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PAPER

EEG-Based Control of a 3D-Printed Upper Limb Exoskeleton for Stroke Rehabilitation

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ABSTRACT

Brain-computer interfaces (BCIs) have emerged as transformative tools for translating users' neural signals into commands for external devices. The urgent need for innovative treatments to enhance upper limb motor function in stroke survivors is underscored by the limitations of traditional rehabilitation methods. The development of communication and control technology for individuals with severe neuromuscular diseases, particularly stroke patients, is centered on utilizing electroencephalographic (EEG) signals to accurately decode users' intentions and operate external devices. Two healthy subjects and a stroke patient were enrolled to acquire EEG signals using the EMOTIV EPOC+ sensor. The experimental procedure involved recording five actions for both motor imagery and facial expression signals to control the 3D-printed upper limb exoskeleton. EEGLAB and BCILAB software were used for preprocessing and classification. The results showed successful EEG-based control of the exoskeleton, representing a significant advancement in assistive technology for individuals with motor impairments. The support vector machine (SVM) classifier achieved higher accuracy in both offline and online modes for both motor imaginary and facial expression tasks. The conclusion highlights the appropriateness of using EEGLAB for offline EEG data analysis and BCILAB for both offline and online analysis and classification. The integration of servo motors in the exoskeleton, allowing movements in five Degrees of Freedom (DOF), positions it as an effective rehabilitation solution for individuals with upper limb impairments.

KEYWORDS

brain-computer interfaces (BCIs), rehabilitation, exoskeleton, electroencephalographic (EEG)

1 INTRODUCTION

Systems known as BCIs translate users' intentions from the central nervous system to external devices [1]. With a better understanding of the functioning of the brain, the introduction of effective low-cost computer equipment, and the recognition of the requirements and potentials of individuals with disabilities, the current focus of BCI research is on creating new technologies for augmentative communication and

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control that will help people with severe neuromuscular illnesses such as spinal cord damage, brainstem stroke, and amyotrophic lateral sclerosis. Modern BCIs derive the user's intent from a range of electrophysiological signals such as EEG, ECoG, and so on. Examples of these signals include mu or beta rhythms, P300 potentials, slow cortical potentials, and cortical neuronal activity recorded by implanted electrodes. They are instantly converted into commands that control a computer display or another device [2, 3]. In particular, over the past ten years, BCI interventions have been investigated as treatments to enhance stroke patients' recovery of their upper limb motor function [4, 5]. The fact that patients may still operate a BCI while having damaged brain tissue is one of the key factors contributing to the increased interest in BCI for stroke rehabilitation. Additionally, the development of innovative treatments is a top priority to alleviate the strain on healthcare systems, as stroke is one of the leading causes of motor disability worldwide [6, 7]. It has been demonstrated that rehabilitation helps stroke victims regain specific motor skills. It is not difficult to regain some range of motion in the shoulder and elbow through effective and intense rehabilitation training, according to several clinically controlled investigations. The rehabilitation of severely paretic wrist and finger control, which sometimes hinders patients from rejoining their families and society, is difficult to improve. Therefore, there is an urgent need to look for innovative treatments to enhance. The motor function of the upper limb. Patients with stroke often experience profound and superficial sensory abnormalities [8, 9]. According to studies, enhancing sensory output and input while exercising may be crucial for the recovery of motor impairments because it encourages the rehabilitation of sensory impairments [10]. The potential for advancements in the field of stroke rehabilitation in the future is believed to be inherent in EEG-controlled exoskeletons, a cutting-edge technology [11]. Either the scalp's surface or the cortical surface directly provides the brain with signals that indicate the overall electrophysiological activity of the brain's nerve cells. It is a neuronal voltage fluctuation that can indicate changes in several physiological states [12]. There are three different approaches for recording the electrical activity of the brain: two of them are invasive (ECoG and intracortical recordings), and one is non-invasive (EEG) [13]. The signal is stronger and has a higher amplitude in the invasive methods compared to the non-invasive ones, which results in more accurate data. The issue is that obtaining these signals often involves risky, costly, and complex surgery. One of the primary shortcomings of the invasive method is that it can only be used for a very limited time before it needs to be withdrawn because it can damage nearby tissue [14]. The most widely used BCI systems are non-invasive because they do not need to be implanted, and their use is neither challenging nor dangerous [15]. The purpose of this work is to explore and develop BCIs as transformative tools for translating neural signals into commands for external devices. The focus is specifically on addressing the urgent need for innovative treatments to improve upper limb motor function in stroke survivors, taking into account the limitations of traditional rehabilitation methods. The research emphasizes the development of augmentative communication and control technologies, particularly for individuals with severe neuromuscular disorders, with a specific focus on stroke patients. The study utilizes EEG signals to effectively decode users' intentions and control a 3D-printed upper limb exoskeleton. The experimental procedure involved recording actions related to both motor imagery and facial expression signals. Ultimately, integrating servo motors into the exoskeleton to enable movements in five DOFs positions it as an effective rehabilitation solution for individuals with upper limb impairments. The work contributes to the advancement of BCIs and their application in providing enhanced rehabilitation solutions for individuals with motor impairments, particularly those with upper limb disabilities like stroke survivors.

