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Department of Electrical-Electronic Engineering

IMPROVED ALGORITHMS FOR EEG – BASED BCI APPLICATION

Master Thesis

Ali Hussein ABDULWAHHAB

Supervisor
Assoc. Prof. Dr. Indrit MYDERRIZI

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Beyin Bilgisayar Arayüzü, beyin dalgası kontrollü birimleri kullanan birçok uygulamada bireylerin Elektroensefalografi (EEG) sinyalleri aracılığıyla cihazlarla iletişim kurmasını sağlar. Bir dronun hareketlerini göz kırpma ve dikkat seviyesi sinyalleri ile kontrol etmek için EEG dalgalarını kullanan yeni algoritmalar sunulmuştur. Elde edilen sinyal tanımanın optimizasyonu, göz kırpmanın bir Destek Vektör Makinesi algoritması ile sınıflandırılması ve yapay sinir ağı üzerinden 4 bitlik kodlara dönüştürülmesi ile gerçekleştirilir. Lineer Regresyon Yöntemi, dikkat seviyesini dinamik bir eşikle düşük veya yüksek seviyeye kategorilere ayırmak için kullanılır ve 1 bitlik bir kod üretir. Algoritmadaki hareketlerin kontrolü iki kontrol katmanı ile yapılandırılmıştır. İlk katman, göz kırpma sinyalleri ile kontrol sağlarken, ikinci katman hem göz kırpma hem de algılanan dikkat seviyeleri ile kontrol sağlamaktadır. EEG sinyalleri, tek kanallı

NeuroSky mindwave 2 cihazı kullanılarak çıkarılır ve işlenir. Önerilen algoritmalar, farklı yaşlardaki beş kişinin deneysel olarak test edilmesiyle doğrulanmıştır. Sonuçlar, 9 kontrol komutu için% 91.85 ve% 90.37 doğrulukla mevcut algoritmalara kıyasla yüksek performansını göstermektedir. 16 komuta kadar kapasitesi ve yüksek doğruluğu ile algoritmalar birçok uygulama için uygun olabilir.

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

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The thesis study of Ali Hussein ABDULWAHHAB titled as IMPROVED ALGORITHMS FOR EEG – BASED BCI APPLICATION has been accepted as MASTER THESIS in the department of ELECTRICAL-ELECTRONIC ENGINEERING by out jury.

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SUMMARY

Brain Computer Interface enables individuals to communicate with devices through Electroencephalography (EEG) signals in many applications that use brainwave controlled units. New algorithms using EEG waves for controlling the movements of a drone by eye-blinking and attention level signals are presented. Optimization of the signal recognition obtained is carried out by classifying the eye-blinking with a Support Vector Machine algorithm and converting it into 4-bit codes via an artificial neural network. Linear Regression Method is used to categorize the attention level to low or high level with a dynamic threshold, yielding a 1-bit code. The control of the motions in the algorithm is structured with two control layers. The first layer provides control with eye-blink signals, the second layer with both eye-blink and sensed attention levels. EEG signals are extracted and processed using a single channel NeuroSky mindwave 2 device. The proposed algorithms have been validated by experimental testing of five individuals of different ages. The results show its high performance compared to existing algorithms with accuracies of 91.85% and 90.37% for 9 control commands. With a capability of up to 16 commands and its high accuracy, the algorithms can be suitable for many applications.

Keywords **:** Electroencephalography (EEG), Brain computer interface (BCI), Drone, NeuroSky mind wave.

ÖZET

Beyin Bilgisayar Arayüzü, beyin dalgası kontrollü birimleri kullanan birçok uygulamada bireylerin Elektroensefalografi (EEG) sinyalleri aracılığıyla cihazlarla iletişim kurmasını sağlar. Bir dronun hareketlerini göz kırpma ve dikkat seviyesi sinyalleri ile kontrol etmek için EEG dalgalarını kullanan yeni algoritmalar sunulmuştur. Elde edilen sinyal tanımanın optimizasyonu, göz kırpmanın bir Destek Vektör Makinesi algoritması ile sınıflandırılması ve yapay sinir ağı üzerinden 4 bitlik kodlara dönüştürülmesi ile gerçekleştirilir. Lineer Regresyon Yöntemi, dikkat seviyesini dinamik bir eşikle düşük veya yüksek seviyeye kategorilere ayırmak için kullanılır ve 1 bitlik bir kod üretir. Algoritmadaki hareketlerin kontrolü iki kontrol katmanı ile yapılandırılmıştır. İlk katman, göz kırpma sinyalleri ile kontrol sağlarken, ikinci katman hem göz kırpma hem de algılanan dikkat seviyeleri ile kontrol sağlamaktadır. EEG sinyalleri, tek kanallı NeuroSky mindwave 2 cihazı kullanılarak çıkarılır ve işlenir. Önerilen algoritmalar, farklı yaşlardaki beş kişinin deneysel olarak test edilmesiyle doğrulanmıştır. Sonuçlar, 9 kontrol komutu için% 91.85 ve% 90.37 doğrulukla mevcut algoritmalara kıyasla yüksek performansını göstermektedir. 16 komuta kadar kapasitesi ve yüksek doğruluğu ile algoritmalar birçok uygulama için uygun olabilir.

Anahtar Kelimeler : Elektroensefalografi (EEG), Beyin bilgisayar arayüz (BCI), Dron, NeuroSky zihin dalgası.

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ABBREVIATIONS

BCI	**:**	Brain Computer Interface
EEG	**:**	Electroencephalography
SSVEP	**:**	Steady State Visual Evoked Potential
TGCD	**:**	Think Gear Connector Driver
LRM	**:**	Linear Regression Method
SVM	**:**	Support Vector Machine
ANN	**:**	Artificial Neural Network
HM	**:**	Human Mind
ATT	**:**	Attention
GUI	**:**	Graphical User Interface
IDE	**:**	Integrated Development Environment

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PREFACE

During the preparation and writing process of this thesis, i would like to thank my esteemed professor Assoc. Prof. Dr. Indrit MYDERRİZİ.

I would like to thank the thesis's jury members for their help in managing this thesis and taking it forward with their valuable comments and suggestions throughout the process. For his contribution to the thesis, Dr.Lecturer. Mussaria K. MAHMOOD. I would like to express my sincere gratitude to Assoc. Prof. Dr. Hacı İLHAN, the staff of Istanbul Gelişim University Electrical and Electronics Engineering Department and the Institute of Science.

Finally, I want thanking my family for their supporting.

INTRODUCTION

The brain neurons are responsible of activating the human movement, and generating the electrical bio-signal inside the brain. These neurons features are invested in several technologies, which are used the mind waves in controlling the applications (Namdev and Mohd, 2015). Usually, control stick is used to control the appliances such as the wheelchair system (WCS), drone and arm robot. Nowadays, there is a huge demand for Brain Computer Interference (BCI) that can be used in situations where typical control interfaces are not an option. The concept of BCI based system has been developed to provide alternate control methods for handicap people, gamming and for special purpose applications (Guger, Werner, Carin and Gert, 1999). BCI is an interfacing technology between the mind and a processor by sensing brain signal and employing it to perform different tasks. By using the right tools and recent developments in brain imaging technologies, reading, recording, and analyzing these signals becomes possible, where every action generated by the brain can be used as input data to control devices. Thus, deployment of BCI system is rapidly increased and exploited as part of systems helping individuals suffering from spinal injury or reductions of motor skills to perform tasks daily. The individuals need only to think in the movement for controlling desired applications (Bates, 2002). There are several neuro-imaging processes capable to scan the brain waves which investing in developing and designing the sensor devices based on BCI system conception. Electroencephalography (EEG) is the most used technique to perform the control various applications. The present study utilizes the EEG technique in controlling a drone, by creating an interface between the human brain and the computer based on BCI system where the sensing device is employed to capture different frequency bands according to EEG rhythm signals. A single channel dry electrode installed in NeuroSky device is used to extract and collect the mind wave from the users' scalp. NeuroSky mindwave 2 device provides many features, such as amplifying the EEG signal in order to boost the weakness amplitude of the captured signals, filtering the signals from muscles movement and noise distortion, processing and digitizing the signals before transmitting over Bluetooth, as well it has high resistance against the external influences (Lim, Chee-Keong, Wai Chong and Siew , 2014).

CHAPTER ONE

PURPOSE OF THE THESIS

1.1.Literature Survey

A lot of researches adopt the BCI system in their works by using the mind waves (EEG signals), muscle movements (Electromyography - EMG), and (Electrooculogram - EOG) in controlling the applications, and the study of nervous activity features.

Shen, Hui-Min, Liang, Kok-Meng and Xin. (2015) present multi-motion robot system to help disable people in controlling an accessory appliance based on bioelectrical signal. The dry electrode single channel NeuroSky module is used to acquire the EEG signal, and invested both frequency and time feature of the device in processing the signals. Six motions are derived by the processed signals for the attention and eye-blink. The system shows an accuracy eye-blink classification 95% with an average time 2.4 sec for implementing the mean attention level.

Stephygraph, L. Ramya, N. Arunkumar and V. Venkatraman. (2015) propose a wireless-mobile robot control by using EEG signal to assist the people who suffers from reduction of motor skills in performing daily tasks. NeuroSky mindwave is invested to capture the mind wave, and eye-blink signal is adopted to develop the controlling algorithm. The discrete wavelet transform is applied to improve the signal resolution in order to increase the accuracy of the classification of the eye-blink in different controlling classes.

Shinde and George. (2016) design a system to control a WCS using EEG headset NeuroSky based on BCI system. The attention and eye-blink signals are adopted in controlling the WCS, where the circumferential sensors are added to the WCS to provide safety control for the users in order to avoid the obstacles during movement. The controlling system presents an average successful detection of the eye-blink 85% to change the WCS direction.

Bright, Dany, Amrita, Devashish and Swati. (2016) develop an algorithm to control a prosthetic-arm using NeuroSky mindwave based on EEG signals, so as to realize two motions of arm fingers (flexion and extension). The arm system is composed of an Arduino connected with servo-motor to perform the flexion and extinction motions, and shows 80% accuracy.

Zhang, Lu, Qingsong and Yishen. (2017) propose the designing of a controlling system by using dry electrode single channel sensor to control a robotic car based on BCI system. The attention level is classified into three different periods (0 – 30, 31 – 50, 51 – 100) depending on the average attention value for each period. For the first period the car moves backward slowly, and remains in same state through the second period. In third period car changes direction to forward in same speed. The robot-car system gets success rate of 85%.

Nafea, Marwan, Nurul and Fauzan. (2018) propose a smart house system controlled by using EEG signals based on BCI system. The system uses NeuroSky device to capture the EEG waves, and pairs with an Arduino to control four appliances via Bluetooth.

Liu, Chang, Songyun, Xinzhou, Xu, Wei and Klaus. (2018) suggest a video-feedback to control a car system based on the Steady State Visual Evoked Potential (SSVEP)-BCI system. Music method is used to improve the performance of the frequency domain analysis by classifying the signals into four directions. The system provides an average control accuracy equal to 87.5%.

Hassan, Mohammad, Hasin and Fariba. (2019) present a control system to help people who lost controlling on their limbs for home appliances. The system performs tasks daily using mind waves. The EEG Headset NeuroSky module is used to collect the EEG signal and detect the eye-blink. The eye-blink detection accuracy of the system is equal to 92%.

Jameel, Huda, Salim and Sadik. (2019) design a WCS to help the disabled individuals using brain waves based on BCI system. The system adopts an Emotive – Insight EEG headset module to capture the mind waves and a DC motor driver to control the velocity of the chair. Moreover, a microwave radar is added to the WCS to provide a safe navigation for the patient in avoiding obstacles during the motion.

