Implementation of a New Algorithm for Drone Control Using BCI system

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Abstract:

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. Brain Computer Interface (BCI) is an interfacing technology between the mind and a processor by sensing brain signal and employing it to perform different tasks. The BCI device used in this research is the one-channel NeuroSky mindwave 2. This paper presents an EEG waves-based method to control a device "here a drone" using two active signals; the eye blinking and the concentration level described by attention signal. The dynamic classification of these signals is performed via Support Vector Machine algorithm and Linear Regression algorithm for attention. Quantified signals are then used to generate a binary code used for drone control. Binary code is used as input for a control algorithm based on two-layer control to manipulate a drone with 9 possible movements. Experiments are conducted with various individuals where the results show its high performance of the developed algorithm and the signal classification methods. The system outperforms most of the existing systems with an accuracy of 90.37%. Moreover, the algorithms offer a capability of performing 16 commands making it suitable for various applications.

Keywords: Brain Computer Interface, EEG signals, NeuroSky device, attention level, eye-blink.

Introduction

There are billions of neurons inside the human mind responsible of human movements, thoughts, emotions and behaviours. These neurons features are invested in several technology, which are used the mind activities to implement different functions [1]. Usually, remote control is used to perform the tasks and application control. Since the work of Hans Berger on mind activities in [2], the researchers work on developing a system to exploit mind internal signals. The Brain Computer Interface (BCI) system is a communication technology between the brain and the computer aiming to create a connection channel for sending and managing the signals from the human mind to the hardware of the system [3]. BCI system adopts two brain signal sensing methods which are; the invasive and non-invasive methods [4].

The invasive method demands surgical involvement for implanting the electrodes in the cerebral cortex to acquire the brain signals providing high quality signals and good SNR [5]. The non-invasive method requires installing the electrodes in a mindset device according to the standardized 10-20 electrodes map without any surgery [6]. By using the right tools, every action generates by the brain can be used as input data to control various applications in medicine, gaming, among others, prompting the increased interest on BCI developing [7]. Recently, controlling a drone, wheelchair for persons with disabilities or BCI-based robot is among the most interesting topics as shown in Fig 1 [8].

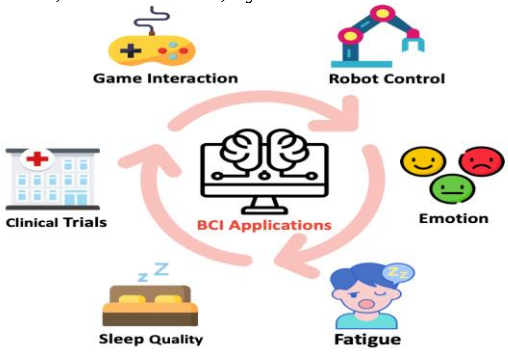

Fig. 1. BCI system in different fields

A hand – free teleoperation system is established to improve remotely robot control in a construction zone using on BCI system in [9]. The mind signals are captured using wearable Electroencephalography (EEG) headset device, to generate the control system's digital commands. The system shows an ability to direct the robotic in space and under-water with 90% accuracy. In [10], A BCI system is emulating a painting artwork using brain signals. The NeuroSky mindwave 2 is used to acquire the attention level for creating an artwork painting composing characters' animation. The system invests to help the museum's visitors in understanding the traditional paintings of Chinese cultural. A prototype BCI-based wheelchair to help the disabled individuals is developed in [11]. With a resulting accuracy of 73%, NeuroSky device is utilized. The system includes also, Arduino Mega, H-bridge and two DC- motor. A BCI-based home automation system is designed using the EEG signals in [12]. The detected data are processed by Brain Waves-Automation-Detection algorithm utilizing Raspberry pi. Double eye-blink is used to, and attention/ meditation signals are used for ON/OFF the appliances. In [13], a smart wireless

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wheelchair system is controlled to help partial-paralysed individuals using brain waves based on BCI system. NeuroSky mindwave 2 is used to capture the EEG signals such as attention, meditation and eye-blink. An Arduino micro-controller is adopted to distribute and recognize the movement commands. The system shows a control accuracy equal to 95%. The brain signals are used for controlling a drone based on BCI system in [14]. The EEG mind waves are captured by using Emotiv - Insight headset device. A Raspberry Pi is used to recognize the incoming brain signals, and distributes the drone's control commands. The system presents an efficient accuracy equal to 88%.

