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A Brain Controlled Robotic Gait Trainer for Neurorehabilitation

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***Abstract*—**This paper discusses a brain controlled robotic gait trainer for neurorehabilitation of Spinal Cord Injury (SCI) patients. Patients suffering from Spinal Cord Injuries (SCI) become unable to execute motion control of their lower proximities due to degeneration of spinal cord neurons. The presented approach can help SCI patients in neuro-rehabilitation training by directly translating patient motor imagery into walkers motion commands and thus bypassing spinal cord neurons completely. A non-invasive EEG based brain-computer interface is used for capturing patient neural activity. For signal processing and classification, an open source software (OpenVibe) is used. Classifiers categorize the patient motor imagery (MI) into a specific set of commands that are further translated into walker motion commands. The robotic walker also employs fall detection for ensuring safety of patient during gait training and can act as a support for SCI patients. The gait trainer is tested with subjects, and satisfactory results were achieved.

***Keywords*—**Brain Computer Interface (BCI), gait trainer, Spinal Cord Injury (SCI), neurorehabilitation.

I. Introduction

SPINAL Cord Injury (SCI) is an injury to spinal cord due to disease, stroke or degeneration of cells. SCI devastates both the physical and psychological well-being of patients. There are around 40 to 80 SCI cases per one million of population and majority of the cases are among young men having an age bracket of 20 to 35 years [1]. SCI injuries are growing every year, almost 25,000 to 500,000 people are suffering from SCI. Nearly 90% of the cases of SCI are linked to traumatic causes [2]. Roughly 12,500 new SCI cases occur each year in the US alone with a total of 27,6000 patients living with SCI [3]. Traffic crashes (driving being the number one cause), sports, falls and violent attacks are the root causes of traumatic related SCI.

Major focus on recovery of SCI patients so far has been to provide them aids, such as a wheelchair or walking stick [4]. This would give patients some measure of independence so that they can perform their basic everyday tasks by themselves. Even the medicine prescribed to these patients aims at stopping further damage rather than curing. Thus most of the tools available to these patients focus on managing the disease, improving the orthotics and increasing patient comfort [5]. Mechanical wheelchairs have been transformed into electronic ones, automated speech recognition software has been developed, and muscle therapy techniques have been established. All these approaches are designed to help the patient with their daily life tasks but fall short when it comes to their rehabilitation. In the long run, they do nothing to cure the patient and instead give way to other diseases such as respiratory illness, pressure based illnesses, osteoporosis, and heart disease [6].

There is no remedy currently present, for patients suffering from spinal cord injuries to recover completely. Treatments that are still in the phase of experimentation like tissue regeneration and stem cell implantations try to repair damaged spinal cord. Nonetheless, the lives of people with Spinal Cord Injuries (SCI) can be significantly improved or in some cases restored to some extent via a Brain Machine Interface (BMI). Using BMI, SCI patients can use brain signals to reflect or translate the state of brain activity using an external orthotic device [7].

Motor Imagery can be defined as a dynamic state in which subjects mentally simulate a specific motor action in working memory without any motor output [8]. MI training helps in enhancing motor performance in SCI patients despite a lack of voluntary control [9]. The main complication in SCI patients is that the signals generating from the brain relating to the movement of lower proximities are not properly transferred due to damage of spinal cord neurons. However, the thought patterns can be captured by a BCI device and further translated to an external orthotic device for lower limbs (a robotic walker) which forces the body to move. This procedure is defined as Spinal Cord Regeneration. Performing this procedure for a certain period can help the body grow new pathways for neural data transfer. The research was done by Christine et al. 2015 [6] explains the successful testing of the for-mentioned concept. The results are promising, the subject was able to achieve information at a transfer rate greater than 3 bits/s and correlation greater than 0.9. The study further explained that there were no adverse events worth mentioning.

Rehabilitation requires a multidisciplinary approach to avoid having further complications for patients. The focus of this paper is to design a robotic gait trainer controlled by a non-invasive brain-computer interface to maximize the rehabilitation by maximizing the movement of lower limbs. The robotic gait trainer is designed to provide physiotherapy as well as aid in rehabilitation for patients with SCI. The combination of brain-computer interface with an orthotic device provides an advanced and innovative approach to rehabilitation. The system offers mechanisms and methods focusing primarily on rehabilitation of motor function after injury or stroke.

