EEG- EMG-BASED INTERFACE FOR UPPER LIMB EXOSKELETON – A REVIEW

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ABSTRACT

The second most common cause of death in the world is cerebrovascular accident or stroke, and rehabilitation plays an important role to help the survivors of such accidents. Rehabilitation exercises are essential to speed up the process of recovery and regain independence, not only for post stroke cases but, also, for every patient who suffers of other neuromuscular diseases, such as spinal cord injuries or multiple sclerosis. The aging of the population, the increase of accident, and therefore, the increase of quality and quantity of rehabilitation needed, have led to the development of new techniques and assistance methods for recovery. Exoskeleton robotic devices have been developed to help the rehabilitation process, complementing the manual work of therapists. What is needed for an efficient and smooth implementation of this device is an advance interface between the wearable robot and the human. In this paper we have presented and analyzed two possible control input signals for exoskeletons, specifically electromyography (EMG) and electroencephalography (EEG). We've delved deeper into these two techniques, studying their advantages and disadvantages. Advantages are for example their inherent intuitiveness and effectiveness. On the other hand there is high inter-subject variability of the EMG, and the non-invasiveness and high temporal resolution but relatively poor spatial resolution of the EEG technique. The purpose of this review is to study and contrast the two main techniques when used as brain machine interface for the control of exoskeletons.

INTRODUCTION

Stroke is a major global health problem, it is the second leading cause of death and the third leading cause of death and disability combined in the world[1,2]. As a result of the population growth and the ageing of the populations, the absolute number of people who have a stroke every year, and live with the consequence of stroke or die from their stroke is increasing[2,3]. Stroke isn't only the second leading cause of death, but it is also the fourth leading cause of lost DAILYs (disability-adjusted life-years) among all non-pediatric populations[4]. The most common and widely recognized impairment caused by stroke is motor impairment, which can refer to a loss or limitation of function in muscle control or movements or a limitation in mobility. This motor impairment, usually, affects the face, arm, and leg of one side of the body[5]. For achieving a better recovery in terms of body functions and activities in the first months after stroke, and to reduce disability and handicap during the years that follow, early stroke rehabilitation is fundamental[6], and it is focused on the recovery of impaired movement and the associated function. Therefore, there is an ongoing need to advance the quality and increase the quantity of rehabilitation. Neuroplasticity is the basic mechanism underlying improvements in functional outcomes after stroke, indeed the recovery process relies on the ability of the brain to heal itself through neuroplasticity. Several studies, such as the one of Zeiler et al.[7] have shown that, after ischemic stroke, there is a time-limited window of enhanced neuroplasticity[8,9]. Several studies have found that assistive exercise, high intensity, repetitive, task-specific, interactive and individualized training are the most promising way to treat post stroke patient[10,11]. These requirements make stroke rehabilitation a labor-intensive process. In this environment, new techniques and assistance methods for recovery emerged, such as robotic technology which are characterized by the ability to deliver high-dosage and high intensity training[12]. Reducing, in this way, the burden on therapists by substituting human intervention. Rehabilitation robots can be broadly divided between therapeutic robots and assistive robots, the purpose of the former is to train lost motor function, whereas the latter is mainly designed to compensate for lost skills[13]. There are two types of robotic therapeutic devices that are used for motor training: the end-effector-type (EE) devices and the exoskeleton-type (Exo) devices. EE robots are connected to patients at one distal point, and their joints do not match with human joints, while Exo robot resemble human limbs as they are connected to patients at multiple points and their joint axes match with human joint axes[14]. The robotic device is combined with a brain-machine interface (BMI) that enables its control. Two of the most common BMI are encephalography (EEG) and electromyography (EMG). The former consists in the measurement of electrical activity in different parts of the brain, whereas the latter consist in the recording of the electrical activity of muscle tissue. In this review we are going to analyze these two BMI, studying their advantages and disadvantages.

