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Title: Estimating Speed-Accuracy Trade-offs to Evaluate and Understand Closed-Loop Prosthesis Interfaces

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Abstract

Objective: Closed-loop prosthesis interfaces, which combine electromyography (EMG)-based control with supplementary feedback, represent a promising direction for developing the next generation of bionic limbs. However, we still lack an understanding of how users utilize these interfaces and how to evaluate competing solutions. In this study, we used the framework of speed-accuracy trade-off functions (SAF) to understand, evaluate, and compare the performance of two closed-loop user-prosthesis interfaces.

Approach: Ten able-bodied participants and an amputee performed a force-matching task in a functional box-and-block setup at three different speeds. All participants were subjected to both interfaces in a crossover study design with a one-week washout period. Importantly, both interfaces used (identical) direct proportional control but differed in the feedback provided to the participant (EMG feedback vs. Force feedback). Therefore, we estimated the SAFs afforded by the two interfaces and sought to understand how the participants planned and executed the task under the various conditions.

Main results: We found that execution speed significantly influenced performance, and that EMG feedback afforded better overall performance, especially at medium speeds. Notably, we found that there was a difference in the SAF between the two interfaces, with EMG feedback enabling participants to attain higher accuracies faster than Force feedback. Furthermore, both interfaces enabled participants to develop flexible control policies, while EMG feedback also afforded participants the ability to generate smoother, more repeatable EMG commands.

Significance: Overall, the results indicate that the performance of closed-loop prosthesis interfaces depends critically on the feedback approach and execution speed. This study showed that the SAF framework could be used to reveal the differences between feedback approaches, which might not have been detected if the assessment was performed at a single speed. Therefore, we argue that it is important to consider the speed-accuracy trade-offs to rigorously evaluate and compare user-prosthesis interfaces.

Introduction

Myoelectric interfaces that leverage electromyographic (EMG) signals recorded non-invasively from the residual muscles of amputees enable the control of advanced upper limb prosthetic devices. These interfaces have been combined with supplementary feedback using noninvasive vibrotactile or electrotactile stimulation and principles of sensory substitution to provide users with useful information regarding the state of the prosthesis. Together, these approaches promise to address the key challenge of closing the user-prosthesis loop to create the next generation of non-invasive interfaces aimed at improving the reliability and intuitiveness of prosthesis control [1], [2].

A key limitation in the development of such closed-loop interfaces is the lack of a more basic understanding of the role of supplementary feedback in user–prosthesis interaction [3]. Researchers in this field have used tools and concepts from human motor learning and control to better understand how subjects integrate supplementary feedback to plan and control their devices. Consequently, supplementary feedback has been shown to aid in learning internal models of the prosthesis [4], [5], improve state estimation [6], and improve psychosocial aspects of subjective experience [7], [8]. This knowledge has been successfully applied to design better interfaces and evaluate existing solutions [9]. Despite these promising recent developments, an understanding of motor control in the context of prosthesis use is still in its infancy.

In a recent study, the authors showed how subjects could take advantage of supplementary feedback to develop flexible prosthesis control policies and exhibit a speed-accuracy trade-off [10]. The speed–accuracy trade-off is a ubiquitous behavioral phenomenon observed in several species and across several tasks, from foraging to tool use [11]. The speed-accuracy tradeoff function (SAF) has been used as an instrument to understand both perceptual and motor ability and has a wide reception in the field of human-machine interfaces, building on seminal work by Fitts [12]. Various tasks inspired by this experimental paradigm have been applied to myoelectric control [13]–[20]. In classical Fitts' style pointing tasks, participants are required to move a cursor to a target location specified by the target width and distance, and their movement time is recorded. Therefore, these experiments determine speed (movement time) as a function of task difficulty, while accuracy in such tasks is given and corresponds to "asymptotic" performance. Alternatively, one could hold task difficulty constant and measure how accuracy changes when the same task is performed at different speeds, a framework that has been successfully used to understand motor skills [21]–[23].

A SAF so measured can be characterized by its intercept, rate, and asymptote without making any assumptions on the functional form of the trade-off, barring monotonicity [24] (see Figure 1). The intercept characterizes the minimum time required to have any chance of success and the rate provides information about how rapidly the trade-off between speed and accuracy can be achieved, and the asymptote characterizes a performance ceiling when one performs the task slowly and carefully. Therefore, SAF has been proposed as a preferred

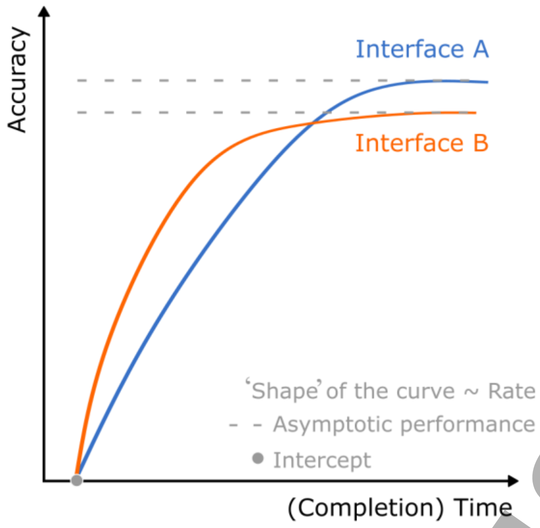

Figure 1: **Speed-Accuracy Trade-off.** A cartoon depicting the concept of speed-accuracy trade-offs as characterized by (1) intercept, (2) rate and (3) asymptotic performance, for two different hypothetical interfaces.

metric for measuring and understanding a participant's overall performance and motor ability [22], [24]. However, no current user-prosthesis interface has been analyzed using this methodology.

