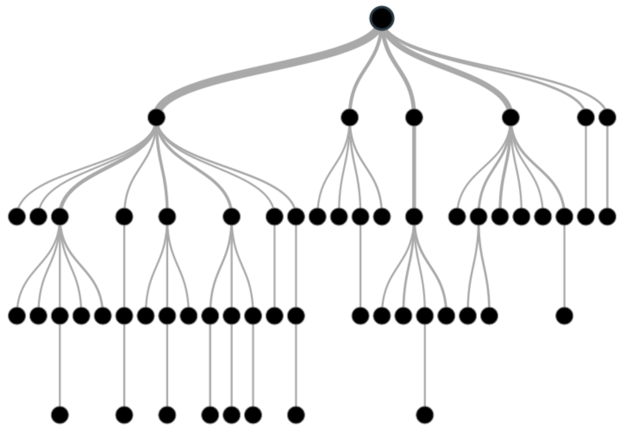


Figure 2.13: Decision Tree Classifier [1]

Support Vector Machine

The Support Vector Machine use hyperplane to identify classes as shown in a figure (2.14). The Support Vector Machine aims to maximize the margins, the distance of nearest training points as shown in figure. The goal of the maximization is to increase generalization capabilities. Linear classification can be applied to the Support Vector Machine using linear SVM. Nonlinear classification can be used with the Support Vector Machine using a kernel trick which increases the complexity of the classifier. The kernel used for this application was the Radial Basis Function kernel. Also, the regularization parameter C enables outliers accommodation and allows errors on the training set [50, 43].

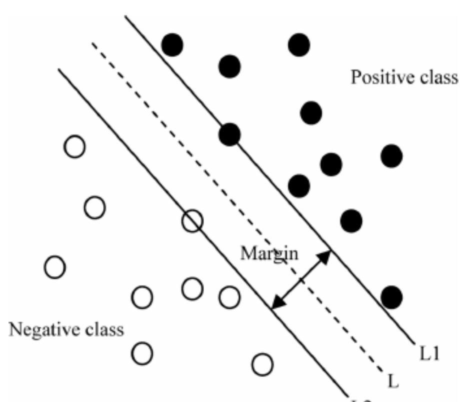


Figure 2.14: Support Vector Machine[45]

K-Nearest Neighbor

K-Nearest Neighbor consists of a feature vector according to its nearest neighbors. K-Nearest Neighbor will produce non-linear decision boundaries because of its ability to approximate any functions [50].

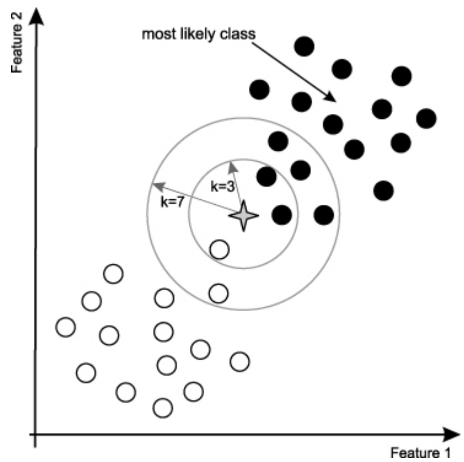


Figure 2.15: K-Nearest Neighbor[28]

2.5.3 Commercial EEG Headset

There are a lot of commercial EEG headsets from the simplest ones to the more sophisticated one. Table (2.2) compares different EEG headset. These different EEG headsets are able to capture different mental states, and different facial expressions. Both emotiv headsets, the EPOC+ and INSIGHT, capture excitement, frustration, engagement, meditation and affinity. Also, Emotiv headsets capture EEG bands which are Delta, Theta, Alpha, Beta, and Gamma. In addition, Emotiv headsets capture some facial expressions such as blinking, smiling, clenching teeth, laughing and smirking. On the other hand, the Neurosky Mindwave Mobile is limited to capturing only two mental states which are meditation and relaxation. Finally, the Muse headset can capture positive and negative emotions. Also, the Muse headset captures EEG bands which are Delta, Theta, Alpha, Beta, and Gamma. In addition, the Muse headset also captures some facial expressions such as jaw clenching and eye blinking. Emotive EPOC+ sensors use saline soaked felt pad technology, and emotive INSIGHT sensors use long-life semi-dry polymer technology. Neurosky Mindwave Mobile and Muse sensors use long life dry technology.

Table 2.5: EEG Headset Specifications

Specification	Emotiv EPOC+ [8]	Emotiv INSIGHT [8]	Neurosky Mindwave [11]	Muse [14]
Channels Num	14	5	1	4
Channels Position	AF3,AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2	AF3, AF4, T7, T8, Pz	FP1	TP9,AF7,AF8, TP10
Sampling rate	128Hz-256Hz	128 Hz	512 Hz	220Hz-500Hz
Bandwidth	0.16 - 43 Hz	0.5 - 43 Hz	3 - 100 Hz	2 - 50 Hz
Coupling mode	AC coupled	AC coupled	—	AC coupled
cost	$799.00	$299	$99.99	$249.99
Battery type	Li-poly	Li-poly	AAA	Lithium
Battery life	12hrs	8hrs	8hrs	5hrs

2.5.4 Neurosky Mindwave mobile

NeuroSky Mindwave Mobile consists of eight parts which are ear clip, ear arm, battery area, power switch, adjustable head band, sensor tip, sensor arm, and think gear chip. The operation of this device is based on two sensors to detect and filter EEG signals. The sensor tip on the forehead detects the electrical signal from the frontal lobe of the brain. The second sensor is an ear clip which is used as ground to filter out the electrical noise. Figure (2.16) shows NeuroSky Mindwave Mobile and Figure (2.17) shows the electrode position of NeuroSky Mindwave Mobile.

This thesis uses NeuroSky Mindwave Mobile for many reasons. First, this project aims to offer a low-cost system, which can be used by everyone. Second, NeuroSky Mindwave Mobile is highly resistant to noise and its signal is digitized before it is transmitted through

Bluetooth [22]. Third, NeuroSky Mindwave Mobile offers unencrypted EEG signal compared to the Emotive and Muse which are encrypted [22].

2.5.5 ESense Signals

It is NeuroSky algorithm to characterize mental states. This algorithm applied on the remaining signal that is acquired from removing the noise and the muscle movements of the raw brain wave signals. Two eSense signal are produced as a result of this algorithm: attention and meditation signals. These signals detect the concentration and relaxation of subject. The values of these signals range from 0-100 in which zero indicates low in concentration or in low in relaxation, and 100 indicates high in concentration or high in relaxation.

2.5.6 Limitations and Issues

One major limitation is the accuracy of the EEG signal captured by NeuroSky Mindwave Mobile, because the NeuroSky Mindwave Mobile Mobile has only one electrode which is FP1. The problem with FP1 is its susceptibility to a lot of noise coming from eye movement and muscle movement. Another possible issue is comfort. One subject claims it is uncomfortable to wear. This is most likely due to the rigid headband design as well as the need for the ear clip as the reference sensor.

Figure 2.16: Neurosky Mindwave Mobile

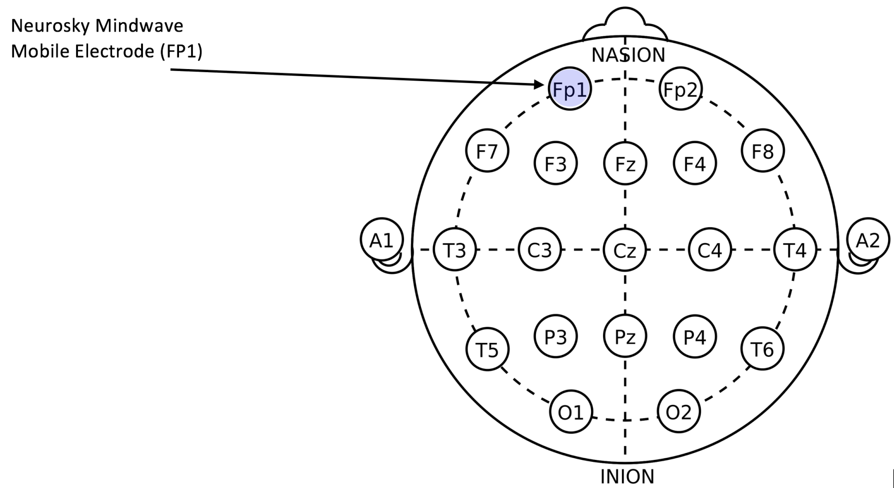


Figure 2.17: NeuroSky Mindwave Mobile Electrode Position

2.6 Wukong Framework

The WuKong project is an intelligent middle-ware built for IoT systems. The WuKong framework is hardware-independent that the IoT applications built on it can be easily configured and dynamically deployed on vendor-independent IoT platforms [48, 15].

2.6.1 Features of Wukong Design

The WuKong IoT middle-ware has the following major features:

- **Virtualized IoT Devices**:

  Virtualized IoT devices enable hardware-independent applications layout. Also, it can make IoT migration services among the devices simple because there is not a need for redefining the applications [48, 15]. Therefore, IoT applications can be deployed on different hardware platform without the need to use hardware and network dependent applications codes [48, 15].

- **Flow-Based Programming Environment**:

  WuKong provides a graphical flow-based programming (FBP) tool. Data and control flow can be defined in each FBP by the user to build an IoT application [48, 15]. Graphical flow-based programming (FBP) tool simplify the designing of IoT application by providing a predefined Wukong component library in which the user can select the desired service from them and drag them to programming canvas, and then connect the components with directed links [48, 15]. During application deployment, the flow diagram of application will be used to map logical services onto appropriate physical devices [48, 15]. Figure (2.19) shows the WuKong based flow program.

- **Heterogeneous and Virtual Services**:

  Virtual machine on the heterogeneous platform provided by WuKong framework that simplifies deploying and migration of IoT applications [48, 15]. In order to support web-based data services or user interface running on servers, computers and smart phone, the virtual IoT services can be implemented using Python programming language [48, 15]. Also, Wukong platform includes Darjeeling-based Java Virtual Machine that can add byte-code dynamically by the system in each device [48, 15].

- **Deployment-time Service Mapping**:

  The binding between logical IoT and physical IoT devices in WuKong framework is postponed until deployment in order to support heterogeneous and constant evolving hardware platforms. Therefore, configuration and platform properties such as port and pin assignment are minimized during application development [48, 15]. The Wukong Master gathers the platform-dependent properties when a device registers itself in a WuKong system [48, 15]. The Master will use these properties to produce a proper configuration and generate required executable code for each IoT application. These platform-dependent properties used by the Wukong Master make a suitable configuration and generate the executable code required for each IoT application [48, 15].

