TRAINING PROSTHESIS CONTROL IN THE LAB AND THE HOME

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ABSTRACT

Historically, experiments involving motor learning-based control schemes use real-time feedback. It is unclear, to what extent previous results are attributable to transient performance effects caused by closed loop adaptive processes, rather than motor learning. To investigate, we performed two long-term experiments. Experiment 1: a lab-based study compared use of continuous and delayed visual feedback to assess long-term stability of skill retention; we trained ten participants using either continuous or delayed visual feedback over four consecutive days with a follow-up probe on week three. Experiment 2: a home-based study validated that the training protocols introduced in experiment one can train forward models outside of the laboratory in an appropriate period. Three participants trained over five days with a goal of maximising proficiency via bespoke training structures.

INTRODUCTION

Motor learning theory claims that the feedback provided to the outcome of an action can have a large influence on learning [1]. While providing real-time feedback can yield rapid performance gains, this effect is often short-lived, and ultimately disappears with time or when feedback is withdrawn [2,3].

Previous learning-based control schemes have typically provided concurrent visual feedback of the participant's control signals real time [4-6]. However, users do not generally have access to real-time closed loop feedback of the state of their control signals [7]. Typically, users only receive terminal feedback as their prosthetic device moves [8], which is relatively slow [9]. Therefore, it is crucial that users can consistently reproduce the correct muscle activity for control in the absence of concurrent feedback. This necessitates that control tasks be learned, internalised, and retained. In this context, online concurrent feedback may contribute to closed loop control [10] allowing participants to develop dependencies on continuous visual cues to generate muscle activations [3]. Feedback dependencies may inhibit retention of the forward models necessary for motor-learning based methods of prosthesis control [2].

Abstract decoding is a learning-based control scheme that exploits the human nervous system's plasticity to resolve the mapping of muscle activity to prosthesis output [4]. Abstract decoding places learning requirements on the user, in return offering reduced overall algorithmic complexity in sensor requirements; the overall promise being the restoration of multiple hand grasps using two electrodes without cumbersome sequential switching [5].

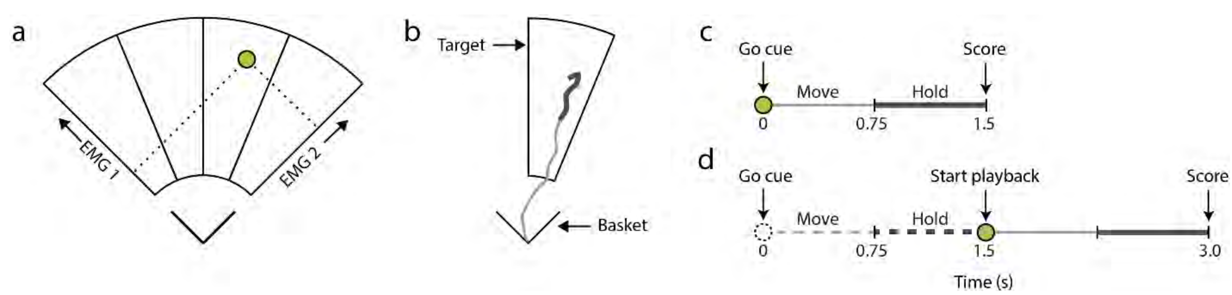

Figure 1: The MCI task. (a) The 2D myoelectric interface space. Cursor position shown in green. (b) A representative cursor trajectory from basket to target. Thick cursor mark denotes the hold period. (c-d) Task timing structure for the Concurrent and Delayed conditions, respectively, denoting cues and the move, hold and playback periods. Dashed traces correspond to the ‘blind’ control input window. Solid traces indicate when the cursor’s motion was visible during a trial.

METHODS

Ethics

All participants gave informed written consent. Ethical approval was granted by the local committee at Newcastle University (Ref: 20-DYS-050).

Myoelectric Task

The myoelectric task involved moving a cursor within a 2-dimensional MCI outlined in Figure 1. Normalized muscle activity recorded from two control sensors determined cursor position on the interface [5]. The amplitude of activity in each muscle determines the cursor position along a single axis. Trials were ∼1.5 s long and comprised two periods of equal length, referred to as move and hold. On target presentation, the aim was to keep the cursor within the target bounds. Figure 1b shows a representative trial from a proficient user. At the end of a typical trial, a score was presented.

