Emerging Trends in BCI-Robotics for Motor Control and Rehabilitation

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Abstract

Neuroengineering research over the last two decades has demonstrated promising evidence on the use of Brain Computer Interface (BCI) to enhance functional recovery and independence in individuals with motor impairments. By translating brain activity, BCI bypasses the impaired neuromotor system, to control computers/machines. BCI-controlled robots are designed for motor assistance to aid paralysed patients as well as for rehabilitation to enhance motor recovery. In this article, we review the advances in BCI and brain controlled robotics for rehabilitation and assistance of upper and lower limb motor functions over the last five years. The article emphasizes on the emerging trends in BCI-controlled robotics to expand its intervention capabilities as well as to resolve existing challenges hindering its widespread clinical use.

Keywords: Brain Computer Interface, Robotics, Stroke Rehabilitation, Neuromotor control

1. Introduction

Brain Computer Interface (BCI) is an emerging neurotechnology that has demonstrated promising potential to enhance the quality of life of people with neuromuscular disorders resulting from stroke, spinal cord injury (SCI) and amyotrophic lateral sclerosis (ALS). Leveraging the advances in neuroscience, robotics and machine learning, BCI research over the past two decades has demonstrated its application as prosthetic, assistive and rehabilitation technology to replace, assist and augment or restore the lost motor functionality of the brain respectively. Assistive and prosthetic technology employ a straightforward implementation of BCI-robotics in which the brain activity elicited by the user is translated into a control output for a robot that executes the intended task [1] thereby imparting independence to the users. Rehabilitation technology employs a more complex neurophysiologically guided design which facilitates neuroplasticity as a result of operant conditioning feedback delivered through

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robot-guided movement of the affected limb contingent upon detecting neuromotor activity by BCI [2]. This mode of BCI rehabilitation has demonstrated evidence of neuromodulation and resultant augmentation in motor outcome for stroke survivors who have reached a functional plateau following traditional rehabilitation [3].

The key components of a BCI-robotic system are task-specific brain activation patterns, brain data acquisition, brain decoding machine learning tools and control/feedback device. Overall clinical efficacy of BCI-robotics heavily rely on how closely the robot movement correlates with the intended movement which in turn relies on the robustness of BCI determined by brain signal quality and the performance of decoding tools [2]. Although invasive intracortical recordings offer more reliable brain data with better spatial resolution [4], the surgical risks in this approach have encouraged most researchers to focus on non-invasive recordings such as Electroencephalography (EEG). The mental state employed by BCI is the kinesthetic imagination/attempt to move the target limb to facilitate cortical reorganization of the lesioned hemisphere [2, 5]. BCIs operated using power modulations associated with inhibition of the contralesional side and excitation of the ipsilesional side have proven to be effective for post-stroke motor recovery [3, 6]. Furthermore, machine learning plays a critical role to generate fast, accurate, and reliable control signals that drive the robotic device. Several decoding algorithms have been proposed in EEG-BCI [7]. However, linear classifiers that decode sensorimotor rhythm based features are extensively used in BCI clinical studies. Furthermore, clinical study designs report the use of different techniques [8] to deliver contingent feedback to the user, by integrating BCI with robotic devices, electrical stimulation and virtual reality.

1.1. Related work

Over the last 2 decades, several BCIs using variety of neural inputs, feedback modalities and experiment protocols have been reported. The most extensively explored application of BCI is post-stroke upper extremity (UE) rehabilitation and comprehensive reviews of this topic have been published recently in [6, 9, 10, 11, 12, 13, 14]. Additionally, [8, 15] reported meta-analyses evaluating the clinical effectiveness of BCI for stroke recovery. Robot assisted rehabilitation, by itself, has shown to promote recovery by employing intensive and repetitive motor training. The robotic devices and exoskeletons that can potentially be coupled with BCI to be used in rehabilitation applications have been reviewed in [11, 16] for UE and [16, 17, 18, 19] for lower extremity (LE). Further, (PDE Baniqued et al., medRxiv doi: 10.1101/2019.12.11.19014571) reported a systematic review of post-stroke hand rehabilitation research using BCI-robotics. The BCI applications for neuromuscular degeneration and spinal code injury have been reviewed in [20, 21, 22].