1.1 Principles of brain-computer interfaces

A BCI consists of several crucial components, such as an input mechanism, usually based on the user's electrophysiological activity; an output system that conveys instructions to the connected device; intermediary elements that convert input signals into actionable output commands; and a structured protocol that governs the timing, methodology, and instances of operation and non-operation. The interaction between the user and the system's adaptive controllers is crucial for the successful operation of BCI. BCI must identify and extract user-controllable features and then precisely and efficiently translate those characteristics into device commands. These components and their primary interactions are illustrated in Figure 1 [1].

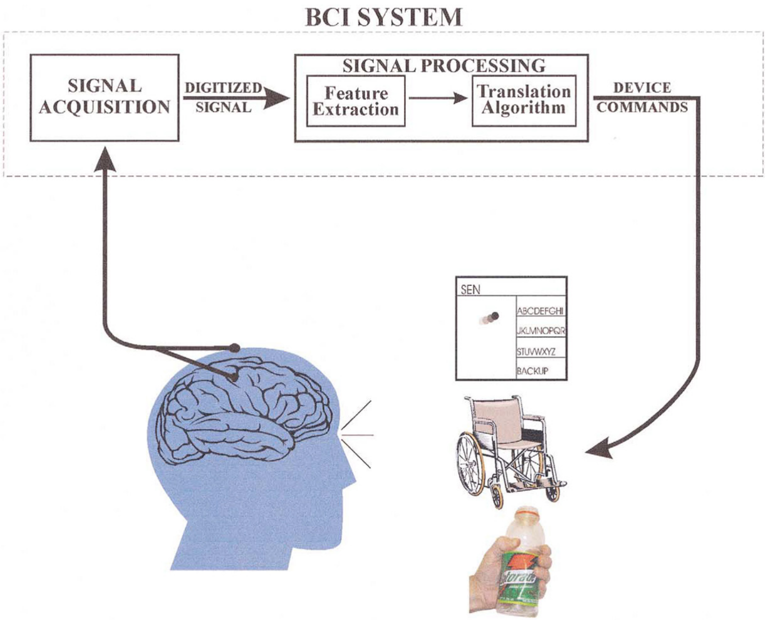

Fig. 1. Basic design and operation of a BCI system [1]

EEG activity can be examined and measured in two different ways: voltage versus time and voltage or power versus frequency. EEG-based communication can take advantage of either type of analysis. Additionally, research has shown that individuals can influence certain EEG characteristics, leading to EEG signals becoming more prevalent than other types of BCIs [16].

2 MATERIALS AND METHODS

2.1 Participants

Two healthy subjects and one stroke patient were recruited as participants in the study, and each of them completed EEG recording sessions under controlled conditions.

2.2 EEG signal acquisition and processing

EMOTIV EPOC+ sensor. According to the international 10–20 system, a reasonably priced, commercially accessible 14-channel EEG EMOTIV EPOC+ Neuroheadset (see Figure 2A) was utilized to collect raw data from electrodes placed at F3, FC5, AF3, F7, T7, P7, O1, O2, P8, T8, F8, AF4, FC6, and F4 positions, in conjunction with two reference electrodes (CMS, DRL), and a gyroscope that provides information about head movements (see Figure 2B).

