EEG-Based Exoskeleton for Rehabilitation Therapy

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Abstract Functional restoration of arm and hand movements is a challenging goal of post-stroke/trauma rehabilitation therapy. The post-stroke/trauma conditions often may lead to partial or total loss of motor function. Therefore, the use of assistive brain-controlled robotic exoskeleton has recently gained a lot of interest from the bioengineering research community. In this study, electroencephalography (EEG) has been used for controlling the exoskeleton and for providing the brain–machine interface (BMI) roadmap. The brain signals were recorded corresponding to different imagined movement by normal subjects using 10–20 standard electrode placement system. A sample of the EEG recorded at a frequency of at least 160 Hz was pre-processed to remove the line frequency interference and artifacts. Features were then extracted from the EEG signal and processed to actuate the exoskeleton, thus ultimately assisting the subject in his/her rehabilitation program. A linear discriminant analysis (LDA)-based classifier is used to map the extracted features to a specific task. This study has achieved the best accuracy of 97.101% using linear classifiers and 72.133% using quadratic classifiers. This paper presents system design and development along with an experimental evaluation of EEG-driven exoskeleton. This exoskeleton could then be used to assist in the rehabilitation program of stroke/trauma patients.

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1 Introduction

Hemiparesis or unilateral paresis is one of the most common aftermaths of stroke-causing weakness of the muscles leading to an abnormal posture, most unpleasant form causes one side of the body to get paralyzed, movement disabilities, thus degrading the quality of life of stroke/trauma patients [1, 2]. According to the World Health Organization (WHO), 15 million people suffer from stroke each year and out of them, more than 30% are left to lead their lives with permanent disabilities [3]. The initial treatment provided to them is physical therapy so that they can perform their basic daily life activities. To some extent, physical therapy helps in easing their lives by enabling them to use wheelchairs, walking on their own, moving upstairs, etc. But the percentage of post-stroke/trauma patients able to perform these tasks is quite depressing [4]. With reference to rehabilitation, it has been shown that high vigor and the repetition of task-specific can improve the motor functionality to a certain extent. Conventional rehabilitation clinics offer a dose of the repetitive task which is insufficient to compensate for neural deterioration and prevent or offset neural decline [5]. This led to a search for new methodologies and techniques that could provide a more promising solution to these motor disabilities such as robot assistive devices and electrical stimulation [6].

Robotic devices have been widely used for the purpose of post-stroke/trauma patients. These robot assistive devices have an edge over the conventional therapy-based system which was based on long hours of intensive exercises in terms of accuracy speed and reliability [7]. Some of the drawbacks associated with these robot-based devices include flexibility, limited communication with the external environment, acclimation, etc. [7].

A more promising approach to overcome these aforementioned shortcomings was put forward in the form of exoskeletons which are far more flexible involving the concept of brain–machine interface (BMI). In this study, an EEG-based exoskeleton has been proposed. BMI extracts information from the human brain, analyzes those patterns corresponding to the neural activity of the brain and then provides these signals as inputs to the machine [8] hence can provide a means for the disabled to interact with the outside world [7]. EEG is most widely used to measure the brain's activity in BMI [9]. The recorded EEG data contains many irrelevant artifacts, so these recorded signals are first processed, then the relevant features are extracted and these features are then classified using linear discriminant analysis. The best accuracy obtained after classification of executed and imagined motion is 97.10 for subject 5.

2 Mechatronic Design

The basic necessity for the proper functioning of a hand exoskeleton is the compatibility with the human arm. The movement of the hand is aided by a wrist joint, elbow joint and shoulder joint. The wrist is a complex junction formed by carpal and forearm bones. It is capable of some distinct set of movements such as flexion and extension, supination and pronation, and ulnar deviation and radial deviation [10]. The exoskeleton in the present work was designed to facilitate the wrist extension and flexion movement along with fingers extension and flexion (see Fig. 1).