The present work purposes a new algorithm for controlling a drone utilizing brain waves skills (attention level and eye-blink) detected by a TGAM Module provided by NeuroSky device. The algorithm comprises 2-control layers. In addition, attention level's dynamic threshold is adopted for improving the algorithm's accuracy.

The paper is organized as follows: The general concept of BCI system and EEG waves classification is introduced in section 2. In section 3 the adopted methodology is presented. The experimental outcomes and the analysis are shown in 4. Finally, section 5 concludes the paper.

General Framework

BCI system

A typical BCI system comprises four processing steps which are signal acquisition and processing, signal feature extraction, translation algorithm, and device command [15]. The brain signals are detected and treatment in the signal acquisition step. They are acquired from the user's scalp using sensors, working with multi-electrode array. Signals are then processed to be suitable for feature extraction. In the feature extraction several techniques are applied for classifying and analysing signals. Once the signals are analyzed the next step is the translation algorithm. The signals are translated into device commands according to the user's intention [15]. There are several types of BCI neuro-imaging processes as listed in Table 1.

Electroencephalogram (EEG)

The EEG is an observation technique to read and record the brain signals. 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 [16].

Table 1.various neuroimaging methods [8]

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

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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 [17]. The EEG headset captures the brain waves in different frequency bands using various channels according to the electrodes map. Usually, The EEG signals are affected by the noise and the other environmentally effects during the acquisition cussing signal distortion and decreasing in the SNR [18].

Brain Waves Classification

The brain has different parts produce several patterns of electric impulses rhythmic [19]. The EEG headset devices detect these electric impulses rhythmic, which is collected in various frequency bands and amplitude. The brain waves are very complex changing according to the verbs and feelings. The EEG waves are comparatively stable and similar in the normal people. There are five kinds of typical brain wave [20]:

Delta Waves: The rhythm of these waves is between 0 Hz – 3 Hz. They are generated when the person in meditation state or deep sleep.
Theta Waves: These waves have rhythm between 4Hz – 7 Hz, and has less amplitude. They are produced when the person in deep meditation, imagination or extreme relaxation.
Alpha Waves: They dominate during the state of relaxed mental, contemplation, visualization, problem solving and resting with eyes closed. The alpha waves have a frequency band is between 8 Hz - 12 Hz.
Beta Waves: the beta waves predominate when the person in alertness state, stable emotion or energy. 13 Hz - 30 Hz is the frequency range bands for the beta.
Gamma Waves: These waves are generated in a high-level information processing. It has frequency range band between 31 Hz -100 Hz with low amplitude as compared to the other brain waves.

Methodology

The brain signals are extracted and processed by TGAM module provided by NeuroSky company. A Graphical User Interface (GUI) using Processing + is designed to project and supervise the coming signals from the EEG headset device. Eye-blink and attention level are adopted as signals to derive the control mechanism of a drone. They are recorded in Excel database using GUI. The collected eye-blink data is classified by machine learning based on Support Vector Machine (SVM) classification algorithm to locate the threshold value. The applied blinking is sorted logically ("1" or "0") by Artificial Neural Network (ANN) trained by the obtained threshold based on signals' intensity.

The attention levels are associated to the concentration of the individual under test and the observation interval. Linear

Regression Method (LRM) is utilized to classify the attention level, yielding a dynamic threshold. 4-bit eye-blink codes are generated using four sequential blinks, and employs together with attention level in controlling a drone's movements. Fig 2 presents the block diagram of the adopted method.

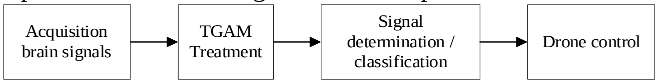

Fig.2. Brain-drone interface block diagram

Acquisition Signals and TGAM treatment

NeuroSky mindwave 2
uses TGAM module to extract and process the brain signals in this system. The TGAM module uses single channel with dry electrode to capture the brain signals and eye-blink from the user's scalp at Fp1 position as clarified in Fig 3.

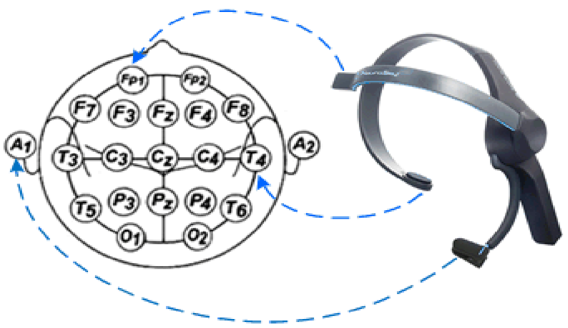

Fig.3. NeuroSky mindwave device [21].