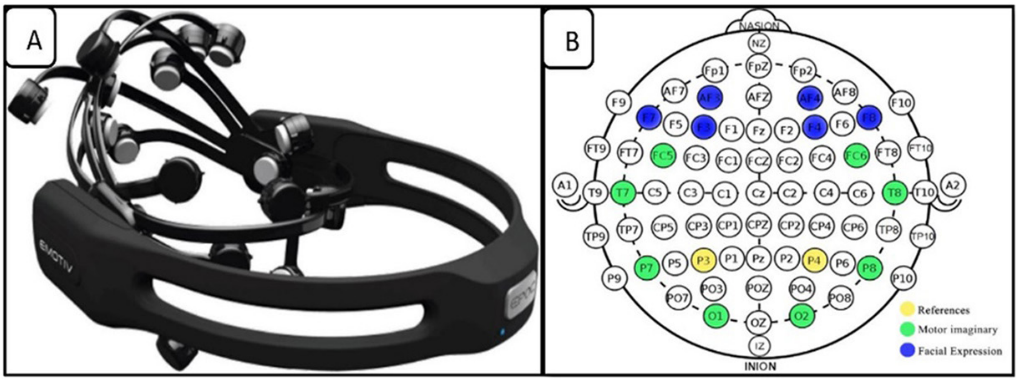

Fig. 2. (A) EMOTIV EPOC+ sensor, and (B) Electrodes locations for motor imaginary and facial expressions of EMOTIV headset based on 10/20 international system

The sensor includes effective classifiers to recognize a variety of facial emotions, such as blinking, left and right winks, raised eyebrows, frowns, smiles, and clenched teeth. Since the headset uses Bluetooth to connect to PCs or other microcontroller devices, it offers greater mobility. The maximum sampling frequency is 128 Hz. All of the EMOTIV EPOC+ headset's standard accessible electrodes were used in this experimental investigation. The signal quality can be improved by using conductive media, such as saline solutions, to reduce impedance and enhance contact quality. Real-time impedance monitoring is possible with the impedance monitoring program included in the EMOTIV EPOC+ headset.

Experimental procedure. The EEG data was obtained using a 14-channel EMOTIV EPOC headset, which was programmed with EmotivPRO and connected to third-party programs (MATLAB Simulink and Emokey) for acquiring motor imagery and facial expression signals within specific paradigms. These signals were then used as input signals for the exoskeleton actuators. EmotivPRO is an Emotiv application used to analyze the output from their EEG headset. It allows users to practice mental commands to operate machines using their minds. It also enables users to examine real-time performance metrics, facial expressions, and motion sensor data streams from their headsets. The first step in properly configuring the EmotivPRO is to place it in the correct position. To do so, verify the reference sensors. If they are green, the position is correct, and it is safe. Each day, three runs were collected during the training data collection. Each run includes five different trials (files) of eight seconds for each case of motor imagery (by visualizing the cubic status: fixed, pull, move left, right, and push) task recordings. In addition, three runs were recorded per day, with each run containing five unique trials (files) of eight seconds for five different facial expressions (frown, clenched teeth, left and right eye blink, and eyes closed). The overall data size for each subject was 15,360 samples for motor imagery and 15,360 samples for facial expressions, calculated as follows: 3 runs × 5 trials × 8 seconds × 128 sampling rates for each day. The data recording process took five days for each person. During the acquisition process, EmotivPRO presents unique images for each instance of motor imagination and facial expression. These images are shown to the subject after giving them specific instructions at a designated time for a set duration, guiding them on the tasks to perform in the depicted sequence, as illustrated in Figure 3.

