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BCI-DRONE CONTROL BASED ON THE CONCENTRATION LEVEL AND EYE BLINK SIGNALS USING A NEUROSKY HEADSET

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ABSTRACT

Brain neurons activate Human movements by producing electrical bio-signals. Neuron activity is used in several technologies by operating their applications based on mind waves. The Brain-Computer Interface (BCI) technology enables a processor to connect with the brain using a signal received from the brain. This study proposes a drone controlled using EEG signals acquired by a Neurosky device based on the BCI system. Two active signals are adapted for controlling the drone motions: concentration brain signals portrayed by attention level and the eye blinks as an integer value. A dynamic classification method is implemented via a Linear Regression algorithm for attention-level code. The eye blinking generates a binary code to control the drone's motions. The accuracy of this code is improved through Artificial Neural Networks and Machine Learning techniques. These codes (attention level and eye blink codes) drive two controlling layers and manipulate nine possible drone movements. The experiment was evaluated with several users and showed high performance for the classification methods and developed algorithm. The experiment shows a 90.37% accuracy control that outperforms most existing experiments. Also, the experiment can support 16 commands, making the algorithm appropriate for various applications.

KEYWORDS

Electroencephalogram; BCI system; Neurosky; Attention level; Eye blink.

1. INTRODUCTION

The human brain contains billions of neurons responsible for various actions and emotions. These neurons are invested in different technologies that allow them to carry out these actions (Peksa & Mamchur, 2023). In most cases, remote control performs specific tasks or controls an application. Researchers have been working to create a system to utilize the internal signals of the mind since Hans Berger's research on mental processes (Berger, 1929). BCI refers to communication technology that connects the brain and the computer (Dave et al., 2020). It employs two sensing techniques to identify the brain impulses transmitted to the computer (Guger et al., 2023). Invasive procedures are usually performed to get high-quality signals from the cerebral cortex using implanting electrodes (Levett et al., 2024). Conversely, the non-invasive technique requires fitting the electrodes into a mindset device without surgery (Islam & Rastegarnia, 2023). Every action the brain produces could be utilized as input data to operate numerous applications in gaming and medicine. There has been much interest in BCI development due to the tools needed to make it happen (Janapati et al., 2023). One of the most exciting topics that emerged was the control of a drone or wheelchair for individuals with disabilities, as shown in Fig. 1 (Gu et al., 2021).

A modular robot-configuration system (MRC) is presented by (Hasbulah et al., 2019). The system is controlled using an electroencephalogram (EEG) signal and a BCI system. The brain wave is then extracted using Neurosky mind wave 2. Based on Hand and Feet, the Imagery Motor is adapted to process incoming EEG signals in four directions. The MRC system is evaluated under two un-trained and trained subjects and shows 20% and 30% success rates, respectively.

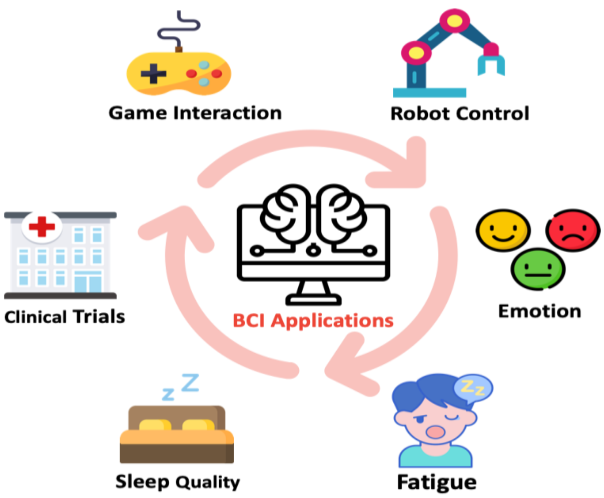

Fig. 1. BCI system applications

A chat application for helping disabled individuals using a Neurosky headset based on the BCI system is discussed by (Rușanu et al., 2020). One and double-eye blink signals are adopted for transiting and selecting the emoticon. The Authors use the MIP application inventor to implement the system. A home automation system that uses EEG signals is created using a Raspberry Pi and a Brain Waves-Detection algorithm (Raja et al., 2020). The system can be programmed to switch on and off various appliances by using attention and meditation signals. (Al-Wesabi et al., 2020) described using brain waves to operate an intelligent wireless wheelchair system to assist those with partial paralysis. EEG signals associated with meditation, attention, and eye blinks are recorded using Neurosky mind wave 2. The movement commands are distributed and recognized by an Arduino microcontroller. The accuracy of this system is equal to 95%. It uses brain signals to control a drone (Marin et al., 2020). These signals are acquired by using a headset that captures the brain waves EEG and a Raspberry Pi that recognizes the incoming signals.

