A Survey on Various Motor Imagery-Based Brain-Computer Interface Techniques

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Abstract—Non-invasive EEG-based motor imagery brain-computer interface (MI-BCI) holds promise to effectively restore motor control to motor impaired patient. When the sensory-motor integration system is malfunctioning it causes a wide variety of neurological disorders, which in many cases cannot be treated with conventional medication, or via existing therapeutic technology. A brain-computer interface (BCI) is a tool that permits to restore the sensory-motor loop, accessing directly to brain information. A potential, promising and quite investigated application of BCI has been in the motor rehabilitation field. It is well-known that motor deficits are the major disability among the worldwide populations. Therefore, this paper aims to review MI-BIC techniques, in order to evaluate the suitability and reliability of this technology.

Keywords—Calibration phase, Electroencephalogram (EEG), Motor Imagery Brain-computer Interface (MI-BCI), Rehabilitation phase, Robotic Rehabilitation, Stroke

I. INTRODUCTION

In healthy individuals, the sensory–motor integration system records sensory information to produce motor actions according to internal and external factors. When this coupling system is malfunctioning it provokes a wide variety of neurological disorders such as stroke, epilepsy, chronic pain, Parkinson's disease, schizophrenia, anxiety disorders and attention deficit hyperactivity disorder; which in many cases cannot be treated with conventional medication, or via existing therapeutic technology. A brain–machine interface (BMI) is a tool that permits to reintegrate the sensory–motor loop, accessing directly to brain information. A BMI typically uses electroencephalogram (EEG) signals recorded via electrodes placed on the scalp. Motor imagery is a specific technique that is applied for BCI, in which the intention of the subject is determined by their imagination of movement of a specific part of the body e.g. feet, arms, tongue, etc. During motor imagery, the voluntary modulations of the sensory motor rhythms in the £ (8–12 Hz) and β (18–25 Hz) ranges are the target signals to be extracted and interpreted.

II. WHAT IS BMI?

The paper “Motor imagery based brain–computer interfaces: An emerging technology to rehabilitate motor deficits”, by Luz Maria Alonso-Valerdi., et al. [1] discusses the various classes and types of BMI.

A. Classes of BMI

BMIs can be divided into three classes: (1) sensory interfaces, which artificially activate the human sensory system; (2) Cognitive interfaces, which try to re-establish the communication of the neural networks; and (3) motor interfaces, which translate brain activity into control commands for a device of interest. In particular, motor BMI is a state-of-the-art technology that is better known as brain–computer interface (BCI). These systems attempt to restore the human-environment interaction making use of brain activity, when individuals have lost any kind of motion.
B. Types Of BCIs
There are two types of BCIs: active and reactive. Active BCIs are controlled via endogenous tasks such as motor imagery (MI), imaginary rotation of 3D objects or mental arithmetic operations. In contrast, reactive BCIs are manipulated using external stimulation (auditory, visual or haptic).

III. ARCHITECTURE OF MI-BCI UPPER LIMB
The architecture of the proposed MI-BCI upper limb robotic rehabilitation which was used in the clinical study proposed by H. I. Krebs, N. Hogan, M. L. Aisen, and B. T. Volpe, "Robot-aided neurorehabilitation"[6] is illustrated in Fig. 1. This synergizes MI-BCI with the clinically-proven MIT Manus robot so that the voluntary drive from the patient is captured as motor intent to drive the rehabilitation of paretic upper extremities.

In the proposed MI-BCI robotic rehabilitation, the MIT Manus robot was coupled with a non-invasive EEG-based MIBCI. There are two phases illustrated in Fig. 1, namely, a calibration phase and a rehabilitation phase. In the calibration phase, the subject was presented with a “go” or “stop” cue on the video screen. For the “go” cue, the subject was instructed to imagine moving the impaired limb without performing actual movement. For the “stop” cue, the subject was instructed not to imagine moving the affected limb. The purpose of this calibration phase was to address the intersubject variability with respect to the characteristics of the brain signals. This is addressed by employing the Filter Bank Common Spatial Pattern (FBCSP) algorithm to perform brain signal processing and machine learning on the EEG measurements acquired. The FBCSP algorithm comprises 4 progressive stages of EEG measurements processing: multiple bandpass filters using zero-phase Chebyshev Type II filters, spatial filtering using the Common Spatial Pattern (CSP) algorithm, feature selection of the CSP features, and classification of the selected CSP features. These 4 stages collectively construct a subject specific motor imagery detection model. As illustrated in the rehabilitation phase in Fig. 1, the FBCSP algorithm detects motor intent in the EEG measurements using the subject-specific model constructed in the calibration phase. If motor intent is detected, the MIT Manus robot directly assists the subject in moving the impaired limb towards the goal. There is a major difference between the proposed MI-BCI based robotic rehabilitation and the standard MIT-Manus robotic rehabilitation, the
IV. VARIOUS EXPERIMENTAL STUDY

A. In the paper “A Clinical study of motor-imagery based brain –computer interface for upper limb rehabilitation”[7] by Kai Keng Ang et. al a study experiment that was conducted is explained. Fig. 2 shows the setup of the proposed MI-BCI robotic rehabilitation in a local hospital. The subject’s brain signals were acquired through non-invasive EEG and the affected limb was strapped to the MIT-Manus end-effector. The screen shows the current position of the end-effector, the goal, and the intensity of the voluntary motor intent detected.