A common practice in the field to evaluate the effectiveness of interfaces involves measuring the performance in a given task at a 'comfortable pace'. We argue that such an evaluation, which corresponds to sampling the SAF at a single point, is an insufficient indicator of the range of performance afforded by the (closed-loop) interfaces. Moreover, a comparison of competing interfaces is compromised when the comparison is based on a single point on SAF. Such a comparison is limited in scope (a single point vs. a full SAF), and it could even entail comparing different points while assuming they are the same (i.e., a 'comfortable pace' might differ across subjects, tasks, and interfaces). On the other hand, determining the SAF allows a comprehensive characterization of performance and can provide unique insights that can be used to make informed choices. For example, consider the two hypothetical interfaces shown in Figure 1. Sampling the two interfaces at different points of their respective SAFs leads to different conclusions regarding which interface affords better performance. Moreover, a user who emphasizes speed may be better off with interface A; however, relaxing this requirement suggests that interface B is a better choice, the information that is only available through the SAF. Such a comprehensive assessment becomes even more pressing as there are several promising user-prosthesis interfaces that use different combinations of control (e.g., direct proportional, pattern recognition, regression, etc. [25]) and feedback interfaces (e.g., force, aperture, and proprioceptive feedback using different modalities [26], [27]). Narrowing down the focus to closed-loop control of grasping force, arguably the critical function of hand prostheses, several feedback interfaces have been proposed in the literature [3], [26], [28].

However, comparisons of these interfaces are difficult because the performance is sampled at a single, and possibly different, point along the SAF.

In this experiment, we empirically studied the SAF in closed-loop myoelectric control, using the prosthesis force-matching paradigm in a functional task – the box and blocks test – to (1) show how SAF can be used to evaluate (closed-loop) prosthesis interfaces and (2) thereby understand how they affect users' ability to control the prosthesis. Specifically, we compared two interfaces that both use direct proportional control to modulate prosthesis velocity but differ in the feedback they provide to the participant – EMG feedback [29]–[31] vs. force feedback (see Table A1 in [3]). We used a prosthesis force-matching paradigm to understand how well the two interfaces enabled participants to achieve the same target force at three different speeds, ordinally defined as fast, medium, and slow (see Methods: Experimental Design). Because the difficulty of the task and the control interface are fixed, the performance differences that arise from this experiment are a consequence of the feedback approach. After sampling the SAF at the three distinct speed requirements, we investigated how the SAF differs for the two interfaces and analyzed how the participants' control policies change across both interfaces and speeds. Finally, using a case study of a single amputee, we investigated whether the results could be extended to amputees.

Methods

Participants

Ten healthy, able-bodied participants (seven men and three women with a mean age of 28 ± 2 years) and one transradial amputee (female, 49 years old, 10 years since traumatic amputation of the non-dominant hand, limited daily use of a single DoF myoelectric prosthesis) were recruited. All the participants signed an informed consent form before the start of the experiment. The experimental protocol was approved by the Research Ethics Committee of the Nordjylland Region (approval number N-20190036).

Experimental Setup

The experimental setup is shown in Figure 2A. The able-bodied participants donned an orthotic wrist immobilization splint to produce near-isometric wrist flexion and extension, and a prosthetic device (Michelangelo hand, OttoBock, DE) was attached to the splint, with the arm placed in a neutral position. A custom-fit socket was created for the amputee. Two dry EMG electrodes with embedded amplifiers (13E200, Otto Bock, DE) were placed over the wrist flexors and extensors of the right forearm, located by palpating and visually observing muscle contractions. Five vibrotactors (C-2, Engineering Acoustics Inc.) were positioned equidistantly around a cross-section of the upper arm, and an elastic band was used to keep them in place. A standard Box and Blocks setup was used for the experimental task. Task instructions were displayed on a computer screen placed at a comfortable viewing angle and distance. The prosthesis was connected to a

