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Feasibility of using discrete Brain Computer Interface for people with Multiple Sclerosis

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***Abstract*— Aim: Brain-Computer Interfaces (BCIs) hold promise to provide people with partial or complete paralysis, the ability to control assistive technology. This study reports offline classification of imagined and executed movements of the upper and lower limb in one participant with multiple sclerosis and people with no limb function deficits. Methods: We collected neural signals using electroencephalography (EEG) while participants performed executed and imagined motor tasks as directed by prompts shown on a screen. Results: Participants with no limb function attained >70% decoding accuracy on their best-imagined task compared to rest and on at-least one task comparison. The participant with multiple sclerosis also achieved accuracies within the range of participants with no limb function loss.**

***Clinical Relevance* — While only one case study is provided it was promising that the participant with MS was able to achieve comparable classification to that of the seven healthy controls. Further studies are needed to assess whether people suffering from MS may be able to use a BCI to improve their quality of life.**

I. Introduction

Loss of limb function is a devastating consequence of a range of neurological conditions including spinal cord injury, limb amputation, stroke, amyotrophic lateral sclerosis, and multiple sclerosis (MS) [1]. Brain-computer interfaces (BCIs) have the potential to provide paralyzed people with a new way of interacting with the world through technology. BCIs act as an artificial communication channel between the brain and external interfaces, such as communication or mobility devices.

While several papers on EEG classification of movements mention that an EEG-based BCI may be useful for people with MS there is currently no work that has been performed with people with MS[2]–[4]. However, some studies have evaluated fatigue in MS participants using EEG [5], [6], and were able to generate brain signals and may be useful for a BCI. However, no studies have yet evaluated the potential for MS participants to use a BCI. Participants with limb function loss, when included in Research studies, are predominantly people with partial or complete paralysis from stroke [7], spinal cord injury[8], or amyotrophic lateral sclerosis (ALS) [9].

This is the first study to report EEG signals from a participant with MS in an offline BCI task with comparison to participants with no limb function loss. In the present study, we evaluated the performance of seven healthy participants and one participant with MS in five executed and imagined movements. We evaluated how within-subject and between-subject performance varied in two-class and multiclass classification and whether movement-related EEG rhythms were subject-dependent or task-dependent.

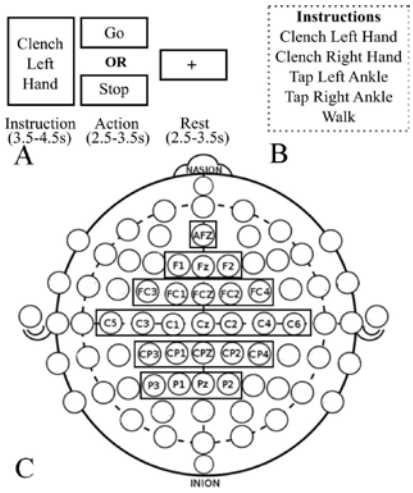

Figure 1. Experimental setup. A. The structure of an individual trial, which either presented an instruction followed by Go/Stop or showed a fixation cross to indicate to rest. B. The instructions shown in the trials. C. The 10-20 EEG positioning system. AFz was the reference electrode and the other 24 boxed electrodes were recorded during the session.

II. Methods

A. Participants

This experiment was approved by The University of Melbourne Human Research Ethics Committee (Ethics ID 1748801). EEG recordings were performed in seven right-handed volunteers (five male and two female) aged 20-23 with no history of neurological disorders (S1-S7) and one 60-year-old female with diagnosed MS (P1). P1's MS manifests

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as weakness of her left leg and right hand, she regularly practices imagining moving the affected hand and leg as well as physiotherapy. The severity of weakness was not assessed.

B. Protocol

Participants participated in a single session lasting less than 2 hours in an electrically shielded, sound-proofed, darkened booth. Participants were seated in a comfortable chair 1 m from a 68 cm computer monitor and instructed to place their feet flat on the floor with their forearms resting on their legs. Instructions were displayed on the monitor using Psychtoolbox-3 [10]. Participants performed a session of executed movements followed by imagined movements.