1.2. Organization and overview

In this paper, we focus on the recent studies within last 5 years that reported rehabilitative and assistive use of BCI-controlled robots that target upper and lower extremities (UE/LE). We present the current state-of-the art stroke rehabilitation for UE/LE as well as research on tetraplegic patients to operate gait exoskeletons and prosthetic arms. In this paper, we emphasize on the recent technological innovations reported in BCI-robotics that show high potential for eventual clinical application. The research trends include the use of decoding tools such as deep neural networks, wearable robots including soft robotics, training protocols exploring BCI for priming and efficacy of other feedback modalities and hybrid BCI systems supplemented with non-brain signals. Lastly, the challenges to be addressed in the current BCI and rehabilitation robotics and a few anticipated directions of future research are presented.

2. BCI-robotics for UE motor rehabilitation

In light of the devastating motor impairments resulting from stroke and its impact on the quality of life of the survivor, the most common focus of clinical application of BCI is post-stroke UE motor rehabilitation. The breakthrough report in this field was published over a decade ago [5] in which a Magnetoencephalography (MEG)-BCI controlled hand orthosis was used for stroke rehabilitation. The study reported that the users learnt to modulate their mu rhythm amplitude to achieve binary control of an orthosis, even though they could not achieve significant clinical improvement. Following this, a multitude of non-invasive BCIs were reported as an intervention tool in combination with feedback delivered using robot or orthosis. BCI for UE stroke rehabilitation have been reviewed and systematically evaluated in [9, 11, 6, 12, 13, 14].

Several controlled clinical trials investigating efficacy of BCI-robotics have reported intervention-induced UE motor improvement in terms of Fugl-Meyer Assessment (FMA) and Action Research Arm Test (ARAT). The studies however vary in the patient demographics, impairment level and lesion location, the intensity and interval between experiment sessions and the type of robot (haptic knob [23], a orthotic device [24, 25, 26], hand exoskeleton [27, 28, 29, 30]). The proof-of-concept study in [24] reported that BCI training with contigent orthotic feedback prior to physiotherapy resulted in significant improvement of FMA in chronic stroke patients. The recent studies using BCI-robotics are listed in Table 1. These studies also explored the neurophysiological evidence of the effect of intervention and progression to motor recovery. To this end, [27, 29] reported evidence of intervention-induced cortical plasticity mechanisms as seen in functional and structural neuronal reorganization. Another topic explored is the long-lasting impact of BCI-intervention. Recent study in [25] reported significant FMA increment after BCI-robotics intervention in chronic stroke subjects and a 6 month follow-up revealed that the patients preserved their FMA scores. In [28], increment in both FMA and ARAT were reported after a repetitive intense rehabilitation during a 2-9 month follow-up after BCI-robotics intervention. A BCI-exoskeleton for elbow training was proposed in [30], which not only reported significant improvement in FMA and ARAT scores, but also reported improvement in post-therapy movement quality based on motion kinematics. Contrary to the classical BCI that trains grasp and reach movement, [contd.]

Table 1: BCI-robotics for post-stroke UE rehabilitation

Study	Number of patients	Robotic device	BCI training	Outcome
(Ramos et.al., 2019)[25]	28 chronic (BCI:16 & Control:12)	Hand & arm orthosis	20 sessions (2hrs/session, 5 sessions/week, 4 weeks)	BCI: Gain in cFMA ($p=0.015$) at 6 months after intervention
(Wu et.al., 2020)[29]	25 subacute (BCI:11 & Control:14)	Hand exoskeleton	20 sessions (1hr/session, 5 sessions/week, 4 weeks)	BCI: Gain in FMA (16.93 ± 2.56, $p < 0.05$) Inter-group differences $p<0.05$ in FMA, ARAT, WMFT
(Frolov et. al., 2018)[27]	Case study 1 chronic	Hand exoskeleton	10 sessions (1 session/day, 2 weeks)	Gain in cFMA>5 at 3 time points
(Carino et.al., 2019)[26]	9 subacute	Hand exoskeleton	12 sessions (1hr/session, 3 sessions/week, 4 weeks)	Gain in FMA for 6 out of 9 patients
(Kondur et.al., 2020)[28]	11 chronic	Hand orthosis	10 sessions (1 session/day, 2 weeks)	Gain in FMA and ARAT ($p<0.05$) at 2 time points
(Bhagat et. al., 2020)[30]	10 chronic	Elbow exoskeleton	12 sessions (2hrs/session, 3 sessions/per week, 4 weeks)	Gain in FMA (3.92 ± 3.73) and ARAT (5.35 ± 4.62), $p<0.05$
(Cheng et. al., 2020)[31]	10 chronic (BCI:5 & Control:5)	Soft robotic glove	18 sessions (1.5hrs/session, 3 sessions/per week, 6 weeks)	BCI: Gain in FMA ($p=0.0431$) No intergroup differences in FMA and ARAT