Permana, Wijaya and Prajitno. (2019) propose a WCS control using brain waves based on BCI system. NeuroSky headset is used to capture and collect the EEG signals. The attention level, meditation level, and high alpha signal are employed to derive four directions movement of the WCS. The WCS shows an average accuracy performance to the four direction; 82.22%, 73.33%, 46.76% and 17.78%, respectively.

NeuroSky EEG headset is used to collect brain signals as part of IoT technology with cloud server aimed for health care applications in (Mansour & Ouda, 2019). So that, the mental and physical mind activities are used to control a robotic car for three movements (left, right, and forward), achieving the average error percentages as 10%, 20%, and 25%, respectively

Jeong, Ji-Hoon, Dae-Hyeok, Hyung-Ju and Seong-Whan. (2020) develop a prototype of brain-swarm interface controlling a swarm of a drone using Steady State Visually Evoked Potentials (SSVEP). An experimental environment is designed to extract and collect the EEG signals which are classified using machine learning for various flight scenarios: hovering, splitting, dispersing, and aggregation.

Avudaiammal , Jasmine, Ashton and Bagavathy. (2020) provide a robot-car and home appliances controlled with brain signals using NeuroSky mobile 2. A micro-controller is employed to distribute and recognize the controlling signals. The attention and meditation signal levels are used to control the movement and the direction change of the robot-car, while the eye-blink is used for switching on /off of home appliances.

Salih and Abdal. (2020) design a system control of a virtual keyboard using brain waves based on BCI system. The NeuroSky mindwave 2 is used to capture the EEG signals and detect the eye-blink to control two designed keyboards (ABC and QWERTT). The attention signal used to scan and initialize the virtual keyboard, and the eye-blink for selecting character and moving the cursor to next row. The system shows an error rate equal to 5%, 5.25%, respectively.

Morshad, Sarwar, Md Rabiuzzaman and Fahad. (2020) Present a classification of the brain waves into different frequency bands and the attention / meditation detection accuracy obtained through the distribution of users into four groups according to the age and sex. The NeuroSky mindwave 2 is used to capture the EEG signals and a Graphical User Interface (GUI) is implemented to collect, process, and analyze their features. The study achieves attention, meditation, and eye-blink average detection accuracies of 47.5%, 54.25%, and 48.25%, respectively.

Tiwari, Prashant, Abhishek, Saurabh, Joydip and Prasenjit. (2020) present a BCI system implemented by Arduino micro-controller to help the users to maneuver a miniature of WCS by non-invasive NeuroSky technique. The attention, meditation and eye-blink are used to develop three various controlling algorithms to execute the maneuvering commands.

1.2.Problem Statement

BCI enables individuals to communicate with devices through Electroencephalography (EEG) signals in many applications using brainwave controlled units. Thus, this lets us concentrate on developing an algorithm to control many devices here; a drone, by using EEG signals. This BCI system provides alternate control methods for handicap people, gamming and for special purpose applications characteristics.

1.3.Aims and Objective

The objective of the present work is developing two algorithms based on attention and eye-blink signals to control a drone. The algorithms include two possible control procedures, the one-layer control which is based on eye-blink only, and the two-layer control based on both attention level and eye-blinking. Also, a dynamic thresholding for attention level classification is used to improve the accuracy of the algorithm. The EEG headset NeuroSky module device is used in this work to capture and collect the mind signal, and then classify according to the users' intention into nine movements which are; Takeoff, Land, Forward, Backward, Up, Down, Left, Right, Stop. Also, the presented work aims to use an instrument with economically cost to acquire the mind signal which classifying to be suitable in maneuvering a drone by various users. The scope of this work is formulated as:

- Using Think Gear Connector Driver (TGCD) for Communicating wirelessly with NeuroSky Mindwave via Bluetooth.
- Design Graphical User Interface “GUI” using processing IDE to collect and record the acquired EEG signal
- Analyzing and classifying the collected data offline using Neural network methods (Linear Regression Method (LRM), Support Vector Machine (SVM), Artificial Neural Network (ANN)).

- Testing and evaluating the system in order to obtain a best implementation for the BCI system.

1.4.Thesis Organization

The thesis is composed of five chapters.

- **Chapter One** presents simple introduction for the proposed system, includes general information, related work, the problem statement, and the objective of the thesis.

- **Chapter Two** provides a theoretical background of the BCI system, the work's methods of the BCI system, the general structure of the proposal system, and types of EEG headset.

- **Chapter Three** presents the adopted methodology for the development of the algorithms with the details.

- **Chapter Four** presents the evaluation of developed algorithms with experimental results.

- **Chapter Five** presents the conclusions and future work.

CHAPTER TWO
THEORETICAL BACKGROUND

2.1. Brain Activity Patterns

Human brain consists of three main parts which are Forebrain, Midbrain, and Hindbrain as presented in the Figure 1. The Forebrain includes cerebrum and the limbic system, while the Midbrain consists of tectum and tegmentum. Finally, the Hindbrain composes of cerebellum, pons and medulla. The cerebrum represents the most significant part of the brain because of it is responsible of thinking, problem-solving and controlling muscular activates from limbs to the eye blinking for the individual. The human movements and thoughts are activated by nervous nudge sending by the neuron's activity (Koslow and Subramanian, 2005).

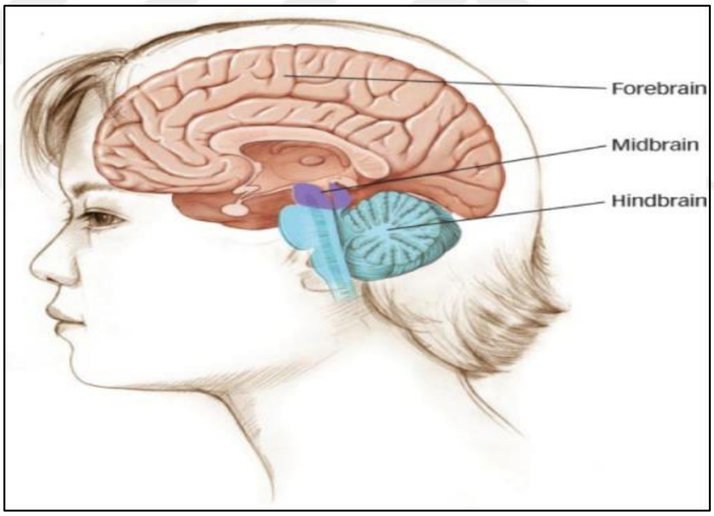

Figure 1. Human Brain parts (Koslow and Subramanian, 2005)

The Hans Berger finds that the electrical activity produced by neurons known as EEG signals can be recorded using electrodes placed on scalp (Berger, 1929). Since Hans Berger discovering, the researchers have worked on developing a system to exploit these brain signals in several fields. The first research is released presenting a system with an alternative transmission channel independent from the normal incidental nerve and muscle output pathways of mind, and knows as the BCI system (Vidal, 1973).

2.2. Brain Computer Interface (BCI)

The BCI system is an interfacing technology between Human Mind (HM) and a processor to control the external devices by using thoughts in the controlling mechanism (Blankertz , Guido, Christin, Roman, Jens, K-R. Muller, Volker, Florian and Gabriel, 2003). The BCI system aims to translate the patterns of human cognizance depending on mind activities by recording the electrical signals in order to create a link course for controlling the devices or outside environments according to human intentions as shown in Figure 2 (Lotte, Fabien, Laurent and Maureen, 1999). The BCI system contains two primitively types which are active-reactive, and passive. The active BCI adopts the mind activities in determining the pattern of the user conscious, yielding to a direct devices control. In an analogous method, the reactive BCI derives the pattern from the mind activities changing according to the reaction that causing by external stimulation, driving applications control (Fetz, 1999). The passive BCI recognizes the perception and awareness of human without needs for the voluntary control to enrich the interfacing between the brain-computer with implicit information (Zander & Kothe, 2011). For the BCI system, there are two types of mind-sensing techniques which are; invasive and non-invasive (Girouard, Audrey, Erin Treacy, Hirshfield, Krysta, Angelo, Sergio and Robert, 2009). In Table 1, several kinds of BCI neuro-imaging processes are listed.

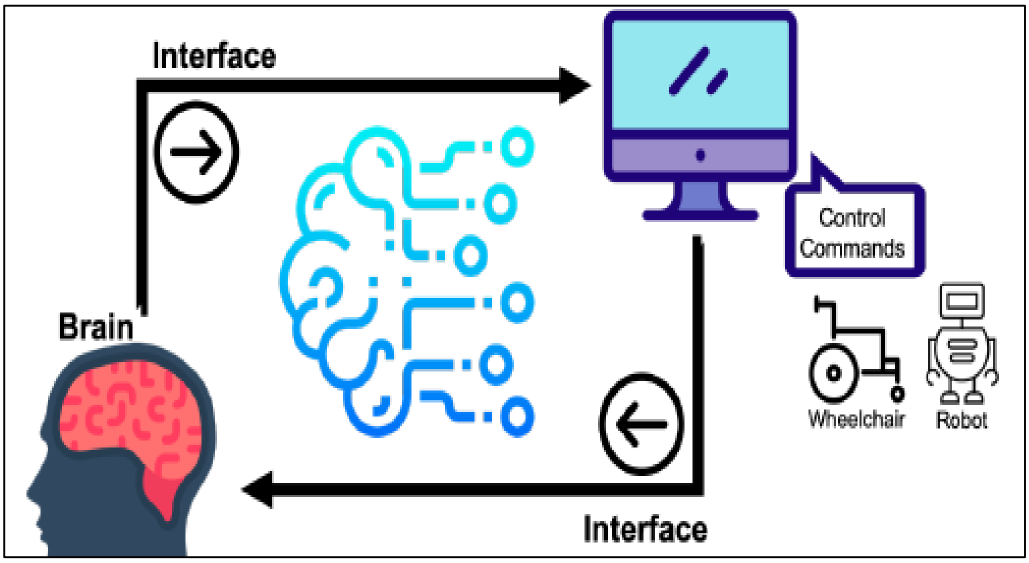

Figure 2. BCI system framework (Gu, Xiaotong, Zehong , Alireza, Peng Xu, Dongrui, Tzyy-Ping Jung and Chin-Teng Lin, 2020).

Table 1.various neuroimaging methods (Anil, Praveen and Gauttam , 2018)

Neuro-imaging Process	Measured Movement	Measurement Method	Possibility Measures	Portability Measures
ECoG	Electrical	Direct	Invasive	Portable
INR	Electrical	Direct	Invasive	Portable
EEG	Electrical	Direct	Non- Invasive	Portable
MEG	Magnetic	Direct	Non- Invasive	Non- Portable
fMRI	Magnetic	Direct	Non- Invasive	Non- Portable
NIRS	Magnetic	Direct	Non- Invasive	Portable

2.2.1. Invasive and / or partially invasive sensing technique

It requires surgical intervention for implanting the electrodes under the scalp to communicate with the human brain. Although this invasive sensing technique provides high sensing accuracy and good signal-to-noise ratio, some scar tissues can be formed after surgery causing weakness in the acquisition of the brain signal and a severe medical state (Abdulkader., Atia and Mostafa, 2015).

2.2.2. The non- invasive sensing technique

It works by installing the electrodes in external headset placed on scalp to capture the brain signal. It is a reliable and efficient method for ordinary users and severely/ partially paralyzed patients to get back forms of communication and control of external devices (Muller-Putz and Pfurtscheller, 2007). In Figure 3, the main monitored brain activity for both invasive-partially invasive and non-invasive methods is presented.