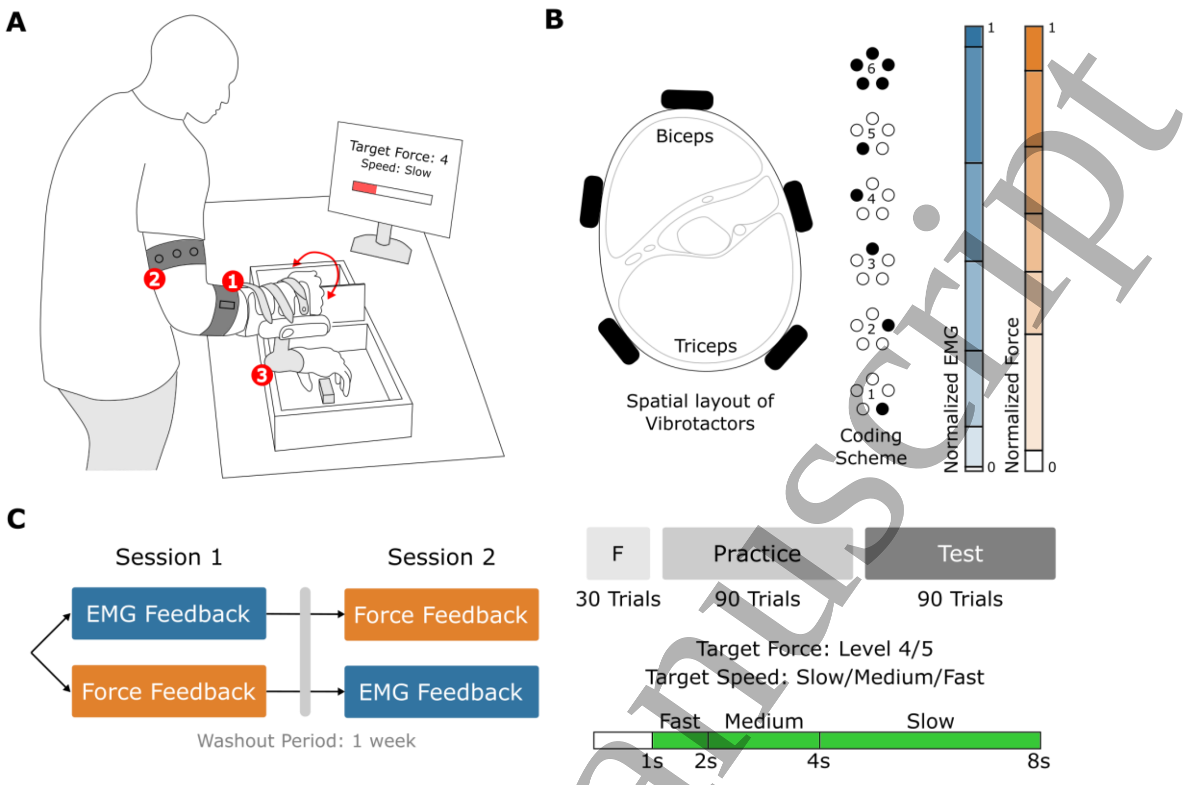

Figure 2: **Experimental setup and protocol.** (A) Sketch of the experimental setup showing 1. Two dry EMG electrodes placed on the forearm, 2. Vibrotactor array for delivering feedback placed on the upper arm and 3. The Michelangelo prothesis. (B) Vibrotactor array arrangement and coding scheme used for the feedback interfaces. Bars indicate how the normalized EMG and Force range was discretized to provide feedback. (C) Experimental protocol indicating the design (AB-BA crossover), trial structure, and force and speed targets.

standard laptop PC through a Bluetooth link, whereas the vibrotactors were connected through a USB port. The control loop for the experiment was implemented in MATLAB Simulink using a toolbox for testing human-in-the-loop control systems [32] and operated on the host PC in real time at 100 Hz using the Simulink Desktop Real Time toolbox.

EMG Control

Participants used near-isometric wrist flexion and proportional control to generate velocity commands to close the prosthesis. Opening the prosthesis was triggered by a strong contraction (see below) of the wrist extensors, instead of proportional control, as fine control of the opening was not relevant for the study. Two electrodes, placed on the flexors and extensors, as explained above, were used to record the root mean square of the windowed (100 ms) EMG signal at 100 Hz through the embedded prosthesis controller. The signals were subsequently filtered digitally using a second-order Butterworth low-pass filter with a 0.5 Hz cutoff. The EMG envelope from each electrode was normalized to 50% of the maximum voluntary contraction (MVC). For flexor EMG, this corresponded to the maximum closing velocity of the prosthesis. Piecewise linear mapping between the EMG amplitude (normalized scale) and closing velocity (normalized scale) was used to design the proportional controller to compensate for the higher variability in the EMG signal at higher amplitudes (stronger contractions). The breakpoints for the mapping were defined as follows: EMG = {0.025, 0.1, 0.27, 0.47, 0.69, 0.95, 1}, velocity = {0, 0.25, 0.42, 0.59, 0.76, 0.9, 1}. Thereby, prosthesis only responded when the flexor signal was above the "dead zone" (i.e., greater than 0.025). For the extensor, however, participants simply needed to reach 0.4 on a normalized range (corresponding to 20% MVC) to trigger the hand opening. Note that both EMG amplitude and prosthesis velocity breakpoints exist on the normalized scale (to 50% MVC and maximum prosthesis closing velocity respectively) and are therefore unitless.

Vibrotactile Feedback Interfaces

In this study, we compared two feedback interfaces: EMG and force feedback. Both interfaces were identical in terms of hardware and encoding (described below) and differed only in the variable that was provided as feedback – participants' own EMG command vs. prosthesis force. Five vibrotactors were placed circumferentially and equidistantly on the upper arm around a cross-section containing the biceps. An elastic band was used to maintain the tactors in place. A spatial encoding scheme consisting of six discrete levels of the feedback variable (EMG command or grasping force) was used for both interfaces. The first five levels were indicated by activating one of the tactors from the array, while the sixth level was conveyed by activating all tactors simultaneously (Figure 2B). If the vibrotactors evoked an unpleasant or poorly localized sensation, their position was adjusted until the participants could easily distinguish between all six stimulation patterns (levels). The vibration frequency for all tactors was set to 200 Hz, and the stimulation pattern was updated at 50 Hz.

EMG Feedback

In this interface, the participants were provided with feedback about the EMG signal that they generated using their flexor muscles to control the closing velocity of the prosthesis. Six discrete levels were defined using the breakpoints of the piecewise linear mapping described in the section "Methods: EMG Control." Therefore, as soon as the participants started contracting their wrist flexors, they received feedback about the EMG level (1-6) they were generating, thereby enabling them to modulate predictively to the target level. The breakpoints of the piecewise mapping were designed such that if the participants reached a particular level of EMG (with the object contact established and stable), they would have applied the same level of force on the object. For instance, if a participant generated and maintained EMG level 2, the prosthesis would close around the object and exert level 2 of the grasping force (force level boundaries defined in the next section). This was possible thanks to the proportional operation of the myoelectric prostheses, in which the generated EMG (myoelectric command) was proportional to the closing velocity which in turn is proportional to the grasping force.