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Fig. 1 Hardware Architecture

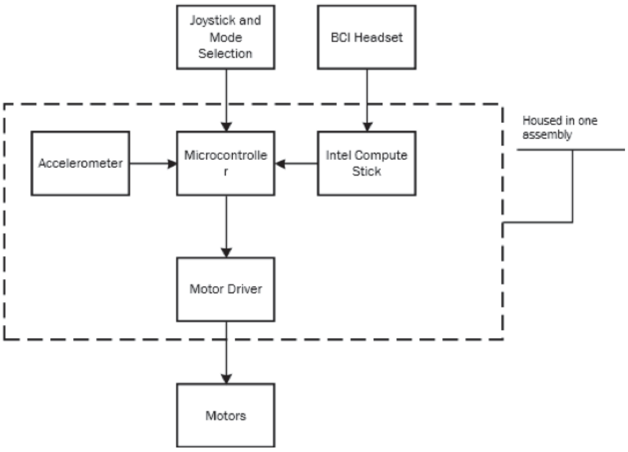

Fig. 2 System Block Diagram

II. Methodology

Brain-Computer Interface is used to detect motor imagery of patient and decode it into an accomplished action by a peripheral device, such as a robotic arm or a limb orthosis. A commercially available walker is partially modified and transformed into a robotic walker. Worm gear motors are attached on the front legs of the walker while ball casters are attached on the rear legs. An indigenously developed electronics module that houses the electronic circuitry, microcontroller, and embedded system hardware is also incorporated in the walker modification. The hardware architecture diagram is shown in Fig. 1. Motion control of walker can be manipulated using both a non-invasive brain-computer interface and a principal control device such as a tri-axial joystick. EEG signals captured by a BCI headset at the frontal lobe of the brain are transmitted to main system software. The software then classifies the signals into one of two classes (right hand MI and left hand MI). After that, it transfers the command to the microcontroller for motion control hence successfully translating thoughts into motion commands. Right hand MI signal is used for implementing walker forward motion and left hand MI signal for stop motion. This allows bypassing spinal cord neurons completely and directly translating thoughts to walkers motion commands. A block diagram representation of the system is shown in Fig. 2.

Intel Compute Stick is used for processing EEG signals and running the VRPN client application. Specification [10] of computer stick meet the requirement of running OpenVibe software and Emotiv SDK. The computer stick also communicates with Arduino microcontroller through serial communication.

A. Brain-Computer Interface

Brain-Computer Interface can be defined as a system that only uses signals from the central nervous system (CNS) [11]. These systems can be employed to substitute for the loss of neuromuscular function by using patients brain signals to interact with the environment. These systems can also be used to restore the impaired motor function. People with impotent motors can use their brain signals for control and communication without using their crippled and incapacitated neuromuscular system. Severely disabled patients have been empowered and enabled to interact with the environment with the help of brain-machine interface that senses brain activity to actuate external peripherals.

BCI is classified into two types: (1) Invasive and (2) non-invasive. Invasive BCI involves the surgical implementation of electrodes into the brain while non-invasive BCIs require no such implementation and enable recording of brain activity using external electrode on the surface of the scalp. A variety of invasive and noninvasive methods for controlling brain-computer interfaces (BCIs) have been probed, from which EEG is the most notable. EEG is the most common methodology for sensing electrical brain activity non-invasively to record neural signals, using specially designed electrodes. Brain activity from a range of frequency bands such as mu (8 - 12 Hz), beta (12 - 30 Hz) and gamma (30 - 100 Hz) can be recorded. Features from these frequency bands can correlate with different imagined motor intents [12]. The strategy of using BCI for a neuro-rehabilitation purpose is showing in Fig. 2. The patient performs motor imagery, and BCI detects and classifies the intention to a motion command for the robotic walker.

Datasets were recorded from a total of 04 subjects (mean age = 21.4 years, SD=1.10, 3 Males, 1 Female). These subjects were healthy and had no nervous system abnormalities in the past. They also had no prior experience of using BCI system. Subjects were asked to comfortably sit in front of computer screen in relaxing position and were specially instructed to feel calm and were asked to not to think of any other thought except for motion during data recording. Two datasets were recorded from each subject. The datasets were collected over a time span of two weeks.

During data recording, subjects were shown a set of arrow and were instructed to mentally stimulate motion in the respective direction. Data recording started with the display of fixation cross on a computer screen. After 3 seconds, a cue appeared in the form of a left or right arrow. The subject is then required to mentally stimulate motion in that direction for 5 seconds. The fixation cross then disappeared, and there is a break of 2 sec. After the break, the next cycle starts. The cue direction was random to ensure best data collection. Duration of one trial was 11 seconds and to avoid over-fitting the data, we randomized the time between two trials in a range of 0.5-1.5 seconds.

