TRANSFER OF ABSTRACT CONTROL SKILLS TO PROSTHESIS USE

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ABSTRACT

Computer interface tasks have shown that motor learning based control schemes enable multi-grip myoelectric control with only two electrodes. However, it is unclear if this control transfers to prosthesis use. Here, we test if training abstract control with delayed feedback transfers to prosthetic control in a 7-session experiment. Two participants completed five 1-hour training sessions in between a pre- and post-test. The abstract decoding scheme ensured participants had access to five grips (power, tripod, point, lateral, and hand open), and the prosthetic tests included a grip matching task, the modified box and blocks task, and a pick and place test. Both participants increased their grip matching score, reaching a classification accuracy of 93.33% and 98.33%. They also increased the amount of blocks they relocated in the modified box and blocks test, completed the pick and place test faster, lowered the amount of objects they dropped, and increased the accuracy of the grips they selected during the pick and place test. These results show that a motor-based training strategy of abstract control transfers to prosthetic use, enabling five grips with only two electrodes.

INTRODUCTION

Myoelectric prosthesis are commonly controlled with a standard agonist/antagonist direct control, while some devices with additional electrodes use pattern recognition (PR) [1]. Studying the use of these devices in a home environment shows that most prosthesis users only use 3 or 4 grips, with the most common grip accounting for around 50% to 80% of use [2], [3]. Simon and colleagues found that users had slightly more configured grips for direct control (4.8) than PR (3.8) when using their prosthesis at home [3], providing more functionality with less hardware requirements. However, accessing all grips in direct control requires users to cycle through the grips with mode switching, making the control cumbersome.

Abstract control, a motor learning based control scheme, allows myoelectric users to access multiple grips without mode switching, using only two electrodes [4]. We have previously shown that people with a limb difference can learn abstract control [4], and that training with delayed feedback allows people to retain this skill [5], [6]. Here, we test if the skill gained during a home-based computer interface task transfers to prosthetic control. Participants took part in lab-based pre- and post-tests, and completed five 1-hour training sessions in their home environment.

METHODS

Participants

Two participants (2 female) who are able bodied and free from neurological or motor disorders were recruited. The study was approved by the local ethics committee at Newcastle University (ref: 20-DYS-050), and participants provided written informed consent prior to the start of the experiment.

Experimental setup

Participants performed a range of myoelectric control tasks, all based on two-channel abstract control. Two EMG electrodes were placed on the extensor carpi radialis and flexor carpi radialis. Signals were acquired using a custom network-enabled myoelectric platform [7]. The platform enables streaming of EMG data over Bluetooth Low Energy to a PC running the AxoPy Python library, allowing real time myoelectric control. Muscle signals were smoothed using the mean absolute value (MAV), with a window length of 750ms. Muscle estimations were updated at a rate of 50Hz.

Abstract control allows participants 5-class myoelectric control (4 movement classes + hand open) with the use of only 2 electrodes. Shortly, EMG channels are calibrated for each participant, where normalized activity for each channel is:

$$\hat{y} = (y - y_r) / (y_c - y_r)$$

where $\hat{y}$ is the normalized muscle activity, y the MAV, y_r the activity when the participant is at rest, and y_c represents a comfortable contraction. The normalized activity of both muscles determines the position of a cursor within a 2D V-shaped interface [4]. For this experiment, the V-shaped interface was divided in 4 targets, each representing a specific grasp. From left to right, the targets represented the following grips: 'power', 'tripod', 'pointer', and 'lateral'. Once the prosthesis was closed, hitting any of the targets resulted in the prosthesis returning to the 'hand open' state.

Experimental design

The experiment consisted of 3 main stages: a pre-test, training phase, and post-test. The pre- and post-test consisted of the same tasks.

Pre- and post-test: Participants wore a transradial bypass socket [8], fitted with the Touch Bionics robo-limb prosthetic hand, throughout the experiment. At the start of the test, both EMG channels were normalized as described above. Subsequently, participants completed 2 blocks of 60 trials to familiarize themselves with the abstract myoelectric control interface. In these blocks, a target was presented at the start of each trial, and the participants could see the cursor moving based on their muscle activity. Once the cursor was in contact with or inside a target for 750ms, the trial was completed. If the participant reached the intended target, this was considered a 'hit'.

The main prosthesis control experiment consisted of three parts:

- Grip matching task: participants were presented with a target on the screen, similar to the familiarisation phase. However, during the target matching task, no feedback was presented to the participant, thereby testing the retention of skill [6]. Each participant completed 2 blocks of 60 trials.
- Modified box and blocks test (MBB): participants completed 5 trials of the MBB test [9]. When participants grabbed more than 1 block in a single movement, the additional blocks were removed from the results.
- Pick and place test: four objects, each associated with a specific prosthesis grip, were placed on a 2x4 grid on a table in front of the participant, with a 15cm distance between grid point. Participants were instructed to move all objects forward from right to left, after which they placed them back on the grid points closest to them from left to right. Participants repeated the trial 4 times. When participants selected the wrong grip, participants were told to open the hand and try again. If they selected the wrong grasp 3 times, participants were told to move on to the next object. Next to the time it took to complete the trials, the amount of repetitions to a grasp, and the amount of objects that were dropped were recorded.