Force Feedback

The force applied to the blocks was measured using a sensor embedded in the prosthesis. The measured force, sampled at 100 Hz by the embedded controller, was normalized and divided into six discrete ranges (levels) with boundaries at {0.05, 0.31, 0.45, 0.58, 0.73, 0.9, and 1} on a normalized scale (0, no force; 1, maximum force). With this feedback interface, participants received feedback on the level of force (1-6) applied to the object. In contrast to EMG feedback, where vibrotactile stimulation was delivered as soon as the myoelectric signal crossed the threshold of the dead zone (e.g., when the prosthesis started closing), in the case of force feedback, stimulation was delivered only after contact was established with the object.

Experimental Design

The experiment was designed as an AB-BA crossover trial over two sessions with a one-week washout period between the sessions (Figure 2C). Half of the participants started with EMG feedback in Session 1 and switched to Force feedback in Session 2, whereas the other half did the opposite. A crossover design was selected to control inter-group variability. In each session, the participants were instructed to perform the box and blocks test with two additional constraints, that is, in each trial, they were required to (1) apply a specified level of force on the object (two levels of force were chosen as target forces – levels 4 and 5, see [10]) and (2) reach the target force within a specific time window. Therefore, we determined the speed-accuracy trade-off in a prosthesis force-matching task.

To adequately sample the SAF, participants were required to perform the task under three speed conditions: slow, medium, and fast, where each condition specified the time window for task completion. During the Slow condition, trials had to be completed within 4 – 8s, while for the Medium and Fast conditions, the speed/time requirements were 2 – 4s and 1 – 2s, respectively. Time windows were defined to capture the relevant domains of the SAF curve. Previous studies suggest that participants in a fast routine-grasping task spend approximately 2s to achieve the required force, while they attained close to 100% accuracy at around the 6s mark [10]. We used a time-band methodology to derive the SAF [24]. Although there exist several methodologies to obtain the SAF [11], [24], we believe that this approach reduces inter-subject variability in learning feedback control. This would not have been the case in, for example, a deadline-based methodology, where participants may have had no incentive to perform the task at a slower speed if they were satisfied with their accuracy while using faster speeds.

The amputee followed the same protocol as the able-bodied participants, starting with Force feedback in Session 1 but returned 3 weeks later (as opposed to one week) to perform the task with EMG feedback.

Experimental Protocol

Initially, all equipment (EMG electrodes, vibrotactors, wrist immobilization splint, and prosthesis) was placed on the participant. Brief calibration and familiarization were then followed in both sessions. During the EMG calibration phase, three 5-second-long maximum voluntary contractions (MVC) for both the flexors and extensors were recorded to calibrate the control interface. The MVC measurements were recorded in the same posture that the participants used to perform the box and blocks task (similar to [33]) to address the effect of arm posture and prosthesis weight on the recorded EMG. Next, the participants were familiarized with the interface and guided to explore how their flexor EMG signal affected the prosthesis closing velocity and how their extensor EMG signal triggered the hand opening. Finally, they were familiarized with the vibrotactile stimulation patterns (common across both feedback interfaces) by performing a spatial discrimination task in which they were presented with two sets of 18 stimulation patterns (three repetitions × six levels, Figure 2B) and asked to identify them. The experiment proceeded after ensuring that the participants achieved at least 95% success in the discrimination task, which normally took less than five minutes.

After familiarization with the control and feedback, the participants performed 30 trials (10 per speed condition) of the modified box and blocks test to practice the time-constrained force-matching task. Each trial began by displaying the force and speed targets. The participants then had to modulate their muscle contraction and use the feedback interface to complete the trial successfully. Once the participant felt that they successfully reached (or overshot) the target, they were instructed to extend their wrist to trigger hand opening. Immediately after the trial ended, the participants received knowledge of the performance, which indicated whether they achieved, overshot, or undershot the target force and speed. During the practice trials, participants were instructed on how to modulate their muscle contraction to control the closing velocity of the prosthesis. They were also instructed on how to avoid eccentric behavior; for example, in the slow condition, they were told not to hold their contraction at a low level until 4 s and then quickly correct upwards, thus inadvertently making a fast/medium condition trial.

After the initial practice trials, the participants performed 90 training and 90 test trials, with a break after every 30 trials. In each block of the 30 trials, the target speeds (slow, medium, and fast) remained the same for 10 trials, while the target forces (4, 5) were presented five times each in random order. In addition, during the first 60 training trials, the speed targets were presented in a specific order: slow, medium, and fast, whereas during the remaining trials, this was also randomized.

Outcome Measures

During each trial, the EMG commands and force measurements were recorded and processed to obtain the primary outcome measures of the reach time and trial success. The reach time was measured from when the participant started generating the EMG input (above the dead zone) to the point at which the maximum force