The important anthropometric data used for the design is as follows:

Hand length = 185.77 mm, palm length = 105.59 mm, finger length = 59.13 mm elbow-wrist length = 263.72 mm [11]. To reduce the material cost, the lengths of the PVC rods of exoskeleton are kept less than the anthropometric data but sufficient to carry out the required function. The range of torque used for wrist flexion was 8.1–14.5 N.m and wrist extension was 6.0–11.5 N.m [12].

To provide the above-said movements, two revolute joints are provided at the wrist and finger joint, respectively. The exoskeleton designed and fabricated in the present work consisted of three main parts, namely elbow support, hand support and finger support.

2.1 Elbow Support

Two rods (length 180 mm; diameter 16 mm) made up of PVC were used to provide elbow support (see Fig. 2a). These were arranged in parallel to each other on opposite sides of the forearm. These rods also supported the servomotors attached to it to carry out the wrist rotation.

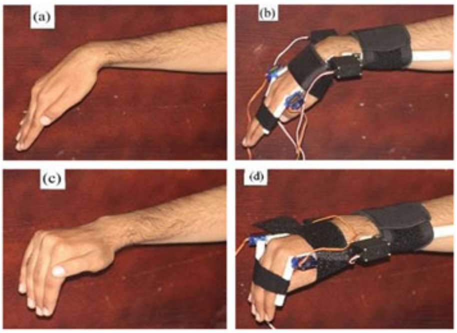

Fig. 1 Shows flexion movement of wrist and fingers with or without exoskeleton **a**, **b**, **c** & **d** respectively

Fig. 2 Shows various parts of Exoskeleton **a** Elbow support, **b** Hand support, **c** Finger support, **d** Assembled exoskeleton

Table 1 Material Properties of PVC rods [13]

Properties	Value
Thermal Properties	
Thermal Conductivity	0.16 W/mk
Specific heat	1000 J/wk
Co-efficient of thermal expansion	7×10^{-5}/k
Mechanical properties	
Elastic tensile modulus	3–3.3 Gpa
Shear modulus	1 Gpa
Bulk modulus	4.7 Gpa
Poisson's ratio	0.4
Ultimate tensile strength	52 MPa
Relative density	1.42–1.48

2.2 Hand Support

Hand support consisted of two parallel rods (length 90 mm; diameter 14 mm) mounted on the two sides of the hand, from wrist to metacarpal joints (Table 1).

These rods are separately connected to the elbow support rods using a shaft. These rods form a turning pair with the elbow support in such a way that with the rotation of servomotor shaft, rods provided the extension-flexion movement to the wrist has been shown (see Fig. 2b).

2.3 Finger Support

This part was designed to provide the movement of fingers. It consists of two separate parallel rods (length 59 mm; diameter 11 mm) attached to both the sides of the hand, from metacarpal joints to the tip of the fingers (see Fig. 2c). Hence, the shaft of servomotor was able to produce the extension-flexion movement to the fingers.

2.4 Fabrication

PVC material was selected due to its lightweight, good wearability, and good insulation properties. Apart from these properties, it remained unaffected by environmental variation. The properties of the material have been shown in Table 2 [13]. The fabricated model of the exoskeleton has been shown (see Fig. 2d).

3 EEG

Electroencephalography (EEG) is a method of recording the brain waves. The observed signal is usually recorded, processed and used for various purposes, here, for BMI. Because of its good temporal resolution [14] and noninvasive nature, BCI operates on an EEG.

Brain activity can be categorized into various frequency bands which are delta, theta, alpha, beta, gamma and mu. These frequency bands correspond to different tasks corresponding to their frequencies. Delta (<4 Hz) occurs in adults sleep state, Theta (4 to7 Hz) occurs during idleness, Alpha (8 to 15 Hz) occurs during the relaxed state, Beta (16 to 31 Hz) during alert working and busy state and Gamma (>32 Hz) occurs in somatosensory state [15]. This study particularly focuses on the motor functions which are almost exclusively found in parts of the primary motor cortex.