Feedback Conditions

The availability and timing of feedback during a trial was manipulated depending on the trial condition. Each group either experienced concurrent or delayed feedback of their control input. In the concurrent condition, the cursor position always reflected the normalized muscle activation levels of the EMG channels used for control at that time frame. In the delayed condition, all feedback was withheld until active control input had ceased. At the end of the trial, the cursor activity was played back to the participant at the same rate as it occurred.

The trial block structure contained two distinct trial structures, acquisition blocks and retention blocks. Acquisition blocks refer to the learning conditions, either Concurrent or Delayed. Retention of ability was assessed using zero feedback trial blocks, where no cursor or score feedback was presented over 40 consecutive trials. Retention was assessed at the start and end of each day.

Experiment 1

Ten participants did four days of training in the laboratory plus a follow-up after an 18-day hiatus. Retention tests were carried out at the start and end of each training session. Each acquisition block consisted of 80 trials.

Experiment 2

Three participants did five days of delayed feedback training with a bespoke structure. Each training session lasted approximately an hour, including setup and breaks. Each training block consisted of 60 trials.

Measures

A ‘decoder score’ metric was used post-hoc to compare MCI task score to classification accuracy of machine learning based systems. The predicted target was calculated offline as the first target the cursor dwelled within consecutively for 240 ms [12]. If the predicted and presented targets agreed a decoder score of one was obtained, otherwise a score of zero was received.

RESULTS

Experiment 1

A comparison of average retention scores in the Concurrent and Delayed groups is shown in Figure 3a. Average acquisition scores in the Concurrent and Delayed groups are shown in Figure 3b. In the Concurrent group, acquisition scores increase but no equivalent trend is observed during retention tests over the four days of training. In contrast, the Delayed group retention scores follow a similar trend of improvement with acquisition.

Significant differences in performance were found in the retention tests performed on day four, first test (Concurrent: 0.32 ±0.12; Delayed: 0.55 ±0.15; $p < 0.05$), final test (Concurrent: 0.28 ±0.13; Delayed: 0.62 ±0.15; $p < 0.05$). There was no significant difference in initial retention performance during the follow-up session (Concurrent: 0.27 ±0.12; Delayed: 0.48 ±0.15; $p = 0.1$). However, after two refresher acquisition blocks the Delayed group retention was significantly higher than the Concurrent group on the final block (Concurrent: 0.34 ±0.13; Delayed: 0.63 ±0.12; $p < 0.05$).

Experiment 2

Data tracking the participants' average score over the five days of training are shown in Figure 3. Confusion matrices of each participant's first and best block decoder score are shown in Figure 3b and c, respectively.

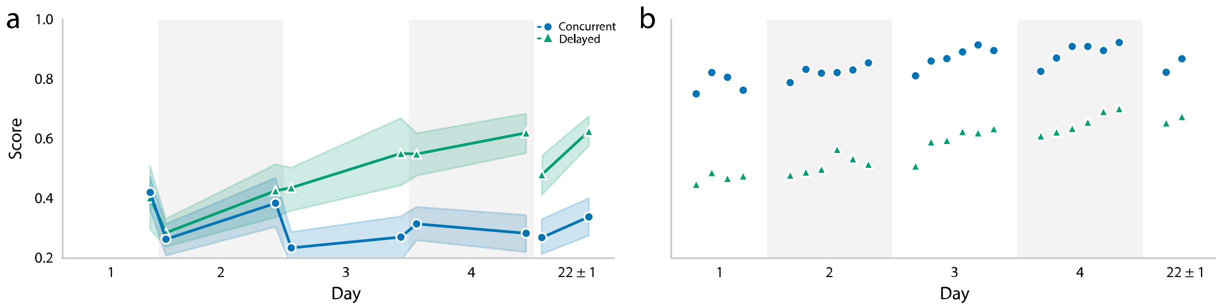

Figure 2: The effect of the feedback conditions on retention and acquisition. Days are separated by alternating gray and white backgrounds. Points show the block mean average. Horizontal axes are temporally aligned such that points are plotted chronologically. (a) Group retention scores over the initial four days of training and the follow-up session. (b) Group acquisition scores over the initial four days of training and the follow-up session.