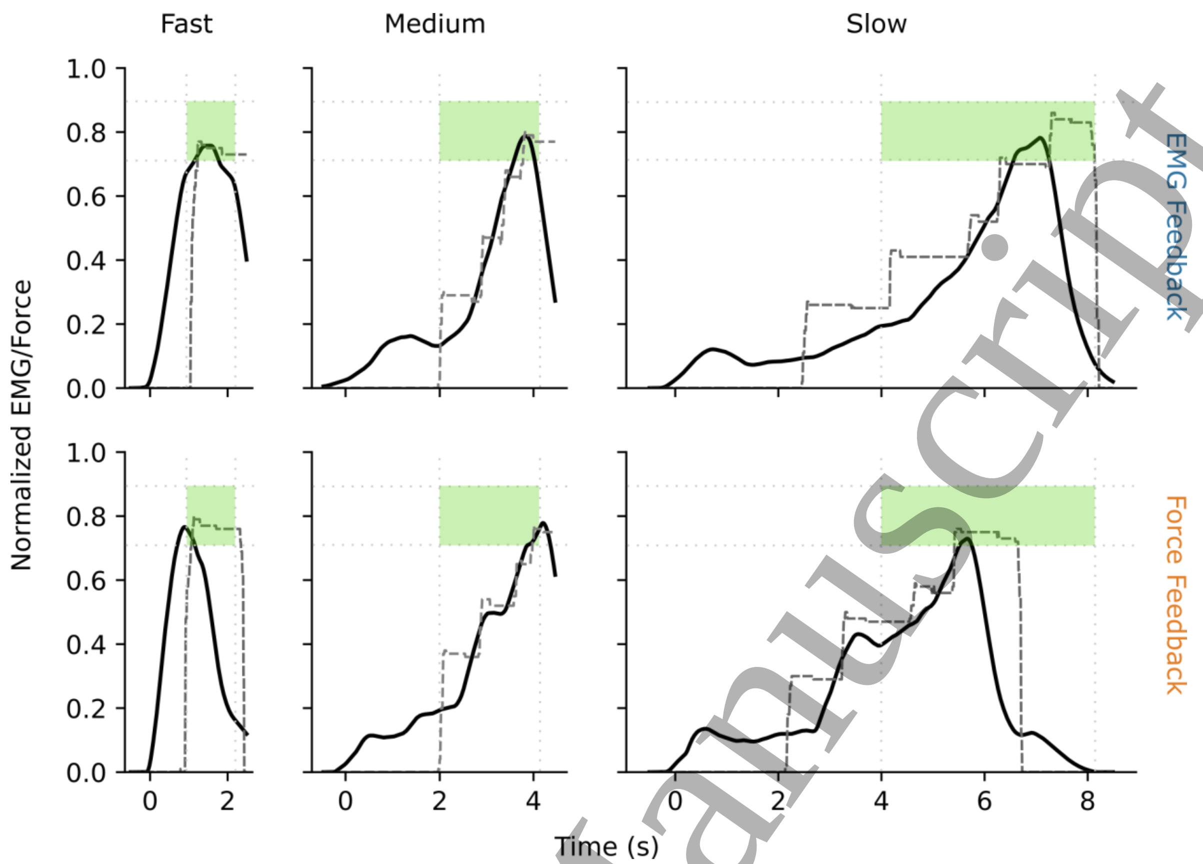

Figure 3: **Representative Trials.** Six representative trials (EMG commands in solid black, prosthesis force in dark gray) as performed by the amputee using the two different interfaces, at the three required speeds for target force Level 5. Faint dotted vertical and horizontal lines indicate time restrictions and force target bounds respectively. Green area depicts how trial success is determined as a combination of reaching the target force (accuracy) during the required time (speed).

was reached during the trial. A successful trial was one in which the reach time satisfied the speed requirement (1 – 2s for fast, 2 – 4s for medium, and 4 – 8s for slow speed), and the reached force was within the corresponding force interval (target level). The trials were aggregated per speed condition to obtain the percentage success rate (S). Subsequently, we computed the rate of trade-off in the success rate (ΔS per second) during fast-to-medium and medium-to-slow conditions to evaluate how quickly the participants traded speed for accuracy. For each participant, we computed the trade-off rate as the difference in success rates (ΔS) between successive speed conditions divided by the difference in the corresponding reach times. For example, the rate of trade-off for participant p for the fast-to-medium transition was computed as $(S_{p|med} - S_{p|fast})/(T_{p|med} - T_{p|fast})$, where $S_{p|cond}$ is the success rate and $T_{p|cond}$ is the average reach time in the condition *cond*.

Furthermore, to understand how the participants planned and executed the task under different speed and feedback conditions, we computed three behavioral metrics. First, we calculated the number of force corrections that the participants made in each trial by counting the number of distinct plateaus (longer than 250ms) in the force trajectory [10]. For example, during the slow condition with EMG feedback, the amputee made four force corrections during the trial shown in Figure 3. Then, we analyzed the generated EMG commands to understand whether one feedback type could enable the participants to generate (1) smoother and (2) more repeatable EMG commands. To evaluate smoothness, we calculated the integrated squared jerk of each trajectory, normalized to the reach time. To measure the repeatability, we computed the trial-by-trial variability of the generated EMG commands. We first normalized all EMG trajectories to 200 time points between the start of the trial and the reach time, and then measured the standard deviation at each of the 200 time points. As the final measure of variability, we computed the median of the standard deviations across the time points, because the distribution of the standard deviations was often skewed.

Statistical Analysis

Statistical analyses were performed on the outcomes obtained from the 90 test trials. 3-factor mixed model ANOVAs were fitted each for success rate, rate of trade-off, and the behavioral metrics as the outcome, with two within-subjects factors – feedback interface and speed condition – and one between-subjects factor "order", which denotes the order in which the participants were exposed to the feedback interfaces. We interpreted the main effect of order as an interaction between the feedback interface and session, while the interaction effect between order and feedback interface was interpreted as the main effect of session, as is common in crossover designs [34]. The assumptions of normality, homogeneity of variance, and sphericity were verified using Shapiro–Wilk's, Levene's, and Mauchly's tests, respectively.

Post-hoc analyses for differences in success rates between the two feedback interfaces at a given speed condition and between speeds for a given feedback interface were performed using pairwise t-tests adjusted using the Holm-Bonferroni method. The threshold for statistical significance was set at $p < 0.05$. The mean ± standard deviation of the outcomes per group of interest are reported throughout the paper unless noted otherwise.

