SKILL ACQUISITION IN PROSTHESIS FORCE CONTROL WITH SUPPLEMENTARY EMG FEEDBACK

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ABSTRACT

Supplementary feedback interfaces for myoelectric prostheses enable users to learn, plan and execute the movements for controlling their prostheses. The ability to execute these movements reliably and accurately – 'skill,' can be studied by assessing speed-accuracy trade-offs (SAF). Here we used the SAF framework to empirically investigate skill acquisition with a closed-loop interface that uses EMG feedback, during a functional prosthesis force-control task. Preliminary results suggest that over 3 days the SAF shifts vertically upwards, while its shape remains consistent. Faster grasping remained less accurate compared to when participants used the supplementary feedback to carefully guide their behavior. We believe that studying the SAF not only enables us to quantify skill acquisition or learning effects, but also to more broadly understand the performance characteristics of closed-loop user-prosthesis interfaces.

INTRODUCTION

Force control is a fundamental problem in the field of myoelectric prostheses. Various control and feedback interfaces have been developed to improve the robustness of grasping with prostheses. Many of the control interfaces require users to learn novel ways of contracting their muscles to control the devices, and several (supplementary) feedback interfaces have been developed to promote learning and execution of these contractions [1 – 3]. However, how users acquire this skill, operationally defined as reliable and accurate movement execution [4], has not been thoroughly investigated in the literature.

Speed-accuracy trade-off (SAF) is a well-known behavioural phenomenon and provides a framework to study motor skill acquisition [4 – 6]. Assessing SAF across days enables better understanding of the changes in speed and accuracy that occur through learning, as opposed to just comparing performance improvements (such as success rates), since such performance could be improved simply by decreasing speed, but skill can be inferred only when both speed and accuracy change in the expected direction (faster speed, greater accuracy) [4, 5]. Here, we use this framework to understand how the learning of skilled prosthesis force control is promoted by using an established feedback interface – EMG feedback [3].

Specifically, in this study we investigated learning induced changes in the SAF in prosthesis force control using a functional box-and-blocks task. Participants used a closed-loop interface comprising of simple proportional control and EMG feedback [2] to perform a force matching task (apply a specified force on the blocks) at four different speeds, over 3 days. The four different speeds targets were imposed through time constraints, named Very Fast (0-2s), Fast (1-3s), Medium (2-4s) and Slow (4-8s). They were chosen to (1) sample the SAF appropriately and (2) emulate scenarios where users either rapidly or carefully and slowly modulate their muscle contractions to apply a desired force with their prostheses. Thereby, we assessed the SAF across days, to understand if/how participants' skill changed with practice and discussed the potential implications regarding (closed-loop) prosthesis interface design.

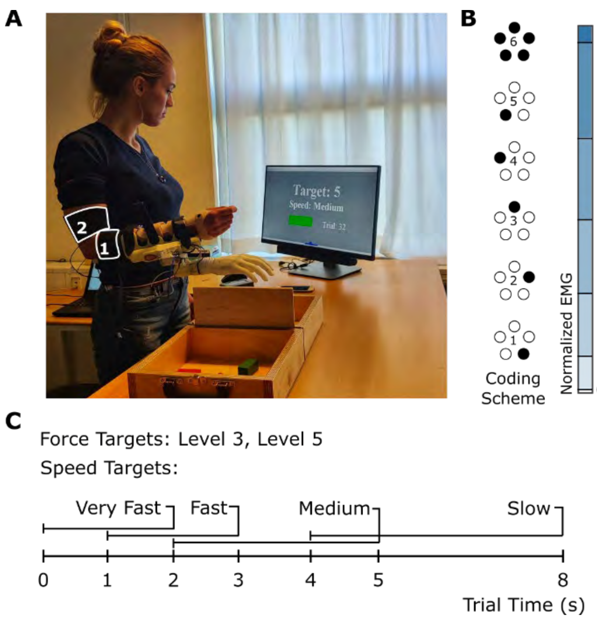

Figure 1: Experimental setup. (A) Experimental setup shows a participant using (1) 2-dry EMG electrodes and (2) 5 vibrotactors to perform a modified box-and-blocks task over 3 days. (B) Spatial coding scheme to convey EMG biofeedback through vibrotactors. (C) Force and speed targets (restrictions) for the task, used to derive a speed-accuracy trade-off.

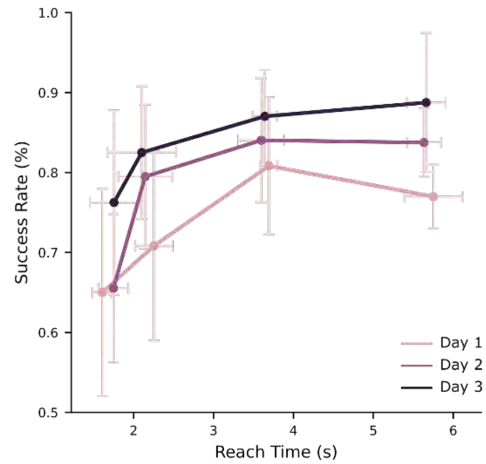

Figure 2: Learning induced changes in the Speed-Accuracy Trade-off. Success rates achieved across speed targets (very fast, fast, medium, and slow) are plotted against the measured reach time in the corresponding condition.

METHODS

Participants

Five healthy able-bodied participants (age: 24.8 ± 1.6) naïve to the task were recruited. All participants signed an informed consent form in accordance with the Research Ethics Committee of the Nordjylland Region (N-20190036).