BCI

Brain Computer Interfaces are a novel technology developed in the last two decades, that bridges the brain with external devices helping to restore useful function to people severely disabled by neuromuscular disorder. Specifically, BCI technologies bypass the body's normal efferent pathways: the path through which the impulses from the central nervous system are conveyed to the peripheral nervous system and further to an effector, such as muscle. The BCI measures brain activity and translates the recorded brain activity into corresponding control signals that reflect the user's intent.

The first demonstrations of brain-computer interface technology occurred in the 1960s when Grey Walter used the scalp-recorded electroencephalogram to control a slide projector[15]. But, since then and into the early 1990s, there has been only a few BCI research studies. In the mid-1990s, the pace of BCI research began to increase rapidly, and this growth has continued into the present. Through these years, studies have led to the development of the BMI technologies and, in the last decades, thanks to advancements in actuation, energy storage, miniaturized sensing, automated pattern recognition, and embedded computational technology[16], they have enabled individuals to control their own paralyzed body parts voluntarily, in combination with actuated exoskeleton. Two of the most utilized brain machine interfaces are EMG and EEG.

EMG

Surface electromyogram signals are measured from the skin, and they capture muscular activation originating from neural signals transmitted from the central nervous system. After stroke, usually, muscle activity is too weak to generate overt movements and, in addition, many stroke patient can suffer of spasticity, hypertonia, and abnormal flexor synergies.

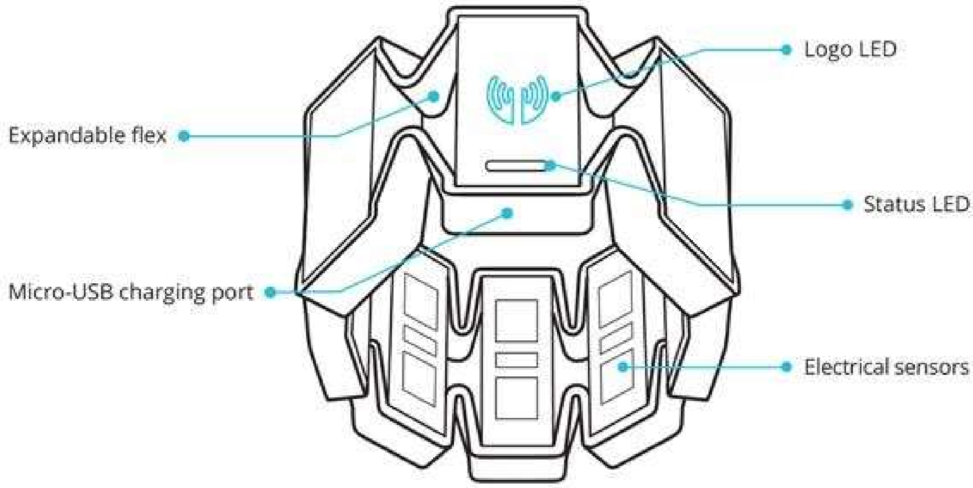

Figure 1: Myo gesture control armband. https://developerblog.myo.com/

However, in exoskeleton powered by EMG signals, even though the human subject is unable to generate sufficient joint torque, their intention can still be detected from residual EMG activity[17–20].

Leveraging this quality of electromyography, many researchers tried to developed devices that enhances motor activity but not replace it. In the article of Lambelet et al.[21], the researchers have used the sEMG method to detect the activity of the wrist extensors and they've implemented a controller that enhances the signals acquired so that sufficient force is generated to perform daily life actions. To detect the EMG signals they've used a commercially available myoelectric measurement device, the Myo armband[22,23] and, to implement the subject intention, they designed a powered and wearable wrist exoskeleton.

The same device to detect the EMG signals has been used in the article of Ren et al.[24], but this time, the BMI controlled an exoskeleton which has the only purpose of training, replacing the motor activity of the dysfunctional limb. Specifically, in order to implement bilateral arm rehabilitation on an upper limb exoskeleton, two Myo armbands, one placed on the upper arm and the other set on the forearm, were used to get the human arm dynamics and the muscle activity. These signals were then used as input of deep learning model, the obtained prediction was used has the desired motion trajectory of the exoskeleton attached to the dysfunctional limb.