FMA: Upper-Limb Fugl-Meyer Assessment; cFMA: Combined hand and arm scores (motor part) from the modified FMA; ARAT: Action Research Arm Test; WMFT: Wolf Motor Function Test [contd.] a BCI-based finger extension training for chronic stroke patients using a finger-individuated orthosis was reported in [32]. The results indicate that the subjects with higher modulation of sensorimotor rhythms (SMR) reported better functional outcomes and improved finger extension ability. This indicates the potential of BCI-robotics to integrate rehabilitation of gross and fine hand movements.

The BCI studies mentioned above use bulky and hard-bodied robots which are often expensive, require complex controls and restrict range of motion [33]. Soft robots are class of robots that are light and wearable and employ flexible mounted actuators. Application of soft robots has been demonstrated to enhance efficacy of hand rehabilitation [34]. Hence, by integrating soft robots with BCI, a non-restrictive, natural and realistic movement can be introduced in the feedback loop which may have a positive impact in intervention. A pilot study in this direction was presented in [31] which reported a stroke rehabilitation system integrating EEG-BCI control of a soft robotic glove and task-specific visual feedback. The study reported improvement in FMA and ARAT and provided evidence of a phenomenon of kinesthetic illusion in subjects. These findings need to be confirmed by large scale clinical trials, and neurological evidence for the link between perceived motor activity and actual motor recovery.

3. BCI-driven exoskeleton for LE motor rehabilitation

Post-stroke LE rehabilitation is a relatively less explored application of BCI. An efficient BCI design involves closed-loop accurate decoding of kinesthetic walking intention and imagery by BCI as well as real-time control of the robot (or exoskeleton). While the former is largely limited by yet non-optimized performance of LE decoding, the latter poses several safety risks. A few studies in literature have demonstrated the feasibility of decoding lower limb joint kinematics and kinetics during walking using BCI. In [35, 36, 37], EEG was recorded as the participant performed robot-assisted gait training. In [35, 36] moderate LE joint kinematics decoding accuracies based on offline analyses were reported. A connectivity analysis in [37], reported significant improvement in gait performance in terms of functional ambulation capacity as well as in functional connectivity and sensorimotor plasticity following the gait training. The modulations in sensorimotor rhythms and movement related cortical potential associated with gait decoding performance have also been investigated in [38]. Furthermore, as recently reviewed by [19], there is a lack of consensus regarding the spectral and temporal dynamics of neural encoding of gait patterns. This limits the use of non-invasive brain data for consistent and reliable gait decoding. Consequently, there are no clinical controlled trials conducted till date that demonstrate effectiveness of BCI-robotics in LE stoke rehabilitation. .

Nevertheless, recent reports on technological advances of BCI gait decoders promise high accuracy and potential for continuous gait decoding. Recently, [39] reported a rigorous comparison of several EEG-based gait decoding approaches to evaluate their feasibility in the design of an online decoding system. Based on the comparison of methods ranging from simple linear decoders to recurrent neural networks (RNN), this study provided technical recommendations on how to attain precise control of BCI-based exoskeleton using variants of RNN based on offline benchmarking. Also, it is worth noting that, a recent study on healthy subjects using a long short-term memory (LSTM) deep neural network achieved robust reconstruction of gait [40] evaluated in both offline and online scenarios.