In each session, participants read and followed instructions on the screen. The structure of each trial is shown in Figure 1A and consisted of a movement instruction, a 'go' or 'stop' cue, and a fixation cross. The instructions that were presented are shown in Figure 1B. Tasks included 'Clench Left Hand' (LH), 'Clench Right Hand' (RH), 'Tap Left Foot' (LF) and 'Tap Right Foot' (RF), which was only used in the imagined instruction set. Participants were told to read the instruction and prepare to either make the movement or imagine moving. If the instruction was followed by a 'Go' cue, the participant was to go ahead with the movement or imagining the movement (go trial). If the prompt was followed by a 'Stop' cue, the participant was told to stay still and not imagine moving, clearing their mind while the fixation cross was displayed; this acted as a control (stop trial). The inter-trial interval was used as the Rest period. Participants S1-S7 completed three 8-minute executed movement blocks. P1 and S1-S7 completed six 5-minute motor imagination blocks.

C. EEG Data Collection

Common average referenced EEG signals were recorded using a TMS Porti 32-channel biosignal amplifier (Twente Medical Systems Incorporated, Netherlands) at a sampling rate of 2048 Hz via a TMSi-MATLAB interface. We used a TMSi EEG cap with 25 electrodes in the 10-20 international electrode location system shown in Figure 1C.

D. Data Processing

Data processing was performed using MATLAB 2016b (MathWorks Inc., Natick, MA, USA). Raw EEG signals were band-passed with a low half-power frequency of 3 Hz and high half-power frequency at 35 Hz. Artifacts from the EEG were eliminated using the automatic artifact removal process published previously by Mammone *et al.* [11]. Enhanced Automatic Wavelet Independent Component Analysis eliminated the non-neuronal components of the EEG. Visual inspection was used to identify aberrant electrodes.

E. Feature Extraction and Classification

Average power in 4-8.5 Hz (theta), 9-15 Hz (alpha), 16-22.5 Hz (low beta), and 23-32 Hz (high beta) frequency bands calculated in 25 ms segments. Power was calculated using the Fourier transform of the autocorrelation sequence calculated with a sliding (rectangular) window of 800 ms [12]. For each participant, the features were standardized (to the mean and standard deviation of each feature). A Support Vector Machine (SVM) was used to classify between 1) imagined/executed movements vs rest; and 2) between tasks (i.e LH vs RH, LF vs RF etc.) with 5-fold cross-validation.

F. Statistics

All statistical analyses were performed in MATLAB 2016b (MathWorks Inc., Natick, MA, USA). The level of agreement between accuracy from the executed and imagined tasks was compared using Bland Altman analysis.

III. Results

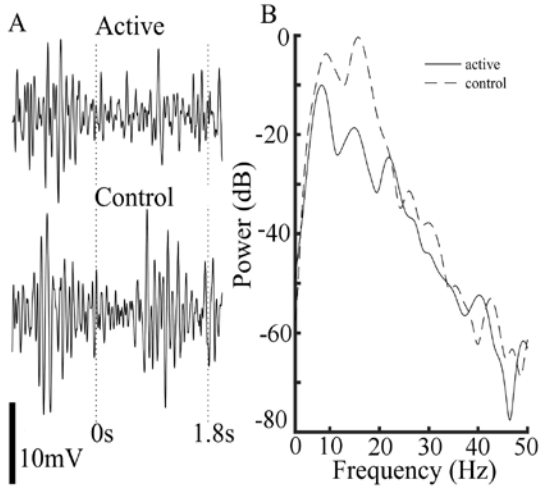

Figure 2: Sample outputs and analyses. A) Sample EEG traces and B) corresponding power spectra from a single electrode (C3) during single active (Clench Right Hand) and control trials.

Figure 2A shows randomly selected EEG traces during stop trial (control) and active (Clench Right Hand) from electrode C3, where '0' indicates the time that 'Go' or 'Stop' cue was presented. Data is from one trial from one able-bodied participant. Figure 2B shows the power spectra corresponding to the EEG traces in Figure 2A. The power spectra were calculated from single-trial filtered data between 0-1.8s (Figure 2B). The power spectra in Figure 2B shows a decrease in the power of the alpha and beta frequencies in the 4-24 Hz range during movement compared to no movement.

A. Executed/Imagined movement vs rest

Figures 3A and B show the evolution of mean +/- standard error of the classification accuracy of the Executed/Imagined movement vs rest. Figures 3A and B show time during executed (Figure 3A) and imagined movements (Figure 3B) vs rest. The asterisk shows the maximum decoding accuracy within the interval starting 0.2-1.0 s after cue presentation. The time of the maximum decoding accuracy during executed movement (0.71 ± 0.1 s, mean ± standard deviation) was similar to imagined movements (0.72 ± 0.1 s).