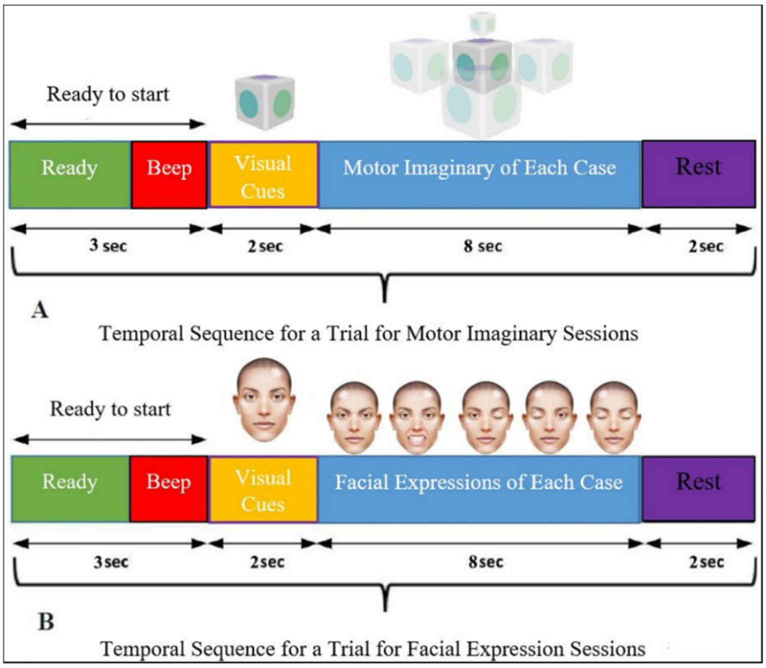

Fig. 3. Experimental protocol for each trial of (A) Motor imaginary, (B) Facial expressions

Motor imaginary signals were used to move the exoskeleton, while facial expressions were utilized to determine which method had the highest accuracy. Every facial expression or motor imagery action corresponds to a movement in the exoskeleton, as illustrated in Table 1.

Table 1. Shows face expressions and motor imaginary actions with corresponding exoskeleton movements

Facial expressions					
Motor imaginary actions					
Desired exoskeleton movement	Hand flexion and extension	Hand abduction and adduction	Elbow flexion and extension	Shoulder flexion and extension	Shoulder abduction and adduction

Facial expressions and motor imagery signals were used to control the exoskeleton, as detailed in Table 1 and described below:

- Furrow brows; or, the cube does not move = Hand flexion or extension
- Clenched teeth; or, the cube is approaching = Hand abduction or adduction
- Left eye blink; or, the cube is moving right = Elbow flexion or extension
- Right eye blink; or, the cube is moving left = Shoulder flexion or extension
- Eyes closed; or, the cube is moving away = Shoulder abduction or adduction

When the setup is finished, the main EmotivPRO window displays, which is separated into two sections.

- The section on facial expressions will capture brain signals and train expressions such as smiling, smirking left or right, frowning, and so on. By selecting the live mode, a face model replicates the facial expressions made in real life. A user must configure the EEG sensor correctly and start training an expression in the training window.
- The section on mental commands involves training and tracking signals of concentration, relaxation, stress, and motor imagery. The system is designed to learn and recognize the user's baseline mental state or neutral condition by capturing a short period of their brain patterns when they are not actively trying to give any commands. Then, training a new mental command is as simple as selecting the correct command label in the training mode. Next, envision a moment of cubic for 8 seconds. For instance, for the left, right, push, and pull commands, imagine the target object floating up into the air.

The cube moves away when the training includes the push command. If the "left" command is triggered, it will move to the left instead. The neutral state is represented by the center. The goal is to refine the instructions to ensure that the disparity between states is significant enough for the EmotivPRO to avoid mistaking one command for another during live mode.

Feature extraction and classification. The statistical EEGLAB software (a MATLAB plugin) was used to pre-process the obtained EEG signal. It included a built-in digital notch filter at 50 Hz and a digital band-pass filter at 60 Hz, covering a frequency range of 0.16–45 Hz. BCILAB is an EEGLAB plug-in used for designing, testing, prototyping, exploring, and evaluating BCI. Both of these applications are MATLAB-based. EEGLAB is well-optimized for processing EEG data and can efficiently handle datasets of different sizes. BCILAB's performance depends on the complexity of the BCI model under development and the computational resources at hand. The choice between them depends on the research or application requirements. The signal processing of raw EEG data occurs in multiple phases to transform it into classified findings that can be accessed by output devices, such as an upper limb exoskeleton. These phases include feature extraction, classification, and translation. The processing stage includes feature extraction, feature selection, and classification. The spatial filter was utilized, and the linear classifier was employed to translate the extracted features into signals independent of device control. The outputs were normalized to have a zero mean and a specific desired value range. Open-source packages and functions can be used to interface with the MATLAB application. It supports the support vector machine (SVM) classifier package from the Libsvm library, which is an extremely effective toolkit for optimizing and implementing SVM models. Libsvm's most essential functions in the MATLAB environment are "svmtrain" and "svmpredict." For classification, the characteristics are directly input into the SVM model and transformed into power spectrum density (PSD) in the frequency domain. Fast Fourier Transform (FFT) is a common method used to convert signals from the time domain to the frequency domain. In this experiment, w1 and w2 represent the weights of the classes for the SVM classification algorithm. W1 and w2 are usually equal to 0.5 when there are two classes and the amount of data in each class is the same. A final EEG signal analysis was performed to categorize the subject's EEG data into two classes: imagining a cube movement and employing a facial expression. The computer sends a command to the upper limb exoskeleton to move the patient's hand using a Simulink controller based on the best signal accuracy categorization. Each trial's data is recorded in a MATLAB matrix file (.mat) with a size of 640×14. Only three runs were required to train the machine-learning module. Before each trial recording, the subject was asked to remain calm, avoid clenching their jaw or blinking their eyes (for both motor imagery and facial expression tests), and to listen to the cue sound (beep) signaling the start of the acquisition procedure. In each trial, the individual performs the task upon hearing the beep sound and stops when hearing another beep after 8 seconds of recording. Three classifiers were implemented: KNN [17], LDA [18], and SVM, with a flowchart shown in Figure 4 below.

