Drone Movement Control by Electroencephalography Signals Based on BCI System

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Abstract. *Brain Computer Interface enables individuals to communicate with devices through ElectroEncephaloGraphy (EEG) signals in many applications that use brainwave-controlled units. This paper presents a new algorithm using EEG waves for controlling the movements of a drone by eye-blinking and attention level signals. 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 to either 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 algorithm has been validated by experimental testing of five individuals of different ages. The results show its high performance compared to existing algorithms with an accuracy of 91.85 % for 9 control commands. With a capability of up to 16 commands and its high accuracy, the algorithm can be suitable for many applications.*

Keywords

Attention level, Brain Computer Interface (BCI), ElectroEncephaloGraphy (EEG), eye-blink, NeuroSky MindWave 2.

1. Introduction

Nowadays there is a huge demand for Brain Computer Interface (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 [1]. BCI is an interfacing technology between the Human Mind (HM) and a processor by sensing ElectroEncephaloGraphy (EEG) signal and employing it to perform different tasks. There are two types of mind-sensing techniques for the BCI system, which are invasive and the non-invasive [2] and [3]. The invasive and/or partially invasive sensing technique 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 [4]. The non-invasive sensing technique 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 [5] and [6]. There are several models of BCI headsets that have wide potential to be used as support technologies and new control methods. These devices capture the activities of the human mind from the scalp and decode it with machine learning methods [7]. NeuroSky company has developed a special algorithm for deriving attention and meditation signals from EEG signals [8]. Attention and meditation signals represent concentration and relaxation/calmness levels, respectively, and have a signal range of 0 to 100 integer values and are influenced by the mental and physical states of individuals.

The BCI system is applied to control the medical device applications and the examination of neural activity characteristics. A prototype WheelChair System (WCS) presented in [9] is designed to assist individuals with disabilities using brain waves based on the BCI system. The system consists of a NeuroSky MindWave 2 headset module to capture the EEG signals and a H-Bridge Arduino controller with PWM Arduino to control the speed of the prototype. EEG waves are used to control the WCS in four directions. The WCS's prototype system provides an accuracy controlling equal to 73.33 %. In [10], a new authentication procedure for the Internet of Things (IoT) using EEG signals based on BCI system is proposed. The method uses NeuroSky MindWave 2 to capture the EEG signals and a camera to detect the gestures of hands. The attention and meditation levels are employed as switch for the authentication, and the gestures of hands for controlling the authentication's process. The evaluation results of the procedure show an accuracy equal to 92 %, an efficiency of 93 % and acceptable user satisfaction. The 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 gender is presented in [11]. In that work, 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 an average detection accuracy for attention, meditation, and eye-blink of 47.5 %, 54.25 %, and 48.25 %, respectively. A BCI system using an Arduino microcontroller to help the users maneuver a miniature of WheelChair System (WCS) by non-invasive NeuroSky technique is proposed in [12]. The system uses attention, meditation and eye-blink to develop three different control algorithms to execute maneuver commands. In [13], a BCI system is implemented by Arduino megacontroller to help the disabled users to control printing letters of keyboard system by non-invasive NeuroSky technique. The attention and eye-blink are used to develop controlling algorithm to execute the printing commands. In [14], a prototype of brains warm interface controls 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. A robot-car and home appliances are controlled with brain signals using NeuroSky mobile 2 in [15]. A micro-controller is employed to distribute and recognize the controlling signals. The attention and meditation signal levels are used to control the change in the movement and the direction of the robot-car, while the eye-blink is used for switching on/off home appliances. The aim of this research is to develop an algorithm based on attention level and eye-blink signals to control a drone using brain waves collected by the single-channel NeuroSky MindWave 2 device. The algorithm includes 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 remainder of the paper is organized as follows: in Sec. 2. the general concept of BCI system is introduced. The methodology adopted for development of the algorithm is explained with details in Sec. 3. and Sec. 4. The experimental results are presented and evaluated in Sec. 5. Finally, in Sec. 6. the conclusions are drawn.