2.6.2 WuKong System Architecture

The users requests and application in WuKoung system are performed as it is distributed computing runtime [38]. Figure (2.18) shows the system architecture of WuKong middleware. The WuKong system has components on the cloud and other in the deployment environment [38, 66]. When we deploy the IoT application, WuKong has one WuKong master, multi-WuKong gateways, and the number of WuKong devices needed by the IoT application [38, 66]. The operation of these devices is described below:

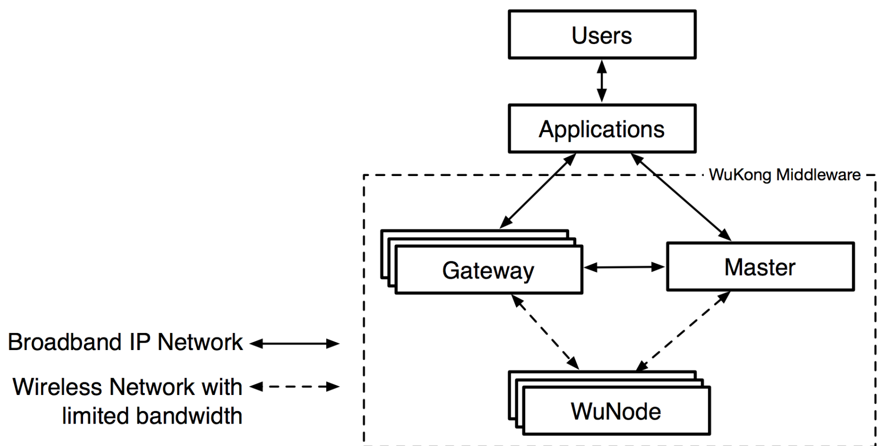


Figure 2.18: Wukong Architecture [66]

- **WuMaster**:

  WuKong master, abbreviated as WuMaster, is responsible to discover, optimize, configure and reconfigure sensors. Communication with sensors is performed through a layer of abstraction in which the details of the underlying sensor hardware and the network platform will be hidden. During the discovery and identification phase, profile framework is used by WuMaster in order to discover the connected sensors capabilities, and configure sensors' parameters. In addition, WuMaster manges the defined service in the system, include FBP deploying to devices, and make in-situ decisions for software upgrades and service remapping [38, 66]. WuMaster deployed on computationally powerful robust server is capable of receiving users requests and services managing. [66, 38].

- **WuGateway**:

  WuKong Gateway, abbreviated as WuGateway, is responsible for two major points: communication gateway and backup master [48, 38]. The communication gateway has the ability to discover devices, forward messages, and dispatch messages in heterogeneous networks. The communication gateway is called the Multiple Protocol Transport Network (MPTN) gateway [66, 38].

- **WuDevice**:

  WuKong Devices, abbreviated as WuDevices, is responsible to represent the networked physical devices in the system [66, 38]. A combination of sensors, actuators, and computation services can be found in every WuDevice . To be part of the WuKong systems, a WuDevice should register itself to WuKong master directly or via WuGateway, identify its own capability via its profiles, and join the system [66, 38]. In order for the WuDevice to be part of Wukong system, a WuDevice has to register itself either to the master directly or through WuGateway, and use the profiles to identify its capability [66, 38]. Applications logic is executed using a virtual environment called WuKong VM [66, 38]. WuKong VM has different components: Darjeeling VM,a networking module, and native profiles. The native profiles are an architecture and platform-dependent C WuClass library that interacts with physical sensors and actuators [66, 38]. Different services accomplished by WuDevices such as sensing, control, and computation are deployed by the master through remote programming [66, 38].

- **WuClass**:

  WuKong Class, allowing access to hardware resources, implement the common processing in the application, implement specific processing. In order to design WuClass it consists of three main parts which are the definition of Wuclass and its properties, the implementation which is the update() function in the WuClass, and finally the generated code for deployment [48].

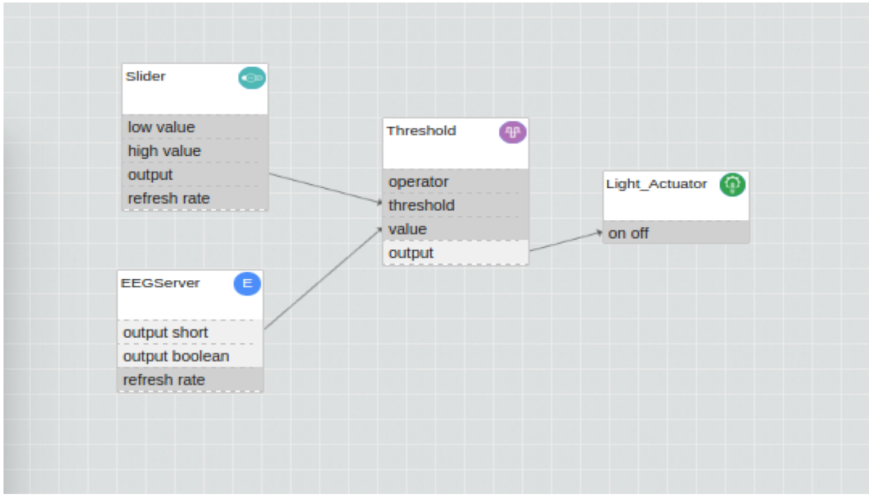


Figure 2.19: Wukong flow based programming

2.7 Related Works

In this section we discuss related research papers, and projects which discuss the same mental tasks presented in this thesis.

2.7.1 Eyes Events

In the paper "Comparison of SVM and ANN for classification of eye events in EEG" [68], Biospac MP36R system is used to record the EEG signal from the participant. This headset has 4 electrodes, FP1 and F3, one electrode placed on the earlobe, and lead set SS2L connects the electrode to Channel 1 of the MP36 system. Two hardware filters are used for this configuration: one is 0.5 Hz high-pass filter, and one 1 kHz low-pass filter. A temporal window of 5 seconds is used in this paper. Three different features extracted are the Kurtosis coefficient, maximum amplitude, and minimum amplitude. Two different classifiers are used in this paper to classify three different eye events which are eyes blink, eyes close, and eyes open. The first classifier is the Support Vector Machine with different kernels which are Linear, quadratic, polynomial order three, polynomial order four and radial basis function. The second classifier is the artificial neural network with two different architectures in which the both of architectures has 4 layers which first layer refer to the input, second and third layer refer to hidden layers and the fourth layers refer to output layer. The first architecture has 3 inputs,20 nodes in first hidden layer, 10 nodes in the second hidden layer, and 3 outputs. The second architecture has 3 inputs,30 nodes in first hidden layer, 14 nodes in the second hidden layer, and 3 outputs. The best accuracy for eyes blink was obtained using SVM with a quadratic kernel which has an accuracy of 91.9%; the best accuracy for eyes close was obtained using ANN with first architecture which has an accuracy of 88.4%; and the best accuracy for eyes open event was obtained using SVM with a linear kernel.

2.7.2 Emotions Classification

Medical Headset

In the paper "Emotional state classification from EEG using machine learning" [73], a very sophisticated headset was used to obtain the EEG signal from the subjects. This headset has 27 electrodes namely FP1–FP2, AF3–AF4, F1–F2, F3–F4, F5–F6, F7–F8, FC1–FC2, FC3–FC4, FC5–FC6, FT7–FT8, C1–C2, C3–C4, C5–C6, T7–T8, CP1–CP2, CP3–CP4, CP5–CP6, TP7–TP8, P1–P2, P3–P4, P5–P6, P7–P8, PO3–PO4, PO5–PO6, PO7–PO8, CB1–CB2, O1–O2. Six subjects participate in this experiment, and movie clips are used to arouse the emotions. The Russel emotional model which has two dimension of emotional use classifies the emotions as shown in Figure (2.20). The best result was with a 1s time window among four different time window periods applied which are 0.5s, 1s, 1.5s, and 2s. Three different kinds of features are extracted which are power spectrum, wavelet, and nonlinear features. However, in order to reduce the number of features, three different techniques are used to reduce the features' dimensions; these techniques are Principle Component Analysis (PCA), Linear Discernment Analysis (LDA), and Correlation-based Features Selector (CFS). Different classification algorithms are used such as Support Vector Machine with different types of kernel, Linear, polynomial, and radial basis function (RBF) kernels. The best average accuracy of classification was 91.77% obtained using an LDA classifier with 30 different features.

Commercial Headset

In the paper "Real Time EEG based Happiness Detection system" [43], Emotive EPOC+ EEG headset which has 14 electrodes namely AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF42 is used to record EEG signals [8]. Ten subjects participate in this experiment: 1 male and 9 female, with an average age of 34.60. The Russel emotional model which has two dimension of emotional use classifies the emotions as shown in Figure (2.20) [8]. Five trials are used in this experiment in which every trial contains happy and unhappy stimuli, and every trial has 60s of happy stimuli and 60s of unhappy stimuli. The stimuli was 10 pictures with one piece of classical music played along for 60 seconds. The pictures were obtained using the Geneva Affective Picture Database (GAPED) [29], and classical music was obtained using the Vampala and Russo method for happy and unhappy stimuli [69]. Preprocessing used a 5th order sinc filter to remove the noise power at 50Hz and 60Hz. The temporal window used in this paper was one second. Five frequency band features which are Delta, Theta, Alpha, Beta, and Gamma are only extracted using Wavelet Transform. Since Emotive Epoc has 14 channel, 70 features were obtained. Normalization was used before classification which scaled the features between 0 and 1. 600 samples were used per participant; 10 participants were involve in this experiment which has a total of 6000. Gaussian Support Vector Machine was used in this paper with average accuracy of 75.62% for subject dependent and 65.12% for subject independent respectively [43].

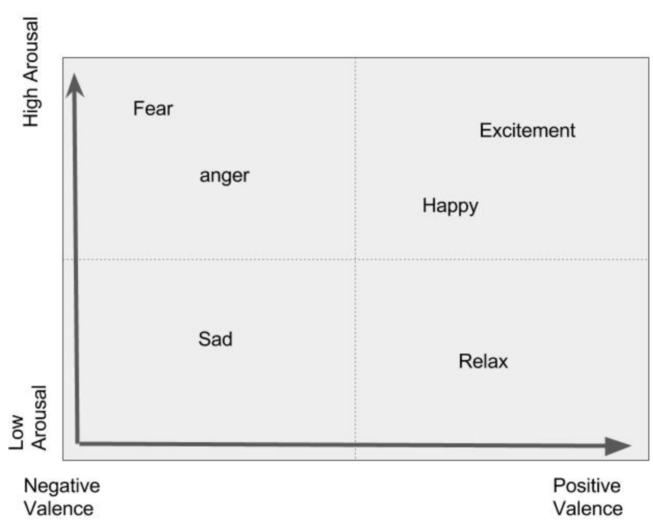


Figure 2.20: Two dimensional Emotional Model

Chapter 3

Applications

This chapter describes different applications of using EEG headset Mindwave with Wukong framework.

3.1 Old People Assistants

3.1.1 Overview

In this application both different eSense signals which are attention and meditation are used to build an application which has the ability to trigger different actions based on different mental states.

3.1.2 Motivation

In the year 2000, people 65+ represented 12.4% of the human population. This number is expected to swell to 19% of the human population by 2030 [6]. These old people need assistance in order to help them with basic home activities such as turning light on or off, playing different types of music, changing the television channel, and so on.

3.1.3 System Architecture

The system of this application is divided into three different parts. The first part can trigger and run the system, keep the same state of the system, and change to a different state. This part uses a Webcam sensor to detect eye movement, blinking four times to trigger the system, or to change between different states. The second part receives EEG signal, and in this application the focus is on eSense signals which are attention signal and meditation signals, both of which scale from 1-100. The third part is the EEG server in Wukong framework in which controlling different devices obtains its control signal from the second part.