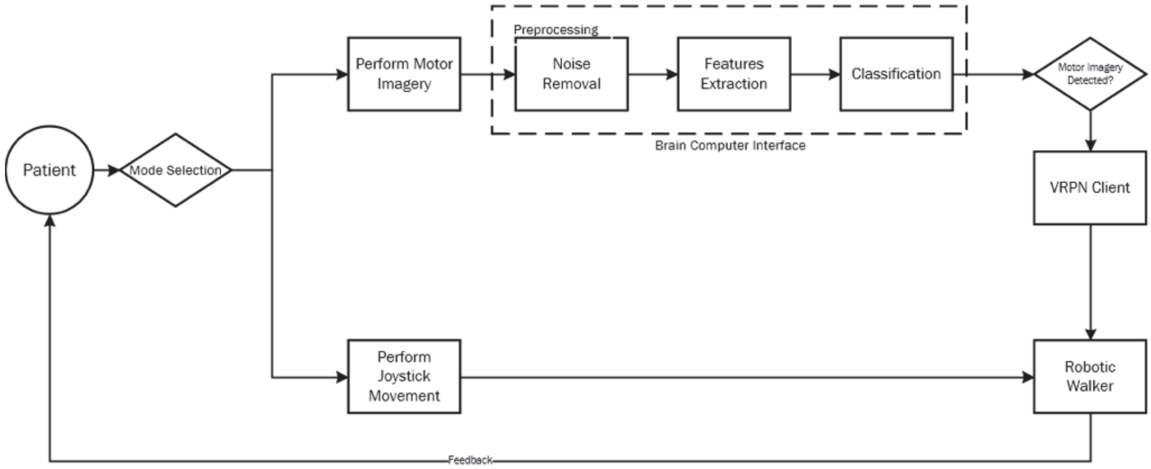

Fig. 3 Strategy of implementing BCI for neuro-rehabilitation

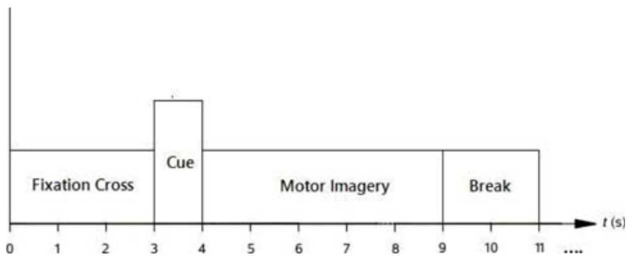

Fig. 4 Timing scheme of paradigm

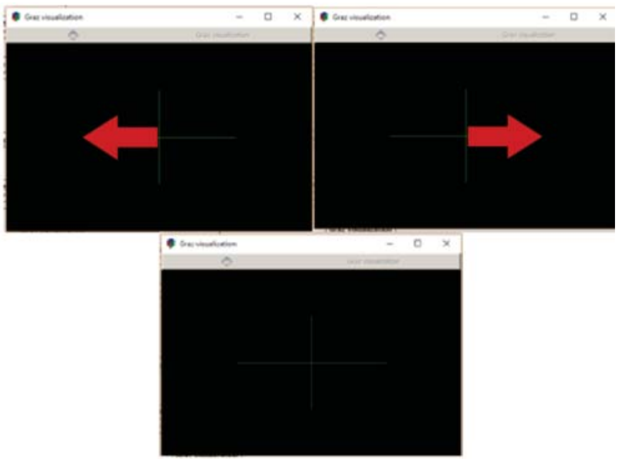

Fig. 5 Motion cues shown to subjects

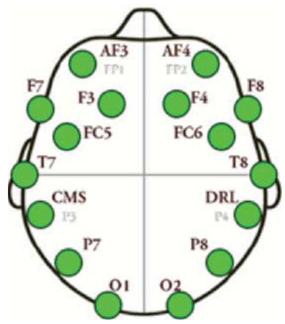

Fig. 6 Placement of electrodes on the scalp

In the brain, chemical and electric signals are transmitted through neurons. Translation of electric signals to chemical signals at the synapse between two neurons produce a voltage spike roughly less than 100 microvolts and 100Hz [13]. With the help of specially designed non-invasive electrodes, these small voltage differences can be measured. Emotiv EPOC, which is a 14-channel headset. Reference [14], is used for signal acquisition. Electrodes were placed on the scalp according to the International 10-20 system [15], standardized by the American Electroencephalographic Society. To place more sensors near the motor cortex, the headset is used in an inverted configuration. To decrease impedance between electrode and scalp contact point, a conductive paste is used. Furthermore, EEG signals were acquired at a sampling frequency of 128 Hz.