The Myo armband from Thalmic Labs is characterized by 9-axis IMU (inertial measurement unit) sensor other than the 8 medical sEMG channels. Furthermore, it has a Bluetooth adapter for wireless communication (Figure 1). One of the main problems of the Myo armband is that, because it is a ring-shaped sensor, there will be a serious crosstalk problem on the obtained signals. Therefore, the original signal needs to be pre-processed to increase the signal-to-noise ratio, since the actual sEMG signal from the muscles is reduced[24,25]. However, there has been many studies who have used this device[23,26–29], which stands out for the facility, convenience and low cost of signal acquiring, conditioning, preprocessing and transmission.

The Delsys Tringo Wireless EMG system is another device used for acquiring non-invasively the EMG signals. We can find an example of its implementation in the article of Leserri et al.[30] where the sensors were used to record the muscle activity of four muscle heads of the human upper arm, involved in the actuation of the lower arm. The aim was to investigate the signal features in terms of the accuracy of a feed-forward neural network (FFNN) model for predicting elbow-joint movements of the human arm, and therefore, control active body support systems. The article of Luzio et al.[31] have used the Delsys Tringo EMG wirless system to record the sEMG signals from injured and healthy hand, in order to extract muscular synergies of each subject and evaluate patient rehabilitation outcome. The subjects went through a 5-week robot-aided therapy program with the Gloreha hand exoskeleton.

EEG

EMG is very effective at detecting the motor intention of the patient by analyzing the residual muscle activity. But, for more severely impaired patients, who aren't able to produce some voluntary movement or high enough levels of muscle activity, the motor intent can be detected using noninvasive scalp electroencephalography. Generally, there are two ways to detect intention through EEG, μ-rhythms (8-12 Hz) or slow movement related cortical potentials (MRCP)[32,33]. The latter is a low-frequency negative shift in the EEG recording that takes place about 2 seconds prior to voluntary movement production[34]. MRCP comprised three events called readiness potential (RP), which reflects movement planning/preparation, motor potential (BP), which reflects movement execution, and movement-monitoring potential (MMP), which reflects control performance (Figure 2). MRCP has been used by Bhagat et al.[32] for intent detection, the researchers have used noninvasive EEG to developed an asynchronous BMI that can detect voluntary motor intent and command an upper-limb powered exoskeleton. The scalp EEG was recorded using 64-channel, active-electrode system[35], and the signal was continuously analyzed so that the subjects were free to attempt the movement any time after the start signal. This is called asynchronous approach, and it differs from the synchronous BMI wherein the EEG signal is analyzed in predefined time intervals. To reduce the false positive rate, the researchers have incorporated in the system an EMG-gate, the BMI detected intention was compared with the EMG activity from biceps and