A 3D-printed arm that uses brain waves has been proposed using BCI technology (Fuentes-Gonzalez et al., 2021). Neurosky Mind Wave 2 is utilized to acquire the EEG signals from the scalp user and three servo-motors to control the arm's fingers. Attention levels are used to control the movement of the arm. The system can close/open the hand's motions with a force equal to 11 N. A Gok-Evolution App game using an Attention level based on the BCI system is designed by (Serrano-Barroso et al., 2021). The attention level is acquired using a Neurosky headset. It tests attention behavior in two groups, 52-not attention deficit hyperactivity disorder (ADHD) and 23 ADHD, which work on detecting attention levels to identify attention skills. The system shows the adopted ability in clinical as an early screening tool for detecting attention to developing attention skills driving Smart-Wheelchairs-System (SWS) based on the BCI system presented by (Khan et al., 2021).

Single-channel Neurosky is used to control the SWS. Arduino Uno is adopted to control the SWS's driving motors. Attention level is used to turn on the SWS's motors, and eye blinking is adopted to select the system directions. BCI system is adopted to design and control home applications using mind signals (Nasir et al., 2021). A neurosky device is utilized to detect mind waves. Attention level and eye blink parameters are used to control the applications. The system shows high accuracy, equal to 90.67%, and can help disabled people. A teleportation system that uses a BCI system is designed to improve the control of a robot in a construction zone (Liu et al., 2021). It uses EEG headset devices to capture brain signals and generate digital commands. The system can direct the robots in underwater and space conditions with 90% accuracy. By (Chen et al., 2021), BCI systems are imitating paintings using brain signals. For this project, the Neurosky Mind Wave 2 uses a brain wave scanner to analyze and create an artwork featuring characters. The adopted system introduces visitors to Chinese culture by showcasing the country's traditional art. A prototype wheelchair was developed using BCI technology (Abuzaher & Al-Azzeh, 2021). It utilizes a Neurosky device and various components, such as an Arduino Mega and a pair of D.C. motors.

Implementing a BCI system for controlling drones using EEG signals is discussed by (Abdulwahhab et al., 2022). Attention levels with dynamic thresholds with double-eye blink are adopted for controlling nine drone motions. The experiment shows stable and highly accurate controlling with an error rate equal to 8.15%. The system can drive more than nine commands to reach 16. By (Shobana et al., 2022), a BCI system controlling a 3-DOF Robotic arm using an EEG signal is proposed. Neurosky single channel is used to control the arm's five motions. The three Neurosky output parameters (attention, meditation, and eye blink) are adopted for driving the arm motions. The system can help disabled individuals take things and implement their actions. Based on EEG signals, BCI-Home auto-motions controlling using Neurosky mind wave is presented by (Selvamathiseelan et al., 2022). An Arduino, relay, DC-Motor, and zero-watt bulb are used to design the BCI-Home system. Two con-trolling methods are adopted for controlling the home system: 2-sequentially eye blink and 3-sequentially eye blink, attention, and meditation. The system shows accuracy equal to 96.1 ± 3.92%. (Alsammarraie and Inan, 2022) designed the Car system using brain waves Based on the EEG signals discussed. Neurosky device detects EEG signals, and Arduino is used to classify the controlled command. D.C.- The motor is used to control the car system's speed. Double eye blinks and attention level is adopted for the controlled command. A smart home is designed and monitored using mind signals Based on the BCI system discussed by (Al-Canaan et al., 2022). A dual-channel EEG signal is used to detect the brain waves.

Multi-layer-perception machine learning and linear-discriminant analysis classify the collected EEG signals. The LDA classifier provides high performance with an accuracy of 95.66% and 96% for training and testing, respectively. (Calp et al., 2022) designed the Internet of Health-Things (IoHT) using EEG signals to control robot vehicles and help patients. Based on the BCI system is discussed. Deep learning and Artificial Neural Networks are widely used in medical applications (Abdulaal et al., 2024) (Talib et al., 2020) (Mohammed et al., 2022), primarily to process EEG signals (Abdulwahhab et al., 2024). Neurosky signal channel, Arduino, DC-motor, and 3-D printed robot car are used to design the experimental model. Attention level is used to control the model's movement, and meditation level is used to determine the model's information (location and sending SMS). The experiment shows an average ac-curacy equal to 99.5%. An intelligent room system using EEG signals to help disabled individuals control their rooms is discussed by (Anandika et al., 2023). Neurosky headset captures the EEG signals, concentration, mediation levels, and the eye-blink signal from the user's scalp. A node MCU microcontroller is used to design the system and control the received commands from the Neurosky device. The concentration, mediation, and eye-blink levels are adapted to drive the commands. (Janani et al., 2023) presented a wheelchair prototype based on the BCI system. The prototype system works in four directions; its control uses a Neurosky headset based on the level of attention and meditation and on the level of eye blinks. An Arduino microcontroller is used to control the derived commands from the head-worn device for the movement of the wheelchair prototype. Neurosky has been used to control the prosthesis arm, which has been based on the BCI system discussed by (Vo, 2023), where through attention and meditation levels, arm movements can be controlled. (Sheikh, 2024) discussed controlling smart applications based on the BCI system. Arduino UNO is used as a control unit for the application system, and the Neurosky device is used to read the eye-blinking strength and drive the control commands. The system achieved an accuracy control equal to 93.3% for four commands.

