2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Long-Term Myoelectric Training with Delayed Feedback in the Home Environment

Simon A. Stuttaford, Sigrid S.G. Dupan, Kianoush Nazarpour, *Senior Member, IEEE* and Matthew Dyson

Abstract— **Myoelectric prosthesis users typically do not receive immediate feedback from their device. They must be able to consistently produce distinct muscle activations in the absence of augmented feedback. In previous experiments, abstract decoding has provided real-time visual feedback for closed loop control. It is unclear if the performance in those experiments was due to short-term adaptation or motor learning. To test if similar performance could be reached without short-term adaptation, we trained participants with a delayed feedback paradigm. Feedback was delayed until after the ∼1.5 s trial was completed. Three participants trained for five days in their home environments, completing a cumulative total of 4920 trials. Participants became highly accurate while receiving no real-time feedback of their control input. They were also able to retain performance gains across days. This strongly suggests that abstract decoding with delayed feedback facilitates motor learning, enabling four class control without immediate feedback.**

I. INTRODUCTION

Myoelectric prostheses work by interpreting neural signals sent from the central nervous systems (CNS) to remnant muscles in the residual limb. User intent can be estimated from recorded electromyographic (EMG) signals of muscle activity, sensed non-invasively with electrodes placed on the surface of the skin [1], [2]. This activity can then be mapped to an output on a prosthetic device via a control scheme.

Abstract decoding is a control scheme motivated by motor learning [3]. With this control scheme, users actively adapt their myoelectric signals in such a way that is distinct from the activations required to achieve the hand grasp naturally [4]. Abstract decoding relies on the human nervous system's ability of performing a vast collection of motor tasks to successfully learn the myoelectric interface such that, with practice, control becomes second nature. As the CNS is tasked with resolving the mapping between muscle activity and prosthesis output, the complexity of motor learning-based systems can be significantly reduced compared to machine learning approaches. In fact, it has been shown that several grasps could be restored based on normalized muscle activity from only two electrodes [5]. These findings were later validated in amputee subjects [6].

*This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC), (grant number: EP/R004242/1) and by the National Institute for Health Research (NIHR) Devices 4 Dignity (D4D) Starworks (project: STWK-006).

S. Stuttaford and M. Dyson are with School of Engineering, Newcastle University, Newcastle, UK {s.stuttaford1, matthew.dyson}@newcastle.ac.uk. S. Dupan and K. Nazarpour are with School of Informatics, The University of Edinburgh, Edinburgh, UK. {sigrid.dupan, kianoush.nazarpour}@ed.ac.uk.

The study of feedback scheduling during practice has been present in neuroscience literature for decades [7], but its effects have yet to be widely explored within the context of myoelectric control. One existing hypothesis in motor learning theory states that frequent feedback is beneficial for correcting errors during the initial acquisition of a skill but detrimental to long-term learning if relied upon [8]. It is found that providing real-time feedback can yield more rapid performance gains but ultimately suffers from a lack of retention when feedback is withdrawn [8]. The process responsible for this phenomenon is referred to as motor adaptation. We use this term here how it is commonly used in upper-limb prosthetics literature [9], [10]. It describes a transient response, sensitive to sensory prediction errors, which iteratively adjusts movements to maximize task performance [7], [11]. On the other hand, motor learning is a set of slower processes which bring about relatively permanent changes in behavior following the practice of a skilled task [11]. Limiting feedback can have the effect of facilitating motor learning, which offers more stable retention of behavior over time [12].

Until now, abstract decoding has provided real-time feedback of the user's input during training [13], [5], [6]. This raises the argument that observed changes may be attributed to short-term adaptation, rather than motor learning. In previous experiments, short time-constrained trials and partial limiting of feedback were used to limit the exposure to adaptive processes [5]. However, it is still possible for adaptation to act on the millisecond level. This implies that previous results would have been affected by fast updates of visual cues to generate compensatory motor commands. As a result, participants would be reliant on the real-time feedback as a source for this error signal. This is problematic when considering that, in general, myoelectric prosthesis users only receive noisy proprioceptive signals from their muscles and augmented feedback from the prosthetic device moving in response to their control signals [14], [4].