The time of the maximum decoding accuracy was normally distributed, and a two-tailed t-test showed no significant difference between the time of imagined or executed movement ($p = 0.15$). The timing of the maximum decoding

accuracy during imagined movement was not different between the participant with MS (0.70 ± 0.2 s) and the healthy subjects' population (S1-S7 mean, 0.72 ± 0.1s).

Figure 3 (S1-S7) shows the mean decoding accuracy between each movement (LH, RH, LF, RF) and rest (intertrial interval). There was no difference between imagined maximum decoding accuracy = 0.73 ± 0.09 or executed maximum decoding accuracy = 0.72 ± 0.07 (mean of LH, RH, LF, RF). However, there was variation between participants in performing the tasks. P1, showed a maximum decoding accuracy of 0.71 ± 0.04 across the four imagined movements. Bland-Altman analysis showed overlapping means for executed and imagined movement with limits of agreement between -0.24 to 0.24 and were not correlated (Spearman ρ = -0.10, p = 0.60).

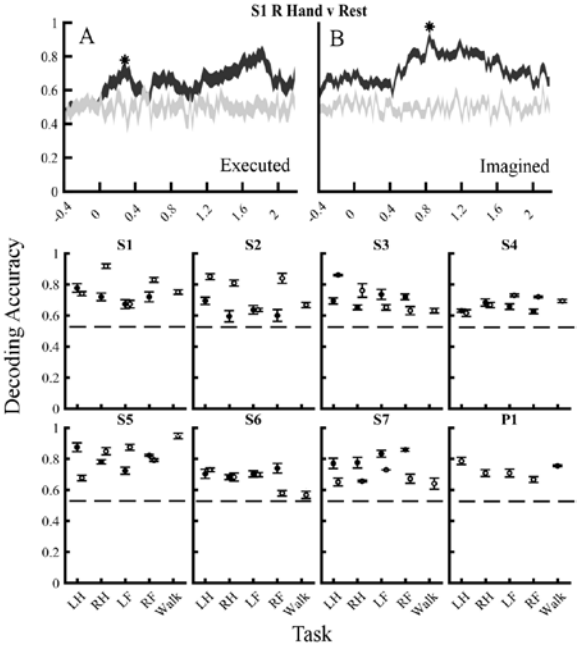

Figure 3: Executed/Imagined Movements vs rest. A and B) Example SVM decoding accuracy vs time (from cue in seconds '0'). The shaded area shows the standard error of the mean. Black traces show decoding accuracy. Grey traces show decoding accuracy with scrambled labels. The asterisk shows the maximum decoding accuracy between intervals starting 0.2-1.0s after cue presentation. Maximum decoding accuracy for each task vs rest in each subject S1-S7 and one participant with MS (P1). Closed circles represent executed movement, open circles represent imagined movement, the error bars represent standard error of the mean. The Dashed line shows the upper limit of the 95% confidence interval of the theoretical chance level (0.5).

B. Classification between individual movements

Figure 4 shows the evolution of classification accuracy for right hand vs right leg in executed (Figure 4A) and imagined (Figure 4B) movements. Timing of the maximum decoding accuracy during imagined movement (0.61 ± 0.3s, mean ± standard deviation) was not statistically significantly different to executed movements (0.69 ± 0.3s, p = 0.15, paired t-test).

Figure 4 (S1-S7, P1) shows classification accuracies between different task pairs. Like executed/imagined movement vs. rest, binary classification between specific movements showed inter-subject differences. A paired t-test showed that there were no statistically significant differences between imagined/executed movement accuracies (p = 0.61). The mean classification accuracy between movements (executed: 0.65 ± 0.05, imagined: 0.66 ± 0.09) was lower than movement vs rest for executed movements (0.73 ± 0.09) but not imagined movements (0.72 ± 0.07). The classification accuracy during imagined movements was 0.66 ± 0.09 for participants S1-S7 and 0.63 ± 0.01 for participant P1.