One of the most compelling applications for BCI technology in the world concerns implementing radically transformative assistive and modal technologies for those with physical disabilities or mobility limitations. These will be incredibly intuitive and non-invasive systems of control, obviating totally the need for traditional physical interfacing. Users can operate advanced equipment much quicker and more efficiently by taking advantage of neural signals—like piloting with drones, for example. It is a game-changer for mobility, not merely in access ways but also in the possibility of autonomy for users who have mobility difficulties. Finally, BCIs apply a new theoretical perspective on human-computer interaction to assistive technology, therefore allowing for more significant potential for the development of applications than reliance on traditional interfaces.

In this research, BCI-Drone Control Based on The Concentration Level and Eye Blink Signals Using a Neurosky Headset is presented. The main contribution is as follows;

1- Using Neurosky mindwave2 to capture the EEG single from the scalp of people with a single channel (Fp1)

2- Design a GUI to present the captured signals in real-time in order to analyze the signals.

3- Dynamic threshold is used for the attention level based on Linear Regression Method (LRM) to generate binary code 1/0

4- Derive four sequential logical bits from the Eye-blink signal using ANN and SVM

5- Using two layers for controlling the drone, the first layer is represented by the eye-blink (4-bits) for setting the movement, and the second layer is represented by the attention level single to run the set movement.

The paper is organized into five sections: the first covers basic concepts concerning the BCI system and wave classification by EEG; the second describes the methodology adopted; the third presents generic results about the study; the fourth summarizes findings from the research work; and the last concludes the study.

2. GENERAL FRAMEWORK

2.1. BCI System

The processing structure of a general BCI system consists of four phases: signal acquisition processing, translation method, signal feature extraction, and device command (Tiwari et al., 2020). The extraction of brain signals takes place in the first stage. The signals are recorded from the scalp of the user using multi-electrode arrays and sensors. After that, the signals are filtered to make them suitable for feature extraction. A feature extraction process identifies and classifies the signals. Once the analysis of the signals is provided, the translation algorithm changes these into commands that the user may need to use on his/her device (Tiwari et al., 2020).

2.2. Electroencephalogram (EEG)

EEG can be explained as a watch mechanism through which one can read and record brain signals. According to their electrical activity, three brain signals exist- Evoked Potentials or E.P., Spontaneous activity, and Bio-electric events generated via one neuron (Sloan et al., 2025). The most common non-invasive method for capturing spontaneous waves is EEG, which has advantages over other neuroimaging techniques because of its low cost, simplicity, speedy response, and adaptability (Jafari et al., 2023). According to the electrode map, the EEG headset records brain waves in several frequency bands using multiple channels. Typically, noise and other environmental factors impact EEG signals throughout the acquisition, causing signal distortion and a drop in SNR (Zhang et al., 2023).

2.3. Brain Waves Classification

Different brain parts produce various types of electric impulses (Conde et al., 2023). An electroencephalogram headset detects these signals and monitors their amplitude and frequency. Brain waves are categorized into five kinds according to verbs and emotions (Morshad et al., 2020).

- Delta waves' rhythm is between 0 and 3 hertz. They are produced when people are in deep sleep or meditation.
- Theta waves are produced when a person is in deep relaxation or meditation and have a range frequency between 4 and 7 hertz.

- The alpha waves are dominant in a person's state of relaxation and meditation. They also occupy a frequency range between 8 and 12 hertz.
- Beta waves are most likely to be produced when a person is in a state of alertness or energy, and they can be found in the 13 to 30-hertz range.
- Gamma waves are produced through a process that involves high-level processing. They have a frequency range between 31 and 100 hertz

3. METHODOLOGY

The Neurosky Company provides a TGAM module to process the brain signals sent by an electroencephalograph headset. It features a GUI that can be utilized to project and supervise the coming signals. In addition, the level of attention and the blinking of the eyes are also used to control a drone. The data are stored in an Excel database. To find the appropriate threshold value, a classification algorithm known as SVM uses machine learning to classify the collected eye blink information. It then trains a neural network to interpret the signals per the intensity of the blinking. The concentration of the test subject and the observation period are related to attention levels. A dynamic threshold is produced by classifying the attention level using the linear regression method (LRM). A total of 4 sequential blinks have been utilized to create 4-bit eye blink codes, which are combined with a level of attention for controlling the drone's movements. The block diagram regarding the chosen approach is depicted in Fig. 2.