OpenVibe Software [16] is used for signal processing and classification. Signal acquisition server of OpenVibe acquires raw values of electrodes using Research Edition SDK of Emotive EPOC. This data is then forwarded to OpenVibe Designer through TCP communication protocol for further processing. After the acquisition of raw data from the headset, classifiers are trained to categories the data into two classes: right hand MI and left hand MI. Training the classifier is important to step, and once it is done, the classifier then trains the unseen data into two classes. A flowchart of the BCI process is shown in Fig. 5.

As most of the information related to motor imagery lies in the beta band, the acquired raw data is first needed to filter between 8 and 30 Hz [17] using a Butterworth filter. The filter has a flat frequency response (unity passband ripple) which means zero change in amplitude in the passband [18].

Noise can be embedded in data due to blinking, jaw movement, facial muscle movement. This noise has to be removed from the data before training the classifier. For this purpose, a spatial filter called surface Laplacian is used. The spatial filter creates the best possible combination of electrodes to acquire data with the least noise and a maximum contribution of each channel to the filtered data.

Spatial filter generates a number of output channels where

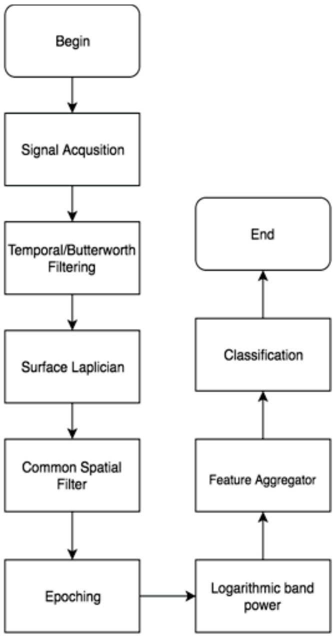

Fig. 7 Flowchart of BCI process

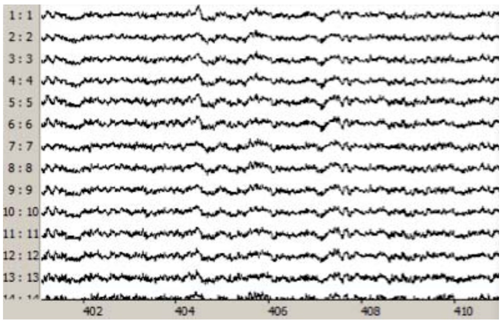

Fig. 8 EEG data without Butterworth filter

each output channel is a lean combination of the input channels. If Ij is the jth input channel, Ok is the kth output channel, and Tjk is the coefficient for the jth input channel and kth output channel in the Spatial filter matrix. Then the output channels are computed this way:

$$O_k = \sum_{j=1}^{n} (T_{jk} * I_j) \tag{1}$$

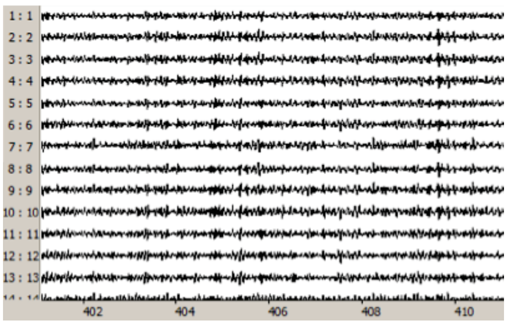

Fig. 9 EEG data with Butterworth filter

where n is the total number of input channels, k is the number of output channels.

According to 10-20 system, signals are most discriminative in C3 and C4 region for MI of the upper limb. In case of any noise, the noise is also observed in the region surrounding C3 and C4 electrodes such as CZ, F3, P3, T3, P4, T4. In surface Laplacian, the recorded data from each of these channels is assigned a specific weight and then subtract from the discriminative weighted sensor. Here the highest weighted sensor is most discriminative. This way, almost all the common noise is subtracted which is helpful in signal classification.