We trained participants without real-time feedback so that no within-trial adaptation could take place. To isolate the internal processes that facilitate motor learning, feedback was presented only once control input had ceased. As motor learning works on a relatively slower scale, we hypothesised that multiple day training was required to observe any long-term changes. As this training structure is difficult and expensive to scale under laboratory conditions it is more suited to take place in home environments.

978-1-7281-1178-0/21/$31.00 ©2021 IEEE

II. Methods

A. Participants

Three participants (1 female, 2 male) were recruited. Each had prior experience with the real-time feedback version of the myoelectric task. All participants were able-bodied, free from neurological or motor disorder, and gave informed written consent. Ethical approval was granted by the local committee at Newcastle University (Ref: 20-DYS-050).

B. Experimental setup

Sensors 1 and 2 were placed over the extensor carpi radialis and flexor carpi radialis muscles, and were used for controlling the task. Signals were acquired at 500 Hz. To ensure the recording sites were consistent over multiple days, the location of each sensor was marked on the arm.

C. Calibration

The calibration routine collected data representative of baseline and contraction activity during either arm flexion or extension for each sensor. Contraction intensity was set such that it was deemed comfortable and repeatable for long periods of time. Activity was smoothed by computing the mean absolute value over a 760 ms window with an update rate of 20 ms. Normalization values were set at rest and activation during dynamic movement.

Participants had the option to set their own EMG calibration at the start of every session. After the EMG calibration was established, subsequent sessions used the previous normalization values. Participants carried out the task with their elbow flexed at 90° and were instructed to keep their wrist in the neutral position.

D. Experimental protocol

The task involved moving a cursor within a 2-dimensional, four target, myoelectric-controlled interface (MCI) (Fig. 1a). The cursor's position on the interface is altered by muscle activity from the two control channels. The amplitude of the activity sensed by each sensor determines the cursor's position along a single axis. Varying levels of co-contraction were necessary to reach the two central targets. The experimental protocol was written in Python and used the AxoPy library [15]. Home testing was enabled through the system described in [16].

Trials began once the participant was in the rest state, corresponding with the cursor being inside the basket (Fig. 1b). Trials lasted a total of 1.52 seconds, which consisted of a *move* and *hold* period lasting 760 ms respectively. Once a goal target was presented, the move period allows the participant to react and begin to move the cursor out of the basket and towards the target. The aim during the hold period is to keep the cursor within the target without leaving the boundaries. During the move and hold periods, the cursor was made invisible, illustrated in Fig. 1c. Therefore, the task was completed without concurrent visual feedback of the cursor's position. After the hold period, active control of the cursor ceased. Then, feedback of the cursor's previously unseen motion was played back at the same rate it was

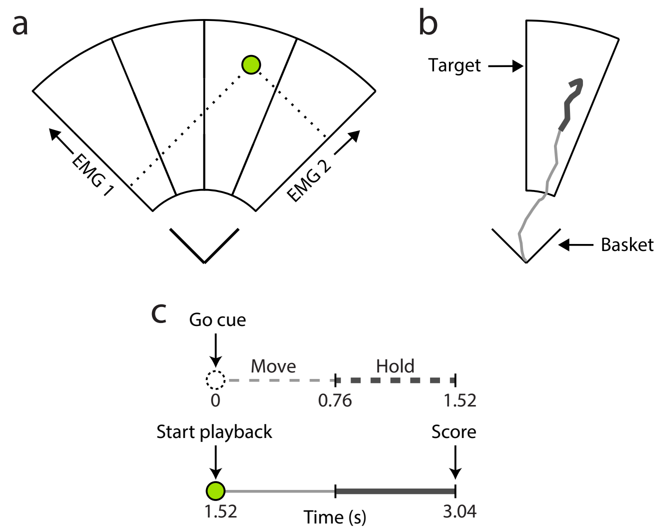

Fig. 1. The MCI task. Figure edited from [5]. a) The 2-dimensional myoelectric-controlled interface space. Cursor shown in green. b) A representative cursor trajectory. c) Task timing structure denoting cues, move, hold and playback periods. Dashed traces correspond to the 'blind' control input window. Solid traces refer to the playback of the cursor's recorded path during the move and hold periods.

captured. This allowed the participants to spectate their performance during the move and hold periods. Once the playback had concluded, a score was presented based on the proportion of the hold period the cursor was within the correct target.