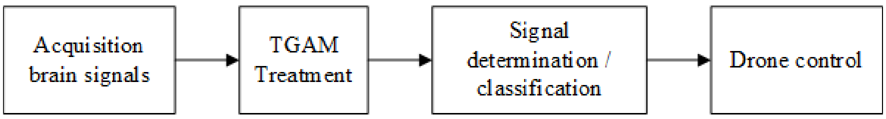

Fig. 2. Brain-drone interface block diagram

3.1. TGAM Model

Fig. 3 shows the TGAM module used in the Neurosky Mind Wave 2 system to process and extract brain signals. It features a single-channel electrode designed to capture the eye blink signal from the individual's scalp at the Fp1 position.

Fig. 3. EEG - Neurosky

The Neurosky TGAM is a brainwave sensor designed for mass-market applications. It features various functions, such as processing EEG signals, monitoring eyeblinks, attention, and meditation. The module has three pins: acquisition, reference, and brain signals. The difference between the acquisition and reference pins helps eliminate noise. The module has a 3.3 V supply to communicate with the Bluetooth device. The other two module pins are the R.X. and the T.X (Neurosky, 2015).

The capture stage usually causes weak signal processing and noise sensitivity of EEG signals. The TGAM module uses a pre-treatment circuit to filter the captured signals before they are sent to the P.C., as shown in Fig. 4.

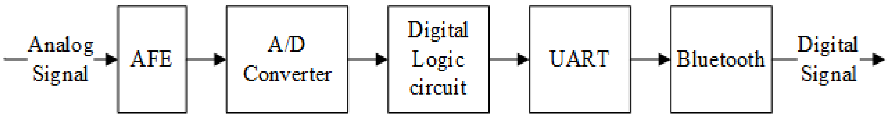

Fig. 4. TGAM Pre-treatment circuits

The pre-treatment circuit comprises an Analog front-end stage, an A/D converter (ADC), and a DLC (Digital Logic Circuit). The Analog Front End (AFE) stage is implemented via three processes: first, pre-amplifier to amplify the signal by x8000; second, analog and digital low and high pass filters to eliminate the 50/60 Hz Ac powerline interference and retain the signal with range 0.5-50 Hz, third; amplify the filtered singles with gain x2000 using post-amplifier. Once the AFE stage is done, the A/D converter stage starts to digitize the signals, and due to the finite resolution of the ADC, quantization noise arises during the digitizing process. Thus, The TGAM samples the filtered signal at 512 Hz and codes it with a resolution of 12 bits with a maximal input voltage equal to 1.8 V. The serial data of ADC is then outputted using the Universal Asynchronous receiver and transmitter (UART) Interface. This is done via a Bluetooth module (Zhang et al., 2017; Neurosky, 2014). Equation (1) is used to convert a raw ADC value to a voltage.

$$voltage = \frac{rawvalue \times \frac{V_i}{2^R}}{G} \quad (1)$$

where G represents the post-amplifier's gain, R represents resolution in bits of ADC, and Vi represents the maximal input voltage, which equals 1.8V.

3.2. Signals Presentation

After pre-treatment, the captured EEG single Neurosky mindwave provides protocol with several key outputs involving EEG RAW data, EEG power spectrums (delta, theta, alpha, beta, gamma), eSense meters, including attention and meditation, and eye-blink strength. The eSense meters use a developed algorithm provided by Neurosky to measure the attention level and mediation level based on the mental state. The level of attention is related to the person’s state of concentration and problem-solving and can be observed especially through changes in the beta value, while meditation is related to the person's state of relaxation and meditation and is evident in the theta values (Kadhim & Mohammed, 2021). Neurosky uses a special algorithm to derive the eye-blink strength from the EEG RAW data and represent it in an integer value range between 0-255. In this work, Attention level and eye-blink signals are used and represented in logic code to control the drone movements.

3.2.1. Attention Level

According to the (Nuys, 1973), human attention level cannot be maintained at a linear or semi-linear high level for a long time. People's attention drops after 10-15 seconds, resulting in irregular fluctuations. In order to accurately define the threshold of attention level, the linear regression (LRM) method is used to determine the threshold value of attention. This classification of aggregated attention levels provides a dynamic threshold that distinguishes strong attention levels from weak ones (binary 1 and binary 0). The LRM is integral to the statistical method representing a relationship between two factors or variables by providing the best linear approximation of experimental data. It can classify collected attention levels into binary-1 and binary-0 (Abdulwahhab, 2021). The genera l LRM equation's form is given by:

$$h = x\,T + y \tag{2}$$

Where h represents the dependent variable, x represents slope, T represents the independent variable, and y represents the y-intercept. The LRM equation's constants are calculated by considering the data collected (a and b) from the attention level.

$$x = \frac{(\sum_{i=1}^{N} \overline{h_i})(\sum_{i=1}^{N} T_i^2) - (\sum_{i=1}^{N} T_i)(\sum_{i=1}^{N} T_i \overline{h_i})}{N(\sum_{i=1}^{N} T_i^2) - (\sum_{i=1}^{N} T_i)^2} \tag{3}$$

$$y = \frac{N(\sum_{i=1}^{N} T_i \overline{h_i})(\sum_{i=1}^{N} T_i)(\sum_{i=1}^{N} \overline{h_i})}{N(\sum_{i=1}^{N} T_i^2) - (\sum_{i=1}^{N} T_i)^2} \tag{4}$$

The data collection process's average duration and the experimental number of readings are represented by T_i, h_i And N, respectively.