2. General Framework

2.1. BCI System

A typical BCI system consists of four components which are: signal acquisition, feature extraction, feature translation commands, and device output [16]. The brain signals are detected and treated during the signal acquisition step. These signals are acquired from the user's scalp using sensors, which are covered with multi-electrode array. The acquired signals are processed to be suitable for feature extraction. High pass, low pass and notch filter are the most used filters in the acquisition/processing step and work to remove noise, artifacts and extract the desired frequency band. Also, the filter can be combined with other components such as amplifiers to improve the SNR and amplitude of the signals [4]. In the feature extraction several methods are applied for extracting feature and classifying the brain signals. Linear classifier, non-linear classifier, nearest neighbor classifier, neural networks or their combinations are used as classification method. Recently, the most widely used method for classification and feature extraction is neural networks [4]. After the signals are classified, the next step is the feature translation algorithm. In the feature translation algorithm, the classified signals are converted to binary codes based on the threshold value determined by experimental tests. These binary codes are applied to execute commands according to the user's intent [10].

2.2. ElectroEncephaloGram (EEG)

The EEG is an observation technique to read and record the brain signals [17]. 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 [18]. EEG is the most popular non-invasive method of spontaneous wave acquisition, and it has several advantages over other neuroimaging processes by providing simplicity, low cost, fast response, and ability to be implemented in many applications [4]. The EEG headset captures the brain waves in different frequency bands using various channels according to the electrodes map. Generally, EEG signals are affected by noise and other environmental influences, resulting in signal distortion and reduction in SNR during signal acquisition [19]. The EEG Brain signals are divided into five waves according to the frequency bands based on the mental state, which are: Delta, Alpha, Theta, Beta and Gamma.

2.3. NeuroSky MindWave 2

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 hair and proximity to the eye, it provides EEG and eye-blink signals as shown in Fig. 1.

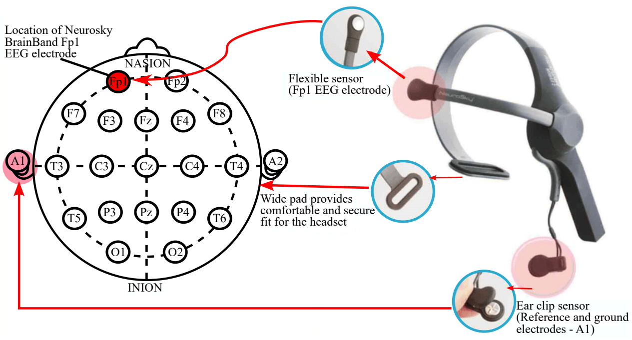


Fig. 1: NeuroSky MindWave 2 device [20].

Due to EEG signals' weak amplitude (10–100 mV), and noise sensitivity during the extraction stage, a pre-treatment circuit is required to improve the SNR and the quality of the EEG signals [21]. The block diagram of pre-treatment circuit is shown in Fig. 2.

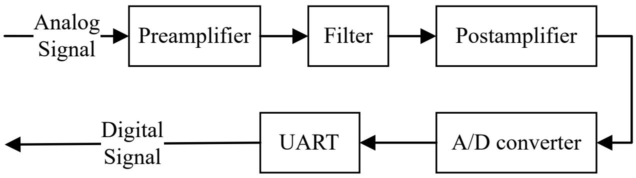


Fig. 2: Pre-treatment circuit block diagram.

The pre-treatment circuit consists of a pre-amplifier stage, a filter, a post-amplifier, an Analog-to-Digital converter (A/D), and a Receiver/Transmitter interface (UART). The pre-amplifier is used to amplify the EEG signals by 8000 times. The EEG signals ranging in 0.5–100 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 to retain the signals in 0–50 Hz bandwidth range. The filtered EEG signals are amplified by the post-amplifier 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 [21] and [22]. The formula for converting raw values to voltage is given by:

$$\text{voltage} = \frac{\text{raw value} \cdot \frac{V_i}{2^{12}}}{G}, \tag{1}$$

where G is the gain of the post-amplifier, V_i is the maximum input voltage equal to 1.8 V.