4. BCI-robotics for motor assistance

BCI using invasive intracortical recordings have been shown to enable neural control of a robotic arm as well as lower limb exoskeleton. A case study in [41] was the first report on using invasive-BCI that allowed a tetraplegic patient with SCI to continuously control a multi-joint robotic arm. Further studies have reported neuroprosthetic control of prosthetic arm by tetraplegic patients paralysed as a result of stroke [42] or ALS [43, 44]. The articles [20, 22, 21] comprehensively reviewed the application of BCI in paralysis as a communication, control and rehabilitation tool. Following this, there has been an increased interest to design non-invasive BCI to control robotic arms with higher degrees of freedom for possible motor assistance as well as rehabilitation. This is in contrast to the classical non-invasive BCI that rely only on uni/bidirectional motor control. Recent studies on non-invasive BCI have reported higher dimensional continuous motor control using novel decoding approaches as well as control strategies to tackle low signal-to-noise-ratio of non-invasive signals. The studies have been evaluated in healthy individuals [45, 46, 47, 48] and in paralysed patients and amputees [49, 50].

A closed-loop prosthetic control by BCI was reported in [50] using EEG and in [49] using MEG. Recently, [45, 46], demonstrated accurate continuous control of a robotic arm with multiple degrees of freedom by combination of two sequential low dimensional controls. In [48], an online BCI control of a virtual robot in a simulated environment using low frequency time domain movement-related cortical potentials was demonstrated. Further, two novel and unconventional research directions were reported in task strategy [51] and in control framework [52] of BCI. In contrast to the conventional collaborative tasks executed by BCI-robots, [51] reported a multitasking strategy by simultaneously controlling a robotic arm using BCI while user's own arm performed another task. In [52], a control framework for BCI-robot was presented that generated a continuous robot trajectory from a stream of discrete BCI outputs. These systems were evaluated by healthy subjects and the results indicated potential for better and realistic robotic control using BCI. The technological advances also include deep learning-powered BCI [47], that continuously controlled a robotic arm to six directions in a 3D space. The study reported a multi-directional convolution neural network-bidirectional LSTM network-based deep learning. With the integration of these technological innovations, non-invasive BCI will be capable of a continuous and highly dexterous control to an assistive robotic device.

Studies that report BCI-control of LE exoskeleton have been reviewed in [17, 53] and are limited to non-invasive BCI. Currently, the studies that demonstrate closed-loop BCI-LE exoskeleton [54, 38] detect gait intention of the SCI user to trigger the movements of the exoskeleton. Several studies that report offline gait decoding (mentioned in Section 3), are yet to be evaluated in a real-time control scenario. Recent studies have also reported the use of steady state visually evoked potential (SSVEP) [55] and imagined hand movement [56] to control LE exoskeleton for healthy subjects.

5. Conclusion and future prospects

BCI research is currently at an exciting juncture, as several studies have confirmed its clinical impact and presented neurophysiological evidence for BCI-induced neuroplastic changes. While the potential of BCI is encouraging, with only limited number of clinical trials available, its intervention efficacy is only moderately conclusive at present. The clinically meaningful differences observed from small sample clinical trials are not generalizable and reports on impact of intervention in activities of daily living are limited. These factors hinder the translation of rehabilitation therapies into standard clinical practices. As mentioned in Section 2, the design parameters in current BCI systems are largely heterogeneous. Hence, future research must consider standardization of the rehabilitation protocols to optimize the intervention effect, as well as confirm the effect size of BCI with large sample size and long-term studies [12, 13, 14, 15]. Nevertheless, several promising results have been reported in recent publications that merit further research and large scale validation. In this section, we discuss these technological trends to be considered that may further enhance the efficacy of BCI-robotics. An illustration of BCI-robotics framework for motor rehabilitation and assistance is given in Fig. 1. The figure also lists the state-of-the-art design practices as well as emerging trends in BCI-robotics.

In rehabilitation BCI, several studies have reported priming the brain prior to intervention to enhance the overall functional outcome. Although some studies [57, 58] have reported tDCS to potentiate the effects of BCI, very limited evidence is available on its efficacy [15]. Recently, pre-movement SMR training to enhance motor performance was demonstrated in healthy [22] and chronic stroke patients [32]. Further, intensive strategies by integrating BCI-robotics with other interventions such as BCI-neuromuscular electrical stimulation [15] and BCI-virtual reality [59] may be considered for positive impact. In motor assistance, several case studies have demonstrated continuous control of robots using invasive BCI. To improve the reliability of non-invasive BCI in delivering precise and accurate robotic-control, a solution proposed in literature is the use of hybrid or shared control [17, 60]. An autonomous control of hand exoskeleton by tetraplegic patients was demonstrated in [60] using hybrid system in which ocular activity supplemented the motor imagination based brain activity. Further, shared control strategy in which sensors mounted on robots to assist in making motor control decision [17] may also be considered.