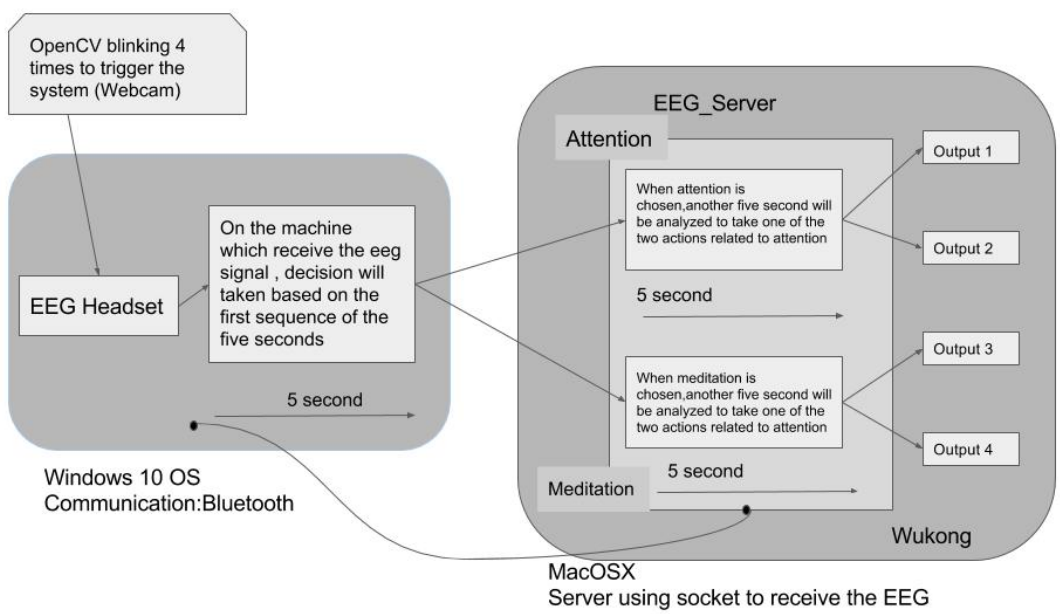


Figure 3.1: System Architecture old people assistance

3.1.4 Implementation

In order to detect eye blinking, OpenCV library is used which is an open-source library of programming functions aimed to offer real-time computer vision. This library is used to detect eye blinking to trigger the system, hold on to a certain state, and change between different states. The algorithm used to classify blinking is Haar Cascades classifier which is a machine learning approach in which the cascade function is trained by a lot of negative and positive pictures, then used to detect objects in other images [70, 12].

In order to obtain EEG signal from Neurosky Mindwave Mobile I used an open-source API written in Python suggested by the Neurosky company. Two major libraries used are bluetooth_headset.py and parser.py. The bluetooth_headset library contains methods to connect the Mindwave Mobile to the computer via Bluetooth either by specifying a MAC address (connect_bluetooth_addr(addr)) or by automatically searching for a device named "Mindwave Mobile"(connect_magic()). If it does not find a device automatically or with the MAC address specified, it will raise an error. The other library parser.py is specific to NeuroSky Mindwave Mobile device. There are two major classes in this library: ThinkGearParser and TimeSeriesRecorder. It must first create a new TimeSeriesRecorder object and then include this object into a ThinkGearParser object, which will package the EEG information and be able to display the data on the computer. The other important library that is necessary for WuKong integration is a socket which creates a new socket that points to the exact IP address of the peripheral device (Intel Edison used for this application).

In order to control a device Wuclass has to be designed. For this project, EEG Server is Wuclass that is able to receive the EEG signal and transform to different actions. Triggering an action will take around 10 seconds as shown in Figure (3.1). Figure (3.2) explains and shows the flow of data and control of the system in Flow based program (FBP).

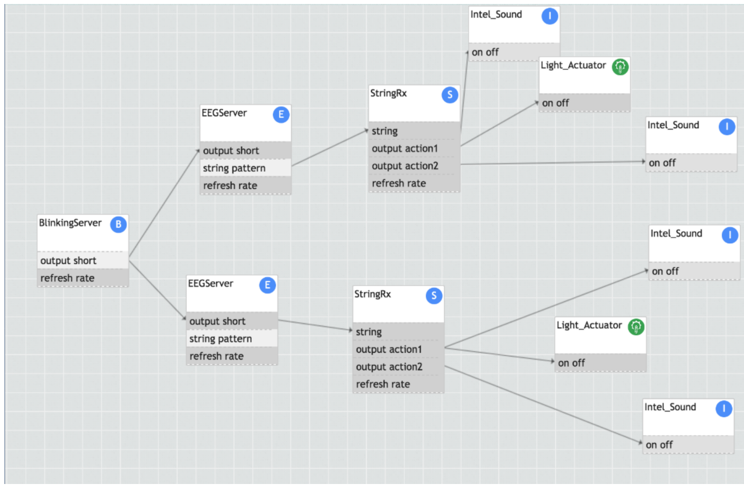


Figure 3.2: Flow Based Program of Old Assistance

3.1.5 System algorithm

Data: Real Time Web cam

Result: Different actions

initialization;

while *not detect four Eye blinking* **do**

detect Eye blinking;

if *detect four Eye blinking* **then**

Receive eSense signal (Attention and Meditation) ;

Using sliding window to build different patterns;

Using pattern-matching algorithm to match pattern and trigger different actions;

else

go back to the eye detection state;

end

end

Algorithm 1: System algorithms

The video demo of this system can be found here https://www.youtube.com/watch?v=7TrcF9qbUQ0.

3.2 Office Mind Reader

3.2.1 Overview

In this application both different eSense signal are used which are attention and meditation. Both signals are used to build the office application which shows different LED patterns based on different mental states.

3.2.2 System Architecture for office application

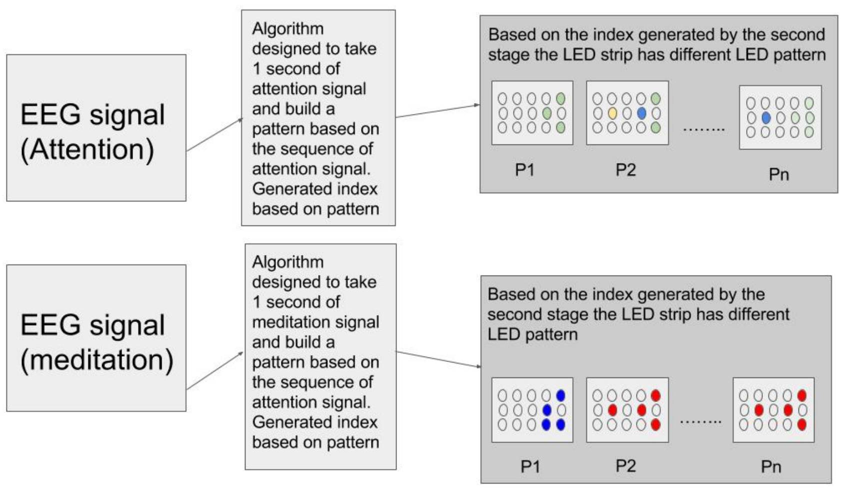


Figure 3.3: System Architecture Office Application

3.2.3 Implementation

The system has four components:

First, in order to obtain EEG signals for attention and mediation. I have modified an open-source API suggested by the Neurosky Mindwave Mobile Company. This new API is able to transfer both eSense signal at the same time for two different sockets which are used for this application. These two signals are received by two different EEG servers in the Wukong

Framework.

Second, in order to build different EEG pattern for attention and meditation, every EEG server received one second of attention and meditation signals, and based on the sequence of these signals, different pattern will be build. In order to build the EEG pattern, two different factors are taken into consideration: the range of the signal and the amplitude of the signal. The range of the signal can be divided into three different regions: the first region is considered to be high, between 60-100; the second region is considered to be medium, between 40-60; the third region is considered to be low between 0-40. The amplitude of the signal can be divided into different types which are either the signal values increasing, values decreasing, or the value staying constant. Based on these two parameters, a pattern can be constructed with three different values: one ,zero , or minus one.

Third, in order to pass a number for the LED Strip, another layer of software is used to distinguish different patterns, and uses sequence matching to construct a different index value in which every index value is responsible for different patterns of the LED strip. The index value is constructed using the EEG pattern. For instance, if the pattern has six adjunct ones that means index value will be zero.

Fourth, in this stage, there are two different LED strips, one responsible for the attention signal, and another responsible for meditation signal. Different patterns will be shown in the LED strip based on the value index from the third stage. Figure (3.5) below explain and show the flow of data and control of the system on Flow based program(FBP).

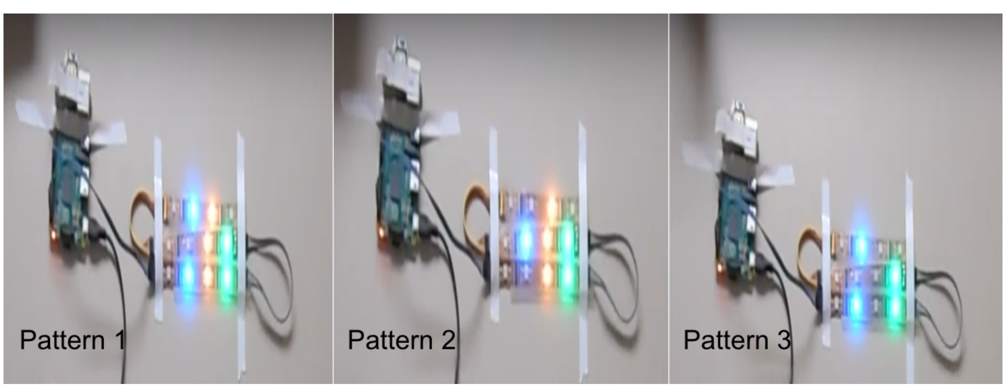


Figure 3.4: Three Different Patterns

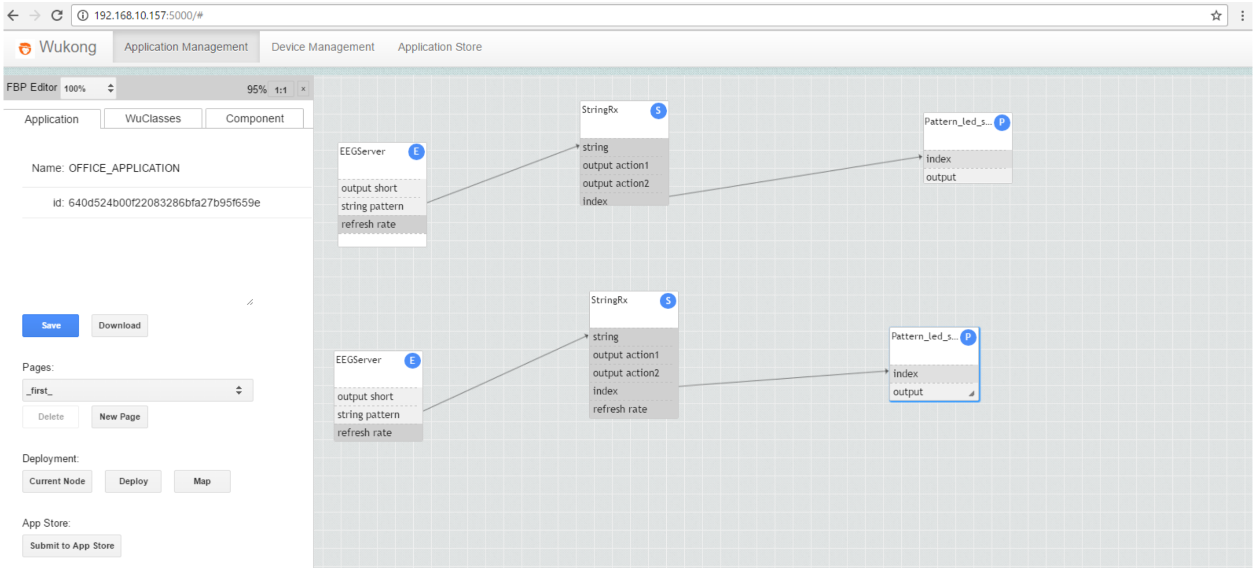


Figure 3.5: Flow Based Program of Office Application

3.2.4 System algorithm

Data: Attention&Meditiation signal

Result: Different LED Strip Patterns

initialization;

while *Attention and Meditation signals is Receiving* **do**

  slicing attention and meditation signal to one second ;

  if *one second slicing* **then**

    Using EEG server to build different pattern using 2 different parameters magnitude and values. Using pattern matching to match different patter and construct index values. LED strip will show different patter based on the index value.

  else

    go back to the attention and meditation signals;

  end

end

Algorithm 2: System algorithms

The video demo of this system can be found here http://bit.ly/2oiHTXc.