Training: In between the pre- and post-test, participant completed five 1-hour training sessions, spread over 1 week. During these sessions, participants completed an abstract control task in their own home, without wearing a prosthesis. At the start of the first training session, the EMG channels were normalized as described above. This calibration was used throughout the rest of the training. During the training, participants performed a delayed abstract control task, as described in [5]. Participants performed blocks of 60 trials, and were told to complete as many blocks as felt comfortable during their training time.

Due to the limited amount of participants, no statistical tests were performed at this time.

RESULTS

Training

Participant 1 (P1) completed 36 training blocks, while participant 2 (P2) completed 35 blocks. P1 reached a maximum hold score of 97.07%, while P2 reached 95.05%.

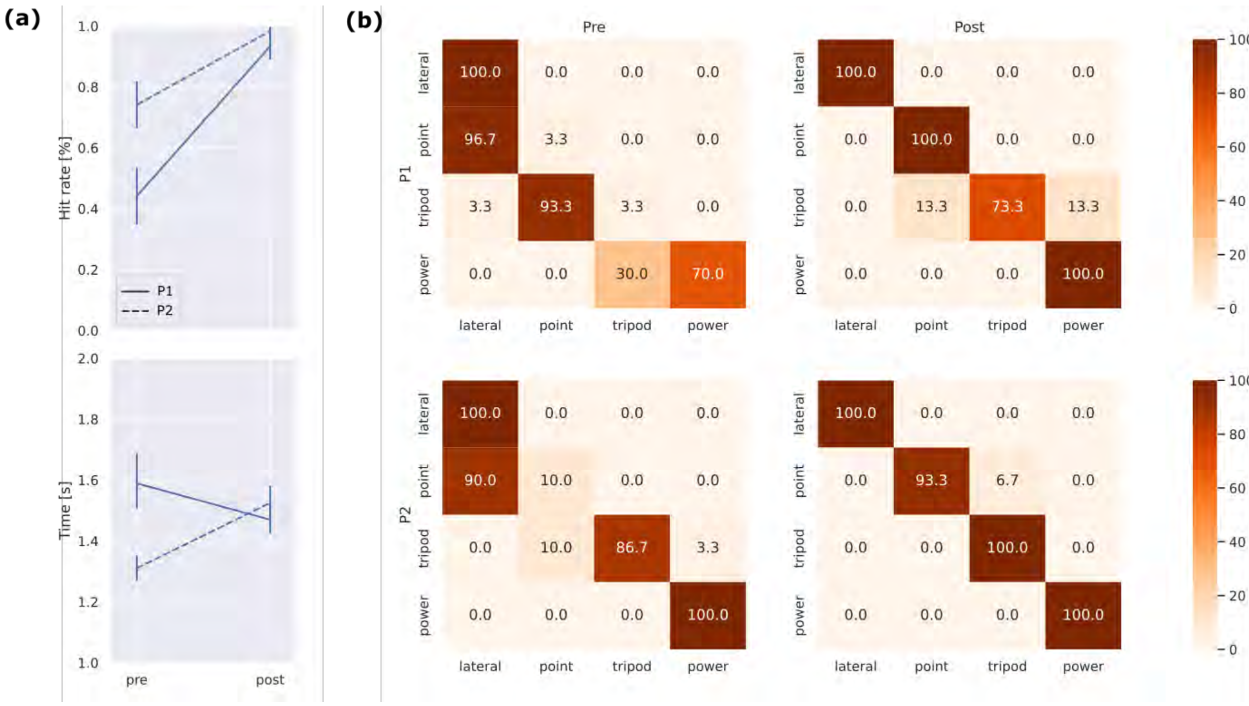

Figure 1: Results of the grip matching task. (a) Hit rate and completion time for pre- and post test, split up by participant. (b) Confusion matrices of pre- and post-test for both participants.

Pre- and post-test

The results of the grip matching task are presented in Figure 1. Training allowed P1 to increase her performance from 44.16 ± 49.66% to 93.33 ± 24.94%, while the score of P2 increased from 74.17 ± 43.77% to 98.33 ± 12.80%. These scores represent the performance without any visual feedback. Subsequently, each trial lasted until the participants selected a grip, and the chosen grip was recorded. Figure 1b shows the confusion matrices for this task. In the pre-test, participants were able to select the lateral and power grip, the grips associated with the corner targets of the abstract interface, but they had difficulties selecting the grips associated with the two middle targets. Training allowed them to select these targets as well.