![Fig 2: The Setup of the Proposed Motor Imagery Brain-Computer Interface Robotic Rehabilitation at a Local Hospital](image)

A screening session was first performed on the subjects to determine if they could operate MI-BCI effectively on the impaired limb. 18 of those subjects were recruited for this study. The upper limb rehabilitation using the MIT-Manus robot employed motor training was in the form of a video game whereby the subject was required to move the impaired limb towards the goal displayed on the video screen. The subject’s impaired limb was strapped to the robot end-effector. If the subject could not perform the motor task after a pre-defined period of 2 s after the onset of the visual cue, the robot would assist and guide the subject’s impaired limb towards the goal. 27 channels of EEG measurements were acquired using Nuamps acquisition hardware with unipolar Ag/AgCl electrodes channels, digitally sampled at 250 Hz with a resolution of 22 bits for voltage ranges of ±130 mV. EEG measurements from all channels were band-pass filtered from 0.05 to 40 Hz by the acquisition hardware. The control group did not involve any EEG measurements. The calibration phase of the experimental group acquired a total of 160 trials of EEG measurements that randomly comprised 80 trials of motor imagery and 80 trials of non-motor imagery. Each trial lasted for approximately 12 s. For each trial, the subject was first prepared with a visual cue for 2 s on the screen. Another visual cue then instructed the subject to perform motor imagery or non-motor imagery for 4 s, followed by 6 s of rest. The subjects were advised to minimize any body movement throughout the process expect during the rest period. 10 minutes of rest were given in between every 40 trials. In the rehabilitation phase of the experiment group, the subject’s impaired limb was strapped to the MIT-Manus robot. The subject was then instructed to perform motor imagery of the impaired limb. The subject was first prepared with a visual cue for 2 s, then a “go” cue would instruct the patient to perform motor imagery for 4 s followed by 6 s of rest. If the voluntary motor intent was detected within the 4 s action period, the MIT-Manus robot would assist the subject in moving the impaired limb towards the goal. The 12-second trial protocol of the MI-BCI robotic rehabilitation limits the number of movements that a patient could perform within a certain time frame. In addition, motor intent could not be detected in some trials. Since each rehabilitation session was constrained to be within 1 hour, the number of movements performed by the subjects from each group differed significantly. On the
average, the experimental group performed 122 robot-assisted movements whereas the control group performed 960 movements. The baseline and outcome measure were performed using the FM upper extremity scale, which is a 66 point ordinal scale that measures motor impairment of the affected upper limb. A similar experiment was conducted on a 64-year-old man with severe left hemiplegia following a hemorrhagic stroke by Cesar Marquez-Chin et al in “EEG-Triggered Functional Electrical Stimulation Therapy for Restoring Upper Limb Function in Chronic Stroke with Severe Hemiplegia” [8].

B. In the paper “A New Gaze-BCI-Driven Control of an Upper Limb Exoskeleton for Rehabilitation in Real-World Task”[9] by Frisoli A et al, another research experiment was done with more inputs. It comprised of a complex system that included a Kinect sensor, an eye-tracking device and a BCI. The Kinect sensor was for the identification of surrounding object, the eye-tracking device determined which the object of interest was for the subject and through the BCI the intended arm movement was transmitted.

C. In the paper “Hybrid BCI Coupling EEG and EMG for Severe Motor Disabilities” [10] by Rouillard J et al, a system that combined both Electromyography (EMG) and electroencephalography (EEG) was discussed. But the system had a disadvantage when combining these signals from various sources into a hybrid interface. Hence this method did not prove to be much success. The solution for this problem was given by Horki P et all in their paper “Combined Motor Imagery and SSVEP based BCI Control of a 2 DoF Artificial Upper Limb”[11]. A hybrid-BCI which combined the different paradigms and motor imagery was use along with steady state visual evoked potentials.

D. Traditional BCIs uses electroencephalography (EEG), functional magnetic resonance imaging, magneto-encephalography, functional near infrared spectroscopy, electro-corticography and intra-cortical recordings. All of these neuro-imaging techniques are capable of generating a BCI based mental switch. However, the accuracy and robustness of these systems are not as optimal as when compared to the traditional physical switches. Hence to provide an accurate and fast BCI based switch interface David Rozado et all in “Improving the Performance of an EEG-based Motor Imagery Brain-Computer Interface using Task Evoked Changes in Pupil Diameter”[12] proposed that the enlargement of the pupil triggered during execution of imaginary hand movements can be detected by video oculography and this feature could be used to improve the accuracy of a traditional EEG-based motor imagery BCI.

REFERENCES
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