The TGAM Module comprises three electrical pins which are; the brain signals acquisition, reference and the GND. The module uses potential difference between the extraction electrode and the electrode of reference for eliminating the noise. The TGAM's TX pin is connected to the Bluetooth's RX pin during the work, that together are supplied with 3.3 V to realize the communication between the modules [22].

The EEG signals suffer from weak amplitude, and noise sensitivity during the capturing stage. Therefore, the TGAM module works on processing and filtering the captured signals using pre-treatment circuit before transmitting to the PC as shown in Fig 4.

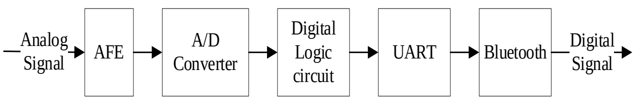

Fig. 4. Pre-treatment circuits block diagram

Essentially the pre-treatment circuit has Analog Front End (AFE) stage, analog-to-digital convertor (A/D), digital logic circuit. Once the AFE stage accomplishes, the signals pass to the A/D converter for sampling at 512 Hz, and coded with 12 bits. The digital logic circuit is used to output the serial data via Universal Asynchronous Receiver and Transmitter (UART) interface. Typically, the UART output is connected to a Bluetooth module UART input for transmitting the signals to the PC [23]. The equation of converting raw value to the voltage is given by:

$$voltage = \frac{raw\ value \times \frac{V_i}{2^N}}{G} \quad (1)$$

where G is the gain of the post-amplifier, Vi is the maximum input voltage equal to 1.8 V, and N is the resolution in bits of A/D. The TGAM module output the

Signals Classification

The attention and meditation level are related to personal mental and physical states. The attention level is increased with the concentration, while meditation requires more training, sustainable mental and physical relaxation process during the experiment. This promotes the use of attention and not meditation [24]. The eye-blink reading can be acquired from the raw wave EEG. The NeuroSky TGAM module reads the eye-blink as an unsigned single byte with range strength between 1-255 integer value. The binary code designed in the present work requires the correct classification of attention and eye-blinking signal to drive the correct control action.

Attention Level Classification

The human's concentration levels cannot continue for a long time in a linear or semi-linear high's levels. After 10-15 seconds, the human's concentration levels start lacking causing irregular fluctuations [25]. For an accurate definition of the attention level's threshold value, Linear Regression Method (LRM) is applied. This classification of collected attention levels provides a dynamic threshold value separating between strong and weak attention level (binary-1 and binary-0). The LRM is a statistical method used for representing a relationship between two continuous variables or factors by providing experimental data's best linear approximation. The general LRM equation's form is given by:

$$S = a\,T + b \quad (5)$$

where, S is the dependent variable, T is the independent variable, a is the slop, and b is the y intercept. The collected attention level's data are used to calculate the LRM equation's constants (a and b) using the following equations:

$$a = \frac{(\sum_{i=1}^{N} \bar{S}_i)(\sum_{i=1}^{N} T_i^2) - (\sum_{i=1}^{N} T_i)(\sum_{i=1}^{N} T_i \bar{S}_i)}{N(\sum_{i=1}^{N} T_i^2) - (\sum_{i=1}^{N} T_i)^2} \quad (6)$$

$$b = \frac{N(\sum_{i=1}^{N} T_i \bar{S}_i)(\sum_{i=1}^{N} T_i)(\sum_{i=1}^{N} \bar{S}_i)}{N(\sum_{i=1}^{N} T_i^2) - (\sum_{i=1}^{N} T_i)^2} \quad (7)$$

where, T_i is data collection time, $\bar{S}_i$ is the average of the experimental attention levels of the five individuals and N is the number of readings.

Eye-Blink Strength Classification
The drone's control commands are executed using eye-blink signal based on the intensity of blink. In order to define an accurate blink threshold separating on-blink represented by 1-binary and off-blink for 0-binary, many tests on different users must be performed. The Support Vector Machine (SVM) algorithm is utilized to classify the collected data. The output of the SVM is the optimal eye-blink intensity used for classification.

Algorithm Development

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The developed algorithm is based on multi-layer order. It is a two control layers where the first is performed using the eye-blink codes (EBC), while the second is activated by the attention level (ATT) as depicted in Fig 5. The EBC represent the First Control Layer (FCL), while the ATT represents the Second Control Layer (SCL).