Table 2 Percentage accuracy obtained using linear and quadratic classifier for different subjects

S.NO.	Subjects	Classifier	Accuracy (%)
1	*S1*	Linear	61.333
2	*S2*	Linear	94.927
3	*S3*	Linear	93.333
4	*S4*	Linear	61.594
5	*S5*	Linear	97.101
6	*Combined data (S1,S2,S3,S4,S5)*	Linear	59.200
7	*Combined data (S1,S2,S3,S4,S5)*	Quadratic	**72.133**

3.1 Data Acquisition

The data used in the paper for research was created by BCI2000 and contributed by physioNet.org which is made publicly available [16]. The data consists of 109 subjects and was asked to perform motor imagery. Each subject has performed various tasks and corresponding to each task, 14 EEG recordings of one or two minutes have been made depending upon the task. The data was recorded by a 64 channel EEG using 10–20 international system.

Experiment Protocols. Every healthy subject was asked to perform 14 experiments as: One baseline experiment (one minute) eyes open and another baseline experiment (one minute) eyes closed.

Task 1—A target appears on either left or right side of the screen and the subject opens and closes continuously the corresponding fist until the target disappears. Then, the subject relaxes.

Task 2—A target appears on either left or right side of the screen and the subject imagines opening and closing of the corresponding fist until the target disappears. Then, the subject relaxes.

Task 3—A target appears on either top or bottom of the screen and the subject opens and closes either both his (target on top) or both his feet (target on bottom) until the target disappear. Then, the subject relaxes.

Task 4—A target appears on either top or bottom of the screen and the subject imagines opening and closing either both his fist (target on top) or both his feet (target on bottom) until the target disappear. Then, the subject relaxes.

Each of these tasks is two minutes recorded EEG DATA using 64 channel EEG placed according to 10–20 international system. These four tasks are repeated various times so as to make an experimental run of 12 and two one-min baseline experiments.

Subset Experiment Dataset. Five subjects have been chosen out of 109 subjects and data related to Task-1 and Task-2 of these subjects only have been considered and worked upon. Essentially the data (executed and imagined) related to opening and closing of fist has been taken. The new data set thus created includes five subjects (S001, S002, S003, S004 and S005) and their executed and imagined motion. Now each subject has a total of 6 experimental runs (3 executed and 3 imagined) of two minutes each.

4 Channel Selection

Any motor movement even a contraction of a single muscle triggers a change in brain activity in the cortex [4]. Sensorimotor rhythm (SMR) is brain oscillations comprising of mu rhythms and beta rhythms. They are located in somatosensory areas and motor areas. The normal motor output is related to brains cortical areas to which mu and beta rhythms are linked. SMR or mu, beta rhythms typically decrease

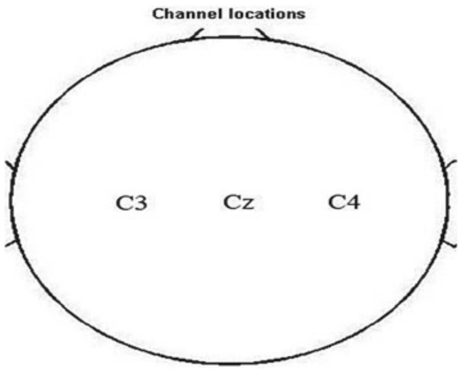

Fig. 3 Selected channels for the feature extraction

when motor areas are activated [17]. It has been shown that brain activity related to the motor function of executed movement is almost exclusively contained within the C3, C4, Cz channels of 64 channel EEG using 10–20 system [14]. The selected channels lie just above the primary motor cortex of the brain to observe the motor activity of the subjects properly (Fig. 3).