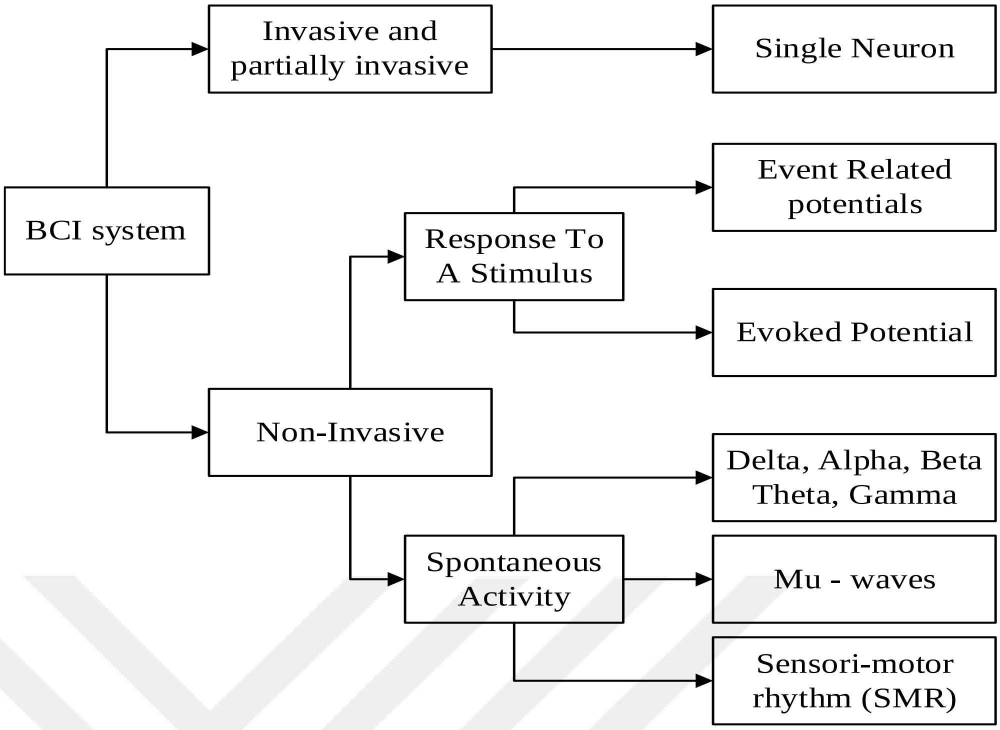

Figure 3. BCI system sensing methods

2.3.ELECTROCOCHLEOGRAM (EEG)

EEG is an observation technique to read and record the mind waves. The mind activities produce some of currents known as neurological ionic currents generating an electrical potential signal, which are sensed by the EEG. The brain signals are classified based on their electrical activity into three types; spontaneous activity, Evoked Potentials (EP), and the bioelectric events produced by a single neuron (Malmivuo and Plonsey, 1995). The spontaneous activity knows as EEG signals, is measured from the individuals scalp in different mindwaves states as done in the NeuroSky device. The EP represents a combination of EEG patterns, and responses to a specified stimulus (electric, auditory, visual, etc.). These signals have low noise level, so it requires several stimuli and signal averaging for improving the SNR. Finally, the bioelectric events are produced from single neurons, and recorded directly by implanting microelectrodes brain. BCI system adopting the non-invasive technique, which is considered as the most common method to capture spontaneous EEG signals, and provides many features such as fast response, simplicity, low cost, and their ability for implementation in many applications, is used in the implementation of the NeuroSky mobile-2 device (Cincotti, , Donatella, Fabio, Simona, Gerwin, Giuseppe, Andrea, Maria and Fabio, 2008) (Gu, Xiaotong, Zehong, Alireza, Peng, Dongrui, Tzyy-Ping and Chin-Teng, 2020). The EEG headset extracts and collects the brain waves in different frequency bands from the scalp with various channel according to the electrodes map. The EEG signals have low quality resolution because of the skull and scalp layers objecting the acquisition path. Moreover, the EEG signals are affected by the noise during the acquisition and other environmentally effects causing signal distortion and weakening the signal power driving a decrease in the Signal-to-noise ratio (SNR) (Zhang et al, 2017).

2.4.The Spontaneous Activity: Brain Waves Rhythms

The thoughts, behaviors and emotions are the result of the communication between the brain’s neurons. The brain waves are produced through the synchronization of electrical impulses from the neuron’s masses because of intercommunication. The brain waves are divided into five basic waves according to the frequency bands based on the mental state as listed in Table 2. The brain waves change according to the doings and feelings. The slower waves dominate during tired, slow movements, and dreams, while the higher waves dominate during feeling weird and hyper alerted. Figure 4 shows the comparison between the five types of the brainwaves.

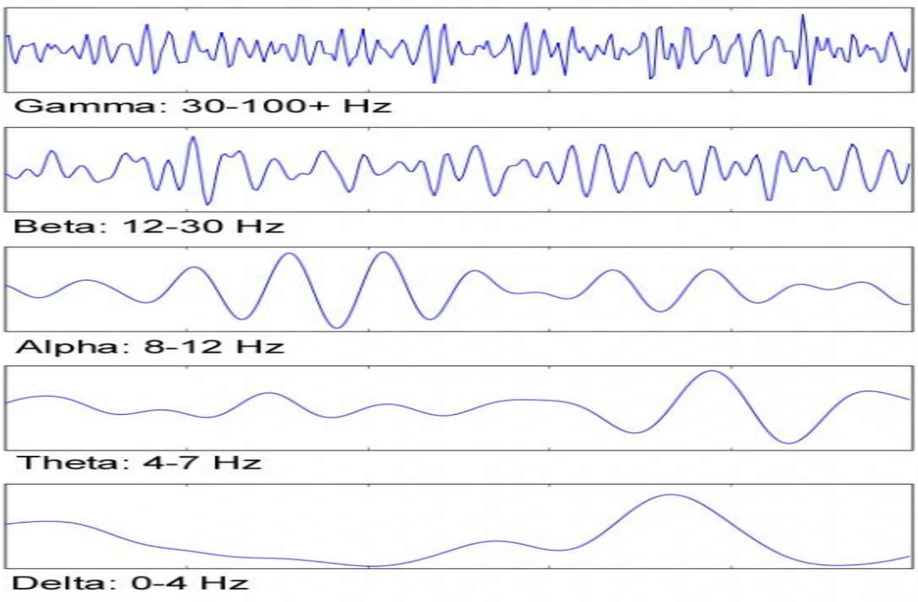

Figure 4. Comparison of EEG bands (Kent, 2010).

Table 2. EEG Signal frequency bands and related mental states

Brainwave Type	Frequency range	Mental behavior
Delta	0 Hz – 4 Hz	▪ Deep dreamless sleep ▪ Associated with healing
Theta	4 Hz – 7 Hz	▪ Extreme relaxation ▪ Meditation and imagination ▪ Increase creativity and problem solving
Alpha	8 Hz – 12 Hz	▪ State of relaxed mental awareness ▪ Reflection, Contemplation, Visualization ▪ Problem solving ▪ Accessing deeper level of creativity
Beta	12 Hz – 30 Hz	▪ Concertation. ▪ During increased attentiveness ▪ Energy, stable emotion
Gamma	30 Hz – 100 Hz	▪ High level information processing

2.5.BCI System Structure

The typical BCI system consists of four components which are: signal acquisition, feature extraction, feature translation, device output blocks as shown in Figure 5 (Tiwari et al, 2020).

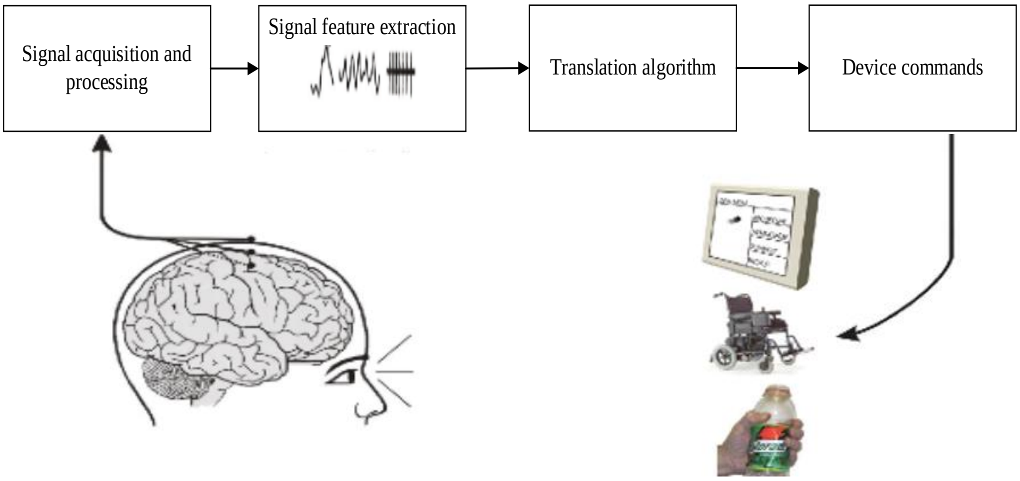

Figure 5. BCI system structure

The brain signals are collected from the scalp of individuals by using sensors, which are devices implemented with multi-electrode array to detect and collect the brain signal. The signal passes through an amplification unit to be appropriate for processing. Moreover, signal is subjected to a filtering unit to eliminate distortion and unwanted signals. After amplification and filtering, the signal is then digitized before transmission to the processing unit. The standard known as (10-20) is used for the correct placement of the electrodes over the scalp as clarified in Figure 6.

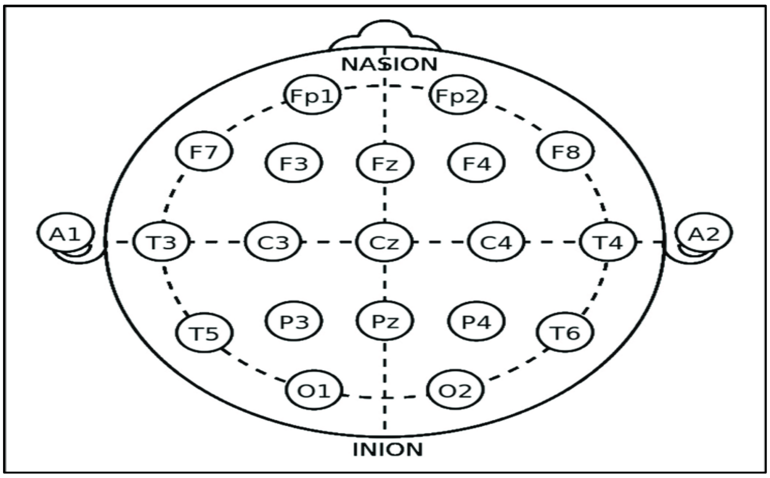

Figure 6. The standard 10-20 electrode position of EEG (Rojas, Gonzalo., Carolina, Carlos E. Montoya, María de la Iglesia-Vayá, Jaime E. Cisternas and Marcelo, 2018).

The processing and analyzing of the digital signals are accomplished through the feature extraction step. Signal characteristics classification, and conversion into commands is implemented with objective of good interconnections with the user's intents. There are several methods are applied to classify the brain signals in the BCI system. Neural Network method is considered one of the popular ways to classify the EEG signals. Although the neural network is proved as good technique in solving the nonlinearly issues, the EEG signal is generally presupposed to be linear (Blankertz, Guido, Christin, Roman, Jens, Muller, Volker, Florian and Gabriel, 2003). The processed EEG signal passes to the feature translation algorithm for converting into commands based on user's intention to control the external devices (i.e. commands that perform user's objective), and transmits over the Universal Asynchronous Receiver and Transmitter (UART) interface using HC-06 Bluetooth module. The external device works by the output commands from the feature translation step of the BCI system. These commands provide functions such as control WCS, drone, select letter, operate arm robot etc.

2.6.Electroencephalography (EEG) Headset

There are various kinds of EEG headset with a dry electrode, wet electrode, or both to extract and collect the brain signals from different area of the scalp. Some EEG headset types are listed in the Table 3.