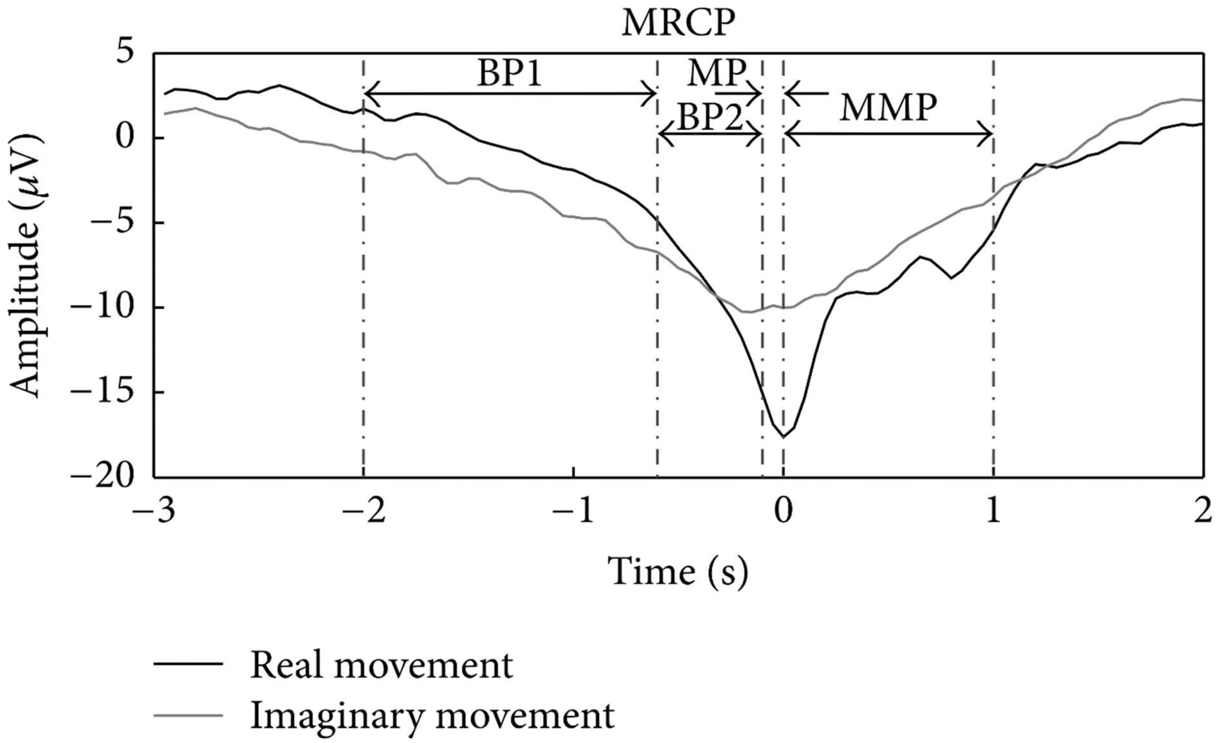

Figure 2: MRCPs of a healthy subject for real and imaginary right ankle dorsiflexion. Time 0 s is defined as the movement onset. BP1 is early BP, BP2 is late BP, MP is motor potential, and MMP is movement-monitoring potential.[39]

triceps of impaired limbs. If the EMG activity was detected within 1s following the BMI's decision, the exoskeleton was activated. In the article of Tongda et al. MRCP has been combined with steady-state visual evoked potentials (SSVEP), where the researchers have developed an active and passive upper limb rehabilitation training system based on a hybrid brain-computer interface of SSVEP and MRCP. Several studies have underscored the potential utilities of MRCPs as neural control signals for the detection of movement intent [41–44], as MRCP features not only can be exploited for movement detection, but also for classification of movement related parameters like speed, force, or even different type of grasps[40–42].

Motor execution (ME) and motor imagery (MI) can change the neural activity in the primary sensorimotor areas, indeed, during actual, as well as mentally rehearsed, or imagined movements the contralateral sensorimotor cortex is characterized by decrease (desynchronization - ERD) or increase (synchronization - ERS) in power of the sensorimotor or μ-rhythms (8-12 Hz)[32,43–45](Figure 3). Sensorimotor rhythms have been used by Nann et al.[46] to developed a BMI interface for an assistive hand exoskeleton for finger paralysis after stroke. Several studies[47–49] have proved that BCI control performance can deteriorate over time, since the voluntary control of sensorimotor-rhythms is cognitively demanding and, furthermore, decline in attention was shown to negatively affect cortical plasticity[50].

Therefore, Nann et al. have studied heart rate variability as a biomarker to predict decline of SMR control.

Another example where ERD/ERS has resulted useful for the control of an upper-limb exoskeleton, is the article of Tang et al.[51] The researchers proposed a BMI based on event-related desynchronization/synchronization and they investigate the classification performance

Figure 3: Upper limb (ArmeoSpring) at SMART Lab, UTP.[1] Multi-joint exoskeleton for shoulder, elbow and wrist joints with seven degrees of freedom controlled through a BMI based on MI-ERD of sensorimotor oscillations in the β-band.

of left versus right hand and left hand versus both feet by using motor execution or motor imagery. The results showed that the amplitudes of ERD/ERS for MI sessions were smaller than those for ME sessions, and they've stated that the reasons might be the absence of neural feedback in MI which may exhibit less activity and, that MI is not a natural behavior and those requires more effort than ME.