Experimental Setup

The experimental setup is shown in Figure 1(A). Two dry-EMG electrodes (OttoBock 13E200) were positioned, one each on the wrist flexors and extensors, located by palpating. A small ink mark was made on both locations to ensure the placement remained similar on all days of the experiment. Five vibrotactors (C3, EAI Inc.) were placed equidistantly around a cross-section of the upper arm. Participants donned a wrist immobilization splint and a bypass socket holding the prosthesis (Michelangelo Hand Prosthesis, OttoBock GmBH). The electrodes output the linear envelope of EMG, sampled by the prosthesis controller at 100 Hz and transmitted to a laptop PC. Based on the received signal, the PC activated the vibration motors to implement EMG feedback to the user, and to transmit commands for the closing and opening of the prosthesis.

Participants used isometric wrist flexion to proportionally control (through a piecewise linear mapping) the closing speed of the hand. The maximum closing velocity corresponded to 50% of maximum voluntary contraction of the flexor activation. Hand opening was triggered by reaching 20% MVC of the wrist extensor activation. The boundaries of the piecewise linear mapping containing 6 levels (Figure 1(B)) between EMG commands and prosthesis velocity were chosen such that (1) the width of discrete levels increased at higher contractions to compensate for the inherent variations in the EMG signal at higher contractions, and (2) there was a one-to-one mapping between the participants' EMG commands and the prosthesis force levels. Participants received discretized vibrotactile feedback of their EMG commands through a spatial coding scheme (Figure 1(B), [7]). In this setup, the EMG feedback enables predictive control of prosthesis grasping force. To achieve the desired force level (from 1 to 6), the participants needed to modulate their muscle contraction to reach the desired EMG level as indicated by the feedback. Due to the one-to-one mapping, the force level attainted after the closing would correspond to the EMG level maintained by the participant.

Experimental Protocol

The experiment was conducted over three consecutive days. On each day, we first measured the participants' MVC to calibrate the proportional control interface, followed by a familiarization phase for both control and feedback interfaces (see [7]). Then, a brief visually guided coaching phase was performed in which the participants were instructed how to modulate their muscle contractions at different speeds relevant to the task.

The participants performed a force-matching task, where they picked up blocks by applying a target force (level 3 or 5) and transported it into an adjacently placed box (Figure 1(A, C)). Additionally, they had to perform the task at specified speeds: Very Fast (0-2s), Fast (1-3s), Medium (2-4s) and Slow (4-8s), with the help of a timer (shown as a bar to them, Figure 1(A)). Participants performed 6 blocks of 32 trials each ([4 repetitions x 2 target levels] x 4 speed conditions), with a self-chosen period of rest between the blocks. The targets were presented in a block-randomized fashion, where the speed target remained constant for 8 trials, within which the force targets were randomized. Each trial started with a beep notification, followed by displaying the target force and target speed for the trial. The participants then used the closed-loop interface to generate appropriate EMG commands to reach the required target force. However, they needed to do this by respecting the timing constraint - if the target force was achieved before or after the indicated time window, the trial was considered failed. Upon reaching the target force, they were instructed to relax and trigger hand opening. After the end of each trial, they received visual feedback about their success/failure in both target force and speed. The same protocol was repeated on all three days.

Outcome Measures and Data Analysis

The EMG commands and the force generated by the prosthesis were recorded for each trial. We defined 'reach time' as the time elapsed between start of the trial and the time at which the maximum force was reached during the trial. Thereby, a successful trial was one in which the maximum force was within the target level and the reach time satisfied the target speed. Thereby, success rates – calculated as % successful trials – were computed to evaluate differences in learning across days. Mean and standard deviation of the success rates are reported.

RESULTS

Preliminary results indicate a clear speed-accuracy trade-off in prosthesis force control with a closed-loop interface, and a significant improvement across days for all speed conditions. Participants started with a performance ranging from 65 ± 13% (Very Fast) to 77 ± 4% (Slow) on Day 1 and improved by Day 3 to 76 ± 11% (Very Fast) and 89 ± 8% (Slow). Surprisingly, participants improved almost identically across all speeds, except in the Medium condition (Very Fast to Slow: 11 ± 20%, 11 ± 10%, 6 ± 6% and 11 ± 9%). Improvements from Day 1 to Day 2 (0.4 ± 7%, 8 ± 13%, 3 ± 7% and 7 ± 5%) were also larger than the improvements from Day 2 to Day 3, except in the Very Fast condition (10 ± 14%, 3 ± 13%, 3 ± 8% and 5 ± 7%).

DISCUSSION

Here we quantified skill acquisition in prosthesis force control using supplementary EMG feedback through changes in the SAF. Building on our previous work [7], we established in the present study that the same (closed-loop) interface, used at different speeds (relating to feedforward vs feedback control policies) yielded very different performance outcomes (here, success rate). The improvement of success rate, observed consistently at all specified speeds (a shift in the SAF itself) is a strong indicator for the improvement in the skill. Such an inference would not have been possible if the performance were sampled only at a single point on the SAF at two separate times (before and after practise, for example). In this case, if the accuracy and speed did not change in expected direction, it would be hard to say if the skill improved, or if the difference in performance was due to sampling the same SAF curve in two different points. Therefore, deriving the SAF enables a more holistic understanding of the range of performance afforded by a particular interface. Moreover, we observed that despite training, the trade-off exists between speed and accuracy, and that the shape of the SAF did not appreciably change, further indicating that SAF is a practically useful framework to quantify how closed-loop interfaces enable users to develop flexible control policies.

While speed-accuracy framework has been used by the prosthesis community, in terms of the Fitts' Law task, here we use a more general formulation applicable to tasks other than pointing or its derivates. The next step in the present research is to increase the subject pool in order to conduct more systematic analysis. Future work can utilize the framework of SAF to evaluate the effect of different (feedback) interfaces on learning, and to understand how different interfaces might enable users not just to have different performance, but different trade-offs.

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