Table 3. EEG headset types (Gu et al, 2020)

Brand	Product	Sensors type	Channel	Location	Sampling rage
NeuroSky	Mindwave	Dry	1	FP 1	512 Hz
Emotiv	EPOC +	Dry	5 – 14	F-C-T-P-O	125-256 Hz
OpenBCI	EEG electrode Cap Kit	Wet	8-21	F-C-T-P-O	250 Hz
Wearable Sensing	DSI 24: NeuSenW	Wet, Dry	7-21	F-C-T-P-O	300/600 Hz
Muse	Muse2	Dry	4-7	F-T	256 Hz

NeuroSky device is adopted in this work. The NeuroSky headset has two lobes to detect and filter the EEG signal as shown in Figure 7 (Cheng, Jeffrey, Griffin and Carlos, 2014). The frontal lobe of the EEG headset is represented by a dry electrode placed above the left eye, and the ear contact lobe working as a headset reference and ground electrodes (Salih & Abdal, 2020). The NeuroSky headset gives three values output which are:

- EEG Raw data: It is a complex signal composed by mind waves and other random waves resulting from the electrical activities of nearby muscle and ambient noise.
- eSense signals: NeuroSky company uses a proprietary algorithm to read user mental state based on Think-Gear technology. The eSense algorithm is applied on the remaining signals after amplifying and filtering the Raw signals (“NeuroSky”, 2014). The eSense meter has two types which are; Attention

eSense meter and Meditation eSense meter. Attention eSense meter is a feature to measure the concertation levels of the human's brain. The attention level meter has range between 0 - 100 integer values, and becomes low during the (mind wandering, Distractions, anxiety) states for the individuals. Meditation eSense meter is a feature to measure the relaxation and calmness levels of the mental state and physically for the individuals. The meditation eSense meter has range level between 0 -100 integer values, and improves during clearing mind, deep breath, closing eye, and imagination states for the users. The attention and meditation eSense meters range divide into five classes as follows.

- Strongly Lower (1 – 20).
- Reduced (20 – 40).
- Neutral / baselines (40 – 60).
- Slight Elevated (60 – 80).
- Elevated (80 – 100).

- Blink strength: The eye-blink reads with an unsigned single byte with range intensity between 1 - 255 integer value. Also, can be measured the eye-blink through the sudden change in the amplitude of the EEG signal.

Figure 7. EEG NeuroSky module (ul Islam & Farooq, 2017)

CHAPTER THREE

METHODOLOGY

3.1.System Overview

The EEG signal is processed by NeuroSky mindwaves-2 device before transmission to the PC. The Integrated Development Environment (IDE) processing + is used to design a Graphical User Interface (GUI) for projecting and supervising the coming signals from the NeuroSky. The GUI is also used to record the attention and eye-blink signals in an Excel database. The collected data of eye-blink is used to define the threshold value by machine learning based on Support Vector Machine (SVM) classification algorithm. The obtained threshold value is utilized to train an Artificial Neural Network (ANN) to sort the applied eye-blink signals as logic "1" or logic "0" according to the strength of the signals. Since the attention signal levels are related to the concentration of the person under test, and the observation period, the Linear Regression Method (LRM) is used for the classification of signals yielding a dynamic threshold. Four sequential eye-blinks are used to generate 4-bit eye-blink codes that together with the attention level are employed in controlling a drone's motions (takeoff, land, left, right, up, down, forward, backward, and stop). The block diagram of the adopted method is shown in Figure 8.

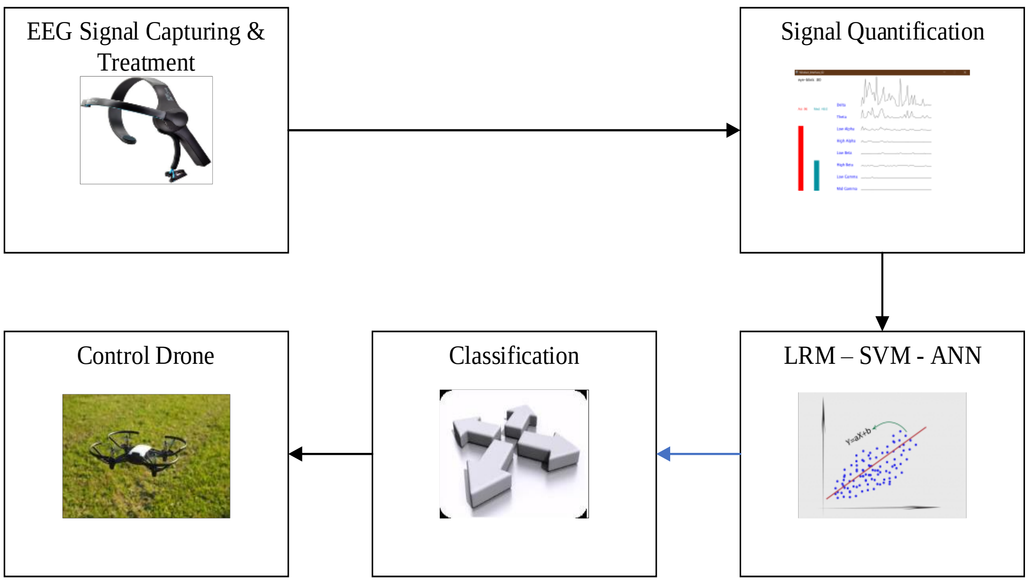

Figure 8. Brain-drone interface block diagram

3.2.Capturing EEG Signal and Treatment

The NeuroSky device uses single channel flexible dry electrode sensor to extract and collect the EEG signals from the pre-frontal left position (Fp1) of the scalp. Owing to the location with minimum hairs and proximity to the eye, it provides EEG and eye-blink signals as shown in Figure 9.

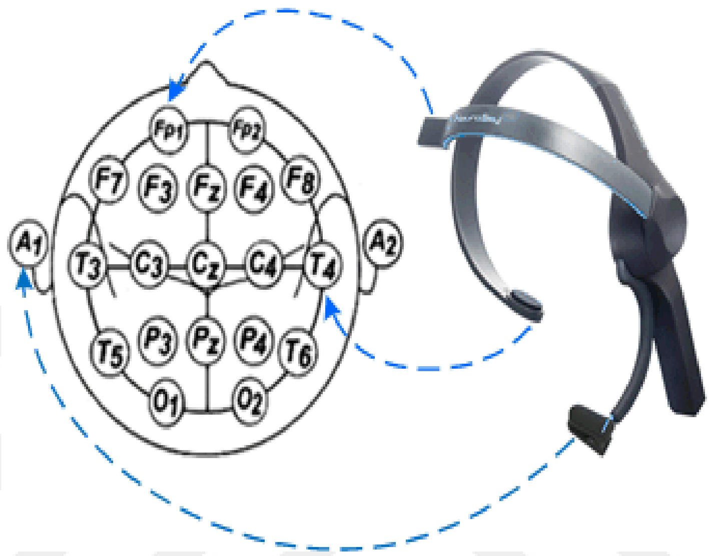

Figure 9. Neurosky Mindwave Mobile Headset (Matiko, Joseph , Stephen and John, 2013).

Due to EEG signals' weak amplitude (10µV - 100µV), and noise sensitivity during the extraction stage, a pre-treatment block is required to improve the SNR and maximize the accuracy of the EEG signals (Zhang et al, 2016). The block diagram of pre-treatment circuit is shown in Figure 10.

Figure 10. Pretreatment steps for the EEG

The pre-treatment circuit consists of a preamplifier stage, a filter, a postamplifier, an analog-to-digital converter (A/D), and a Receiver / Transmitter interface. The preamplifier is used to boost the EEG signals by 8000 times. The EEG signals ranging in 0.5 Hz - 100 Hz bandwidth are exposed to distortions due to the muscle movements and environmental effects. Thus, the filtering unit comprised of analog and digital low and high pass filters is used to eliminate the 50/60 Hz AC powerline interference, and other distortions in order to retain the signals in 0 – 50 Hz bandwidth range. The filtered EEG signals are amplified by the postamplifier block with gain equal to 2000, before passing to the A/D converter. In A/D converter the EEG signals are sampled at 512 Hz and coded with 12 bits and transmitted over a Universal Asynchronous Receiver and Transmitter (UART) interface using HC-06 Bluetooth module (“NeuroSky”, 2014). The formula for converting raw values to voltage is given by:

$$voltage = \frac{raw\ value \times \frac{V_i}{2^N}}{G} \qquad (3)$$

where G is the gain of the post-amplifier, V_i is the maximum input voltage equal to 1.8 V, and N is the resolution in bits of A/D. Table 4 presents the NeuroSky mindwave 2 outputs after pretreatment.

Table 4. Protocol output of Neurosky mindwave (Mohd, 2015).

Output data	Band range and sampling
Raw EEG data	sampled at 1 Hz
Delt - power	Bandwidth frequency 0.5 – 2.75 Hz
Theta - power	Bandwidth frequency 3.5 – 6.75 Hz
Low Alpha - power	Bandwidth frequency 7.5 – 9.25 Hz
High Alpha - power	Bandwidth frequency 10 – 11.75 Hz
Low Beta - power	Bandwidth frequency 13- 16.75 Hz
High Beta - power	Bandwidth frequency 18 – 29.75 Hz
Low Gamma - power	Bandwidth frequency 31 – 39.75 Hz
High Gamma - power	Bandwidth frequency 41 – 49.75 Hz
Attention eSense	Attention level integer value 0 - 100
Meditation eSense	Meditation level integer value 0 - 100
Poor signal	0 is good signal / 200 is off-head state.
Blink strength	Eye – blink integer value 0 -255

3.3.Signals Quantification

There is a strong correlation between attention and meditation signals because they both characterize the concentration and relaxation of an individual. The selection of attention level instead of meditation is based on the complexity of meditation process which requires more training, and sustainable relaxation-concentration process during the experiment.

EEG signals known as α, β, δ, θ, and γ are represented using eight waves as illustrated in the designed GUI of the Figure 11. However, the most related waves to human mind states are those related to α, β, δ, and θ signals (Hasegawa & Oguri, 2006). The energy value of each signal can be given by (Liu, Chang, Songyun, Xinzhou, Duan, Wei and Klaus, 2013):

$$E_{\alpha} = \sum_{freq=8}^{13} P_{freq} \qquad (4)$$

$$E_{\beta} = \sum_{freq=14}^{30} P_{freq} \qquad (5)$$

$$E_{\delta} = \sum_{freq=0.5}^{3} P_{freq} \qquad (6)$$

$$E_{\theta} = \sum_{freq=4}^{7} P_{freq} \qquad (7)$$

where P_{freq} is the power of the signal, and $freq$ is the frequency of the signals in a range of 0.5 Hz – 30 Hz

The correlation between α, and β is exploited to derive the ratio equation as a feature to evaluate the mental attentiveness level (Hasegawa & Oguri, 2006),

$$R = \frac{E_{\alpha}}{E_{\beta}} \qquad (8)$$

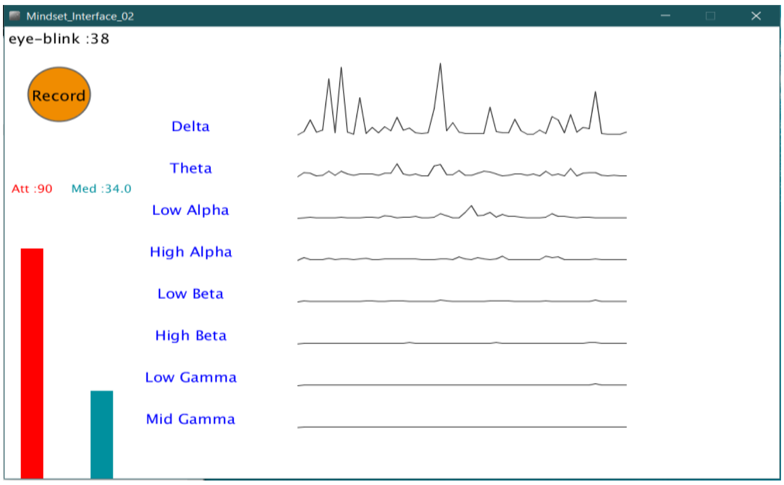

Figure 11. Designed GUI for projecting and recording of NeuroSky outputs

3.3.1. Commands based on Eye-blink signals

The eye-blink signals are used to generate control commands according to the blinking intensity strength. For an accurate determination of the blinking threshold, five individuals with different ages are required to generate six successive reading for each one as shown in the Table 5. Individuals are asked to produce three slight blinks and three strong blinks in a random order.