4.1 Feature Extraction

For the extraction of relevant features from the raw EEG data, certain statistical parameters are chosen as Interquartile range (IQR), Median absolute deviation (MAD) and energy (E). IQR is defined as a measure of statistical dispersion, which equals to the 75th and 25 quartile or upper quartile or lower quartile. MAD is defined as the median absolute deviation is defined as the variability of a univariate data. In this way, a total of nine features are selected. Two tasks (each task is repeated three times per subject) have been assigned to each subject one executed and other one imagined, so for each subject the size of the feature matrix is (9 × 375) for the executed motion. Similarly, feature matrix of the same size is for the imagined task.

$$MAD = \text{median}(|X_i - median(X)|) \tag{1}$$

$$E = \sum_{i=1}^{N} Xi^2 \tag{2}$$

where,

E = energy of the signal

Xi= ith amplitude of the EEG signal

MAD = median absolute deviation

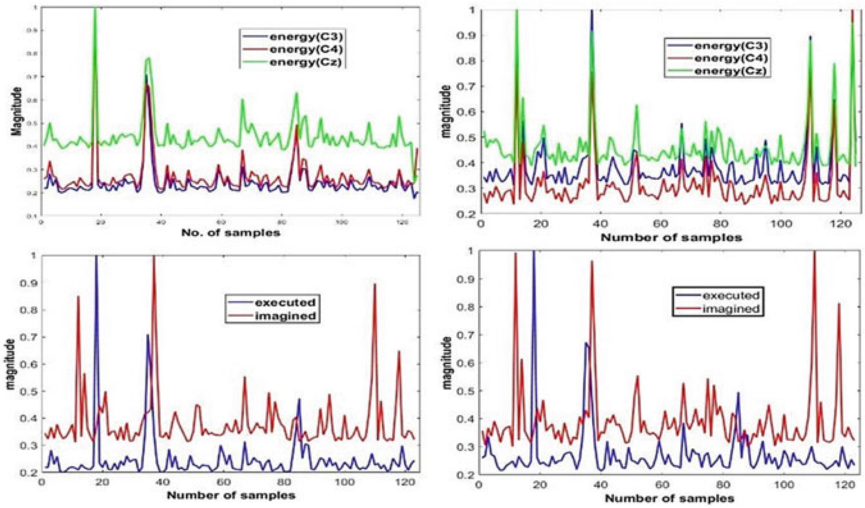

Fig. 4 Shows energy plots of EEG data: Fig. 4a & b Shows executed motion and imagined motion energy plot across the channels (C3, C4, Cz) respectively. Figure 4c & d Shows classified executed and imagined data at channel C3 and C4 respectively

Feature extraction is carried out as follows—first, the windowing signal for each second is done and the number of samples per second is 160. After that, features are extracted for each window using statistical parameters and are stored in a feature matrix of maximum size (9*375). This is repeated for each subject. Finally, the extracted features are classified into executed and imagined using LDA-based classifier. The extracted data energy plots are shown below (see Fig. 4).

The first two plots correspond to the extracted energy feature of executed and imagined motion across the selected channels (C3, C4 and Cz), respectively (see Fig. 4a & b). Then, the particular channel is chosen and the extracted data corresponding to Executed and imagined motion has been plotted (see Fig. 4c & d).

5 Results and Discussion

Table 2 shows accuracies corresponding to different subjects which are obtained by using three features (IQR, MAD and energy). Linear and quadratic classifiers are used for classification. S5 provides the best accuracy for the classification and it can be observed from the plots that the classified data and the imagined data are distinctive in the time domain (see Fig. 4c and d). For the combined dataset, the accuracy has been improved by using quadratic classifier and can be further improved by using deep learning tools.

6 Conclusion

In this research, a simple and efficient exoskeleton has been developed. The lightweight and good wearability of the fabricated exoskeleton further make it ergonomically effective. Categorization between the imagined and executed motion has been performed with sufficiently good accuracies, by using an LDA-based simple classification. More improvement in the accuracies can be achieved by using classifiers based on deep learning. It offers a promising and potential roadmap to BCI.

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