3.3 Classify Eye Events on the Edge

This application attempted to make the system smart by working with raw brainwave data and incorporating machine learning algorithms to distinguish between different eye states. This application is done as a collaboration with Zhenqiu Huang which part of this work appeared in his Phd dissertation "Progression and Edge Intelligence Framework for IoT Systems".

3.3.1 Overview

This application used the progression property of the WuKong framework. This progressive system supports edge intelligence which allows streaming processing capability on the edge device and provides streaming analytics in order to simplify programming of intelligent IoT applications.

3.3.2 System Architecture

The system is divided into two parts. The first part is focused on storage and transmission of the EEG data for two different events: when the subject's eyes are open and when eyes are closed. From researching brain waves, it was discovered that brain activity would be different between the two events. After careful study and testing, the conclusion was drawn that when the eyes are open, the Alpha and Beta wave features which are generated from the raw EEG signal are high. When the eyes are closed, Alpha and Beta features were low. However, these features were not enough to give reliable and appropriate results for the classification of these two events. Therefore, we tried to use different features, adding more features to the system to increase the reliability of the system. After working with one feature and two features, we extended the system to work with four different brain wave features in the range of 0.5 to 30 with a sampling rate of 512. These features are Delta, Theta, Alpha and Beta.

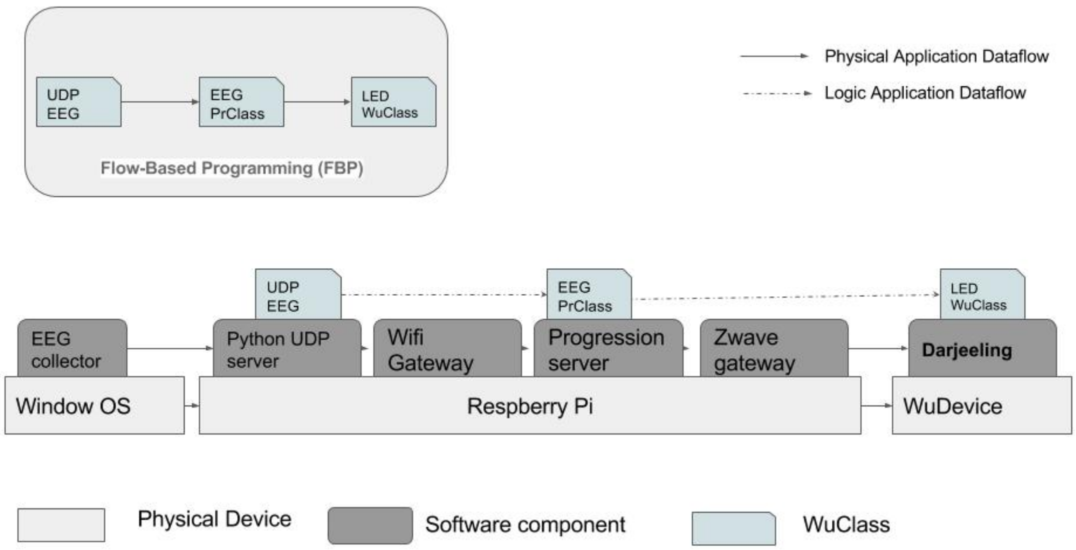


Figure 3.6: Software and System Architecture

3.3.3 Offline Classification

The raw EEG data recorded from three subjects for one minute. They are male with ages between 22-30. The sampling rate using to transfer and store the data from EEG headset was 512Hz. Figure (3.7) shows one second of Raw EEG signal.

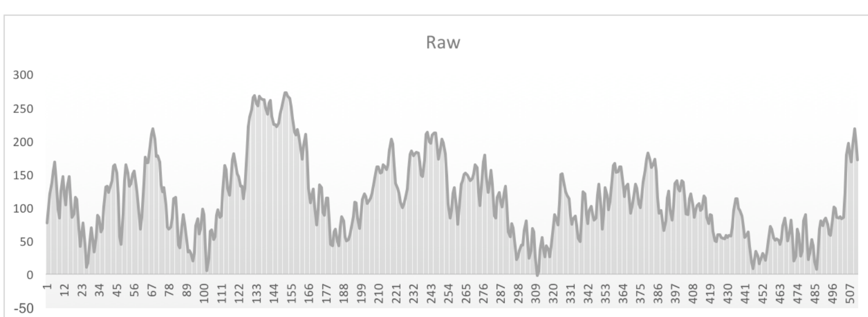


Figure 3.7: Raw EEG Signal

There are different ways to filter and process EEG signal such as Fourier Transform and Wavelet transform to extract EEG bands which are Delta, Theta, Alpha, Beta and Gamma. In this thesis the extraction was done using Fast Fourier Transform. Figure (3.8) shows 1 millisecond comparing between 4 different EEG features.

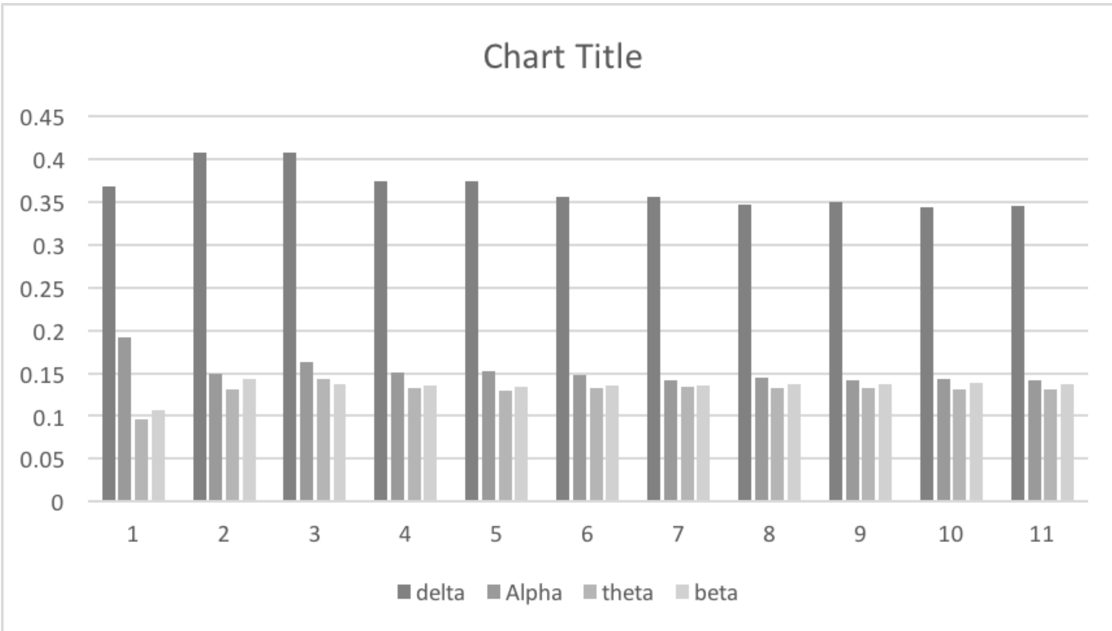


Figure 3.8: EEG Features

In this study, six different classifiers with two features (Alpha and Beta), and four features (Delta, Theta, Alpha, and Beta) are used to classify eye open state and eye close state . Algorithms used to classify eye states are Adaptive Boosting (AdaBoost), Random Forest, Decision Tree, Support Vector Machine with Linear and Radial Basis Function kernel, and K-Nearest Neighbor.

Experiment 1: One Subject with One Feature

In order to understand the best features we can choose for our classifier, we started by choosing one feature that was well researched previously. This feature correlated with eyes open and eyes closed. We tried to build a classifier based on this feature with 120 observations from one subject. After implementing this, the model resulted in an accuracy of 50.8%. Using cross validation with 10 folds as evolution metrics. After using out-data sampling, the accuracy drops.

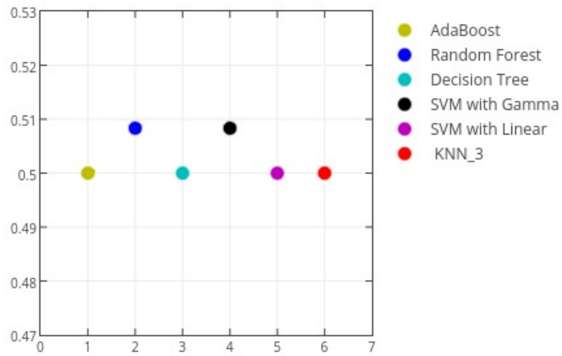


Figure 3.9: 240 Observation Alpha Feature

Experiment 2: One Subject with Two Features

To achieve higher accuracy, we started to augment our model by using 120 observations from the same subject but also used two features, Alpha and Beta. After training the model, we used cross validation as the evolution metric for our model. We produced an accuracy of 61.8% and 56.8% using Adaboost and Support Vector Machine with Radial Basis Function Kernel respectively. Unfortunately, this model did not show promising results with the out-data sample; the accuracy was still low so we needed to think of different ways to tune our model.

Experiment 3: Two Subjects with Four Features

In this step, we augmented our data set with different data coming from different subjects. We augmented our data set with 120 new observations using four different features. The new model now has 480 observations: 240 from the first subject and 240 coming from the second

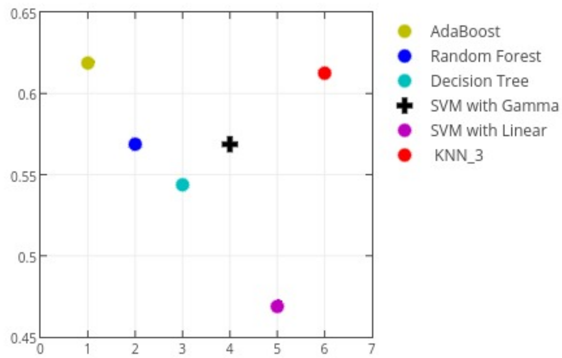


Figure 3.10: 240 Observations Features are Alpha and Beta

subject. After training this model with different classifiers, we used cross validation with 10 Fold as our metrics validation. The accuracy for the out-data sample was 76%. However, because there is a different pattern for a different subjects each time, the accuracy was not as high as we expected. As a result, we tried to increase our model's accuracy by adding more observations and more features.