3. Methodology

In this section, the drone movement control details, acquisition and classification of signals, conversion to commands and implementation of the algorithm are mentioned. 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 used to train an Artificial Neural Network (ANN) to sort each eye-blink of a 4 consecutive eye-blinks input as logic "1" or logic "0" according to the strength of the participant's eye-blink and output a 4-bit binary code. 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. The 4-bit eye-blink codes and attention level are used to control the drone's movements (take off, landing, left, right, up, down, forward, backward and stop). The block diagram of the adopted method is shown in Fig. 3.

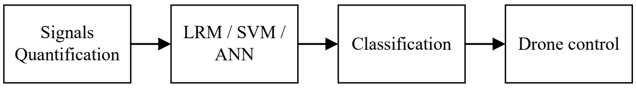


Fig. 3: Brain-drone interface block diagram.

3.1. Signals Quantification

According to the output of NeuroSky there are 4 signals, which are attention signal, meditation signal, EEG signals and eye-blink signal. In general, there is a strong correlation between attention and meditation signals because they both characterize 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 [23]. In the NeuroSky output, the five EEG signals (delta, alpha, theta, beta, and gamma) are represented by eight waves namely Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gamma, and Mid Gamma. However, the most related waves to human mind states are those related to α, β, δ, and θ signals [24]. The energy value (E_x) of each signal can be determined by using the sum of signals power (P_{freq}) depending on frequency ranges, the frequency ranges of the signals are as follows [24]; E_δ: 0–4 Hz, E_θ: 5–7 Hz, E_α: 8–13 Hz, E_β: 14–40 Hz and E_γ: 41–200 Hz. The correlation between α and β is exploited to derive the ratio equation as a feature to evaluate the mental attentiveness level [25]:

$$R = \frac{E_\alpha}{E_\beta}. \tag{2}$$

3.2. Command Based on Eye-Blink

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. Individuals are asked to produce three slight blinks and three strong blinks in a random order. The collected data is analyzed and classified using SVM algorithm resulting in an optimal threshold of 72 eye-blink intensity. The threshold separates eye-blink into two blink classes (strong or slight) as shown in Fig. 4.

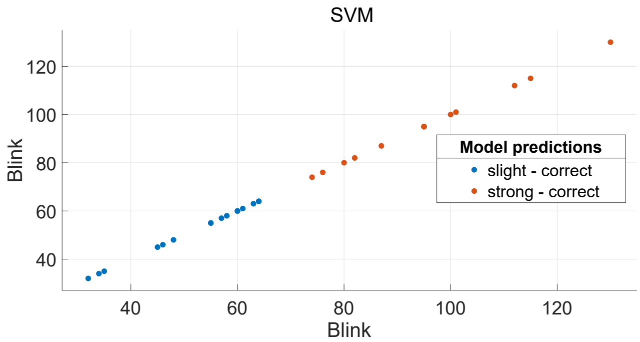


Fig. 4: SVM classification.

Four consecutive eye-blinks are randomly collected from the participants. These consecutive eye-blinks are used as input data for the ANN trained with the threshold obtained from the previous step, and each eye-blink is sorted as logic "1" or logic "0". ANN outputs a 4-bit binary code for every four consecutive eye-blinks input. The block diagram of adopted ANN net is shown in Fig. 5.

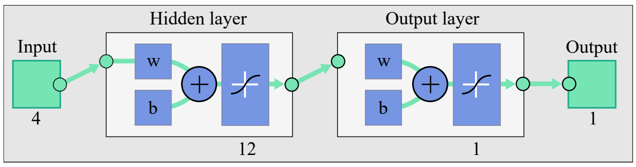


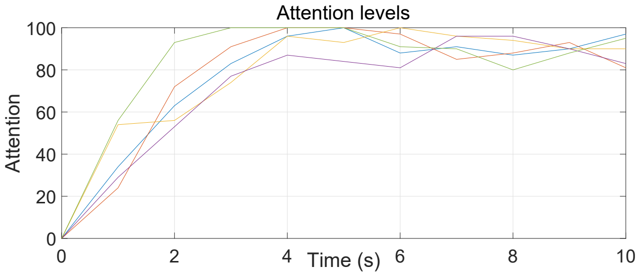
Fig. 5: The adopted ANN block diagram.