Participants completed a series of blocks, each consisting of 60 trials. Targets were presented in a pseudo-random order. Participants carried out the experiment at home over five days. They were allowed to practice at their own convenience and choose how many blocks to complete in a given session.

E. Analysis

A post-hoc 'decoder score' was used as a metric to compare hold score to classification accuracy of machine learning based systems. The predicted target was assigned as the first target the cursor dwelled within consecutively for 240 ms [17]. A decoder score of 1 was obtained when the predicted target was indeed the presented target. A score of 0 was obtained otherwise. All reported values represent the mean and standard error of the mean. Significance values were calculated using a two-tailed Mann-Whitney-Wilcoxon test.

III. Results

Participants 1 and 2 calibrated once, and used the same normalization values throughout all training sessions. Participant 3 recalibrated at the beginning of day 2, and continued to use the second set of normalization values for the remaining four sessions.

Fig. 2 shows data from three participants during the five day training period. Each column corresponds to an individual participant. Participants 1-3 completed 22, 31 and

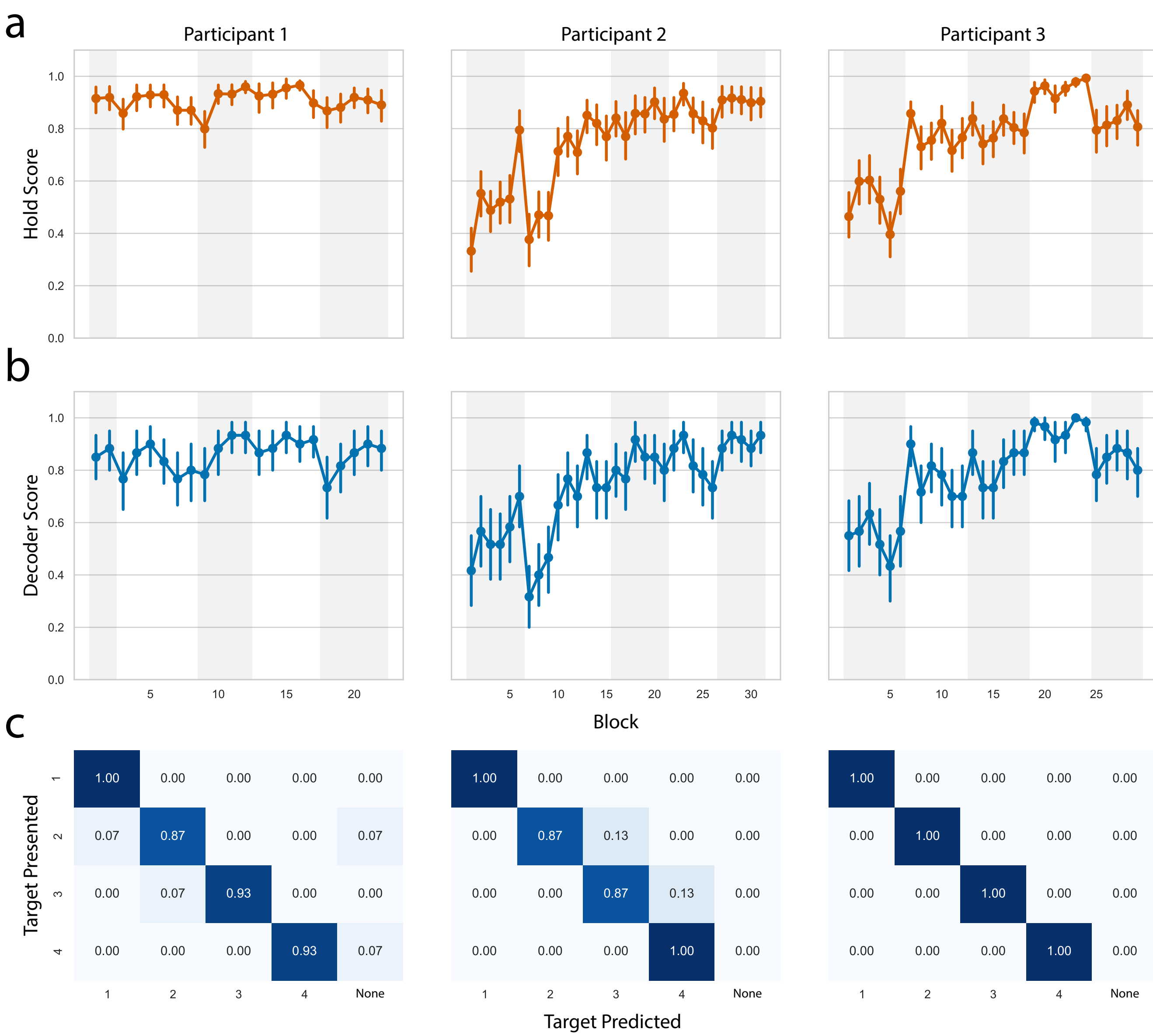

Fig. 2. Overview of participant performance during the home training task. (a-c) Refer to a row of plots where each column represents data from a single participant. (a-b) Hold score and decoder score performance during the five day training period. Alternating gray and white vertical highlights denote blocks completed on the same day. Points, means; error bars, 95% confidence interval. c) Example heat maps showing decoder score performance across targets over 60 trials. Targets are numbered anticlockwise from 1-4.

29 blocks, respectively. This equates to a combined total of 4920 trials.

Fig. 2a shows hold scores across participants. The hold score relates to the proportion of time the cursor dwelled within the correct target during the hold period. Participant 1 did not show a trend of improvement, between day 1 of training (0.92 ± 0.001) and day 5 (0.89 ± 0.008). Participant 1's scores could not be tested for significance due to the number of blocks completed. However, there was a significant improvement in hold score for participant 2 between day 1 (0.54 ± 0.06) and day 5 (0.91 ± 0.003), ($p < 10^{-2}$). Finally, participant 3 significantly improved hold score between day 1 (0.53 ± 0.03) and day 5 (0.83 ± 0.02), ($p < 10^{-2}$).