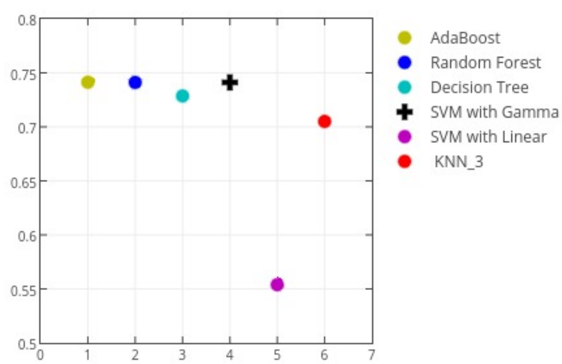


Figure 3.11: 480 observation Delta, Theta, Alpha, Beta Features

Experiment 4: Three Subjects with Four Features

In this step, we gathered different samples from different subjects. This new sample had 240 observations: 120 for eyes open and 120 for eyes closed. Our model after this step had 600 observation from three different subjects. We worked with this data set and used different classifiers and different parameters to tunes each classifier. We produced better results with cross validation as our metrics evaluation and reached an accuracy of 90% using Support Vector Machine with Radial Based Function kernel. Because of the accuracy, we decided to use this as our model, It also gave us promising results in the online study.

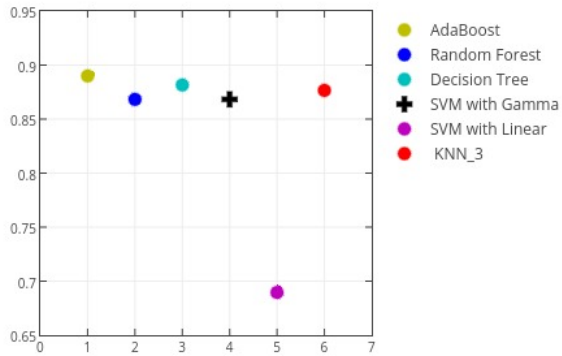


Figure 3.12: Raw Data Extraction and Classification

Tuning SVM Parameters

After choosing Support Vector Machine with Radial Basis Function(RPF), we tried to tune two of the SVM RPF parameters, Gamma and C. Gamma is defined as how far the influence of a single training example reaches, with low values meaning "far" and high values meaning "close" [13]. C is defined as trade-off misclassification of training examples against simplicity of the decision surface [13]. A low C makes the decision surface smooth, while a high C aims at classifying all training examples correctly by giving the model freedom to select more samples as support vectors [13]. After tuning these parameter using a binary search algorithm, we concluded the best Gamma = 106 and best c = 1. This will give us an accuracy of 90%.

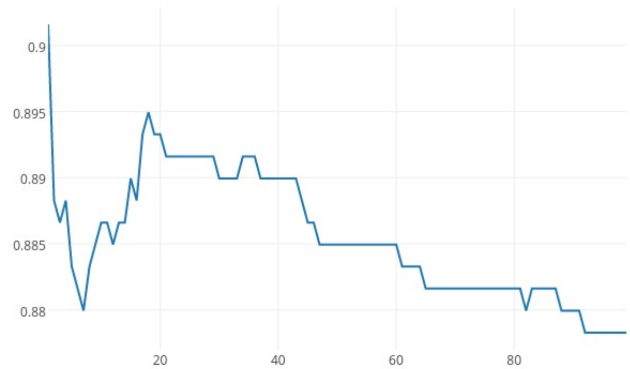


Figure 3.13: C Parameter Values

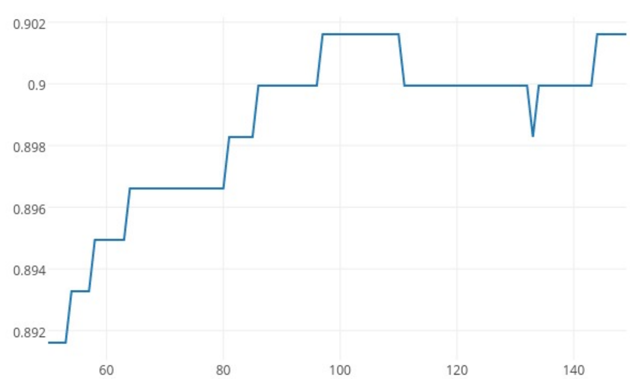


Figure 3.14: Gamma Parameter Values

3.3.4 Online Classifier

In the online stage we used the Support Vector Machine as our classifier, and we build that using different version of Wukong framework which is Wukong Progression Framework support building the classifier on the Edge.

Build EEG Edge Class

After offline training and tuning model parameters through using data collected every 5 seconds, the last step is to use the WuKong edge framework to connect EEG signal with the SVM model and control the physical LED light. Now, in this application intelligent component called EEG Edge Class to do the signal classification in real-time.

The EEG Edge class runs on an edge server. The server provides a programming API to help developers to receive WKPF messages from other component in the FBP, and in the meantime trigger the business logic inside to generate control commands for the target component of the FBP.

Define Edge Class

An Edge class is a powerful WuClass that has internal data storage and time series data processing capability. Like every WuClass, an edge class should be assigned a unique WuClass ID, which should be refered to in WuKongStandardLibrary.xml in master. In the EEGEdgeClass, the ID is explicitly defined by the WuClass annotation, so that the object instance of EEGEdgeClass can be discovered by the master.

According to the property declaration of WuClass in WuKongStandardLibrary.xml, a developer needs to define inputs and outputs for the edge class, and use the annotations for the edge framework to help developers to declare what kind of data structure they want to use to temporarily store upcoming time series data. The input property is declared as a buffer (DoubleRingBuffer), whose data ring capacity is 2000 data points, index ring capacity is 30 units, and index is built every 1000 miliseconds. Therefore, the buffer will hold data in a time window of 30 seconds; it will at most keep 2000 data points. The buffer will store raw signal from EEGDevice from which time series operators will fetch data and generate features. For every output property, an Edge class needs to define the corresponding set function. So, that a written WKPF property message will be generated and sent out when its value is updated. In the example, output is a property of output, whose property is 1. After defining properties as inputs and ouputs of the intelligent component, we implement two important methods of Edge Class. The register extension function will return a list of extensions, each of which is a handler of a specific stage in the data processing pipeline. In the EEG Edge Class, we registered EEGFeatureExtractinExtension and EEGExecutionExtension, both of which will be introduced in detail later. Beside providing data processing pipeline, the edge server also provides the communication pub/sub capability, so that an offline model can be initialized and updated through a pub/sub topic. model is loaded locally, so that there is no topic needed.

Define Feature Extraction Extension

In the feature extraction extension, developers can use the native operators to extract features from data in buffer. In the EEG Edge class, we want to use the relative intensive ratio operator to calculate the intensive ratio of Alpha, Beta, Gamma and Theta. For each operator, we need to define where to get data. Features extracted are ordered by the same order with operators in the returned list.

Define Execution Extension

Since models are offline trained in the EEG study, we ignore the online learning extension, and only focus on how to use models to do online classfication on the features extracted. Here, the EEGExecutionExtension implements both Executable Number and Initiable. Within the init function, we firstly load the model from local file system. The model is generated by libsvm on the training data and tuned SVM parameters (C and Gamma). The execute function accepts features in a list as the first parameters, and execution context as second parameter. Within the function, we use the model to classify whether we should label the features as eyes close or eyes open. Once we can know the probability of both eye close and eye open, we set 0.88 as the probability threshold to really trigger eyes close action by setting the output value. We tested the application on real physical devices. Its demo can be found at https://www.youtube.com/watch?v=E0U9MoJzxoo.

Chapter 4

Emotions

4.1 Overview

The importance of emotions lies in every-day-human-to-human communication and interaction. Understanding and recognizing human emotional status play an important role in human communication [58]. Human-computer interface can play the same role of the human being to understand and recognize human emotions, and adjust its setting to fit with their human emotions. There are different approaches detecting and recognizing human emotions. First, facial expression is one of the earliest techniques used to detect human emotions and voice recognition based on the voice tone can detect emotions. However, these techniques are susceptible to deception, and vary from one situation to another [21, 57]. Second, Physiological signals are also used to detect emotion such as electrocardiogram (ECG) and respiration. This approach provides more complex information than what is needed to detect emotion. Third, brain wave signal is used to detect emotion such as electroencephalogram (EEG), Electrocorticography (ECOG) and Functional magnetic resonance imaging (fMRI). The advantages of using brain wave are its strong relevance for emotions and that it is not prone to deception [73].

4.2 Emotions Background

There is a spectrum of emotions which can differ from one person to another. There are different models presented by the research community to model human emotions. One model presents the basic emotions as happiness and sadness [74], another model presents the basic emotions as fear, anger, depression and satisfaction [41]. Another model uses multiple dimensions or scales for emotion categorization. In this model emotion characterize by two main dimensions, valence and arousal. Valence emotions range from positive to negative whereas arousal emotions range from low to high [61]. For instance, fear can be defined as a negative valence and high arousal, whereas excitement can be defined as a positive valence, and high arousal [63]. Figure (4.1) shows the dimensional model of emotions.

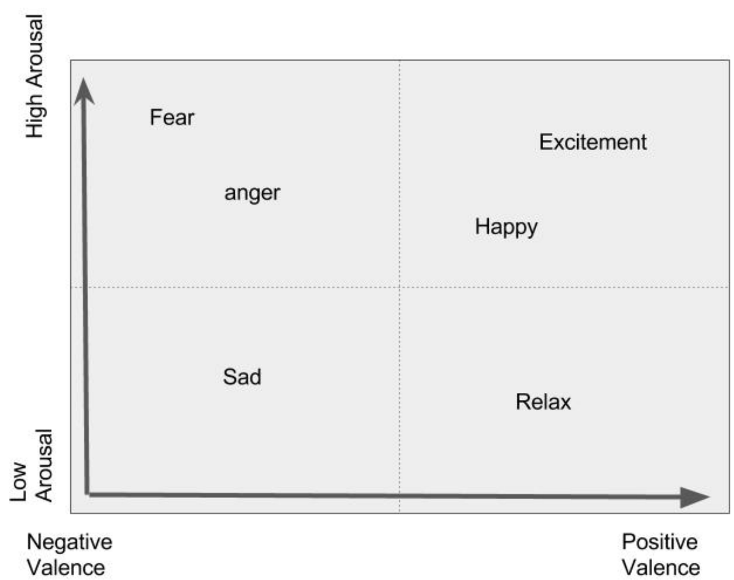


Figure 4.1: Two Dimensional Emotional Model

4.3 Implementation

In order to implement the emotions experiment, six factors have to be taken in to consideration. These factors are participants, model of emotions, stimulus, features, temporal window, and classifier.