Results

Representative Trials

Figure 3 shows representative trials of the amputee in all target speeds, with level 5 as the force target. Firstly, we can notice that both feedback types allowed the participant to flexibly control the prosthesis at different speeds and still succeed in the task, i.e., reaching the target grasping force within the given time window. Then, we can notice that the participant was slightly faster when using Force feedback than EMG feedback (especially noticeable in the slow trials), a feature that also holds across participants (see Figure 4A). Secondly, we can observe a difference in the "quality" of the generated EMG commands across the feedback conditions.

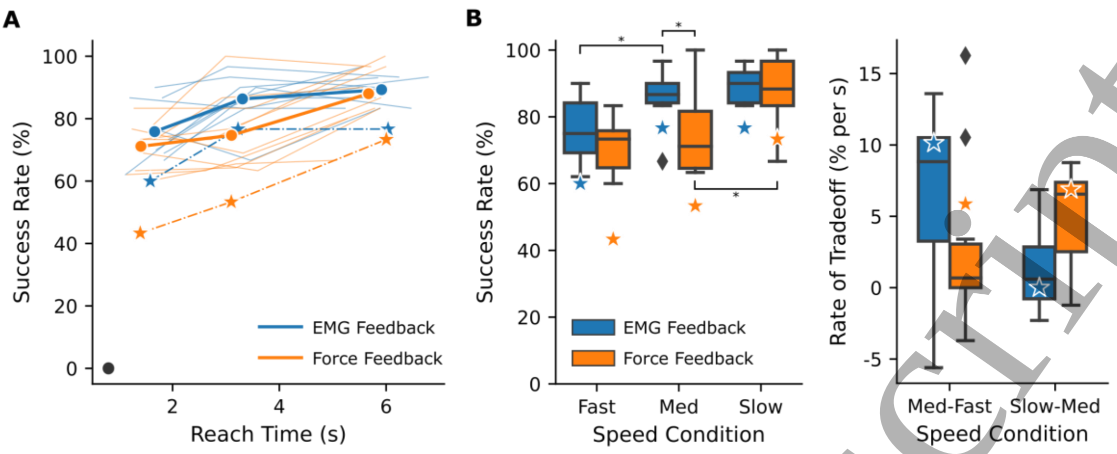

Figure 4: **Speed-Accuracy trade-offs in prosthesis force control.** (A) Individual speed-accuracy trade-off curves are plotted for each participant (faint lines), group means (bold lines) and the amputee (dashed lines and stars). Black circle indicates the time (X-intercept) when success is zero. (B) Same as A, but box plots show success rates of all participants during each of the ordinal target speeds (left). Box plots showing rate of trade-off (% per s) across the target speed transitions (right). Colored stars represent results of the amputee, black diamonds represent outliers.

While the EMG commands produced during the fast condition are largely similar between the feedback types, the EMG signal generated during both medium and slow trials is smoother during EMG feedback as opposed to Force feedback, where the EMG commands exhibit distinct "jumps".

Speed-Accuracy Trade-offs

The participants' speed–accuracy trade-off curves showed a general tendency to be monotonic (14 out of 22, Figure 4A), and when they were not monotonic, they were only off because of a few trials (1 – 3 trials), whereas the mean SAFs across participants were monotonic for both feedback interfaces. Next, we fit a 3-factor ANOVA by treating the speed condition as categorical to analyze the effect of the feedback interface and speed condition on the success rate. We observed a significant effect of the feedback interface ($p=0.006$) and speed condition ($p=2.3\times10^{-6}$) on the success rate as well as a significant effect of the session (feedback interface × feedback order interaction effect, $p=0.003$).

We then analyzed whether the feedback interface affected the performance under each speed condition. In the Fast condition, we did not observe a significant effect of the feedback interface (EMG: 75.8 ± 9.4%, Force: 71.1 ± 7.4% see Figure 4B), while in the Medium condition, we observed that participants performed significantly better using EMG feedback than Force feedback (EMG: 86.3 ± 8%, Force: 74.6 ± 12.2%, p-adj=0.022). In the Slow condition (asymptotic performance), as expected, we observed that the interface had no significant effect on performance (EMG: 89.2 ± 4.8%, Force: 88 ± 10.2%). Taken together, we see that

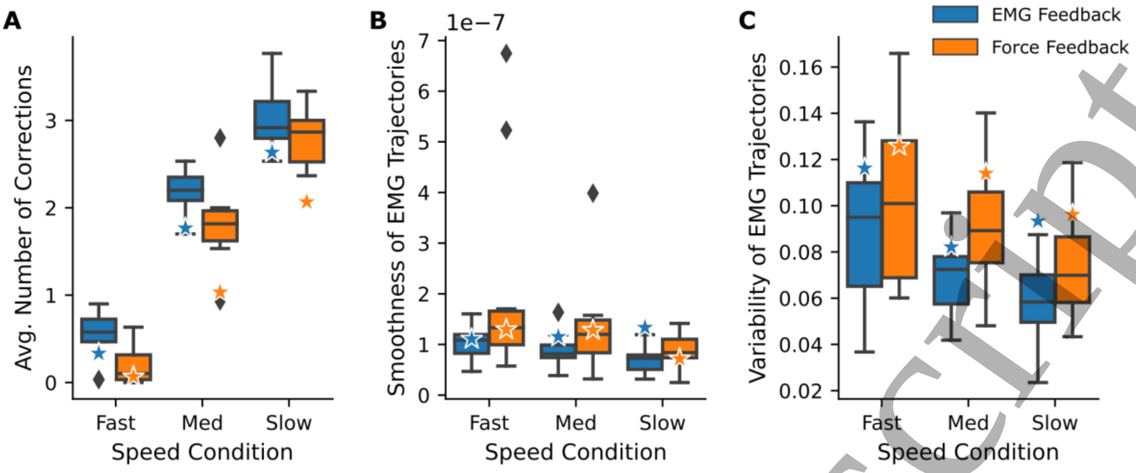

Figure 5: **Behavioral metrics for both interfaces, across participants.** (A) Average number of force corrections (distinct force plateaus) per trial. (B) Smoothness of EMG trajectories (commands) generated by the participants, computed as integrated squared jerk of the normalized EMG amplitude. (C) Trial-by-trial variability of EMG commands generated by the participants. Stars represent results of the amputee, black diamonds represent outliers.