Fig. 2b shows plots representative of the decoder score. The decoder score for participant 1 did not show a trend of improvement between day 1 (0.87 ± 0.01) and day 5 of training (0.84 ± 0.03). Whereas, participant 2 was able to significantly improve during training between day 1 (0.55 ± 0.03) and day 5 (0.91 ± 0.01), ($p < 10^{-2}$). Similarly, participant 3's decoder score improved significantly from day 1 (0.54 ± 0.02) compared to day 5 (0.84 ± 0.02), ($p < 10^{-2}$).

Fig. 2c shows a row of heat map plots corresponding to the block with the maximum average decoder score for each participant. This occurred on block 11 for participant 1, which corresponds to day 3, and on block 23 for participants 2 and 3, corresponding to day 4.

IV. CONCLUSIONS

To the best of the authors' knowledge, this is the first example of retention of four grasp classes with the use of two electrodes based purely on motor learning i.e. with no explicit algorithmic control. We have shown that a physiologically abstract motor behavior can be retained and consistently reproduced in the absence of concurrent visual feedback. During real prosthesis control there can be significant end-to-end delays between intent and grasp completion [18], [19]. The delayed feedback method used here more closely approximates the user-device feedback loop during real control. Therefore, our findings suggest no additional hardware is necessary to provide feedback of the user's input to restore four grasps. This supports abstract decoding's claim of being easily implemented into existing dual-site control devices.

Prior motor learning-based myoelectric control studies were not able to distinguish if the observed changes in performance should be accredited to short-term adaptation or true motor learning. We trained participants with a feedback paradigm which prevented within-trial adaptation. We found that participants were still able to significantly improve their score over five training sessions. Also, as training progressed, participants were able to retain their performance between days. These results strongly suggests that abstract decoding with delayed feedback does facilitate motor learning.

While only three participants were tested, a combined total of 4920 trials were collected over five days of training. Our results show the variability of learning rates between individuals. Participant 1 was highly accurate from the onset of the experiment, achieving >90% accuracy within the first block. This suggests that their motor behavior learned in the real-time feedback task generalized to the delayed feedback condition. Performance from participants 2 and 3 followed a more typical learning curve, eventually becoming highly accurate during training. These results highlight the importance of personalized, multi-day training during the assessment of motor learning-based control schemes.