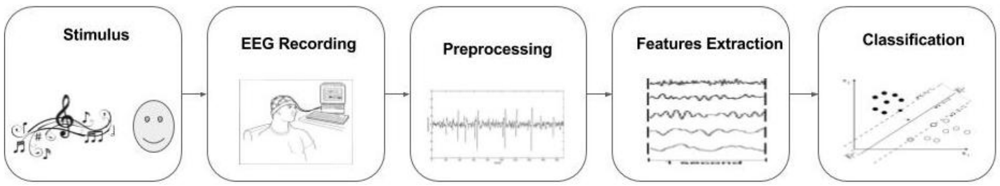


Figure 4.2: The Process of Emotion classification

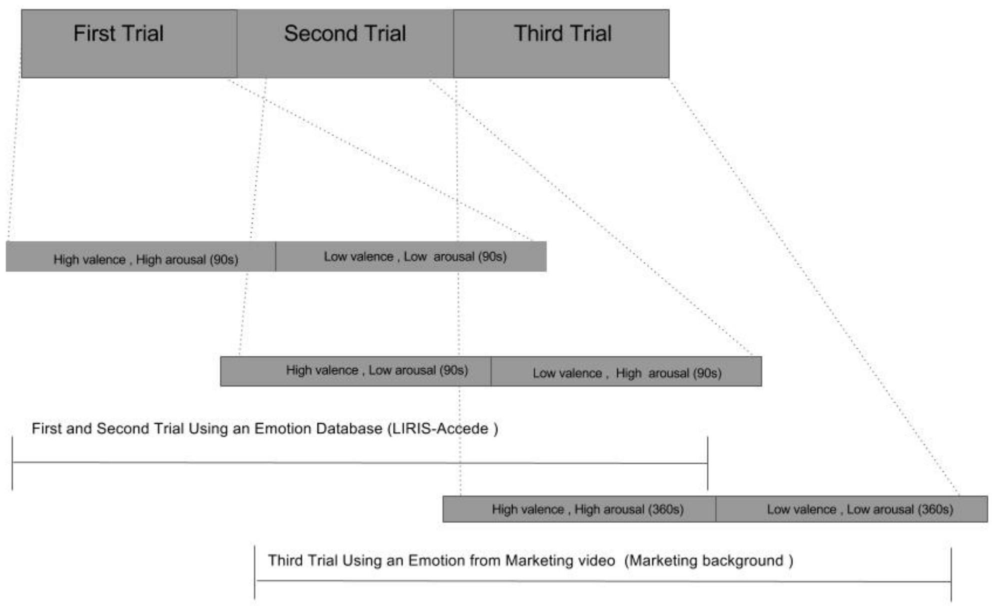


Figure 4.3: The Process of the Experiment

4.3.1 Participants

Six different subjects participate in this experiment. The subjects range from age 25 to 35 years old: 4 males and 2 females. The subjects are from different backgrounds and different ethnicities. Three subjects of the subjects are left-handed, and the other three are right-handed. Every subject spends between 15 and 20 minute to do the experiment. Self-Assessment Manikin scale is used by the subjects to reflect their emotional status. Self-Assessment Manikin is a pictorial non- verbal technique that measures the valence,arousal, and dominance associated with subject's affective reaction to different stimuli [24]. Figure (4.4) shows the technique used by the subject in this experiment to reflect about their emotional statues.

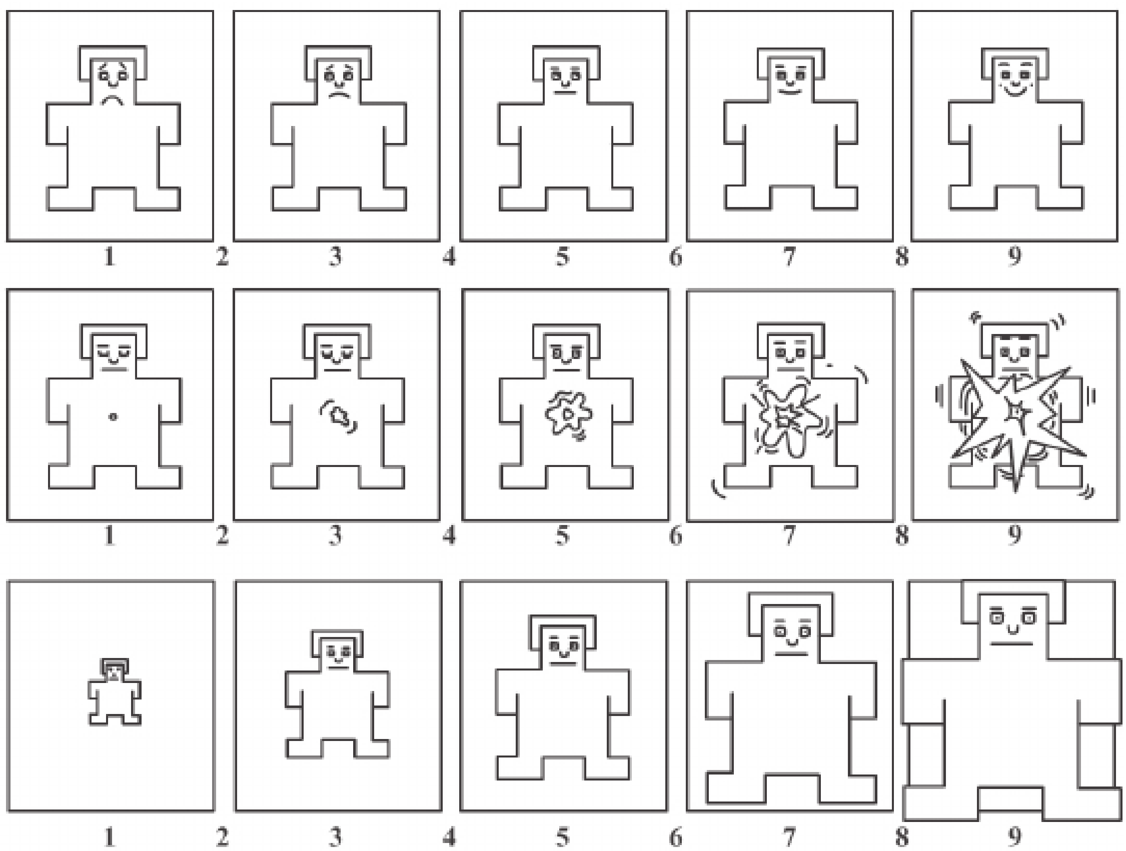


Figure 4.4: Self Assessment Manikin[24]

4.3.2 Model of Emotion

Every lobe in the brain has a different function which is explained in Chapter 2. So, in order to choose which model of emotion will be used, we have to keep in mind that the Neurosky Mindwave Mobile has only one electrode located on the left of the Frontal polar lobe. So, due to limitations of this sensor, this thesis used to choose the two dimensional emotion scale in order to distinguish only between the two different emotions: happy (High valence, High Arousal), and sad (Low valence, Low arousal).

4.3.3 Stimulus

There are different type of stimuli to trigger emotion: self-eliciting, recalling, and using external stimulus [43]. In order to stimulate the subject's emotion in this thesis, I used excerpt videos from Liris-accede library. LIRIS-ACCEDE library has around 9800 good quality video excerpts used to induce different types of human emotions[20]. This thesis used the library videos in the first trial and in the second trial. The third trial used a different resource to trigger emotions through videos that has marketing background. Only two emotions captured in the third trial which are High valence-High arousal, Low-valence and Low arousal. Figure (4.5) shows some images from these different video excerpts.

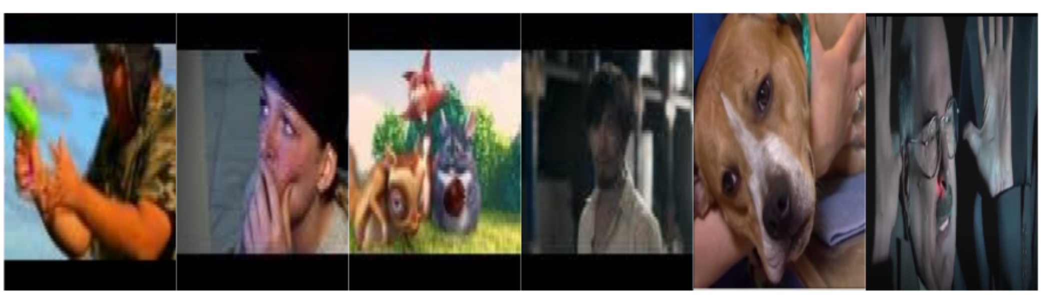


Figure 4.5: Video Excerpt Stimulus

4.3.4 Temporal Window

The length of temporal window depends on the desired emotion; the duration of different emotions will last when it is triggered between 0.5 - 4 seconds [46]. Using unsuitable window might lead to misclassified emotions, because too long or too short duration might cover the desired emotions. In the research literature, there is no optimal duration for the size window to detect emotion. In this thesis, I used temporal window of one second.

4.4 Dataset

This thesis takes 60 observations of raw data for High valence High arousal stimulus, and 60 observation for Low valence Low arousal for every subject. The number of the observations of the data for all subjects was 720 observations. 360 observations are for high valence high arousal, and 360 observations are for low valence low arousal.

4.4.1 EEG Feature

After preprocessing the raw EEG signal using sampling rate of 512 Hz, and using Fast Fourier transform to extract the signal from 1 Hz to 31 Hz, this transformation removes artifact signals such as EMG and EOG. After the preprocessing, we use a segmentation of one second for all the processed signals to extract the features. This thesis uses three types of specific features which are time domain features, power spectrum features, and nonlinear features such as fractals. The table below shows previously mentioned features.

EEG Features	
Time Domain Features	Frequency Domain and Nonlinear Features
Mean Absolute Value	Power Spectrum $\alpha, \delta, \theta, \beta, \gamma$
Mean Square Root	Entropy
Sign Slope Zero	Higuchi Fractal Dimension
Waveform length	Fisher information
Zero Crossing	Hjorth parameters (activity, complexity, morbidity)
Autoregressive	Hurst Exponent
Expect Max peak	Petrosian Fractal
Expect Min peak	First order difference
Max Standard Division	-
Min Standard Division	-

4.4.2 Normalization

After features extraction we normalize the features in which the values of features are adjusted to have a common scale. This step is very important to accelerate the learning process of a classifier.

4.4.3 Feature Selection

From 34 different features that have been extracted, 24 features are selected to build the model. The features selection is done using greedy algorithm to maximize the accuracy performance of a classifier. There are different algorithms for features selection such as sequential forward selection, Sequential Backward Selection, Sequential Floating Forward Selection, Sequential Floating Backward Selection and Exhaustive Features Selection. In this thesis, the Sequential Forward Selection method is used to select the features. Sequential forward Selection methods will be selected to maximize the accuracy performance of classifier. After applying the same algorithm on these different classifiers: Bayes Classifier, Support Vector Machine, K-nearest Neighbor, Decision Tress, Gradient Boosting classifier, Linear Discernment analysis, Perceptron, and Neural Network.

4.5 Result and Evaluation

4.5.1 Subjects

With 24 different features, this thesis used different classifiers to maximize the accuracy of our classifier. Figure (4.6) shows the difference of classification accuracy for subjects with different classifiers. The same experiment is done on the other six subjects, and takes the mean of accuracy among these six subjects.