3.2.2. Eye Blink signals

The blink signal is used to derive four-bit logic and generate control commands based on the blink intensity. To define the accurate blink threshold, blinks are separated by a binary of 1, and off-blinks are separated by a binary of 0. In this task, the Support Vector Machine (SVM) algorithm is used to define the optimal blink intensity for classification to distinguish between blink on and off (Al-Ghrairi et al., 2022; Mohammed et al., 2023).

3.3. Proposed Algorithm

The algorithm is based on a multi-layer order. It divides the task into two control layers: The First Control Layer (FCL) by the eye blink codes represented by 4 binary bits - from 0000 to

1111 and the Second Control Layer (SCL) by the attention level binary code represented either by 1 or 0 activated by the eSense Attention meter (ATT), as shown in Fig. 5, and Fig. 6 illustrate the various components' works. The brain signals generated by the algorithm are then analyzed and programmed to control the drone's movements. It can be programmed to execute actions such as takeoff, landing, and moving forward. Each movement is carried out in a sequence using both layers, except for the stop motion, which is only executed using the EBC due to its importance. The drone generates the first blinking signal and can be programmed to generate an EBC for a duration of 5 seconds. The ATT is then detected after the drone has executed the movement. It can be programmed to detect the ATT greater than or equal to the detected "h" 7 seconds after the drone has executed the movement. For SCL, the ATT should be greater than the detected "h" during (3 seconds). After the devices have been linked, the drone will be ready to receive the Takeoff command. It waits for the next movement commands to be executed based on the user's intent. If the drone gets the land's command, "0000," it will automatically stop and turn off after 15 seconds.