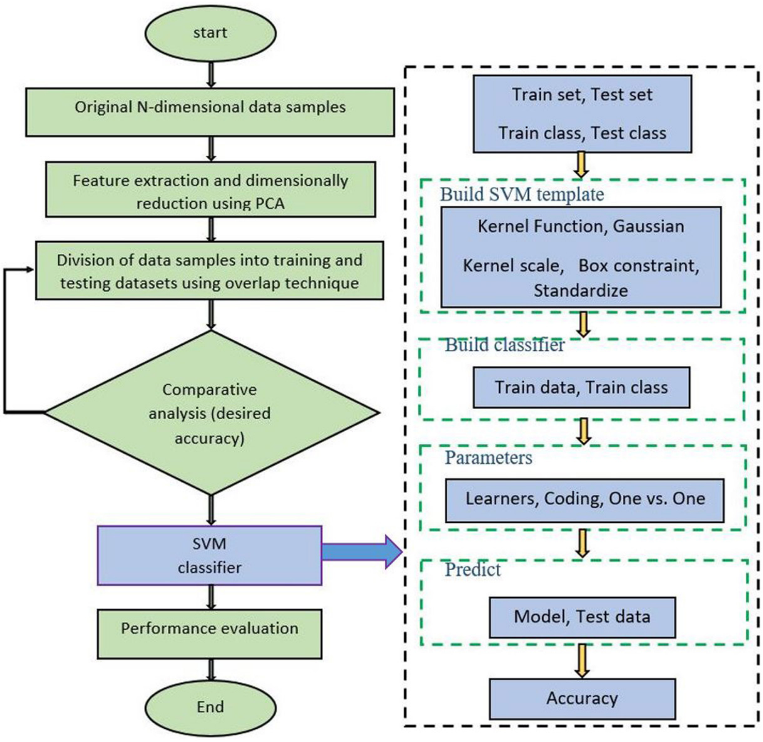

Fig. 4. Proposed flowchart of SVM classifier used

The architecture of the EEG paradigm is shown in Figure 5.

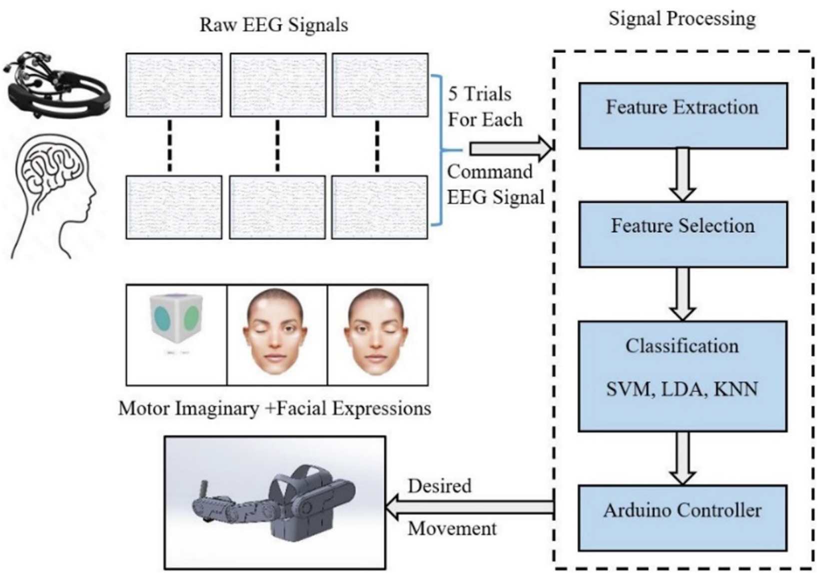

Fig. 5. Proposed architecture of EEG paradigm for online control of upper limb exoskeleton