Table 5. Eye-blink experimental reading

No. Blink	S 1	S 2	S 3	S 4	S 5
1	64	76	80	32	100
2	95	61	34	55	101
3	74	57	130	115	60
4	64	95	82	95	35
5	45	112	60	95	87
6	55	46	48	63	58

The collected data is analyzed and classified using SVM algorithm. SVM works on constructing a hyper-plane or group of hyper-plane in dimensional space, which is used to classify the input data into output classes, here into slight or strong blinks. A good separation accuracy is achieved through the creation of a large margin zone between the hyper planes and any nearest training data for both classes as clarified in Figure 12 (Mohd, 2015).

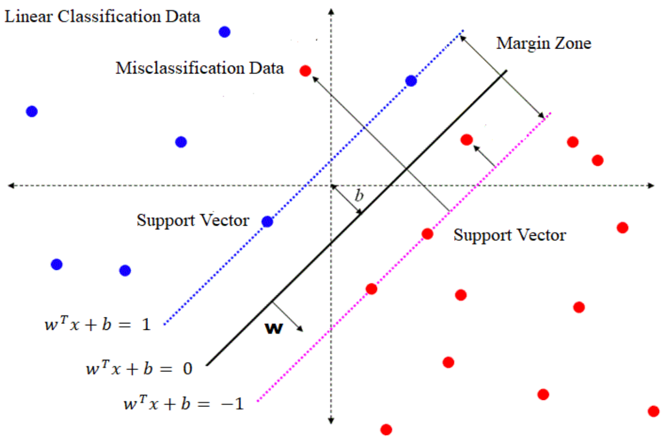

Figure 12. SVM Margin Zones

The SVM algorithm classification for the collected data resulting in an optimal threshold of 72 eye-blink intensity. The threshold separates eye-blink into two blink classes (strong or slight) as presented in the Figure 13-A. The confusion matrix shown in Figure 13-B indicates that one of the predicted strong blinks is considered as slight one resulting from an incorrect blinking of the individual S1. Later, the ANN is trained with the obtained threshold and the collected data is sorted as logic "1" or logic "0". ANN including several hidden weighted neurons (Li, and Chin, 2009), and the distribution of experimental data are shown in Figure 14 and Figure 15, respectively. Four blinking sequence is used to produce a four-bit code according to the selected motion as defined in Table 6. Each eye-blink code is generated during a period of 5 sec, which has been set based on a series of experimental tests for different individuals.

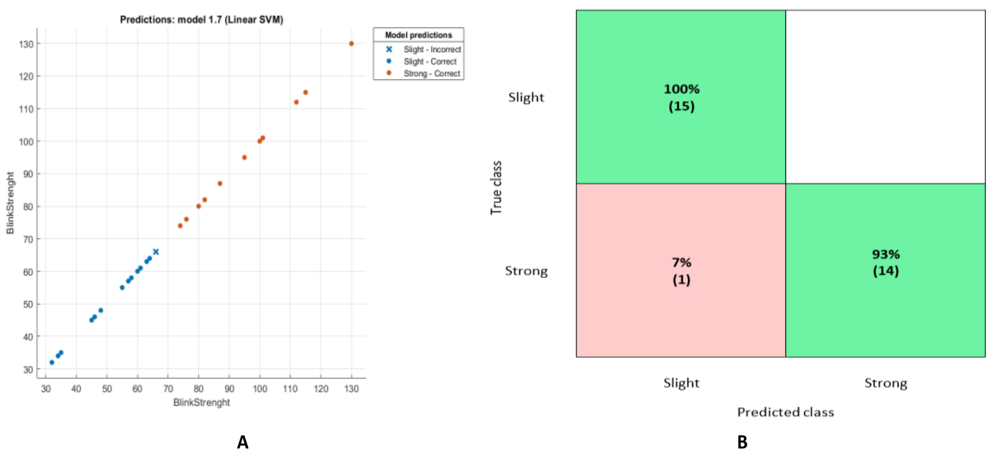

Figure 13. Eye blink signals classification (A) SVM classification (B) Confusion matrix

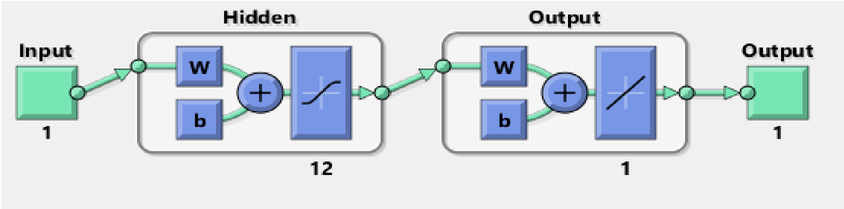

Figure 14. The adopted ANN block diagram

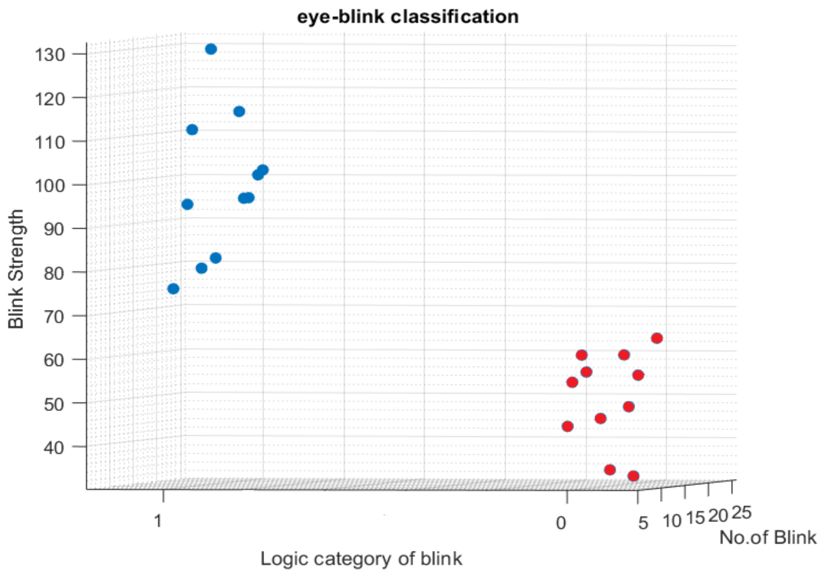

Figure 15. Distribution of collected eye-blink signals

Table 6. Eye-blink code commands

Motion	Eye-blink code
Takeoff	1111
Land	0000
Up	1001
Down	0110
Forward	1110
Backward	0001
Right	0011
Left	1100
Stop	1010

3.3.2. eSense attention meter classification

The attention levels' data to be collected is determined by performing tests to five individuals for three different time intervals as illustrated in Figure 16. From the Figure 3.9-a, it can be seen that the best interval for collecting attention levels' data can be defined as 10 sec. After 10 sec time is exceeded irregular fluctuations start occurring due to the lack of concentration of the individuals under test.

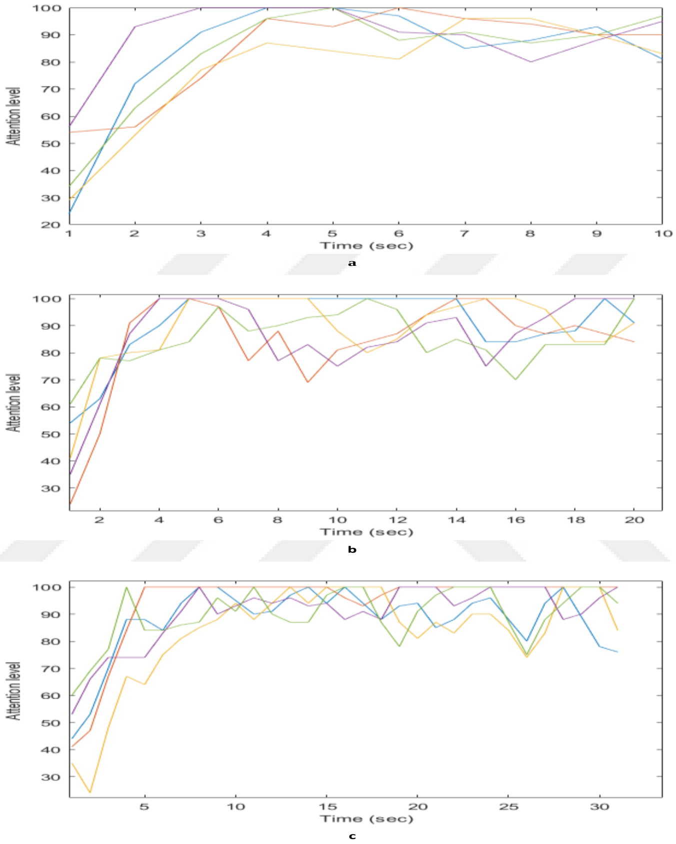

Figure 16. Attention level of the five individuals (a) 10 sec interval, (b) 20 sec interval, (c) 30 sec interval.

After data collection, LRM is applied to locate the threshold value of the attention level. The LRM is a statistical method to give the best linear approximation of the experimental data through the relationships between two continuous variables or factors as presented in Figure 17(Apprey-Hermann, 2020). It is used here to give the dynamic threshold value for the attention level according to the collected data in Table 7. The general form of the LRM equation is given by:

$$y = ax + b \qquad (9)$$

where, y is the dependent variable, x is the independent variable, a is the slop, and b is the y intercept.

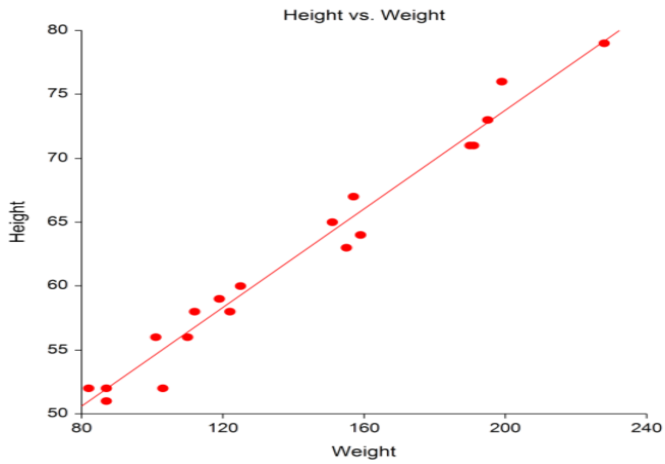

Figure 17. Linear Regression Method concept (Linear Regression and correlation, n.d, Chapter 300).