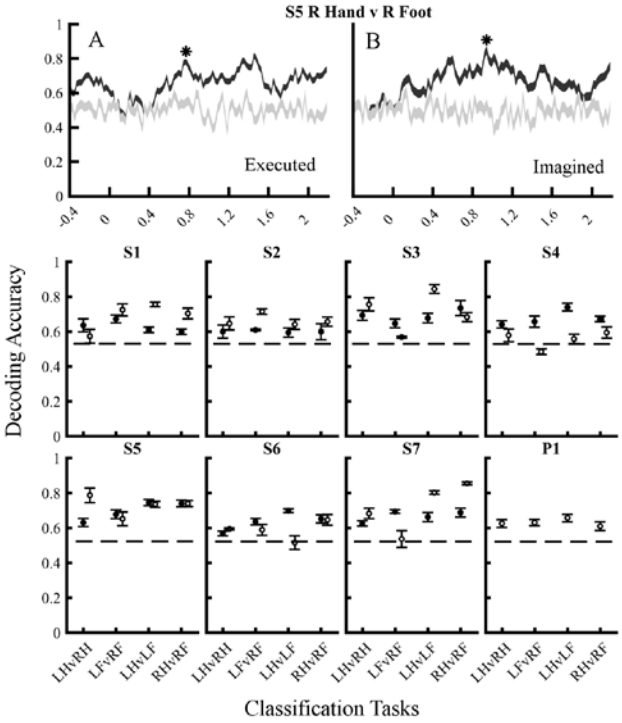

Figure 4: Classification between tasks. A and B show examples of the SVM accuracy vs time from cue '0'. The asterisk shows the leading edge of the 800ms analysis window representing the maximum between 0.2-1.0 s after the cue. The shaded area depicts the standard error of the mean. The black trace represents accuracies from true labels and the grey trace represents accuracies with scrambled labels. Maximum decoding accuracy for each combination of tasks in each subject S1-S7 and one participant with MS (P1). Closed circles represent executed tasks, open circles represent imagined tasks, the error bars represent standard error. The Dashed line shows the upper limit of the 95% confidence interval of the theoretical chance level (0.5).

IV. DISCUSSION

All participants (including the participant with MS), achieved decoding accuracy above chance level with greater than 70% accuracy in the task vs rest demonstrating that accuracy was sufficient for use as a brain-computer interface (BCI) [13]. There was no difference between imagined and executed movement classification accuracies and there was no difference between movement classification accuracies.

Decoder performance for the participant with MS was comparable to healthy participants. MS is a heterogeneous disease with many variations of symptoms, however sufferers with partial or complete paralysis could benefit from BCI use.

The participant with MS (P1) was able to achieve comparable classification accuracy to the healthy participants while imagining the different motor tasks. This would suggest that P1 is still capable of producing classifiable Sensory Motor Rhythms (SMR) changes despite having some loss of function in some of the tasks. Whether the participant's regular motor imaginings contributed to her classification performance is also unclear. It is worthwhile investigating with a larger participant pool whether people with MS generally retain the ability to produce classifiable signals while performing imagined motor movements. If it is a general feature, then BCIs may be able to assist people with MS to retain their motor ability with the help of a BCI-linked muscle stimulator or exoskeleton. Such a system could improve the participant's function and protect them from the muscle wasting associated with partial and total paralysis.

Participants' abilities in movement execution may not translate to movement imagination. Interestingly, there was no correlation between the accuracies of decoding imagined movements and executed movements. A participants performance in an execution task could not be used to determine how well they may perform in an imagined task. Intuitively, it may be assumed that people who can perform an action can equally be able to imagine movement-generating EEG signals. However, this was not the case; some participants whose decoding accuracy was high in imagined tasks only achieved chance level accuracy in the movement task and vice versa. Considering that conditions such as MS and motor neuron disease are progressive, it may be beneficial to train people with these conditions before complete loss of limb function, which may help reduce training time and lead to greater adoption. It is tempting to think of a BCI as augmenting or using existing ability to achieve control. However, the disassociation between movement execution and imagination indicates the ability to control a BCI may need to be treated as a new skill that needs to be acquired. Research on training effects on BCI control has been promising but not conclusive [14], [15]. Further work on the effect of long-term training for a BCI use would be required.

V. Conclusion

This study demonstrates the future possibilities of EEG-based SMR to be utilized to implement a BCI to meet the needs of people with MS. Promisingly, the participant with MS was able to achieve comparable classification to the seven healthy participants. Future work should include a measure of MS. The case study shows that people with MS can use a BCI. There is an imperative to further investigate how MS progression affects motor activity in the brain using EEG with larger participant pools and with long-term studies.

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