2.3 Mechanical design

The exoskeleton was created using a manufacturing technique known as 3D printing. This method allows for the construction of computer-aided design (CAD) models using thermoplastics, specifically polylactic acid (PLA). 3D printing offers customization, simplicity, affordability, and access to open-source designs. It is composed of five DOFs as follows:

1. Shoulder abduction or adduction and flexion or extension: The shoulder servo motor enables the exoskeleton to move the arm away from or towards the body, replicating the natural abduction and adduction movements.
2. Elbow flexion or extension: The servo motor in the elbow region enables the exoskeleton to bend and straighten the user's arm, replicating the flexion and extension actions.
3. Wrist flexion or extension: One of the hand region servo motors controls the wrist's flexion and extension movements, which are essential for accomplishing various daily tasks.
4. Wrist abduction or adduction: The second servo motor in the hand region enables the exoskeleton to execute abduction/adduction movements.

Individual parts and the final design are shown in Figure 6.

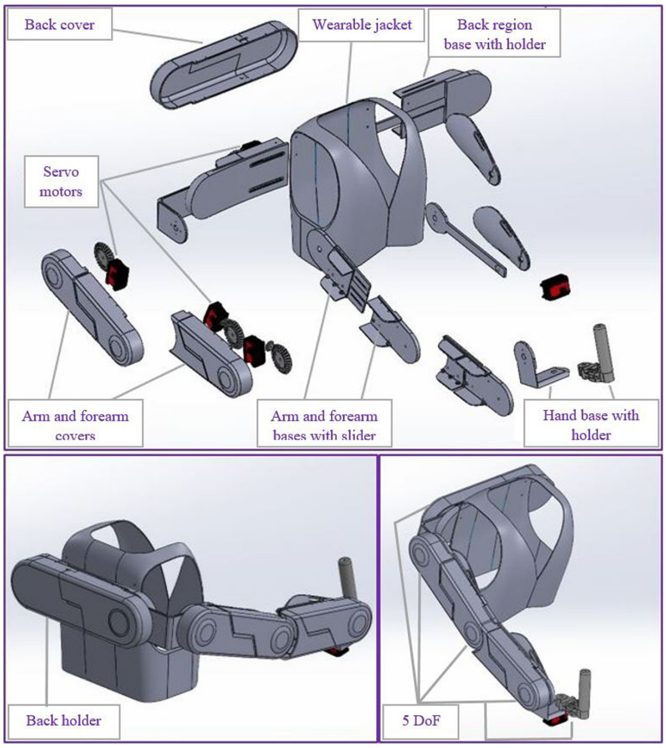

Fig. 6. Shows individual parts and final design with five DOFs

3 RESULTS AND DISCUSSIONS

The successful deployment of EEG-based control of an upper limb exoskeleton utilizing five distinct facial expressions represents a significant milestone in the field of assistive technology. Individuals with poor motor function can control a variety of complex actions within the exoskeleton by analyzing EEG signals associated with five specific facial expressions. This unique approach leverages the brain's capacity to create intricate neural patterns, enabling users to seamlessly coordinate movements such as flexion, extension, adduction, and abduction simply by evoking the corresponding facial expressions. The proposed classification approach has been applied to the recorded EEG data to develop a model capable of classifying motor imagery and facial expression EEG signals. A subset of the best channels was chosen, and three classification techniques—SVM, KNN, and LDA algorithms—were used to test the performance. Better accuracy was achieved with the SVM classifier in both offline and online modes. A single trial took eight seconds to complete at a sampling rate of 128 Hz, producing a total of 1024 samples. The motor imagery channels (FC5, FC6, T7, T8, P7, P8, O1, and O2) and the facial expression channels (AF3, AF4, F7, F8, F3, and F4) were selected. Figure 7 displays raw data from eight channels of single-trial EEG signals.