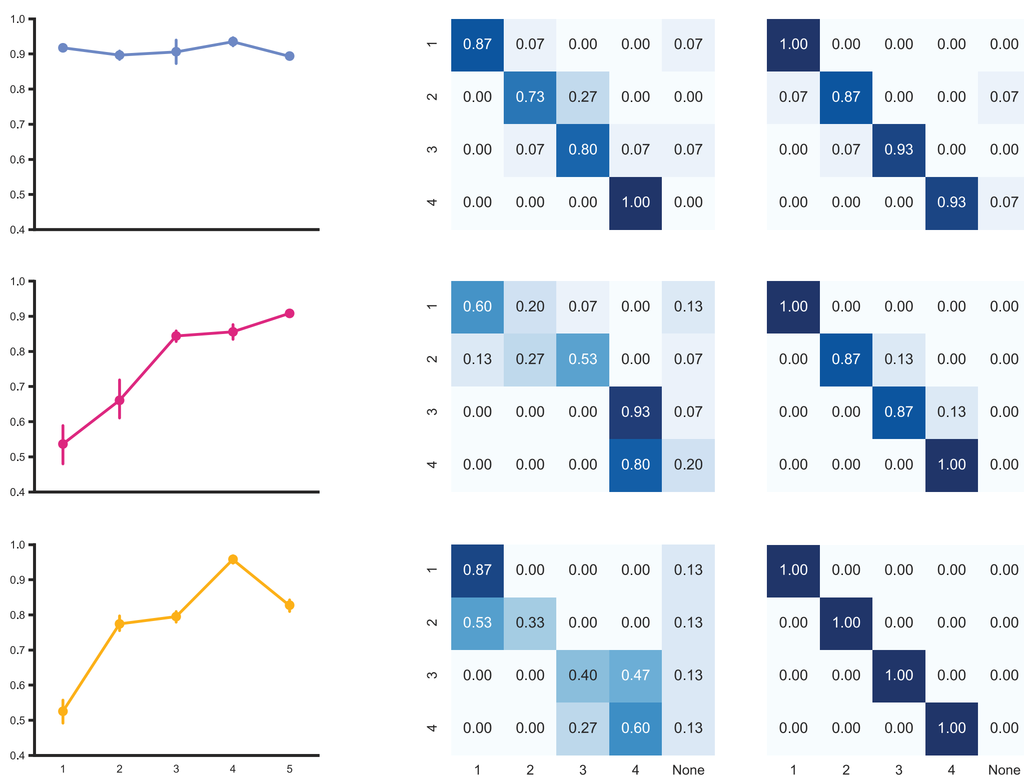

Figure 3: Overview of home-based training performance. (a-c) Refer to a column of plots, each row relates to the performance of a single participant. (a) Participant mean scores and cumulative blocks experienced over the five days of training. Error bars correspond to the standard error of the mean. (b-c) Decoder score heatmaps of the first and best delayed feedback blocks, respectively.

CONCLUSION

Myoelectric control schemes based on motor learning have historically provided concurrent feedback during training and assessment of participant control acuity. While impressive performance can be achieved with the assistance of such feedback mechanisms, this has little meaning unless the user has access to a similar feedback loop during real control. This is problematic when considering that, in the real-world users typically do not have access to concurrent feedback of their control input. Our results show that with appropriate training it is possible to learn and consistently reproduce distinct abstract muscle contractions in the absence of concurrent feedback. This suggests no algorithmic assistance or additional hardware is necessary to restore four grasp classes to existing dual-site control devices.

Retention of skill can only be measured in the absence of the augmented feedback that was provided during training. To show that retention can be achieved with appropriate training, we collected on the largest closed-loop myoelectric control datasets that we are aware of i.e. 32,000 trials. Figure 1a-b shows that although lower scores are initially obtained with delayed feedback, the skills learned are retained over days. Conversely, the higher performance gains observed with concurrent feedback dissipates during retention tests. Figure 3c shows the equivalent of 4-class confusion matrices which reflect the upper bounds of what is possible with this abstract decoding interface. Preliminary experiments are showing similar control rates in prosthesis control.

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