According to the coming signals from the brain to generate EBC, the approved algorithm is employed to control various drone's movements as follow; 0000/ Land, 1111/Take-off, 1001/Up, 0110/Down, 1100/Left, 0011/Right, 1110/Forward, 0001/Backward and 1010/Stop. All the movements are executed using both layer in a successive manner except the stop motion, which is executed by using only the EBC because it can be a critical movement.

Regardless of the blink strength, a timer of 5 seconds is triggered with the first active blink for generating the EBC. Once the generating EBC, the ATT is detected based on the movement to be executed, and detects during a surveillance period of 7 seconds. The ATT must be greater than detected "S" during 3 seconds to execute the SCL, else the device carries on with the current movement.

Once the devices are coupled, the drone is ready for receiving the Take-off command. After Take-off, the drone waits to receive for the next movements' commands based on the user's intention. As soon as the drone is received the land's command "0000", the drone is down, and turns off after 15 seconds if not Take-off again.

Experimental Results

The system is evaluated through a practical experiment including five participants. The practical experiment is executed in a convenient position and quiet ambience free of the negative factors affecting.

4.1 Evaluation of dynamic attention threshold

A period of 11 seconds is adopted to collect the attention levels' data for five individuals experimentally as shown in Table 2. After calculating the LRM's constants by the equations 5, 6, and 7, the attention level's dynamic threshold is credible as:

$$S = 3.0273x + 65 \quad (8)$$

The adopted mechanism of the attention level for controlling is as follows; achieving strong value (logic "1") by raising over the attention level more than the threshold value for three second.

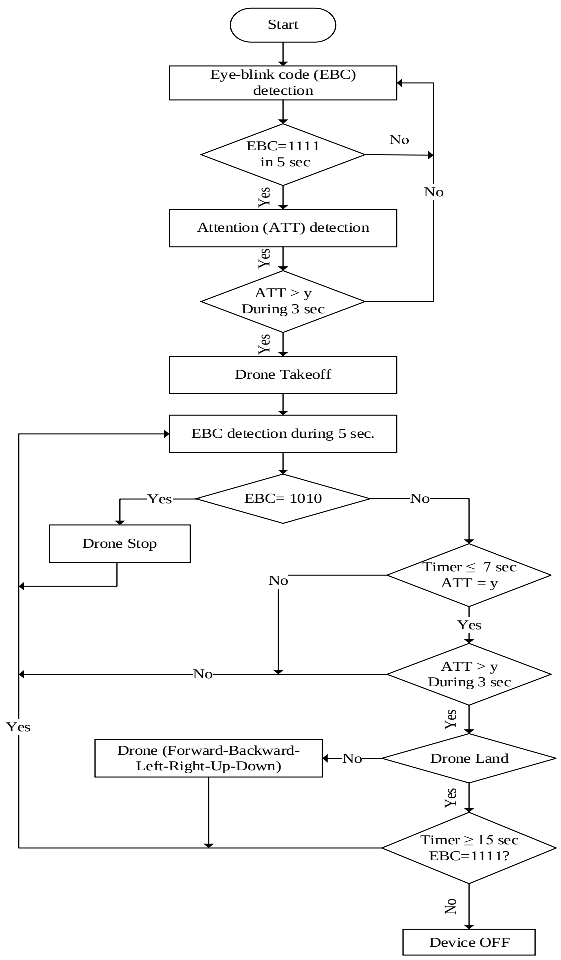

Fig. 5. Drone control algorithm

Table 2 Calculation of LRM constants

T_i	S_i^{I}	S_i^{II}	S_i^{III}	S_i^{IV}	S_i^{V}	$\overline{S_i}$	T_i^2	$T_i\overline{S_i}$
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

In agreement with the attention level's work mechanism, the attention level shows an improvement with the time according to the dynamic threshold as compared to the static threshold as clarified in Fig 6. In Table 3, the comparison

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between the thresholds value shows the gradually adapts of the dynamic threshold with the attention level's changes over the time as compared with the static threshold.