The decoder score was added post-hoc as a metric to provide a comparison of hold score to classification accuracy of machine learning systems. It should be noted that changes in muscle response were motivated by maximizing the presented hold score, not the offline calculated decoder score. In addition, the asynchronous timed constraints of both scoring methods would necessitate different motor behavior. For example, decoder scoring would penalize curved cursor trajectories that take place during the move period, which would be tolerated by the hold score. We hypothesize that enhanced decoder scores would be obtained if participants were trained congruently. The use of such a decoder is by no means the finalized method of interpreting outputs in abstract decoding. This experiment is part of a larger study, which will include real-time prosthetic control experiments.

REFERENCES

[1] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews™ in Biomedical Engineering*, vol. 30, no. 4-6, 2002.

[2] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: detection, processing, classification and applications," *Biological Procedures Online*, vol. 8, no. 1, pp. 11–35, 2006.

[3] E. E. Fetz and D. V. Finocchio, "Operant conditioning of specific patterns of neural and muscular activity," *Science*, vol. 174, no. 4007, pp. 431–435, 1971.

[4] S. M. Radhakrishnan, S. N. Baker, and A. Jackson, "Learning a novel myoelectric-controlled interface task," *Journal of Neurophysiology*, vol. 100, no. 4, pp. 2397–2408, 2008.

[5] M. Dyson, J. Barnes, and K. Nazarpour, "Myoelectric control with abstract decoders," *Journal of Neural Engineering*, vol. 15, no. 5, p. 056003, 2018.

[6] M. Dyson, S. Dupan, H. Jones, and K. Nazarpour, "Learning, generalization, and scalability of abstract myoelectric control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 7, pp. 1539–1547, 2020.

[7] T. Kitago and J. W. Krakauer, "Motor learning principles for neurorehabilitation," *Handbook of Clinical Neurology*, vol. 110, pp. 93–103, 2013.

[8] R. A. Schmidt, "Frequent augmented feedback can degrade learning: Evidence and interpretations," in *Tutorials in Motor Neuroscience*. Springer, 1991, pp. 59–75.

[9] J. M. Hahne, S. Dähne, H.-J. Hwang, K.-R. Müller, and L. C. Parra, "Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 4, pp. 618–627, 2015.

[10] J. M. Hahne, M. Markovic, and D. Farina, "User adaptation in myoelectric man-machine interfaces," *Scientific Reports*, vol. 7, no. 1, pp. 1–10, 2017.

[11] R. A. Schmidt, T. D. Lee, C. Winstein, G. Wulf, and H. N. Zelaznik, "Motor learning concepts and research methods," in *Motor Control and Learning: A Behavioral Emphasis*, 6th ed. Champaign, IL: Human Kinetics, 2019, pp. 283–286.

[12] S. P. Swinnen, R. A. Schmidt, D. E. Nicholson, and D. C. Shapiro, "Information feedback for skill acquisition: Instantaneous knowledge of results degrades learning." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, vol. 16, no. 4, p. 706, 1990.

[13] T. Pistohl, D. Joshi, G. Ganesh, A. Jackson, and K. Nazarpour, "Artificial proprioceptive feedback for myoelectric control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 3, pp. 498–507, 2014.

[14] J. A. Scoufield and S. Schreiner, "Design of a myoelectric prosthetic training and assessment system," in *IEEE 30th Annual Northeast Bioengineering Conference, 2004. Proceedings of the*. IEEE, 2004, pp. 200–201.

[15] K. R. Lyons and B. W. L. Margolis, "AxoPy: A Python library for implementing human-computer interface experiments," *Journal of Open Source Software*, vol. 4, no. 34, p. 1191, 2019.

[16] M. Dyson, J. Olsen, and S. Dupan, "A network-enabled myoelectric platform for prototyping research outside of the lab," in *Proc. of the IEEE Engineering in Medicine and Biology Annual Conference*. IEEE, October 2021 (Accepted).

[17] H. Wu, M. Dyson, and K. Nazarpour, "Arduino-based myoelectric control: Towards longitudinal study of prosthesis use," *Sensors*, vol. 21, no. 3, p. 763, 2021.

[18] A. Chadwell, L. Kenney, S. Thies, J. Head, A. Galpin, and R. Baker, "Addressing unpredictability may be the key to improving performance with current clinically prescribed myoelectric prostheses," *Scientific Reports*, vol. 11, no. 1, pp. 1–15, 2021.

[19] T. R. Farrell and R. F. Weir, "The optimal controller delay for myoelectric prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 1, pp. 111–118, 2007.