One potential challenge in deployment of BCI-controlled robotics for clinical application is the acceptance and ease-of-use for the user. Whether it is movement generated by the robot or robot-guided movement of the limb, the efficacy of the system depends on whether the user perceives a realistic movement and

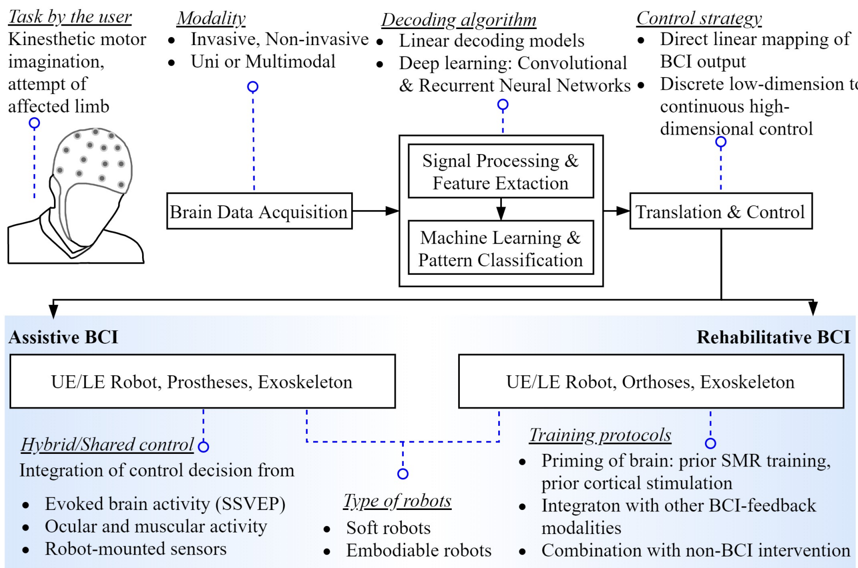

Figure 1: **Schematic of BCI-robotics system.** BCI system employs invasive and non-invasive modalities to acquire neural activities generated when the user performs a motor task. The signal processing and machine learning tools then extract relevant features from the acquired signals. A control signal to operate a robotic device is generated by classification and translation of these features. Assistive BCI enables the user to control movement of robots. Rehabilitative BCI facilitates robot-guided motor training and targets recovery of neuromotor function of the user. The research and advances in each component that merits further investigation are listed.

can experience a sense of ownership/agency (SoO/SoA). This factor of embodiment has been found to have beneficial effects in rehabilitation [61] as well as in neuroprosthesis [62]. Hence, a design consideration in future BCI-robotics may be to include subjective assessment of SoO/SoA [61]. In rehabilitation applications, based on satisfaction and usability assessment by user [34], soft robots have been reported to be acceptable by individuals with neurological impairments. Hence, natural and non-restrictive movement delivered BCI-controlled soft robotics is a step in the right direction to enhance overall efficacy of BCI in stroke rehabilitation [31].

Lastly, one of the critical factors that determines the overall efficacy of BCI is the machine learning tools that it employs for motor detection. Currently, the clinical studies report the use of linear decoders for both UE and LE decoding [17]. It is worth noting that most of the high-performing classification and decoding algorithms reported in recent BCI publications have not yet actually been validated in closed-loop BCIs. We emphasize the evaluation of the powerful innovative decoders [39, 63] as well as control strategies [52] to generate smooth, accurate and reliable control of robots with higher degrees of freedom for higher clinical impact.

In summary, over the last few years, as highlighted in this article, several technological advances that can enhance clinical capabilities of BCI-controlled robotics have been reported. Further research and large-scale clinical evaluations are essential to fully exploit the benefits of BCI in motor control and rehabilitation.

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