while the feedback interface had a significant effect on the success rate overall, it was the Medium speed condition from which this difference originated. Furthermore, EMG feedback enabled participants to reach asymptotic performance sooner, with participants significantly improving their performance between the Fast and Medium conditions (p-adj=0.03) but not between the Medium and Slow conditions. On the contrary, participants exhibited significant improvement between the Medium and Slow conditions (p-adj=0.004) while using Force feedback. The two feedback types are therefore characterized by SAFs that are qualitatively different while still allowing similar asymptotic performance.

Therefore, we analyzed whether the observed rate of trade-off in success rate (% per s) for the Fast to Medium and Medium to Slow transitions was significantly different between EMG and Force feedback (see Figure 4B, right). The mean rate of trade-off for EMG feedback during Fast to Medium was indeed higher than that of Force feedback (EMG: 6.6 ± 6.3%, Force: 2.7 ± 6.1% per second) and the opposite for Medium to Slow transition (EMG: 1.3 ± 2.8%, Force: 5.1 ± 3.5% per second). However, the differences were not statistically significant.

The performance of the amputee followed the trends of able-bodied participants (Figure 4, stars). While the asymptotic performance was nearly identical (EMG: 76.6%, Force: 73.3%), the amputee participant achieved higher success rates with EMG feedback in both the Fast and Medium conditions, with the largest difference in the latter (Medium condition; EMG: 76.6%, Force: 53.3%).

Behavioral Analyses

We also sought to understand the behavioral differences between the feedback types, that is, how the different interfaces allowed participants to plan and execute movements (Figure 5). First, we investigated whether the participants developed different strategies for different speed targets. We found that both the feedback interface (p=0.005) and speed condition (p<1e-15) had a significant effect on the number of corrections made by the participants (Figure 5A), and the feedback and session exhibited significant interaction (p=0.02). Therefore, the participants were able to flexibly modify their control policies by using the available feedback, especially during the Medium (EMG: 2.2 ± 0.3, Force: 1.8 ± 0.5 corrections per trial) and Slow conditions (EMG: 3 ± 0.4, Force: 2.8 ± 0.3 corr. p/trial) compared to the Fast condition (EMG: 0.5 ± 0.3, Force: 0.2 ± 0.2 corr. p/trial).

Next, we analyzed the generated EMG commands by measuring smoothness and trial-by-trial variability (Figure 5B, C). We found that the feedback interface had a significant effect on both metrics (p=0.03 for smoothness; p=0.002 for trial-by-trial variability). That is, EMG feedback enabled the participants to make smoother and more repeatable commands than Force feedback. Additionally, the speed condition had a significant effect on both metrics (p=0.01 for smoothness, p=0.0006 for variability), whereas the session significantly influenced trial-by-trial variability (p=0.001).

The behavior of the amputee followed the results of the able-bodied participants. However, the smoothness of EMG commands with EMG feedback was worse than that with Force feedback in the Slow condition.

Discussion

Speed and accuracy are critical factors in the context of human-machine interfaces. Investigating speed-accuracy trade-off functions provides a thorough understanding of task performance and motor ability but has not been applied to study user-prosthesis interfaces. Here, we empirically derived the SAF using a prosthesis force-matching paradigm in a functional box-and-blocks task for two different closed-loop interfaces, which only differed in the feedback provided to the participants – EMG feedback vs. Force feedback. As expected, the speed at which participants performed the force-matching task imposed a trade-off with accuracy, regardless of the feedback type. However, the SAF was different for the two interfaces, as EMG feedback substantially outperformed Force feedback in the Medium speed condition, thereby enabling participants to reach asymptotic performance sooner. In addition, we found that the EMG feedback enabled smoother and more repeatable EMG commands. Therefore, the results demonstrate that the SAF methodology can provide crucial insights into both the evaluation and understanding of closed-loop interfaces for prosthesis control in functionally relevant task settings.

SAF to Evaluate Closed-Loop Interfaces

The evaluation and comparison of user-prosthesis interfaces are challenging and multifaceted. Despite the rapid development of promising control and feedback interfaces [25], [26], their comparison has received less attention, barring a few exceptions [30], [35]. While it is a difficult undertaking owing to various reasons such as incomparable experimental setups and tasks, here we showed that it is additionally compounded by measuring the performance only at a single speed (sampling at a single point on the SAF). For example, if we had only measured performance in the Fast condition in this study, we would infer that both interfaces enable similar performance, whereas they are significantly different when used at Medium speed. Therefore, we argue that it is valuable to compare interfaces at more than a single point on the SAF, particularly because the shape of the SAF afforded by different interfaces is unknown.