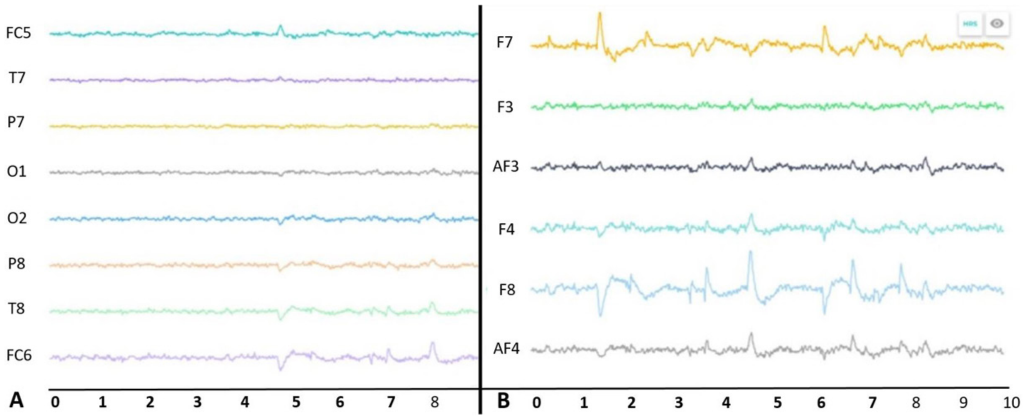

Fig. 7. Selection of (A) eight channels in the motor imagery and (B) six channels of facial expression case of a single-trial EEG

Table 2 shows the classification accuracy for facial expressions and motor imaginary EEG signals during 10-fold cross-validation.

Table 2. Classification accuracy for facial expressions and motor imaginary of EEG signals

No. of Folds	Facial Expressions Accuracy % (20% Test and 80% Train)			Motor Imaginary Accuracy % (20% Test and 80% Train)		
	SVM	LDA	KNN	SVM	LDA	KNN
1	90	88	86	77	72	65
2	89	85	82	73	70	61
3	87	79	88	69	65	63
4	91	90	87	70	61	60
5	92	87	80	67	78	72
6	88	90	77	74	70	71
7	90	89	81	68	64	62
8	92	91	86	80	77	60
9	92	90	88	79	75	68
10	90	90	78	81	77	70
Average	90.1	87.9	83.3	73.8	70.9	65.2

As shown in Table 2, the SVM classifier performed the best in both facial expressions and motor imagery sessions. The average accuracy for facial expressions with the SVM classifier was 90.1% and 73.8% for motor imagery. There was no difference in terms of movement performance among the volunteer participants, but there was a disparity in the speed of the patient's adaptation to the exoskeleton, which was slightly slower compared to that of typical individuals. Referring to some studies in this field, in the study [19], there was an issue with the duration of the rehabilitation. The MI group utilized two rehabilitation procedures, leading to a longer rehabilitation period compared to the control group, which impacted the scoring. In the study [20], only signals from imagination were utilized, and the predicate was applied to a healthy individual using only two electrodes EEG sensor, and a whole-arm manipulator.

Below is an analysis of various aspects of the study:

1. DOFs and movement complexity: The incorporation of five DOFs in the upper limb exoskeleton allows for a nuanced and naturalistic replication of upper limb movements. The inclusion of multiple movements, such as hand and elbow actions, shoulder flexion and extension, and abduction and adduction, addresses the complex nature of upper limb motor function. In addition to the achieved accuracy, the range of motion is comparable to that of a healthy individual, and the response time is estimated to be one second.
2. Control mechanism with EMOTIV EPOC sensor: The utilization of the EMOTIV EPOC sensor for controlling the upper limb exoskeleton reflects a novel and non-invasive approach. The sensor, designed to measure and interpret electrical brain activity, offers an intuitive and user-friendly interface for individuals with motor impairments. This BCI enables users to control the exoskeleton using their thoughts, improving the overall user experience and enabling smooth control.
3. Relevance to rehabilitation: The selected set of movements closely aligns with the requirements of upper-limb rehabilitation. By enabling hand, elbow, and shoulder movements, the exoskeleton can be customized to meet the specific needs of individuals recovering from various upper limb impairments, including stroke survivors. This personalized approach is crucial for effective rehabilitation and relearning of motor skills.
4. Integration of EMOTIV EPOC sensor data: The success of the study in integrating the EMOTIV EPOC sensor data into the control mechanism demonstrates the feasibility of translating neural signals into precise and coordinated movements. The accuracy and efficiency of this integration are crucial for the exoskeleton's effectiveness in rehabilitation settings.
5. Challenges and future considerations: While the current study highlights promising outcomes, future research may need to address potential challenges such as calibration accuracy, real-time responsiveness, and adapting the system to different levels of motor impairment. Additionally, user feedback and long-term usability studies could provide valuable insights for refining the technology.