Four blinking sequence is used to produce a 4-bit code according to the selected motion as follows: "Take off/1111", "Land/0000", "Up/1001", "Down/0110", "Forward/1110", "Backward/0001", "Right/0011", "Left/1100", "Stop/1010". Each eye-blink code is generated during a period of 5 seconds, which has been set based on a series of experimental tests for different individuals.

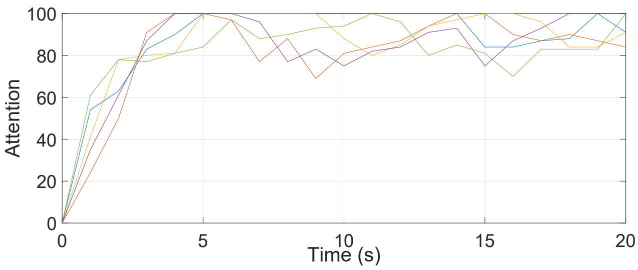
3.3. eSense Attention Level Classification

The attention levels' data collected is determined by performing tests to five individuals for five different time intervals as illustrated in Fig. 6.

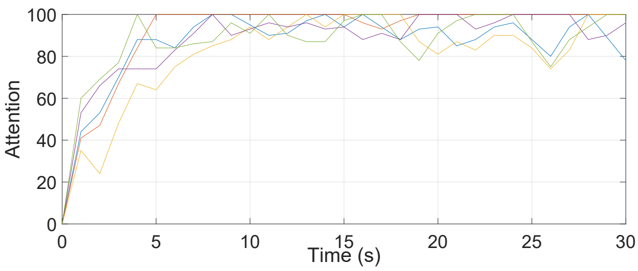
From the Fig. 6(a), the best interval for collecting attention levels' data can be defined as 10 seconds. After 10 seconds, irregular fluctuations start occurring due to the lack of concentration of the individuals under test. After data collection, Linear Regression Method (LRM) is applied to locate 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. It is used here to give the dynamic threshold value between strong and weak at-



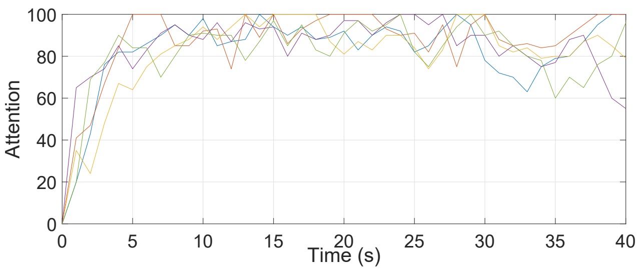
(a) 10 seconds interval.



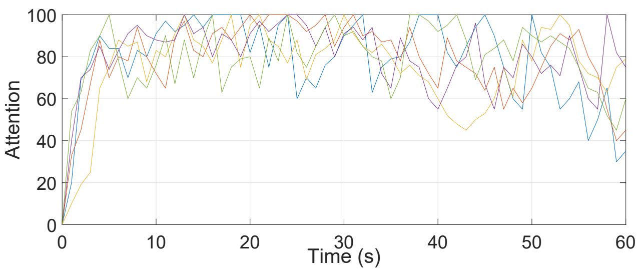
(b) 20 seconds interval.



(c) 30 seconds interval.



(d) 40 seconds interval.



(e) 60 seconds interval.

Fig. 6: Attention levels of the five individuals.

tention level according to the collected data in Tab. 1. The general form of the LRM equation is given by:

$$y = ax + b, \tag{3}$$

where y is the dependent variable, x is the independent variable, a is the slope, and b is the y intercept. The constants a and b are calculated using the collected data as follows:

$$a = \frac{\sum_{i=1}^{N}(\overline{y_i})\sum_{i=1}^{N}(x_i^2) - \sum_{i=1}^{N}(x_i)\sum_{i=1}^{N}(x_i\overline{y_i})}{N\sum_{i=1}^{N}(x_i^2) - \left(\sum_{i=1}^{N}x_i\right)^2}, \tag{4}$$

$$b = \frac{N\sum_{i=1}^{N}(x_i\overline{y_i})\sum_{i=1}^{N}(x_i)\sum_{i=1}^{N}(\overline{y_i})}{N\sum_{i=1}^{N}(x_i^2) - \left(\sum_{i=1}^{N}x_i\right)^2}, \tag{5}$$