EMG + EEG

Both EMG and EEG have their own disadvantages that hinder further development. Several studies have tried to overcome their limitations by combining these two techniques[52–55]. In the article of Zhang et al.[56] electrooculography (EOG), electroencephalography, and electromyogram has been combined to obtain a multimodal human-machine interface system (mHMI) that can provide a variety of control instructions necessary for multi-task real-time control of a soft robot. Their aim was to obtain a system that can increase the number of commands and enhance classification accuracy, reduce errors and, meanwhile, overcome the limitation of the single mode of BCI. The EEG was used to detect the intention of left- or right-hand movement. The EMG was used to identify hand gestures, which were obtained from forearm muscle activities through the Myo Armband, to facilitate control of the robot. And EOG, was used, by double blinks, to select different actions within a selected category. The results of the study show that with the mHMI the subjects were able to perform a greater number of instruction than the ones achievable with the individual mode. Furthermore, the classification accuracy was enhanced.

The parallel usage of EEG and EMG were, also, been explored in the article of Leeb et al.[57], the control abilities of both modalities were fused enabling the subjects to achieve a good control of their hybrid BCI independently of their level of muscular fatigue. In the article of Chowdhury et al.[58] EEG and EMG were combined using the spectral power correlation to create a hybrid BCI device for controlling a hand exoskeleton. They've proved that the hybrid BCI significantly improved the classification accuracy.

DISCUSSION

As it's emerged from the previous paragraph, EMG and EEG are both very valid interfaces between the wearable robot and the human, indeed, they are the mainly used techniques for the control of exoskeletons or prosthetic devices in post stroke rehabilitation.

EEG and sEMG are both non-invasive recording procedure and, therefore, they are safer and easy to apply. EEG is potentially applicable to almost all people including those seriously amputated and paralyzed and, EMG-based control interface are widely used because of its easy access and generation, and its direct correlation to the movement intention.

However, EEG and EMG have their own disadvantages[59,60]. Electromyography requires significant signal processing due to its broad bandwidth and low amplitude[61]. Furthermore, some of the EMG limitations are caused by the complexity of the musculoskeletal system and, due to differences in body composition or electrode placement, sEMG signals vary strongly between subjects. Additionally, slightly different motion pattern might cause huge changes in the signals and, the muscle contractions can lead to measurement inaccuracies, as the electrodes shift on the skin during muscle movement.

As for electroencephalography, its main drawbacks are the high trial-to-trial variability and poor signal-to-noise ratio, the long training period to learn to modulate specific brain potentials, the need to attach multiple electrodes on the scalp, the low information-transmission rate due to the filtering properties of the skull, and high variability of the brain signals due to changes in background activity[61,62]. Furthermore, the brain activity of stroke patients is very different from that of a healthy intact brain, resulting in significantly different

EEG features. In addition, EEG signals do not have sufficient spatial resolution to be used to control individual finger movement.

There are several studies that have try to overcome these limitations by combining the two modalities. The results are promising, however, whether the single mode or the hybrid one, these interfaces still possess some shortcomings, such as the limited number of possible commands and poor real-time capability.

CONCLUSION

In this paper we have reviewed the EEG- and EMG-based control interface, which are the most commonly used BCI for the control of upper limb exoskeleton. In the last decades the development of these two modalities has allowed the human brain to directly communicate with the outside environment and, nowadays, they can play an important role in the post stroke rehabilitation process. Both EMG and EEG have their own advantages and limitations, some of the latter ones can be overcome by a hybrid BCI that combined the two technologies. The studies presented in this paper have shown the potentials of EEG and EMG, however, there are still a lot of drawbacks that hamper the everyday life implementation.

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