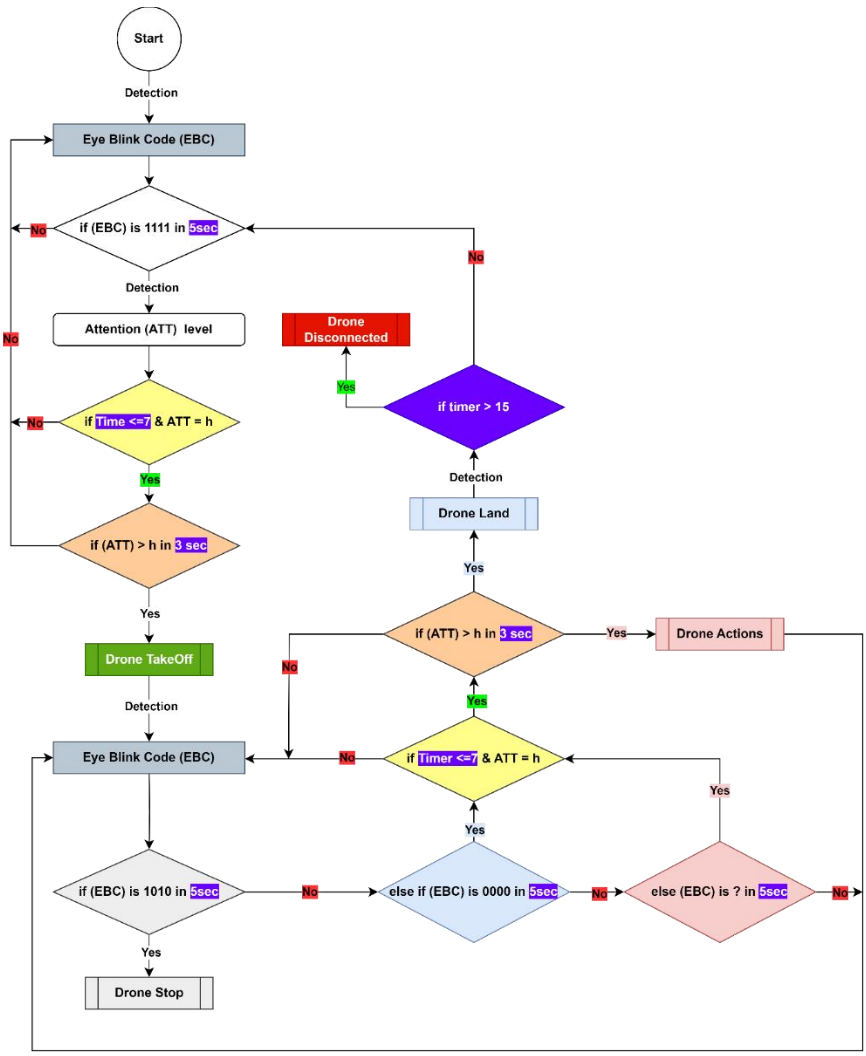

Fig. 5. Drone control algorithm

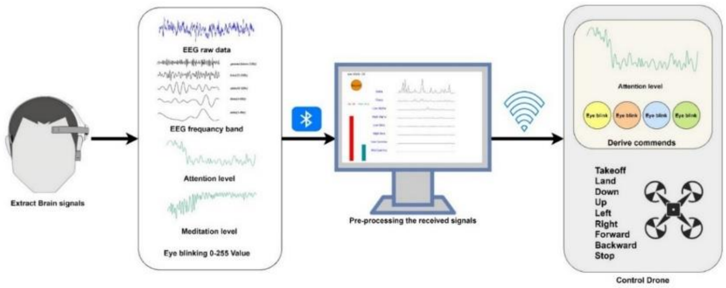

Fig. 6. Hardware components

4. EXPERIMENTAL AND DISCUSSION

This approach aims to evaluate the system's effectiveness practically. It is conducted in a quiet environment with no harmful influences.

4.1. attention threshold evaluation

Five people participated in collecting attention signal data in 11 sec, as shown in Table 1. The collected data are used to collect the attention threshold, and two types of thresholds are collected. First, the dynamic threshold based on LRM, as mentioned in section 3.2.1, the LRM constants based on the given equations in 2, 3, and 4, respectively, are measured using the collected data to confirm the level's dynamic threshold. After the calculation, the dynamic attention threshold value is set to 65, and it can be given as;

$$h = 3.0273T + 65 \quad (5)$$

second, the static threshold is selected to be 85 due to the stabilization of the attention level above 85 after the 3 sec in a critical linearity. According to the control method, it raises the attention level to achieve a higher value logic "1." This occurs by going over the threshold value (3 sec). The static threshold considers any attention value above 85 acceptable, while values below it are deemed unacceptable. Static thresholds are simple and easy to implement because they neither change with time nor adapt to variations in the dataset. This rigidity makes them computationally efficient, as they rely on straightforward comparisons with a fixed value. However, their inability to adapt to dynamic or variable environments often leads to inaccuracies, as evidenced by the higher number of faulty readings (Bold versus normal numbers) in Table 2. The dynamic threshold adjusts dynamically with real-time changes in the system or variations in context. Dynamic thresholds are not fixed like static thresholds; they learn from the trends in the attention level and do a self-recalibration of values. Because it is dynamic, dynamic threshold systems are capable of automatic readjustment according to any changes in the distribution of the data. It reduces the errors found during dynamic or noisy environments, as seen by the reduced number of faulty readings in Table 2. Dynamic thresholds, offering much higher accuracy and robustness toward evolving data, come at the cost of greater computational complexity. Dynamic systems have to operate on real-time analysis of data, constantly readjusting the threshold and updating the algorithms with the same. Despite these additions to the complexity, their ability to adapt to fluctuations in the levels of attention makes them particularly fit for environments with unpredictable or highly variable conditions. All in all, the choice between static and dynamic thresholds boils down to an issue of simplicity versus adaptability. Static thresholds, which are computationally inexpensive, are inflexible; their inflexibility makes them vulnerable to errors during dynamic conditions. While computationally costly, dynamic thresholds provide a more accurate way to classify the attention levels in a context-sensitive manner.

Table 1. Calculation of LRM constants

T_i	S_i^{I}	S_i^{II}	S_i^{III}	S_i^{IV}	S_i^{V}	$\bar{h}_i$	T_i^2	$T_i\bar{h}_i$
1	38	24	54	29	56	40.2	1	40.2
2	66	72	56	53	93	68	4	136
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

* S: Attention participants
* h: Average attention across the five participants
* T: Recoded time

Table 2. Comparison of the types of thresholds

	Static (85)					Dynamic				
T	S_i^{I}	S_i^{II}	S_i^{III}	S_i^{IV}	S_i^{V}	S_i^{I}	S_i^{II}	S_i^{III}	S_i^{IV}	S_i^{V}
1	38	24	54	29	56	38	24	54	29	56
2	66	72	56	53	93	66	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

*The Bold numbers present the faulty attention level readings

4.2. Eyeblink threshold evaluation

Five people are asked to blink six times to create six random blinking signals, as shown in Fig.7. The data collected by the algorithm is classified according to the intensity of the eye blink using SVM to set the threshold between the firm and slight reading as shown in Fig. 8. After defining the threshold, four sequential bits are generated randomly collected from different participants, and use as input for the ANN based on SVM threshold in order to logically sorts the collected information between "1" and "0" as shown in Fig. 9. According to the four bits, 16 commands are generated. An experimental test revealed that the code generation period for each participant is five seconds.