Table 7. Calculation of LRM constants

x_i	y_i^{I}	y_i^{II}	y_i^{III}	y_i^{IV}	y_i^{V}	$\bar{y}_i$	x_i^2	$x_i\bar{y}_i$
1	34	24	54	29	56	39.4	1	39.4
2	63	72	56	53	93	67.4	4	134.8
3	83	91	74	77	100	85	9	255
4	96	100	96	87	100	95.8	16	383.2
5	100	100	93	84	100	95.4	25	477
6	88	97	100	81	91	91.4	36	548.4
7	91	85	96	96	90	91.6	49	641.2
8	87	88	94	96	80	89	64	712
9	90	93	90	90	88	74.2	81	667.8
10	97	81	90	83	95	89.2	100	892
11	81	84	97	96	100	93	121	1023

The constants a and b are calculated using the collected data as follows

$$a = \frac{(\sum_{i=1}^{N} \overline{y_i})(\sum_{i=1}^{N} x_i^2) - (\sum_{i=1}^{N} x_i)(\sum_{i=1}^{N} x_i \overline{y_i})}{N(\sum_{i=1}^{N} x_i^2) - (\sum_{i=1}^{N} x_i)^2} \qquad (10)$$

$$b = \frac{N(\sum_{i=1}^{N} x_i \overline{y_i})(\sum_{i=1}^{N} x_i)(\sum_{i=1}^{N} \overline{y_i})}{N(\sum_{i=1}^{N} x_i^2) - (\sum_{i=1}^{N} x_i)^2} \qquad (11)$$

where, x_i is data collection time, $\overline{y_i}$ is the average of the experimental attention levels of the five individuals and N is the number of reading; here equal to 11.

After the calculation of a and b, the dynamic threshold equation of attention level is given by:

$$Y = 3.2016\,X + 65 \qquad (12)$$

The static attention level threshold is determined to be 85 based on the recorded experiment for an observation period of 10 sec, which are shown the attention level of the five individuals stabilizes over the 85 value after 3 to 4 sec in critical linearity way. The improvement in the attention level identified by the dynamic threshold compared to that of the static threshold (y = 85) is shown in The Figure 18, and the comparison between the two thresholds is given in Table 8. The dashed red line in the figure shows the pattern of the dynamic threshold whereas the black one represents the static threshold.

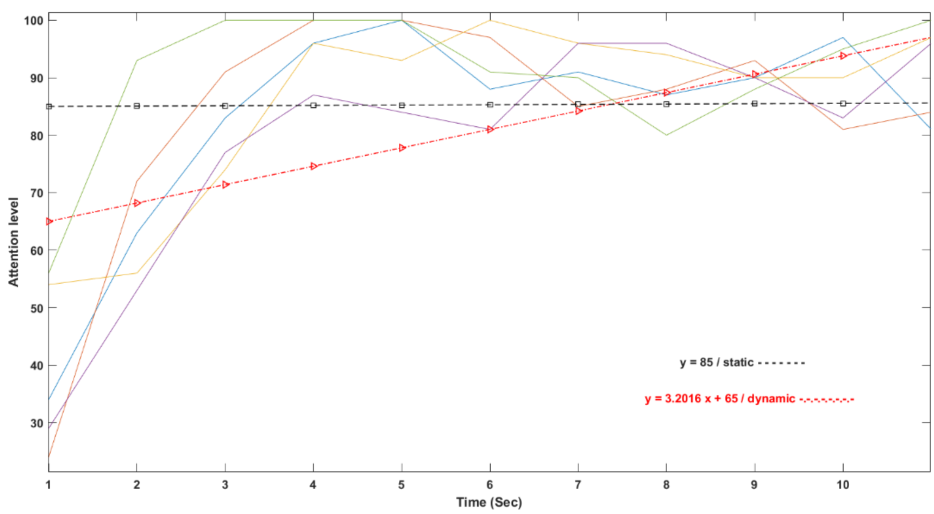

Figure 18. Dynamic and static thresholds of attention levels

Table 8. Comparison of threshold types

Time	Static threshold						Dynamic threshold				
	y1	y2	y3	y4	y5		y1	y2	y3	y4	y5
1	34	24	54	29	56		34	24	54	29	56
2	63	72	56	53	93		63	72	56	53	93
3	83	91	74	77	100		83	91	74	77	100
4	96	100	96	87	100		96	100	96	87	100
5	100	100	93	84	100		100	100	93	84	100
6	88	97	100	81	91		88	97	100	81	91
7	91	84	96	96	90		91	84	96	96	90

*cells in red present faulty readings of attention level

The left part of the table is for static threshold and the right one is for the dynamic threshold. These values demonstrate a clear improvement by using dynamic threshold derived from LRM because it gradually adapts to the attention level changes during time for all individuals. The working mechanism of the attention level going to be adopted for controlling is be as follow; the attention level must be greater than the dynamic threshold for three seconds to achieve positive attention level (1-logic). The table shows that in the case of static threshold, one individual out of five (y4) fails to get this requirement in contrast to the dynamic threshold case accomplishing without fails. Also, the dynamic threshold results show higher number, constant, and homogeneous distribution for the positive threshold check, which is important for algorithm reliability.

3.4.Algorithm Development and Implementation

Binary codes from the attention level (1-bit) and the eye-blink (4-bit) are exploited to develop two algorithms based on two controlling layers as depicted in Figures 19 and Figure 20. The first control layer uses eye-blink code, while the second control layer uses the attention level code. For the algorithm one, the first control layer is adopted to perform the frequent motions (left, right, stop, up, and down) whereas both layers are adopted for implementing the important and critical motions (forward, backward, and takeoff) in a successive manner. With regard to the algorithm two, the first layer is adopted to perform the stop motion whereas both layers are adopted to perform the rest of the motions (takeoff, land, up, down, left, right, forward, backward) in a successive manner. The first active eye-blink triggers a timer for 5 seconds to generate an eye-blink code. Then, related to the motion to be performed, the attention level can be detected during an observation period of 7 seconds. If the attention level is greater than the detected dynamic threshold during 3 seconds the second control layer is executed otherwise the device proceeds with the current motion.

The GUI is designed to project video feedback screen with visual stimulators in order to provide an information about the location and the status of the drone to the user and clarify the work mechanism' of the layers separately and sequentially as shown in the Figure 21.

The presented algorithms are used to control various motions of a drone according to generated codes from mind signals. As soon as the devices are connected, the drone is ready to receive the takeoff command using both control layers. After takeoff, the drone is on hold to take the next movement commands. After receiving 0000 eye-blink code for landing, the drone goes down and after a 15-second wait time the device turns off.