Both participants increased the amount of blocks they picked up during the MBB post-test, from 5.2 ± 1.47 to 8.2 ± 0.75 and from 8.2 ± 1.67 to 8.8 ± 0.98 for P1 and P2 respectively. They also increased all measures during the pick and place post-test: they completed the trials faster (P1: 109.69 ± 2.92s to 68.71 ± 8.58s; P2: 69.99 ± 8.64 to 55.50 ± 7.05s), had to repeat less grips per trial (P1: 4.5 ± 3.20 to 2.00 ± 1.00; P2: 2.25 ± 0.83 to 1.00 ± 0.71), and managed to not drop any objects during the post test (pre-test: 0.5 ± 0.5 for P1, and 0.25 ± 0.43 for P2).

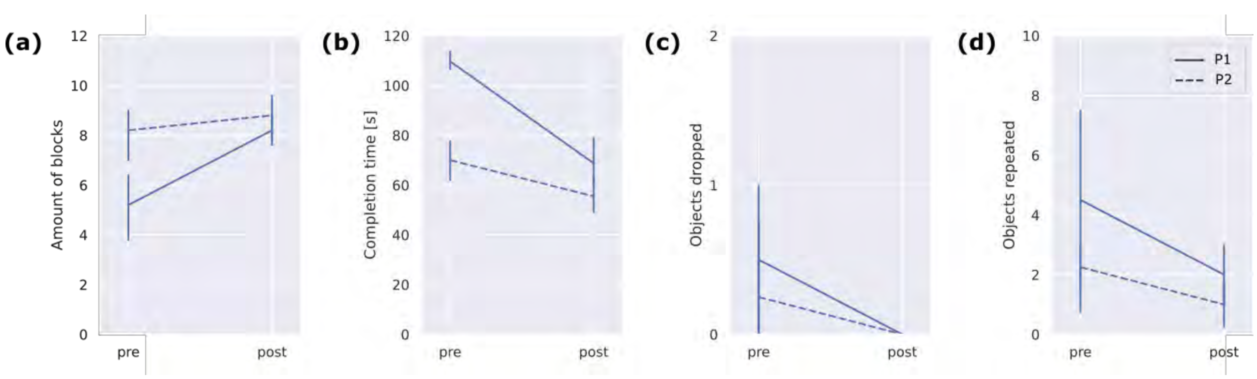

Figure 2: (a) Results of modified box and blocks test. Completion time of trials (b), the amount of objects participants dropped per trial (c), and the amount of times participants had to repeat a grip per trial due to initially selecting the wrong grip (d).

CONCLUSION

This paper shows that abstract myoelectric control, trained by performing a computer interface task, translates to prosthetic control. We designed a training protocol based on delayed feedback, allowing participants to retain their skills when no feedback is available, or when using a prosthesis. As a result, participants were able to reliable control five grips (hand open + four closed grips) with 2 electrodes, suggesting prosthesis users could have access to the same amount of grips without the need for additional hardware or mode switching. Currently, we only have data for two participants. However, due to the improvement in all functional tasks for both participants, we expect our full dataset to show the same pattern.

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REFERENCES

[1] D. Farina *et al.*, “Toward higher-performance bionic limbs for wider clinical use,” *Nat. Biomed. Eng.*, pp. 1–13, 2021, doi: 10.1038/s41551-021-00732-x.

[2] L. Resnik, F. Acluche, and M. Borgia, “The DEKA hand : A multifunction prosthetic terminal device — patterns of grip usage at home,” 2018, doi: 10.1177/0309364617728117.

[3] A. M. Simon, K. L. Turner, L. A. Miller, L. J. Hargrove, and T. A. Kuiken, “Pattern recognition and direct control home use of a multi-articulating hand prosthesis,” *IEEE Int. Conf. Rehabil. Robot.*, vol. 2019-June, pp. 386–391, 2019, doi: 10.1109/ICORR.2019.8779539.

[4] M. Dyson, S. Dupan, H. Jones, and K. Nazarpour, “Learning, generalization, and scalability of abstract myoelectric control,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 7, pp. 1539–1547, 2020.

[5] S. A. Stuttaford, S. Dupan, K. Nazarpour, and M. Dyson, “Long-term myoelectric training with delayed feedback in the home environment,” in *2021 43th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, 2021, pp. 6437–6440.

[6] S. A. Stuttaford, S. S. G. Dupan, K. Nazarpour, and M. Dyson, “Training prosthesis control in the lab and the home,” in *MEC Symposium Conference*, 2022, p. [submitted].

[7] M. Dyson, J. Olsen, and S. Dupan, “A network-enabled myoelectric platform for prototyping research outside of the lab,” in *2021 43th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, 2021, pp. 7422–7425.

[8] M. D. Paskett *et al.*, “A Modular Transradial Bypass Socket for Surface Myoelectric Prosthetic Control in Non-Amputees,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 10, pp. 2070–2076, 2019, doi: 10.1109/TNSRE.2019.2941109.

[9] H. Vette, “Normative data for modified Box and Blocks test measuring upper-limb function via motion capture,” vol. 51, no. 6, pp. 919–932, 2014.