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 readings: here equal to 11. After the calculation of a and b, the dynamic threshold equation of attention level can be given as:

$$y = 3.2016x + 65. \tag{6}$$

Tab. 1: Calculation of LRM constants.

x_i	y_i^{I}	y_i^{II}	y_i^{III}	y_i^{IV}	y_i^{V}	$\overline{y_i}$	x_i^2	$x_i\overline{y_i}$
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 static attention level threshold is determined to be 85 based on the recorded experiment for an observation period of 10 s. It is seen that the attention levels of five individuals stabilized above 85 after 3 to 4 seconds in a critical linearity. The dynamic threshold is determined as 65 using Eq. (6) derived from the applied LRM. The improvement in the attention level identified by the dynamic threshold compared to that of the static threshold ($y = 85$) is shown in the Fig. 7, and the comparison between the two thresholds is given in Tab. 2.

4. Algorithm Development

Binary codes from the attention level (1-bit) and the eye-blink (4-bit) are exploited to develop an algorithm based on two controlling layers as depicted in Fig. 8. The first control layer uses eye-blink code, while the second control layer uses the attention level code. The first control layer is adopted to perform the frequent

Tab. 2: Comparison of threshold types. Cells in red present faulty readings of attention level.

Static threshold (85)					Dynamic threshold				
y_i^{I}	y_i^{II}	y_i^{III}	y_i^{IV}	y_i^{V}	y_i^{I}	y_i^{II}	y_i^{III}	y_i^{IV}	y_i^{V}
34	24	54	29	56	34	24	54	29	56
63	72	56	53	93	63	72	56	53	93
83	91	74	77	100	83	91	74	77	100
96	100	96	87	100	96	100	96	87	100
100	100	93	84	100	100	100	93	84	100
88	97	100	81	91	88	97	100	81	91
91	84	96	96	90	91	84	96	96	90

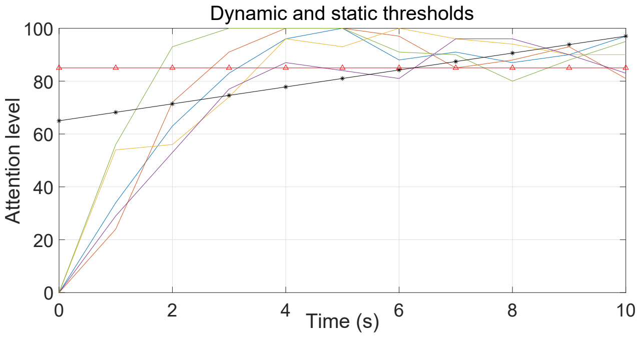


Fig. 7: Dynamic and static thresholds of attention level.

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. 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 for 3 seconds, the second control layer is executed; otherwise, the device proceeds with the current motion. The presented algorithm is 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.