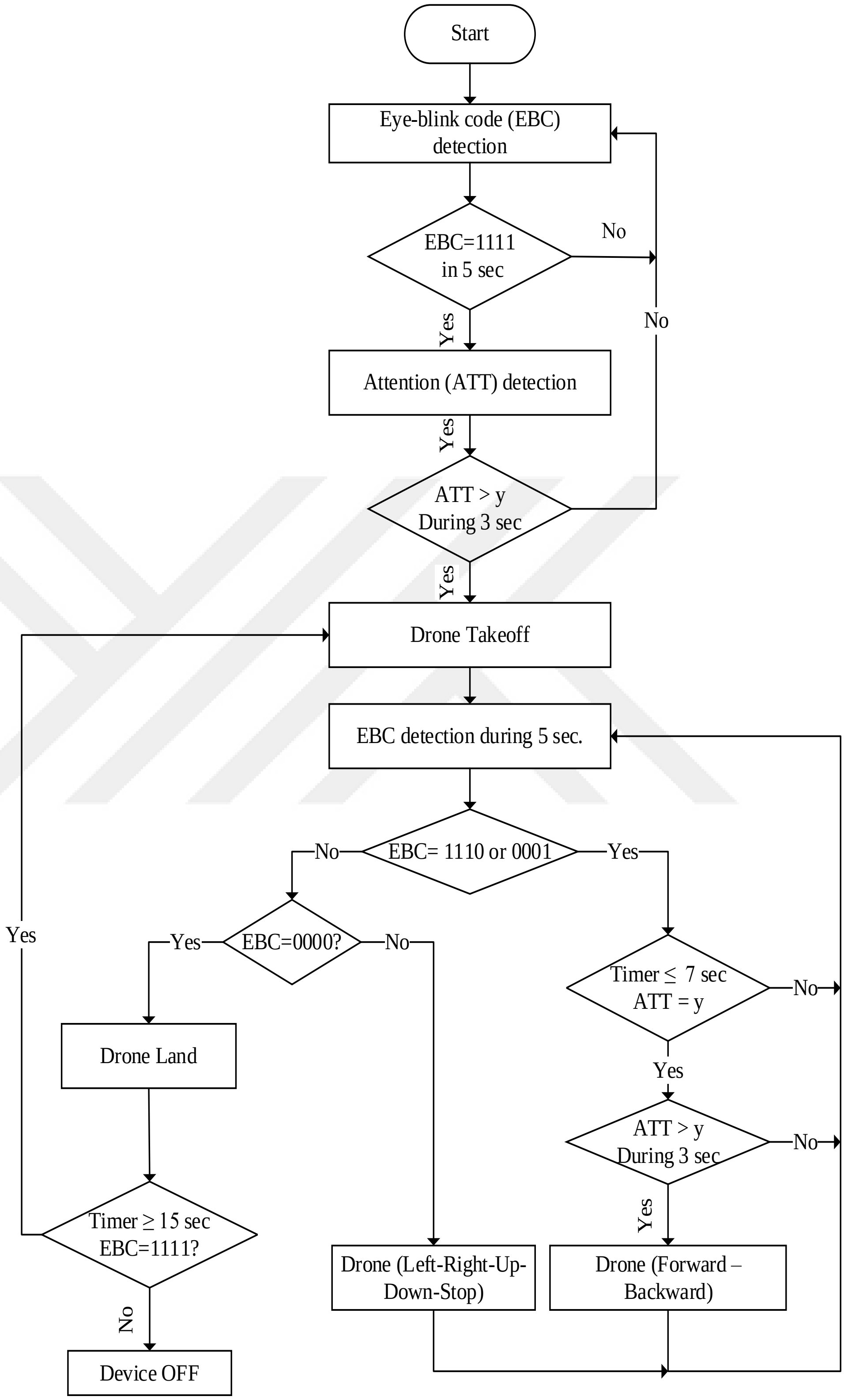

Figure 19. Drone control algorithm-one

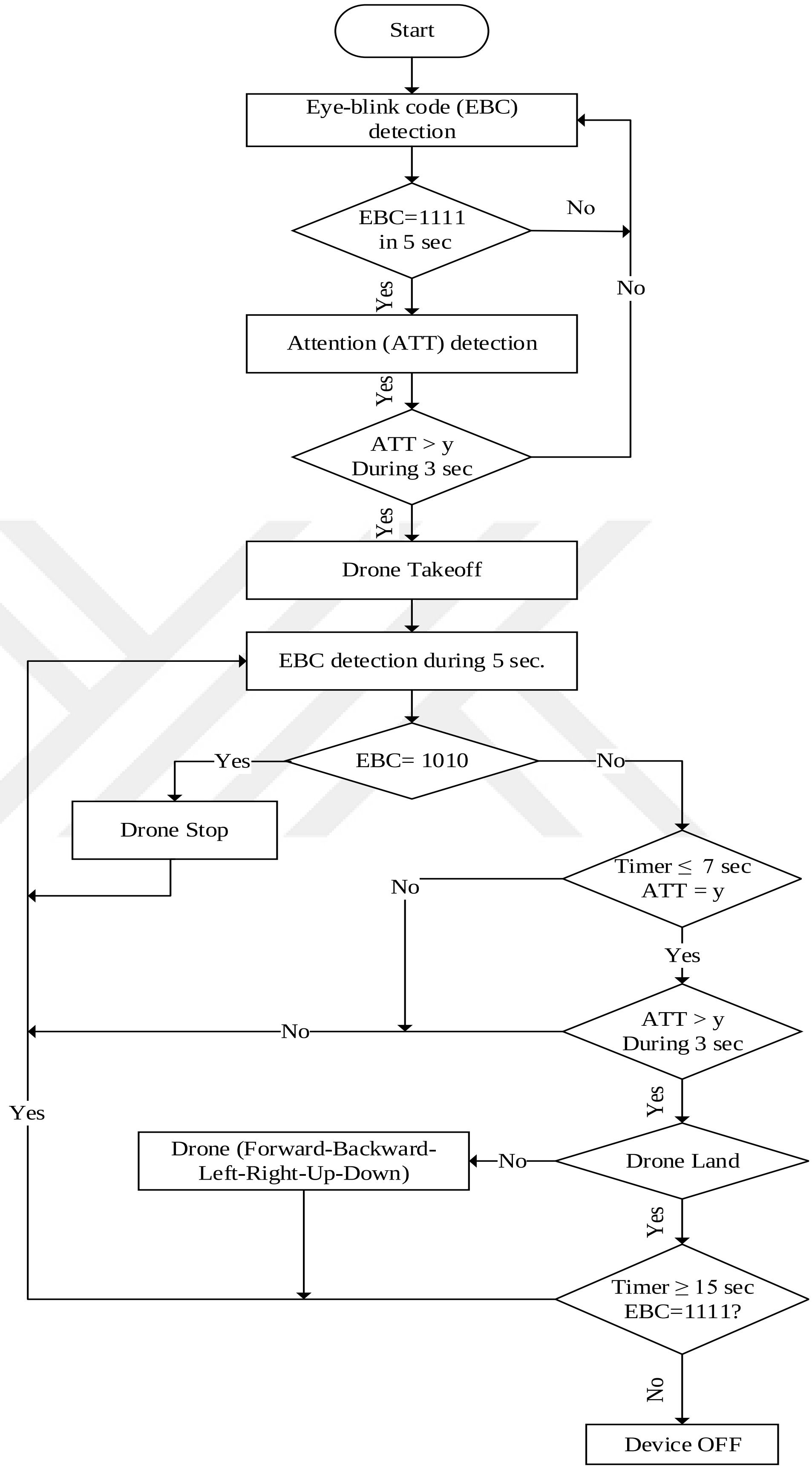

Figure 20. Drone control algorithm-two

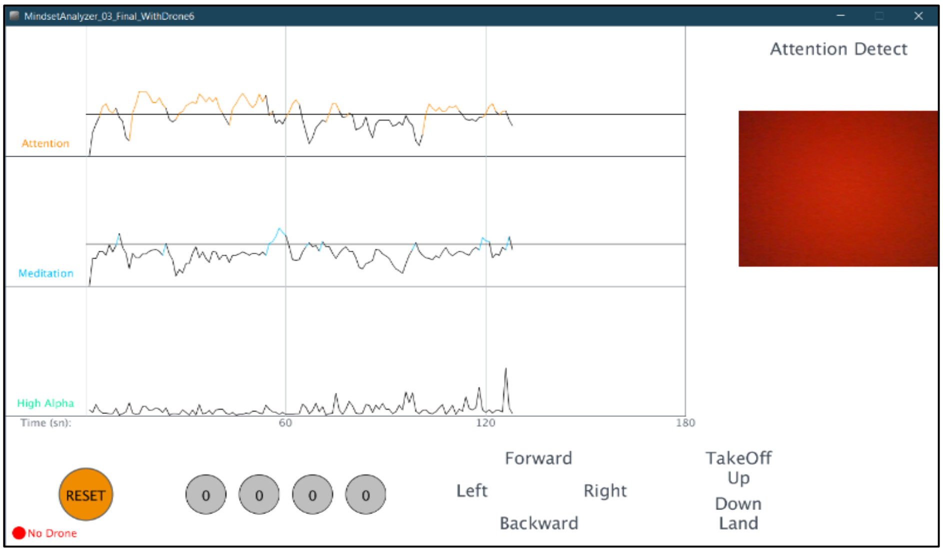

Figure 21. Designed GUI for projecting of drone controlled

CHAPTER FOUR
DRONE CONTROL IMPLEMENTATION

4.1.General

This chapter presents the practical experiments of the adopted algorithms, and discusses the obtained results from the experiments. Finally, comparing the obtained results with the recent works.

4.2.Experimental Results

The evaluation of the two algorithms is carried out by including individuals with ages between 20-30 in the test experiment. The individuals are placed in a comfortable position and in a quiet environment free from negative factors. The two algorithms follow same testing procedure by requiring participants to make three attempts for each movement, and the average time for the movement performed is calculated.

4.2.1. First experiment.

The evaluation performance of the algorithm-one in controlling the drone is presented in this section. The participants exhibit different average times for mental attentiveness and eye-blinking speed as shown in Table 9. In Figure 22 the average elapsed time required to perform each motion is presented. Note that the average times of eye-blinking and attention level code generations based on Table 9 and Figure 22 are determined as 5, and 10 seconds (7 seconds for threshold detection and 3 seconds for obtaining the code), respectively. The experimental results for the performance accuracy of all motions are shown in Table 10. Also, the table gives the average accuracies obtained for each motion and each participant in the test experiment.

Table 9. Average elapsed time for each individual / algorithm-one

Motion	S1	S2	S3	S4	S5
Stop	3	3.8	4	3.5	3.7
Land	3.7	3.63	4.4	3	4
Up	4	3.31	3	3	4
Down	3.82	3.8	4	3.45	3.2
Right	4	3	3.7	4.2	3
Left	3	4.3	3.6	3.4	4.2
Takeoff	12.4	12.2	11.6	11.3	13
Forward	11.87	11.6	12	12.43	12.77
Backward	12.8	12	11.75	11.5	11.9

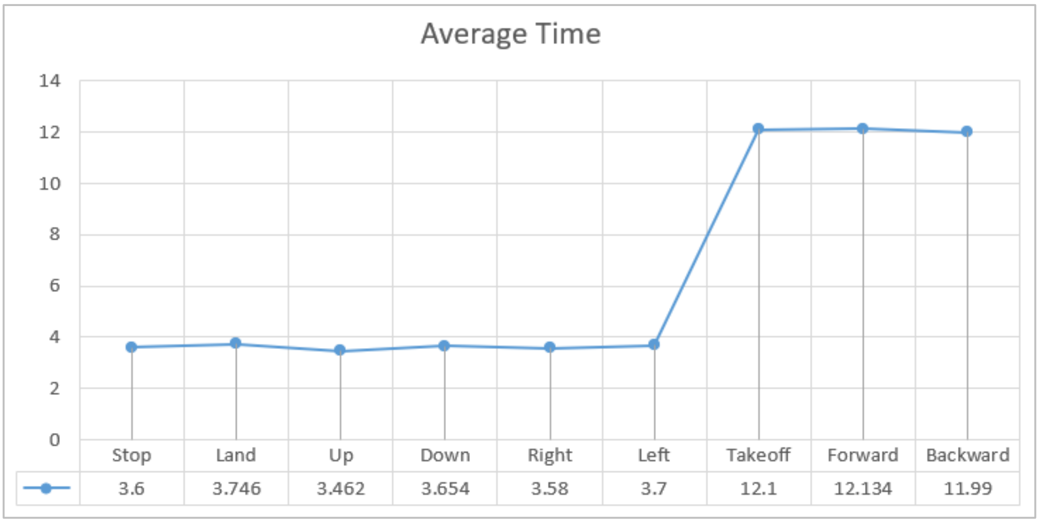

Figure 22. Average elapsed time for each motion / algorithm-one

Table 10. Drone control algorithm-one accuracy

motion \ subject	S1	S2	S3	S4	S5	accuracy per motion
Takeoff	2|3	3|3	3|3	3|3	3|3	93.33%
Land	3|3	2|3	3|3	3|3	3|3	93.33%
Up	3|3	3|3	2|3	3|3	3|3	93.33%
Down	3|3	2|3	3|3	3|3	2|3	86.67%
Right	3|3	3|3	2|3	3|3	3|3	93.33%
Left	3|3	3|3	3|3	2|3	3|3	93.33%
Forward	3|3	2|3	3|3	3|3	3|3	93.33%
Backward	3|3	3|3	3|3	2|3	2|3	86.67%
Stop	3|3	2|3	3|3	3|3	3|3	93.33%
	96.29%	85.18%	92.59%	92.59%	92.59%	91.85%

The total movements under the test are 15 (three per person). The Takeoff motion shows 14 out of 15 success-controlled attempts with 93.33% accuracy. This result is repeated for land, up, right, left, and forward motions. The down motion shows 13 out of 15 success-controlled attempts with 86.67 % accuracy. This result is repeated for backward. The total average control accuracy per participant is between 96.28% and 85.18%, and the total average performance of all movements is about 91.85%.

4.2.2. Second Experiment

In second experiment, the evaluation performance of the algorithm-two is presented. In the Table 11, the different times for attention level and eye-blinking speed detection is listed, and the average elapsed time required to perform each motion is presented in the Figure 23. Note that the average times of eye-blinking and attention level code generations based on Table 11 and Figure 23 are determined as 5, and 10 seconds (7 seconds for threshold detection and 3 seconds for obtaining the code), respectively. The experimental results for the performance accuracy of all motions are shown in Table 12. Also, the table gives the average accuracies obtained for each motion and each participant in the test experiment.

Table 11. Average elapsed time for individual / algorithm-two

Motion	S1	S2	S3	S4	S5
Takeoff	13.5	11.8	11	12	13.4
Land	10.43	12.66	13	11.3	12.6
Up	12	10	11	12.42	11
Down	11.67	12	14	11.55	11.3
Right	11	11.5	10.88	11	10.7
Left	10.67	13	11.7	10.95	11
Forward	12.33	13	10.3	12.3	10.87
Backward	11.67	11.23	10	12	10.95
Stop	3	3.8	4	3.5	3.7

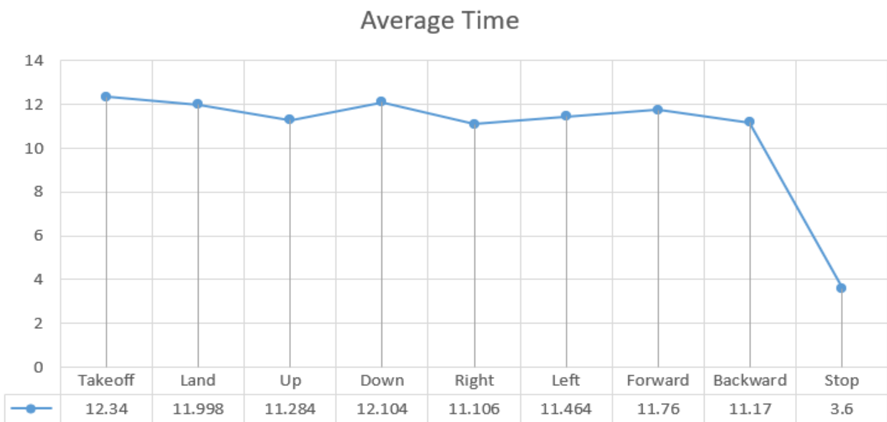

Figure 23. Average elapsed time for each motion / algorithm-two

Table 12. Drone control algorithm-two accuracy

motion \subject	S1	S2	S3	S4	S5	accuracy per motion
Takeoff	3|3	3|3	3|3	2|3	3|3	93.33%
Land	3|3	3|3	3|3	3|3	2|3	93.33%
Up	2|3	3|3	3|3	3|3	3|3	93.33%
Down	3|3	2|3	2|3	3|3	3|3	86.67%
Right	2|3	3|3	3|3	3|3	3|3	93.33%
Left	3|3	3|3	3|3	2|3	2|3	86.67%
Forward	3|3	2|3	2|3	3|3	3|3	86.67%
Backward	3|3	2|3	3|3	3|3	2|3	86.67%
Stop	3|3	2|3	3|3	3|3	3|3	93.33%
	92.59%	92.59%	85.18%	92.59%	88.89%	90.37%

The total movements under the test are 15 (three per person). For example, the Takeoff motion shows 14 out of 15 success-controlled attempts with 93.33% accuracy. This result is repeated for land, up, right, and stop. The down motion show 13 out of 15 success-controlled attempts with 86.67 % accuracy. This result is repeated for backward, and forward. The total average control accuracy per participant is between 92.59% and 85.18%, and the total average performance of all movements is about 90.37%.