Figure 8a shows the topographical map of the scalp for each motor imagery case (natural, push, pull, left, and right) and (b) the topographical map of the scalp for facial expressions in each case (eye closed, clench teeth, frown, wink left, and wink right).

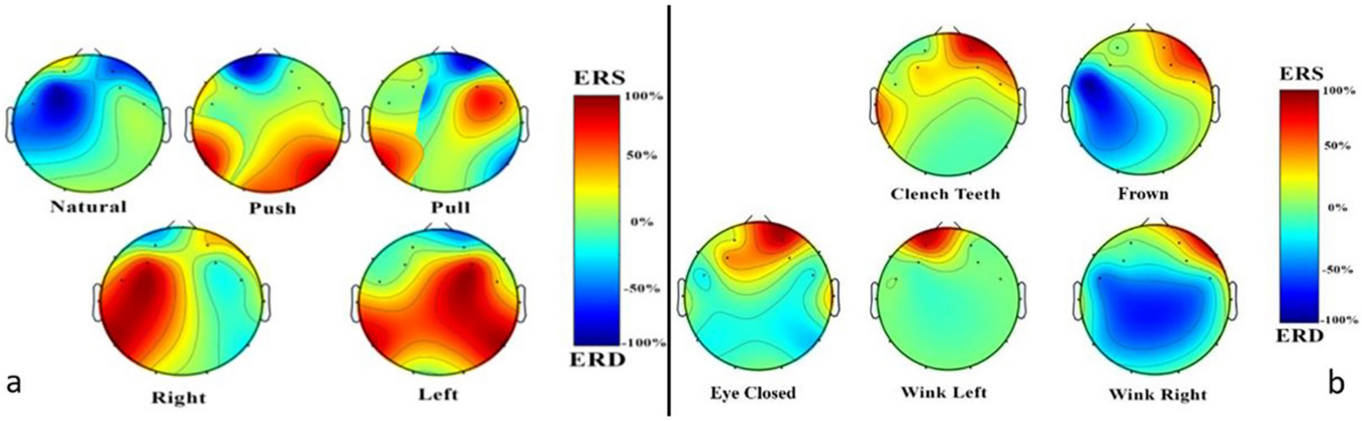

Fig. 8. The topographical map of the scalp for each motor imaginary (a) and facial expressions (b) cases respectively

The results can be summarized in the following points:

1. More than one method was used to control the exoskeleton, such as facial expressions and motor imagery.
2. The combination of the number of upper-limb movements and the extent of each movement enhances the effectiveness of the rehabilitation process.
3. The exoskeleton is designed to be easy to wear so that it does not burden the patient.
4. More than one classifier was used to achieve the highest possible accuracy.

Performance was measured in the following ways:

1. Classification accuracy according to three classifiers: LDA, KNN, and SVM.
2. The response time was approximately one second.
3. The range of movement was completely similar to that of a normal person.

4 CONCLUSION

EEGLAB is more suitable for offline analysis of EEG data, while BCILAB is optimal for both offline and online analysis and classification of EEG data, as well as for real-time transfer of classification results to external applications. The integration of these servo motors in the back, shoulder, elbow, and hand regions, along with the five primary movements, guarantees that the upper limb exoskeleton offers an efficient and adaptable rehabilitation solution. It enables people with upper limb impairments to recover their independence, develop their motor skills, and reclaim a better quality of life. Higher accuracy was achieved using the SVM classifier for both motor-imaging and facial expression tasks in both offline and online modes. The criteria used to assess the benefits and performance of the exoskeleton for rehabilitation were established based on input from physical therapy specialists. This input was used to develop software that includes:

- The repetition of movements,
- The time of each movement, and
- The training time.

5 STATEMENTS AND DECLARATIONS

5.1 Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

5.2 Competing interests

The authors declare that there are no financial or personal links that could be considered competing interests.

5.3 Consent to participate

All of the study's subjects provided informed consent.

5.4 Consent to publish

The authors affirm that human research participants provided informed consent for publication.

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