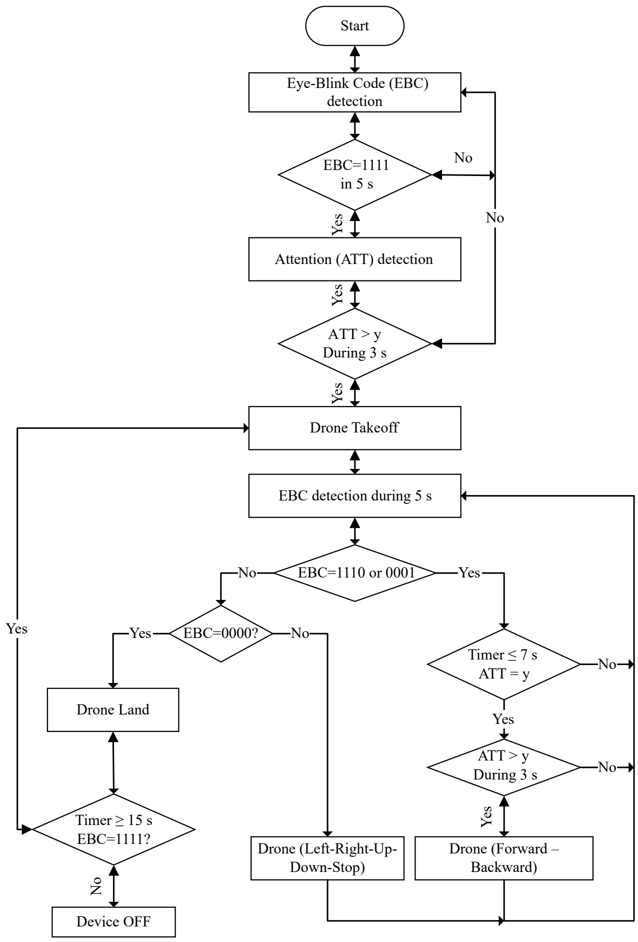


Fig. 8: Drone control algorithm.

Tab. 3: Average Elapsed Time (AET) for each individual.

Motion	S^1	S^2	S^3	S^4	S^5	AET
takeoff	12.4	12.2	11.6	11.3	13	12.1
land	3.7	3.63	4.4	3	4	3.746
up	4	3.31	3	3	4	3.462
down	3.82	3.8	4	3.45	3.2	3.654
right	4	3	3.7	4.2	3	3.58
left	3	4.3	3.6	3.4	4.2	3.7
forward	11.87	11.6	12	12.43	12.77	12.134
backward	12.8	12	11.75	11.5	11.9	11.99
stop	3	3.8	4	3.5	3.7	3.6

5. Experimental Results

The evaluation of the system 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 test requires participants to make three attempts for each movement, and the average time for the movement performed is calculated.

The participants exhibit different average times for mental attentiveness and eye-blinking speed as shown in Tab. 3. Also, the table presents the average elapsed time required to perform each motion. Note that the average times of eye-blinking and attention level code

Tab. 4: Drone control algorithm accuracy.

Motion	S^1	S^2	S^3	S^4	S^5	Accuracy
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 %
	96.2 %	85.1 %	92.5 %	92.5 %	92.5 %	91.85 %

Tab. 5: Comparison of performance of different algorithms.

	Number of control commands	Control layers	Control parameters	Error rate	Accuracy
Present work	9	one & two	4-bit eye-blink & attention	8.15 %	91.85 %
[9]	4	one	EEG waves	26.67 %	73.33 %
[21]	3	one	attention	15 %	85 %
[26]	3	one	1-bit eye-blink	18.33 %	81.67 %
[27]	4	two	2-bit eye-blink & attention	17 %	83 %
[28]	4	two	2-bit eye-blink	15 %	85 %

generations based on Tab. 3 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 Tab. 4. Also, the table gives the average accuracies obtained for each motion and each participant in the test experiment.

The test is performed with 15 movements (3 per person) in total. The Takeoff, Land, Up, Right, Left, and Forward motions show 14 out of 15 success-controlled attempts with 93.33 % accuracy. The Down and Backward motions show 13 out of 15 success-controlled attempts with 86.67 % accuracy. 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 %. The comparison of the developed algorithm with the previous works in terms of commands issued, control layers, error rate, and accuracy, is shown in Tab. 5. All previous selected works use a static threshold value and fewer bits for eye-blink. The algorithms they developed are derived based on one or two control layers represented by attention, meditation, EEG signals and/or eye-blink signals.

The results show that the proposed algorithm with 91.85 % accuracy, has a much higher performance than the others. Additionally, the number of commands controlling the movements of the drone has been significantly increased.

6. Conclusion

A new algorithm using EEG waves collected and transferred by a BCI system is presented. The proposed algorithm is developed to control the movements of a drone by eye-blinking and attention level signals. The algorithm is configured with two control layers. The first layer uses eye-blink signals classified by an 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 algorithm is validated by a test experiment using the single channel NeuroSky MindWave 2 device. The proposed algorithm shows a high performance with 91.85 % accuracy. Moreover, the algorithm offers a capability of performing 16 commands making it suitable for various applications such as wheelchair, robot arm, smart home, etc.

Author Contributions

A.H.B. developed the algorithm, performed the analytic calculations, and carried out the experiment. I.M. and M.K.M contributed to the final version of the manuscript. I.M. supervised the project.

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