4.3.Results Comparison

The comparison of the developed algorithms with the previous works in terms of commands issued, control layer, error rate, and accuracy, is shown in Table 13.

Table 13. Comparison of performance of different algorithms

	No. of commands	Control layer	Error rate	Accuracy
First experiment	15	One -Two	8.15%	91.85%
Second experiment	15	One -Two	9.63%	90.37%
(Awais, 2020)	4	Two	17%	83%
(Permana, 2019)	4	One	45%	55%
(Rahmania, 2019)	3	One	18.33%	81.67%
(Mansour & Ouda, 2019)	3	One	33.33%	66.67%
(Tiwari et al, 2020)	3	One	NA	NA

The results show that the proposed algorithms with 91.85% and 90.37% accuracies, have a much higher performance than the others. In additional, the number of commands controlling the movements of the drone has been significantly increased.

CHAPTER FIVE
CONCLUSIONS AND FUTURE WORK

5.1. Conclusions

The people suffering from spinal injury or reductions of motor skills will have the ability to perform tasks and communicate with the society by using BCI system. New algorithms using EEG waves collected and transferred by a BCI system are presented. The proposed algorithms are developed to control the movements of a drone by eye-blinking and attention level signals. NeuroSky device with single channel and dry sensitive electrode is used to extract the brain waves signal from scalp and transmit to the computer via Bluetooth unit. The algorithms are configured with two control layers. The first layer uses eye-blink signals classified by a SVM and generated as 4-bit code by an ANN. The second layer categorizes the attention levels with 1-bit code by specifying a dynamic threshold with LRM. The algorithms are validated by a test experiment using single channel NeuroSky module. The proposed algorithms show a high performance with 91.85% and 90.37% accuracies. Moreover, the algorithms offer a capability of performing 16 commands making it suitable for various applications.

5.1 Future Works

The following suggestion can be taken in consider to develop the work presented in this study.

1- In military field by adding radar for the drone in order to avoid the enemy attacks.
2- Employ meditation level as an alert indicator in order to record a report of the mental state to provide stable controlling.
3- In medical field by helping the patients to control the applications such as wheelchair, robotic arm, keyboard and printing the characters.

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ANNEXES

ANNEXES A. MATLAB Support Vector Machine algorithm

```
function [trainedClassifier, validationAccuracy] =
trainClassifier(trainingData)
% [trainedClassifier, validationAccuracy] =
trainClassifier(trainingData)
% returns a trained classifier and its accuracy.
This code recreates the
% classification model trained in Classification
Learner app. Use the
% generated code to automate training the same
model with new data, or to
% learn how to programmatically train models.
%
%  Input:
%      trainingData: a table containing the same
predictor and response
%       columns as imported into the app.
%
%  Output:
%      trainedClassifier: a struct containing the
trained classifier. The
%       struct contains various fields with
information about the trained
%       classifier.
%
%      trainedClassifier.predictFcn: a function to
make predictions on new
%       data.
%
%      validationAccuracy: a double containing the
accuracy in percent. In
%       the app, the History list displays this
overall accuracy score for
%       each model.
%
% Use the code to train the model with new data.
To retrain your
% classifier, call the function from the command
line with your original
% data or new data as the input argument
trainingData.
%
```

```
% For example, to retrain a classifier trained
with the original data set
% T, enter:
%   [trainedClassifier, validationAccuracy] =
trainClassifier(T)
%
% To make predictions with the returned
'trainedClassifier' on new data T2,
% use
%   yfit = trainedClassifier.predictFcn(T2)
%
% T2 must be a table containing at least the same
predictor columns as used
% during training. For details, enter:
%   trainedClassifier.HowToPredict

% Auto-generated by MATLAB on 21-Dec-2020 14:04:43


% Extract predictors and response
% This code processes the data into the right
shape for training the
% model.
inputTable = trainingData;
predictorNames = {'Blink'};
predictors = inputTable(:, predictorNames);
response = inputTable.type;
isCategoricalPredictor = [false];

% Train a classifier
% This code specifies all the classifier options
and trains the classifier.
classificationSVM = fitcsvm(...
    predictors, ...
    response, ...
    'KernelFunction', 'linear', ...
    'PolynomialOrder', [], ...
    'KernelScale', 'auto', ...
    'BoxConstraint', 1, ...
    'Standardize', true, ...
    'ClassNames', categorical({'Slight';
'Strong'}));

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:,
predictorNames);
```

```
svmPredictFcn = @(x) predict(classificationSVM,
x);
trainedClassifier.predictFcn = @(x)
svmPredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'Blink'};
trainedClassifier.ClassificationSVM =
classificationSVM;
trainedClassifier.About = 'This struct is a
trained model exported from Classification Learner
R2019a.';
trainedClassifier.HowToPredict = sprintf('To make
predictions on a new table, T, use: \n  yfit =
c.predictFcn(T) \nreplacing ''c'' with the name of
the variable that is this struct, e.g.
''trainedModel''. \n \nThe table, T, must contain
the variables returned by: \n  c.RequiredVariables
\nVariable formats (e.g. matrix/vector, datatype)
must match the original training data.
\nAdditional variables are ignored. \n \nFor more
information, see <a
href="matlab:helpview(fullfile(docroot, ''stats'',
''stats.map''),
''appclassification_exportmodeltoworkspace'')">How
to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right
shape for training the
% model.
inputTable = trainingData;
predictorNames = {'Blink'};
predictors = inputTable(:, predictorNames);
response = inputTable.type;
isCategoricalPredictor = [false];

% Perform cross-validation
partitionedModel =
crossval(trainedClassifier.ClassificationSVM,
'KFold', 5);

% Compute validation predictions
[validationPredictions, validationScores] =
kfoldPredict(partitionedModel);
```

```
% Compute validation accuracy
validationAccuracy = 1 -
kfoldLoss(partitionedModel, 'LossFun',
'ClassifError');
```

ANNEXES B. MATLAB Artificial Neural Network (ANN) code

```
function [Y,Xf,Af] =
myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation
function.
%
% Auto-generated by MATLAB, 21-Dec-2020 19:43:57.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these
arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 1xQ matrix, input #1 at
timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at
timestep ts.
%
% where Q is number of samples (or series) and TS
is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = 32;
x1_step1.gain = 0.0204081632653061;
x1_step1.ymin = -1;
```

```
% Layer 1
b1 = [16.849994941240371 56;13.745122789286884 31;-
10.691032556924428221;-
7.653162960198578 4461;4.695803336860346 4552;-
1.5739335747245091213;2.3407626088064246161;3.9188
40682064241853 8;-7.5740803098497471169;-
10.703589746677687 7;13.662259150088395643;-
16.893687341665025059];
IW1_1 = [-16.750005059728543699;-
16.800331831279557093;16.799948533266725548;16.792
94945616195988 7;-
16.767623312400029789;16.787946688524773009;16.739
247517797114284;17.567313945506885631;-
16.815219774512712547;-
16.786131561316835814;16.859732667190726829;-
16.707465868930828634];

% Layer 2
b2 = 0.31840314317402917954;
LW2_1 = [-0.58102547356635192433
0.47022438442524200353 0.20041390174049411588
0.0088254561548415377814 0.0035120749790415253799
0.0064985425505877519869 -0.095995941324274330908
1.1001639980151693976 0.012572931627286763195 -
0.0040480726233702319511 -
0.00025866624594574896216 -3.4058863992268318 82e-
05];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 2;
y1_step1.xoffset = 0;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
    Q = 0;
```

```
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    Xp1 = mapminmax_apply(X{1,ts},x1_step1);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing
Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-
```

```
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

ANNEXES C. IDE Processing + algorithm-one: eye-blink code commands

```
void commandsFunction() {
  if (eyeSet(1,1,1,1)) {
 order = "Takeoff";    /////////// forward Attention_Detect
  }
  if (eyeSet(0, 0, 0, 0)) {
      sendTelloCommand("land");
    isLand = true;
}
   if (eyeSet(1, 0, 0, 1)) {
    sendTelloCommand("up ");
    isUp = true;
   }
  if (eyeSet(0, 1, 1, 0)) {
    sendTelloCommand("down ");
    isDown = true;
  }
   if (eyeSet(1, 1, 0, 0)) {
    sendTelloCommand("left ");
    isTurnLeft = true;
  }
  if (eyeSet(0, 0, 1, 1)) {
    sendTelloCommand("right");
    isTurnRight = true;
  }
```

```
    if (eyeSet(1, 0, 1, 0)) {
        sendTelloCommand("Stop");
        isStop = true;
     }
     if (eyeSet (1,1,1,0)){
      order = "forward";    /////////// forward Attention_Detect
     }
     if (eyeSet ( 0,0,0,1)){
       order = "backward";  /////////// backward Attention_Detect
     }
     }
```

ANNEXES D. IDE processing + algorithm-two: eye-blink code commands

```
    void commandsFunction() {
 if (eyeSet(1, 1, 1, 1)) {
  order = "takeoff";        /////////// Attention_Detect
 }
 if (eyeSet(0, 0, 0, 0)) {
   order = "land";        /////////// Attention_Detect
}
 if (eyeSet(1, 0, 0, 1)) {
    order = "up";        /////////// Attention_Detect
  }
 if (eyeSet(0, 1, 1, 0)) {
    order = "down";        /////////// Attention_Detect
 }
  if (eyeSet(1, 1, 0, 0)) {
   order = "left";        ///////////  Attention_Detect
 }
```

```
 if (eyeSet(0, 0, 1, 1)) {
   order = "right";       /////////// Attention_Detect
 }
if (eyeSet (1, 1, 1, 0)){
 order = "forward";    ///////////  Attention_Detect
}
if (eyeSet ( 0, 0, 0, 1)){
  order = "backward";  ///////////  Attention_Detect
}
  if (eyeSet(1, 0, 1, 0)) {
   sendTelloCommand("stop");
   isStop = true;
  print("Stop");
  }
}
```

ANNEXES E. IDE Processing + Attention Detection Code

```
 if (order== "involved_motion") {
firstTimer.countUp();
isAttention_Detect = true;
if(time == 6){
 order = "time_off";
}
if (attValue > 65 ){
 order = "????_start";
 isAttention_Detect = false;
}
 if (order == "time_off"){
      starttimer_off.stop_timer();
  firstTimer.reset();
}
```

```
if (order == " involved_motion _start" ) {
  secondTimer.countUp();
  firstTimer.reset();
  if ( time == 3){
    sendTelloCommand("involved_motion ");
        //println("involved_motion ");
     isForward = true;
              order = " involved_motion _stop";
}
 if (attValue < 60 && time < 4) {
     order = " involved_motion _stop";
}
   if (order == " involved_motion _stop"){
      starttimer_off.stop_timer();
     secondTimer.reset();
}
  }
```

RESUME

Personal Information

Surname, name : Ali Hussein ABDULWAHHAB

Nationality : Iraq

Education

Degree	Education Unit	Graduation Date
Master	Electrical-electronic engineering	2021
Bachelor	Electrical engineering	2016/2017
High School	Al-nahriyn school	2012

Work Experience

Year	Place	Title
2017-2018	Baghdad-Iraq	Site engineering

Foreign Language

Arabic - English

Publications

1- *Fusing stereo images into its equivalent cyclopean view*

2- *Drone Manipulation by Electroencephalography Signals based on BCI system (Submitted)*