Subjects	Sex	Age	Hand	Classifier	Accuracy (offline)	Accuracy (Online)
Subject 1	M	35	L	LDA	86.9%	86.1%
Subject 2	M	32	L	LDA	72.7%	63.89%
Subject 3	F	30	R	LDA	70.2%	52.78%
Subject 4	M	27	R	LDA	91.16%	83.33%
Subject 5	M	28	R	LDA	76.2%	75.93%
Subject 6	F	30	L	LDA	78.7%	61.11 %
Avg	----	30.33	-----	----	79.31%	70.52%

Figure 4.6: Classifier Accuracy

We choose Linear Discernment analysis as our classifier. In order to tune its parameters we

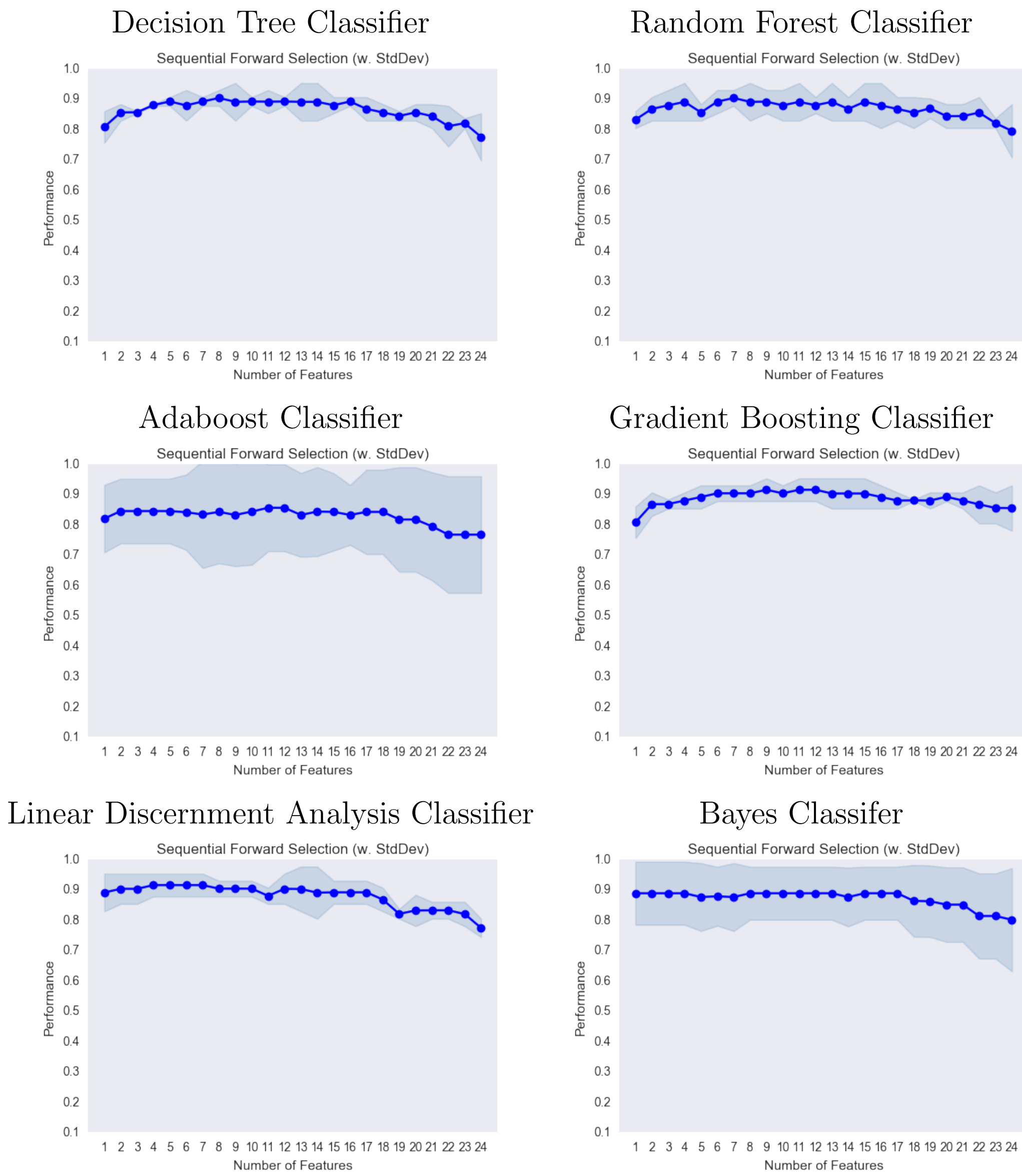


Table 4.1: Classifier Accuracy Subject 4

used gradient decent search which is an optimization algorithm that finds the local minimum of function. In order to test our classifier, we split our data to test and train data, with using cross validation of 2 folds for model evaluation in offline classification. The average accuracy of the classifier in offline classification is 79.31%, and the average accuracy for the classifier for online classification is 70.52%. The table below show the different accuracy among the six different subjects. I used subject 4 model to evaluate because it is the best model give us high accuracy among other subjects.

4.5.2 Model evaluation

In order to evaluate the Model, we used four methods of evaluation. First, the confusion matrix is a matrix table that describes the performance of classification model as shown in figure (4.7). Second,the F-1 score is the weighted average of precision and recall in which the highest score is 1 and the lowest is 0 as shown in figure (4.8). Third, Receiver Operating Characteristic (ROC) curve is used to evaluate the classifier output quality as shown in figure (4.9). Finally, the learning curve compares the learning between test dataset and training dataset as shown in figure (4.10).

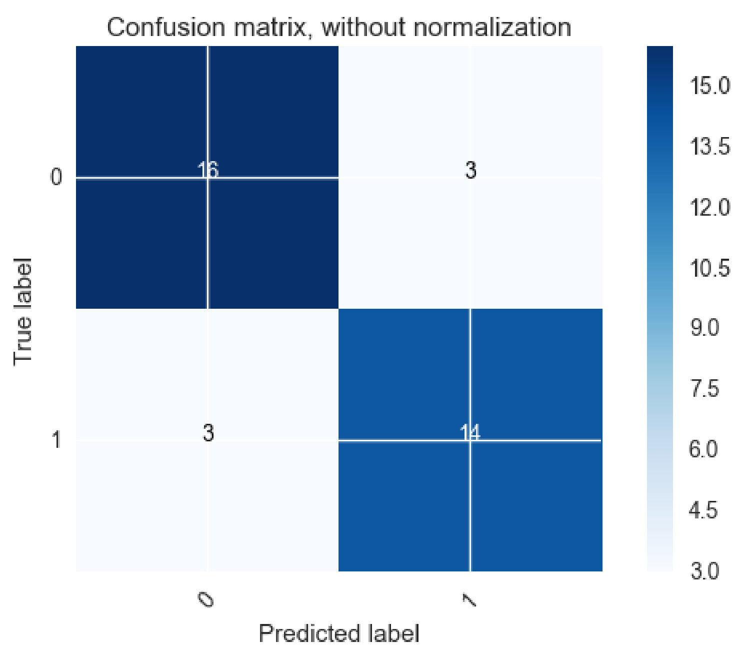


Figure 4.7: Confusion Matrix Subject 4

In the confusion matrix shown in figure (4.7), the diagonal of the matrix is darker than the rest of matrix, which implies the classifier is able to classify every class with very high precision.

Model Evaluation

	precision	recall	f1-score	support
Class-0	0.84	0.84	0.84	19
Class-1	0.82	0.82	0.82	17
avg / total	0.83	0.83	0.83	36

Error: 16.67%
accuracy: 83.33%
per-class accuracy: 83.33%
per-class error: 16.67%

false_positive_rate: 17.64%
true_positive_rate: 84.21%
precision: 84.21%
recall: 84.21%
sensitivity: 84.21%

Figure 4.8: F-1 Score Subject 4

Figure (4.8) shows F-1 that is another metric to evaluate the classifier, as we can see the avg of f-1 is 83%.

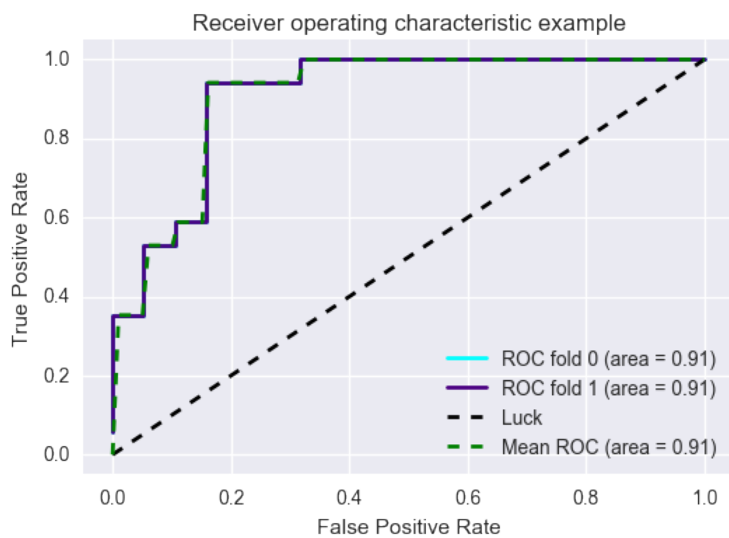


Figure 4.9: Receiver Operating Characteristic (ROC)

Figure (4.9) shows ROC that is another metric to evaluate the classifier, and the area under the curve for this classifier is 91%.

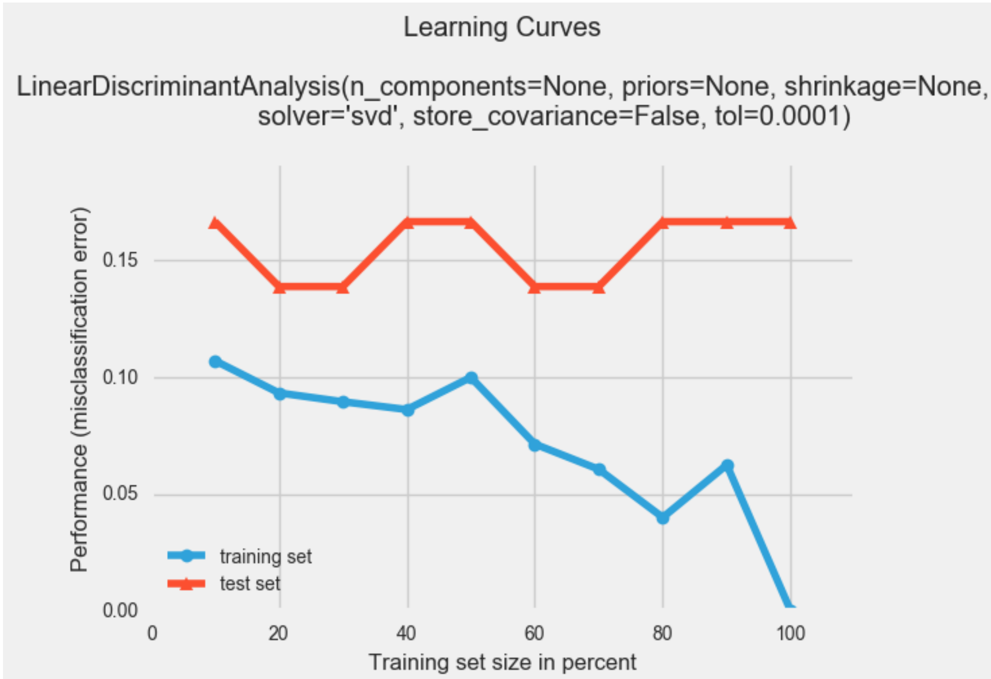
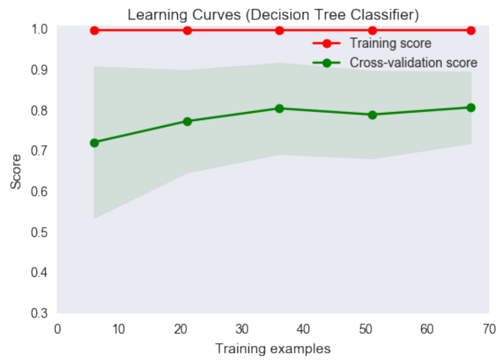


Figure 4.10: Learning Curve Test and Training Dataset Subject 4

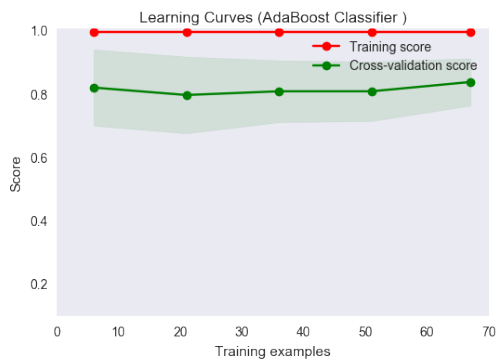
This is the Learning Curve on the Test and Training data set, using misclassification error as performance metrics. Figure(4.10) shows the misclassification on the test dataset ranging between 12% and 17%. In Table 4.2 shows different classifiers learning curve for subject 4.

