Preliminary EEG Characterisation of Intention to Stand and Walk for Exoskeleton Applications

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Abstract—**Wearable lower limb exoskeletons aim to mobilize and improve the quality of life of people with lower limb paralysis. However, all the current commercially available exoskeletons require good upper limb function to operate them effectively. This limits their use for people with higher-level impairments, such as tetraplegia. In this paper we investigate the possibility of being able to decode from the user's brain signals, their intention to perform various actions, including standing up and walking, with a view to eventually controlling an exoskeleton with a brain-computer interface. As such, we present some preliminary results that show statistically significant changes in Mu band power, when preparing to execute movements and during the execution of movements.**

I. Introduction

THE loss of sensorimotor function is a key implication in spinal cord injury (SCI) and so many patients use wheelchairs to restore a degree of autonomy. Wheelchair use, however, increases the risk of a number of conditions associated with prolonged periods of immobility, such as pressure sores and urinary tract infections [1]. Standing regularly has been shown to decrease the incidence of urinary tract infections and improve bowel function [1]. Therefore, patients are beginning to turn to lower limb robotic exoskeletons—wearable devices that are rigid and move congruously with the user—both as mobility aids and to improve overall quality of life [2] [3].

All current commercially available exoskeletons require good upper limb function, either to use crutches to provide balance (e.g. Ekso Bionics, Indego etc.), or to manipulate a joystick to control the device (e.g. Rex Bionics) [4]. For SCI patients with tetraplegia initiation of movement using a joystick is either extremely difficult or impossible. Therefore, in order to bypass the affected neuromuscular system, some researchers have proposed to control such exoskeletons directly from the user's brain signals [7]. In this case, the participant was asked to *imagine* performing various tasks (e.g. walk, rest etc.).

However, we want to see if we can predict when someone actually *prepares to perform*, and *goes on to perform*, these tasks in an unconstrained environment, with a view to providing a generic starting point for a decoder to be used by SCI patients.

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In order to bypass the peripheral nervous system, reliable neural signal correlates can be mapped for intention and for specific actions. The electrical activity of the brain can be monitored non-invasively in real time using an array of electrodes, which are placed on the scalp in a process known as electroencephalography (EEG). If these signals can be identified reliably, they may be used to control a lower limb exoskeleton using a brain-machine interface (BMI), without the need for a joystick or any upper limb function. The novelty of this investigation stems from the protocol that encompasses all the movement primitives that an exoskeleton performs. In this way each movement can be classified, and the features from each classification may be linked to the correspondent movement. Therefore we may be able to create a state-based exoskeleton control paradigm, by decoding natural movement intentions from EEG. In future, a biometric algorithm may also be used to automatically identify the exoskeleton's current user and adapt the parameters of the classification process to maximize the BMI performance.

The aim of this study is to identify the change in Mu power leading up to movement and during a movement when compared to baseline activity. This could later be used in the development of a full brain-machinr interface.

II. Materials and Methods

A. Electroencephalography (EEG)

When subjects have the intent to move a part of the body, event related desynchronization (ERD) of the underlying neuronal populations in the corresponding area of the motor cortex manifests itself as a decrease in Mu band (8-12Hz) power, which can be successfully detected [5].

We acquired EEG data at 512Hz using g.Tec's 16-channel active electrode system. The electrodes were located over the motor cortex at the International 10–20 system locations Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4. The right ear lobe was used as a reference and the electrode at AFz was used as the ground. To minimize artefacts in the data, the participant was asked to refrain from blinking and relax facial muscles (including swallowing) during the trials. They were also asked not to swing their arms actively whilst walking but keep them relaxed.

B. Experiment Protocol

Ethical approval for this study was obtained from the University College London Research Ethics Committee

(8715/001). In this paper, we present the preliminary data from a 21-year-old able-bodied male volunteer participant. First, whilst the participant was comfortably seated, we explained the experiment protocol and set up the EEG montage. The participant was then asked to perform a number of specific tasks a few seconds after a visual or audio cue. These tasks were: stand up; take two steps forward; turn twice in place; take two steps backward; sit down. In order to minimize any interference from potentials evoked by the external cue stimulus, the participant was asked to move approximately 3 seconds after each cue. Once movement was initiated, a trigger was pressed by the experimenter in order to label events. There was a pause of at least 5 seconds after each movement was completed, during which the participant could rest. This was repeated 10 times.

Our protocol allowed for voluntary initiation unlike cue-based tasks that measure reaction, where the volunteer is advised to move immediately after the cue is heard or seen. This is necessary as the neural signals that are associated with instructed tasks have been shown to have differences to those associated with spontaneous tasks [6].

C. EEG Data Processing

We pre-processed the EEG data by applying a notch filter at 50Hz to remove any mains interference and then we bandpass filtered the data from 1-40Hz. Next we applied the spatial Laplacian filter to enhance the signal-to-noise ratio. [8]. To ascertain differences between periods of rest, pre-movement, and post-movement epochs, we first computed the power spectral density (PSD) for each EEG channel. We then estimated the PSD features using the Welch method over: the baseline (random one second intervals during the resting period); one second leading up to movement onset (pre-execution); and one second immediately after movement onset (execution).

We assessed statistical differences across conditions using the non-parametric Kruskal-Wallis test.

III. Results and Discussion

As we can see from Fig. 1, looking at the Cz electrode, the Mu band power during the execution epochs significantly decreased compared with the baseline ($p<0.001$). Moreover, at the same location, the Mu band power also significantly decreased during the pre-execution epochs ($p<0.001$).

This decrease in power could be attributed to the ERD and therefore correlated to the intention to move. The fact that we see this phenomenon at the Cz electrode is neurophysiologically plausible, since it is located close to the feet and leg area of the motor cortex. Whilst our detected features look promising, we have not yet implemented an equivalent to the real-time closed-loop system developed in [7]. We will further need to integrate a data-driven approach to refine the decoder to the idiosyncrasies of each end-user's EEG patterns.

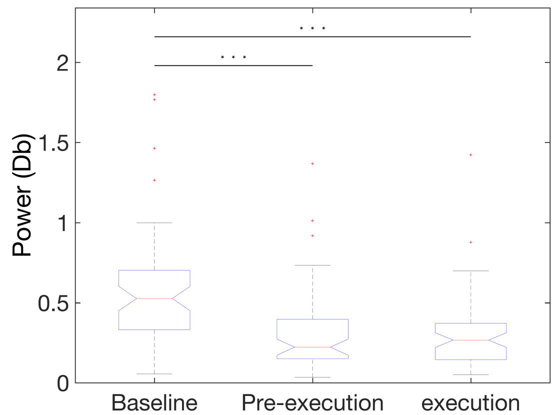

Fig. 1. The mean Mu band power (8-12Hz) of channel Cz (***$p<0.001$).

IV. Conclusion

The data in this preliminary study suggests that we could identify the intention to initiate an action prior to execution. However, we are currently collecting data from more participants to increase the power of our results and to see if we can discriminate between different actions such as starting to walk, compared with standing up or sitting down. Our analysis has been post-hoc, so it remains to be seen as to whether or not these features can be used in an online real-time system where single trial detection is required. That said, this study suggests that we may be able to create a state-based exoskeleton control paradigm, based upon decoding natural movement intentions from EEG.

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