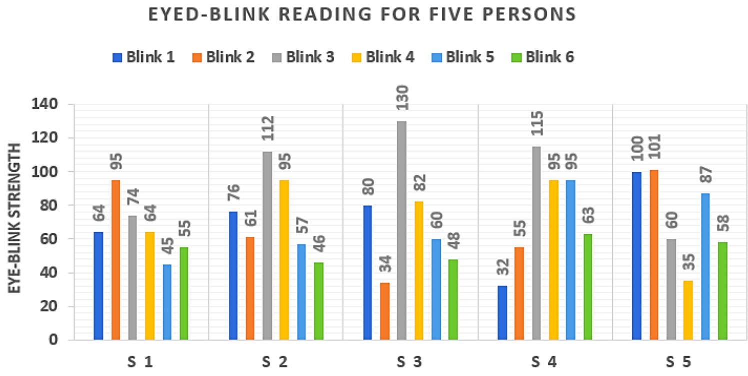

Fig. 7. Eyed-blink reading for five persons

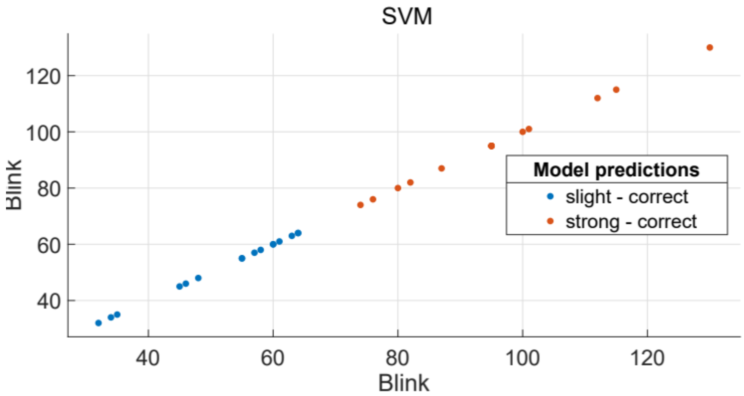

Fig. 8. SVM classification eye-blink reading.

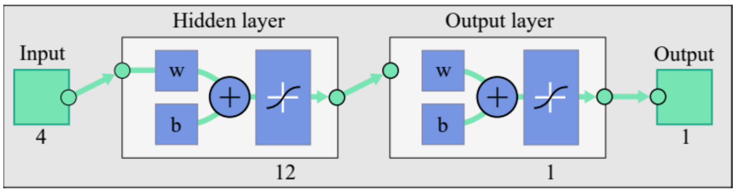

Fig. 9. Adopted ANN block.

4.3. Experiment result

The results of the drone control experiment using the Neurosky Mindwave 2-based Brain-Computer Interface (BCI) system are summarized in Table 3 and Table 4, highlighting the system's performance in terms of execution time and accuracy. Table 3 demonstrates that the "Takeoff" command required the longest average execution time (12.34 seconds), followed by "Land" (11.998 seconds) and "Down" (12.104 seconds), whereas "Stop" exhibited the shortest execution time (3.56 seconds), indicating a rapid response. Among directional commands, "Right" had the lowest execution time (11.016 seconds), while "Forward" required the most time (11.76 seconds). These variations likely reflect differences in cognitive effort, command complexity, and individual user factors, with commands like "Takeoff" and "Land" requiring greater focus and precision, while simpler commands such as "Stop" involved less mental effort. Table 4 highlights the accuracy of the BCI system, which averaged 90.37% across all movements, with commands like "Takeoff," "Land," and "Up" achieving the highest accuracy (93.33%). At the same time, "Down" and "Left" recorded slightly lower accuracy for certain subjects, with a minimum accuracy of 85.18% observed for "Down" by S3. Significantly, the generally poorer performance of S3 means that inter-subject variability is a contributor to system performance because of individual differences in cognitive processing and signal consistency. In general, these results would support the hypothesis that the Neurosky Mindwave 2-based BCI system is capable of effectively controlling a drone for reasonable execution times with high accuracy on most of the given commands. Besides, strong performances for tasks such as "Stop" and "Takeoff" hint at real-time applications where fast responses are vital.

Table 3. Average spent time for implementing every command

Commands	S_1	S_2	S_3	S_4	S_5	Spent time
Takeoff	13.5	11.8	11	12	13.4	12.34
Land	10.43	12.66	13	11.30	12.60	11.998
Up	12	10	11	12.42	11	11.284
Right	11	11.50	10.88	11	10.70	11.016
Down	11.67	12	14	11.55	11.30	12.104
Left	10.67	13	11.70	10.95	11	11.464
Forward	12.33	13	10.3	12.3	10.87	11.76
Backward	11.67	11.23	10	12	10.95	11.17
Stop	3.3	3.7	3.9	3.4	3.5	3.56

Table 4. Drone-based BCI control algorithm accuracy

Movements	S_1	S_2	S_3	S_4	S_5	Accuracy
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%
Down	3|3	2|3	2|3	3|3	3|3	86.67%
Up	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%
Right	2|3	3|3	3|3	3|3	3|3	93.33%
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%