Decision Tree Classifier

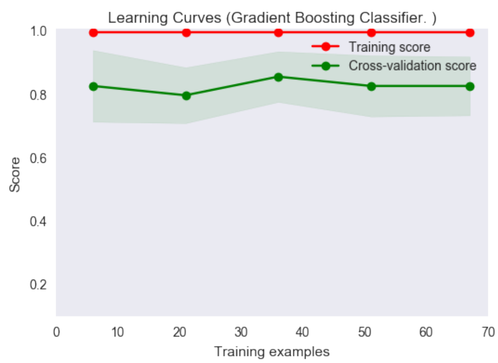


Random Forest Classifier

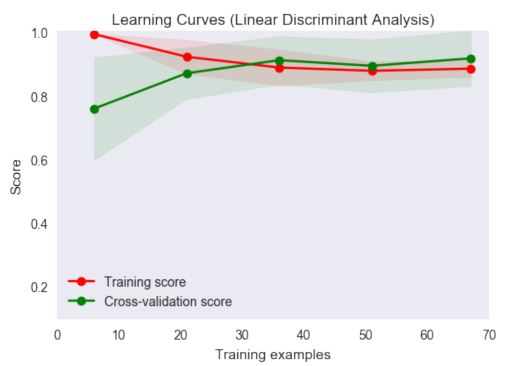
Adaboost Classifier



Gradient Boosting Classifier



Linear Discernment Analysis Classifier



Bayes Classifier

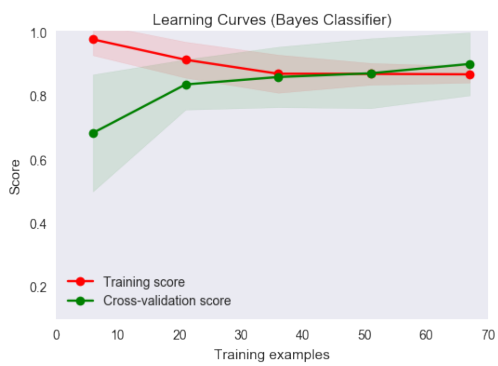


Table 4.2: Learning Curves Classifiers Subject 4

Chapter 5

Conclusion and Future Work

5.1 Conclusion and Discussion

The aim of this project is to investigate the ability of a low-quality cheap commercial EEG Headset to classify different mental tasks. The EEG signal in this thesis was acquired using a single electrode placed on the forehead. The EEG signal was sent to the computer via Bluetooth. In order to integrate the EEG headset with the Wukong framework, the EEGServer Wuclass has been designed and built for the first two applications. Also, in order to build edge classification, the EEG edge WuClass has been designed and built for the third application.

5.1.1 Internet of Thing Framework Integration

In the first two applications, this thesis intends to integrate the EEG headset with the Internet of Things framework "WuKong" to allow the user to control external applications, such as turning lights on/off, playing music, etc. Two applications is built one application aimed to assist old people to do different tasks and the second application aimed to read a mind in an office. In the Old People Assistant Application, the system was built using two sensors. The first sensor is the camera, which captures eye blinking using the Haar algorithm from OpenCV library to classify and detect the eye blinking. The second sensor is the EEG headset which capture eSense signals, defined as attention and meditation signals and their values ranging from 0 to 100. Different patterns are built based on the attention or meditation signal values. In order to change from one state to another, or to keep on a certain state, the number of eye blinks has to be detected by the system. The result are shown in Chapter 3 for switching between 2 LEDs, but they can be extended to play different types of music and switch different LEDs, as shown in Figure 3.2. The second application is designed to show the mind state of a person inside in an office. In this application two WuClass have been built,the first is the EEG server WuClass which receives EEG signals, builds different patterns, and generates different index number for different pattern. The second Wulclass is the LED strips WuClass which receives the index number and plays the patterns that corresponds to the index number. In this application both eSense signals send to two EEG server in WuKong,then the WuKong framework has the ability to receive two different signals, attention and meditation.

5.1.2 Edge Classification

The third application is called classification eye states on the edge. In order to do this, the first step is to capture the raw EEG signal from EEG headset which done using a python code. The second step to build this application was the preprocessing steps that are applied to the collected EEG signals, including Fast Fourier Transform, removing EMG and EOG artifacts, and segment the EEG to one second segments. The third step was to extract the EEG features, namely the power spectrum density features. In this application three different subjects volunteer to give their EEG signal, which acquired, preprocessed, and extracted the power spectrum density features. After collecting the EEG data we applied different machine learning algorithms in order to classify between two different eye states. We Used the accuracy of the classifier as our evaluation measurement. We reach 90% accuracy to classify between two different eye states using Support Vector Machine with Radial Basis Function kernel as our classifier. In order to use this classifier online in real time, we used the progression WuKong framework which supports intelligent edge. We built an EEG Edge class which has two components: first, feature extraction extension that uses relative intensive ration operator to calculate the intensive ration of EEG features; second, execution extension that loads the model which was generated offline, and based on the on the probability of the eye events, the threshold was chosen to be 0.88 to trigger an action when the eyes are closed.

5.1.3 Emotions Detection and Classification

The emotions application presented in Chapter 4. The emotions application was implemented in order to classify between two different types of emotion. Using video clip from LIRIS-ACCEDE library which is designed to trigger these different emotion. Six subjects participated in this experiment which lasted for 60 seconds for high valence, high arousal and another 60 seconds for low valence, low arousal. Different types of features are extracted from the collected EEG signals, included time,frequency and nonlinear features, and 24 of these features are selected in order to use them with machine learning algorithms. Different machine algorithms are applied on the collected data, and the average accuracy using Linear discernment analysis was 79.31%. The model was evaluated using confusion matrix, which showed the diagonal is darker than the others, and those implies that the classifier is a good classifier . The second method used to evaluate the model was f1-score, which show an average of 83% for the subject number 4. The last method used to evaluate the model was Receiver Operating Characteristics which show the area under the curve with 91% for subject number 4. The last method used to evaluate the model was the learning curve in which the learning curve showed a misclassification range from 12% to 17% for the subject number 4.

5.2 Discussion

This thesis studies and discusses the ability of low-cost headset EEG to classify different eye events, and different mantel tasks such as attention, meditation and emotions. Table 5.1 compares different research literature that applied eyes events classification, using different EEG headset ranging from 4 - 14 electrodes with a cost of $799. Different features and classifiers are used to classify eye events. The accuracy ranges from 73% to 95%. The thesis presents a different approach to classify eyes events using low cost EEG headset that does not exceed $100. The power spectrum density features extracted , and Support Vector Machine with Radial basis function is used for classification. In this thesis, an accuracy of 90% is obtained to classify between eyes open and eyes close. With 90% accuracy of this work using only one electrode, and only cost of $99 is a better solution to detect the different eye states compared to other studies shown in Table 5.1.

Table 5.1: EEG Base Eyes Events Recognition Research

Ref	Year	EEG Headset	Cost	Electrodes	Features	Classifier	Result
[68]	2011	Biospac MP36	–	4	Kurtosis&Amplitude	SVM&ANN	90.8%&86.8%
[65]	2013	Emotive Epoc+	$799	14	–	KStar	94%
[71]	2014	Emotive Epoc+	$799	14	–	IAL	73%
[35]	2012	Emotive Epoc+	$799	14	PSD	SVM	95%
Ours	2017	Mindwave Mobile	$99	1	PSD	SVM	90%

Table 5.2 shows data from research literature that discusses emotions classification using different EEG headsets. The electrodes numbers range from 5 to 64 electrode. Different emotions have been classified such as classification of different four features, which are joy ,relaxation,sadness and fear and the classification of two different features, which are positive and negative emotions. Different stimuli are used in research such as movie clips, and

pictures that target different emotions. Different features are extracted, which are Power Spectral Density(PSD), Higher Order Spectral(HOS), and Common Spatial Pattern (CSP) [43]. Different temporal windows ranging from 1s to 4s are used with different classifiers such as Support Vector Machine (SVM) and Linear Discernment Analysis (LDA). The accuracy of the different research ranges from 66.51% to 92.5%. This thesis presents a new approach to classify two different classes of emotions which used low cost EEG headset with only one electrode placed on FP1 position according to 10-20 system. Three different types of features were extracted, time domain (TD), power spectrum density (PSD), and fractal dimension (FD) features. The average accuracy obtained in this thesis is 79.31% to classify two different type of emotions. The solution presented in thesis has accuracy of 79.31% and cost of only $99 which can consider to be a good solution of applications that do not need high percentage of accuracy.

Table 5.2: EEG Based Emotions Recognition Research

Ref	Year	Elec Num	Emotions	Stimulus	Features	Temp Win	Classifier	Result
[72]	2011	64	Joy,Relax,Sad,Fear	Movie	PSD	1s	SVM	66.51%
[37]	2010	5	Calm,Exited	Picture	HOS	2s	SVM	82%
[53]	2011	62	Positive,Negative	Movie	PSD	1s	SVM	87.53%
[47]	2009	62	Positive,Negative	Picture	CSP	3s	SVM	92.5%
[42]	2013	5	Positive,Negative	Picture	PSD	4s	SVM	85.41%
[68]	2014	62	Positive,Negative	Picture	LDA	1s	LDA	91.77%
Ours	2017	1	Positive,Negative	Movie	PSD&FD	1s	LDA	79.31%

5.3 Future Works

This thesis was subject to different limitations imposed by the hardware and software used.

5.3.1 EEG Headset Design and Electrodes Number

The EEG headset used in this thesis was Neurosky Mindwave Mobile which is powered by the Neurosky chip. This headset was a single dry-electrode with only one channel and ground electrode placed on the left ear. This device can be easy to use, and can be setup faster compared to other advanced EEG headset. However, one channel is not enough to detect very complex mental tasks like emotion because different brain lobes are responsible for different functions, and this headset only cover the frontal polar lobe area which is responsible mostly for attention tasks and meditation tasks. Another way to overcome this limitation is to restructure the EEG headset by changing the position of the electrode. For instance, vision activity can be detected better by locating the electrode on the area that contain occipital lobe which is in the back of the skull. Also, positive and negative emotions states have been shown more dominant in the left and right frontal cortices respectively[63]. So, better detection for emotion signal might be achieved by relocating the electrode position to be on the frontal cortices as the desired applications. Another study [51] shows the minimal electrodes can be used to detect the emotion is 4 electrodes located on these positions F3, F4, FP1, FP2 or in these positions O1, O2, P3, P4. So, In order to get a better result the EEG headset can be redesigned to get a better result for detecting vision and emotions activity. Also, increasing the number of the electrodes to 4 can get a better result for detection the emotions.

5.3.2 Stimulus Types

In this thesis, I used LIRIS-ACCEDE library to trigger emotions. This library contains videos that selected to trigger different type of emotions. Another type of stimulus can be used in order to get better result. There are different systems designed by cognitive psychologist and neuroscientists to trigger emotions. The two systems are International Affective Picture System (IAPS), and International Affective Digital Sounds (IADS). Another database can be used to trigger emotion is Geneva Affective Picture Database (GAPED)[29]. These different system and database can be used to improve our accuracy results in the emotions experiment.

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