The Common Spatial Filter is employed to increase signals variance and thus improving the discrimination of signals (e.g., left hand MI versus right hand MI). The CSP filter is trained, and afterward,, the trained CSP is used to train the classifier and to classify online data. The information presented in EEG signals is very much concentrated and thus not suitable for pattern recognition. The signal was expanded in the time axis, each 1/16s of the incoming signal to 1-sec window called Epoc. A total of 16 epochs were obtained for a signal of 1 sec. After epoching, logarithmic band power is applied using simple DSP [19] to all 16 epochs for feature extraction.

$$u(x) = \log(1 + x^2) \tag{2}$$

Using feature aggregator plugin in OpenVibe, the 16 epochs after feature extraction using log band power are then concentrated into a single vector for the classifier. The classifier classifies input data into one of two classes thus categorizing the thought pattern (right hand MI or left hand MI) of the patient. Three classifiers namely LDA, C-SVM, and nu-SVM were tested with the dataset.

After classification of the signal into one of two classes, the signals are sent to Microcontroller for implementing motion control of walker. For sending data from OpenVibe to Arduino microcontroller for walker motion, VRPN server [20] in OpenVibe is used to send data to VRPN client. VRPN client application, developed in C++, acquires data from OpenVibe VRPN server. After necessary processing, the application further forwards the motion commands to Arduino microcontroller. If the signal belongs to Class 1 (right-hand movement), the walker forward motion is executed otherwise if the signal belongs in class 2(left-hand movement), the walker stop motion is executed.

B. Joystick Control

The use of the principal control device such as Joystick to control orthosis device is the most commonly available solution to the patients. For the patient comfort, a 3-axis Joystick is also incorporated in the robotic walker and joystick can act as a primary control interface between a patient and the walker. The y-axis of the joystick is used to give forward or reverse motion to the walker. For clockwise rotation, the differential value of the joystick controller causes a difference between the speed of both right and left motor. Joystick push button is used for mode switching between BCI and Joystick control.

TABLE I
PERCENTAGE ACCURACY OF CLASSIFIERS

Data Sets	C-SVM(%)	LDA(%)	NU-SVM(%)
1	53.06	51.48	50.00
2	60.46	60.05	60.46
3	55.92	54.90	46.93
4	64.18	62.91	63.10
5	59.54	58.01	59.49
6	59.28	58.11	59.39
7	60.41	60.00	60.61

```
Cross-validation test accuracy is 77.0946% (sigma = 0.808281%)
  Cls vs cls      1     2     3     4
  Target  1:   74.5  25.5   0.0   0.0 %, 4757 examples
  Target  2:   20.8  79.1   0.0   0.1 %, 4623 examples
  Target  3:    0.0   0.0  73.7  26.3 %, 4489 examples
  Target  4:    0.0   0.0  19.0  81.0 %, 4690 examples
Training set accuracy is 77.1108% (optimistic)
  Cls vs cls      1     2     3     4
  Target  1:   74.7  25.3   0.0   0.0 %, 4757 examples
  Target  2:   20.9  79.0   0.0   0.1 %, 4623 examples
  Target  3:    0.0   0.0  73.7  26.2 %, 4489 examples
  Target  4:    0.0   0.0  19.1  80.9 %, 4690 examples
```

Fig. 10 Four class validation result

C. Unbalance Detection

A fall can be a risky event for people with SCI, , and it can result in serious injury. In the case of unbalance gait of the patient during training, the walker has to act differently to prevent the patient from unbalancing and falling. A tri-axial accelerometer is employed to measure acceleration in the y-axis continuously. If the value of Ay is greater than a threshold value, Walker front leg motors run in a reverse direction with full speed to avoid toppling of the walker. This help to balance the walker and similarly preventing the patient from falling.

D. Mechanical Design

Fig. 1 shows the mechanical architecture of the Robotic Gait Trainer. A commercial walker is modified into a robotic walker by keeping in mind the ease of usage, task specificity and safety for the patient. The platform is equipped with two worm gear motors that are used to drive the walker. Two ball casters are attached on rear legs to ensure smooth movement of the walker. While modifying the walker, following criteria was kept in mind to enhance patient safety during gait training; (1) the robotic walker should not topple during training (2) the walker must not freewheel because of the patient weight, and (3) the walker should be able to support patient weight and should also act as a support for patient to stand.

III. RESULTS AND DISCUSSION

The percentage accuracy of the classifiers is shown in Table I. To test our algorithm, we downloaded 4 class dataset from online BCI competition. The accuracy obtained is displayed in the Fig. 10. The gait trainer was tested with 05 subjects, and they gave satisfactory feedback with Walker control, fall detection and ease of usage.

Fig. 11 Testing of gait trainer

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