4.4. Comparison and Discussion

The BCI system is vital to the progress of biomedical technology, especially for disabled persons, through direct communication between the brain and other external devices. BCIs will have the solution to change the lives of individuals afflicted with motor disability by empowering them to control things such as prosthetics, wheelchairs, or any other assistive device through their brain signals, thereby improving their lifestyles. Besides, BCIs have given great impetus to neuroscience and biomedical engineering in deciphering brain activity, developing sophisticated signal processing techniques, and encouraging user-oriented efficient systems suitable for real-world applications. Recent works involving BCI development show a variety of approaches toward increasing functionality and performance. As listed in Table 5, (Kandemir et al., 2018) presented a system with 7 commands, utilizing one layer and relying on attention level, while (Rusanu et al., 2020) implemented five commands with two layers, emphasizing eye blinks as a key parameter. (Prasath et al., 2021) Introduced a 6-command system using one layer with EEG signals, whereas (Nasir et al., 2021) designed two systems: one with three commands and one layer using 3-bit eye blinks, and another with five commands and two layers combining 2-bit eye blinks and attention level. Similarly, (Shobana et al., 2022) implemented a 5-command system with one layer incorporating attention, meditation, and eye blinks, and (Selvamathiseelan et al., 2022) developed a 4-command system with one layer combining these same parameters. Minimalist designs like (Pham et al., 2022), with two commands and one layer using attention level, and (Vo et al., 2023), with four commands and one layer relying on 1–4 eye blinks, demonstrate simplicity, while (Sheikh et al., 2024) further refined a 4-command system using multiple eye blinks. In contrast, this work aims to advance BCI technology by implementing a system with nine commands, utilizing two layers, and combining 4-bit eye blinks with attention level as control parameters. The increased complexity, defined by more commands and layers, demonstrates superiority over previous studies by offering more robust and versatile control. Unlike earlier systems with fewer commands and single-layer classification, this work integrates multi-parameter inputs with a sophisticated two-layer structure, enabling greater precision and adaptability. The combination of 4-bit eye blinks and attention level addresses the limitations of simpler systems, providing a benchmark for advanced BCI systems suitable for more complex applications.

Table 5. Comparison of the performance of different algorithms

Ref.	C	L	Parameters	Err.	Acc.
(Kandemir et al., 2018)	7	One	Attention level	17%	83%
(Ruşanu et al., 2020)	5	Two	Eye blink	N. A	N. A
(Prasath et al., 2021)	6	One	EEG signals	N. A	N. A
(Nasir et al., 2021)	2	One	3-bit eye blink	9.33%	90.67%
	5	Two	2-bit eye blink & ATT level		
(Shobana et al., 2022)	5	One	ATT level& Med level & eye blink	N. A	N. A
(Selvamathiseelan et al., 2022)	4	One	ATT level& Med level & eye blink	3.9%	96.1%
(Pham et al., 2022)	2	One	ATT level	8.07%	91.93%
(Vo et al., 2023)	2	One	ATT & Med level	20%	80%
(Sheikh et al., 2024)	4	One	Eye blink1,2,3,4	6.7%	93.3%
Presented work	9	Two	4-bit eye blink & ATT level	9.63%	90.37%

***C:** No. of Command**, *L:** No. of Layers**, *ATT:** Attention**, *Med:** Meditation**, *Acc:** Accuracy**, Err:** Error rate

5. CONCLUSION

The study aims to develop a new algorithm using brain wave signals acquired through a BCI system to control a drone, which has potential applications for individuals with physical disabilities or limited mobility, as well as in gaming or specialized contexts. The proposed algorithm utilizes two layers of control, based on eye blink and attention levels, and employs two original methods for signal classification, SVM and LRM. The study found that dynamic signal classification, using the attention level's dynamic threshold, improved the accuracy of the algorithm's execution. The experiment conducted using a single-channel Neurosky module verified the effectiveness of the proposed algorithm, with an accuracy rate of 90.37% and support for 16 commands. The contributions of this study lie in developing a new algorithm to control a drone based on EEG signals, which has potential applications for individuals with physical disabilities, gaming, and specialized contexts. The consecutive layers algorithm is used for the first time in the current study, which has not been widely used in previous studies. Furthermore, the study proposes a novel approach for dynamic signal classification, which has been shown to improve the accuracy of the algorithm's execution. Compared to previous studies, this paper enriches the study of BCI systems for controlling drones by proposing a new algorithm that utilizes eye blink and attention level signals for control, employing a unique approach for signal classification, and demonstrating high-accuracy rates in a test experiment. Additionally, the proposed algorithm supports more than 10 controlling commands, making the algorithm appropriate for a range of implementations. Addressing noise explicitly would strengthen the system's applicability in practical use cases and ensure robust performance.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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