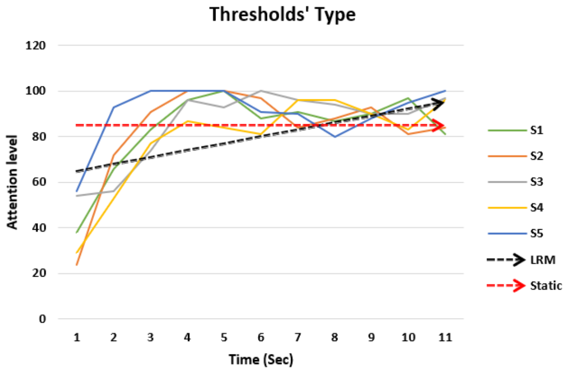

Fig.6. Dynamic and static thresholds of attention levels

Table 3 Comparison of threshold types

	Static threshold (85)					Dynamic threshold				
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

*Cells in red present faulty readings of attention level

4.2 Experimental evaluation of Eye-blink threshold

The five persons are asked to generate six consecutive blinking of different strength in random way as shown in Fig 7. The SVM algorithm is utilized to classify the collected data, and results an optimal threshold equal to 72 eye-blink intensity separating between the strong and slight eye-blinks reading. After the threshold's definition, the collected data is sorted logically ("1" and "0") using the trained ANN with the obtained threshold as shown in Fig 8.
The Logically classification is used to generate the command code, its composed of 4-bit generating by four sequential reading of eye-blink, this provides 16 commands are; 0000, 0001, 0010, 0011, 0100, 0101, 0110, 0111, 1000, 1001, 1010, 1011, 1100, 1101, 1110, 1111. According to an experimental test for different participants, five seconds period has been fixed to generate each eye-blink code.

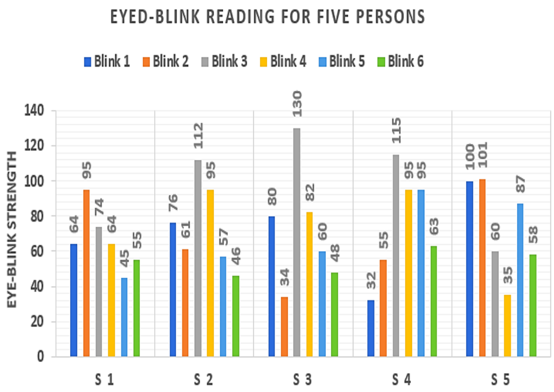

Fig. 7. Eyed-blink reading for five persons

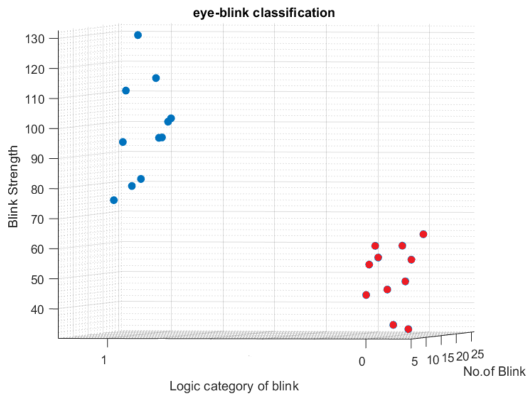

Fig. 8 Distribution of collected eye-blink signals

4.3 Experimentation of the developed algorithm

Ones the eye-blink and attention dynamic thresholds are defined, the drone control via the algorithm can start. Each participant makes three trials for each motion during the experiment, and the executed motion's average time is calculated. Table 4 shows different average times for each participant in performing motions, and the demanding average elapsed time to implement each movement.
In Table 5, the total performance accuracy of the practical experiment, the average accuracies of each participant and each movement in the experiment is listed.
The proposed algorithm's results show an efficient accuracy equal to 90.37 with 9.63% error rate providing higher performance than the other algorithms. Moreover, the commands' number of controlling the drone's motion has been significantly raised.

Table 4 Average elapsed time for every motion

Motion	P1	P2	P3	P4	P5	elapsed time
Take-off	13.5	11.8	11	12	13.4	12.34
Land	10.43	12.66	13	11.3	12.6	11.998
Up	12	10	11	12.42	11	11.284
Down	11.67	12	14	11.55	11.3	12.104
Right	11	11.5	10.88	11	10.7	11.016

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Left	10.67	13	11.7	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	3.8	4	3.5	3.7	3.6

Table 5 Drone control algorithm accuracy

Motion	P1	P2	P3	P4	P5	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 %
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 %

Conclusion

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 algorithm/method using EEG waves collected and transferred by a BCI system is presented. The case study in this research is focused into controlling a drone wit many movements, but results can be generalized for many applications. A two-layer control algorithm based on eye-blink, and attention levels is tested foe many volunteers. Two original methods are used for signal classification which are the SVM, and LRM. Dynamic signal classification is positively reflected to the algorithm execution accuracy.

The algorithm is validated by a test experiment using single channel NeuroSky module. The proposed algorithm shows a high performance with 90.37% accuracies. Moreover, the algorithms offer a capability of performing 16 commands making it suitable for various applications.

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