Here, we used the SAF framework to rigorously compare the two closed-loop interfaces in a functional force-matching task. By enforcing task execution at different speeds, we elicited a range of success rates that were significantly affected by the feedback interface. We expected that EMG feedback would enable better success rates during the Fast condition because it promotes predictive control [29], [30], but this was not the case. We believe that this is likely because of two reasons. First, the Fast condition might have been too restrictive, with a short 2 s window, for the participants to exploit the EMG feedback effectively for online adjustment of control commands. Second, the task included only two force levels and the participants received training before performing the test trials. The training might have enabled participants to acquire a reliable internal model and achieve good performance when using Force feedback, despite the short time window (which precluded the use of force feedback to drive the corrections). However, we noticed a large difference in the success rates between the two interfaces in the Medium condition. Therefore, the results demonstrate that the expected advantage of EMG feedback over Force feedback occurs in this range of movement speeds, where the former allows users to predictively modulate their contractions to reach the target level, as opposed to jumping 'reactively' between levels. Finally, the feedback interfaces resulted in similarly high performance in the Slow condition, as the participants had enough time to reach the goal by focusing on either of the two feedback signals. Therefore, the present study demonstrates that SAF allows the identification of the time interval in which feedback (Force or EMG) becomes an important factor for the effectiveness of the control loop.

Taken together, we found that the asymptotic performance for both interfaces was similar, but EMG feedback allowed participants to approach asymptotic performance sooner. Note that this important characterization of the two feedback types is derived from the trade-off itself, and cannot be obtained if the performance is assessed at a single point. More generally, SAF provides a way to estimate the expected completion time to guarantee a given (e.g., 90%) performance in a task, and therefore, can be a relevant instrument for meta-analytic comparison of interfaces across studies. Moreover, we believe that determining the SAF will be advantageous for person-based approaches to designing prosthesis interfaces [36], for example, by determining the appropriate user-prosthesis interface for the amputee based on their inherent speed preferences (see Figure 1). Therefore, in the present study, we provided a holistic comparison of the performance afforded by two established interfaces in a functional task, thereby adding a novel approach to a pool of methods that have been recently developed to assess the performance as well as the behavior of users of closed-loop prostheses [15], [37].

SAF to Understand Closed-Loop Interfaces

Closed-loop user-prosthesis interfaces are a promising technology that is likely to be translated into clinical applications, but currently still face several conceptual and implementational barriers [1], [28], [38]. A key prerequisite for designing better closed-loop interfaces is to understand the complex interplay between the feedforward and feedback control processes of the users and how different interfaces facilitate it [3], [6], [10]. We believe that studying the SAF, as described here, is an effective instrument to approach this point, as it enables an understanding of how users interact and exploit different interfaces to achieve specific (time-bound) goals.

In addition to measuring performance, we used the SAF to understand how participants planned and executed movements in a functional prosthesis task. We found that both closed-loop interfaces enabled the participants to develop flexible control policies. That is, they were able to incorporate feedback to varying extents to guide their behavior under different speed conditions, as reflected in the number of force corrections they made. On average, participants made more corrections during the EMG feedback condition. This is likely due to the nature of EMG feedback, which allows participants to better control their EMG commands both during closing (to generate a lower initial force) as well as after contact (to make gradual force increments). The EMG commands generated when the participants used EMG feedback were also smoother than when they used Force feedback (Figure 5B), enabling them to generate smaller force increments when increasing the force from the initial to the target force level (hence, more corrections overall). Interestingly, this further suggests that, even though participants received discretized feedback, they could exploit EMG feedback to modulate their contractions to generate an overall smooth control input. On the other hand, Force feedback enforces participants to wait until feedback onset and produce fewer (larger) corrections due to jerkier commands. Combined with the low trial-by-trial variability across speed conditions, EMG feedback effectively reduced the uncertainty in generating prosthesis commands, which is a central aim of implementing supplementary feedback [6], [36]. Therefore, our results add to the body of evidence that underscores the promise of some form of predictive feedback regarding users' own intentions [5], [29], [30].

Together, the flexibility, smoothness, and repeatability measures, which are hallmarks of skilled behavior, help us understand how participants incorporate supplementary feedback in their control policies. Investigating the SAF provides a suitable framework for such an analysis. Finally, we found that all outcome measures had similar trends in the experiment with the amputee, despite the slightly lower performance. We believe that this is an encouraging result, albeit expected, because motor planning and execution should remain comparable across able-bodied participants and amputees [3], [39], [40]. While the amputee had more experience using direct proportional control, we believe the simplicity of both control and feedback interfaces ensured that all participants experienced and interacted with the interfaces similarly. It remains to be seen if this trend persists with interfaces which require more complex muscle contractions (e.g., pattern recognition).

Limitations and Outlook

A limitation of the current study is that we always required participants to make 'strong' contractions (30-45% MVC) to reach the target forces. However, the trade-offs (SAF) may be influenced by the force users want to generate. Another limitation is that, while we performed a single-session study to establish the conceptual framework of SAF, the shape of the SAF may change across days; in this case, the SAF for both interfaces may become identical after practice, but this remains to be investigated.

Measuring SAF can be an instrument for the assessment of prosthesis control with general applicability. Future studies should therefore be conducted to investigate how the control interface (direct control, pattern recognition, etc.) of the user-prosthesis loop affects the SAF relative to the effects of the feedback interface, as explored here. In addition, this approach can be used to compare feedback interfaces that differ only in their encoding schemes (e.g., discrete vs. continuous) while the feedback variable remains the same. The intercept (see Figure 1), which characterizes the minimum time required to have any chance of success, did not play a role in our current setup, because the control interface was always the same (direct proportional control). However, when one wishes to compare interfaces that allow different maximum velocities (e.g., owing to different sensitivities for the proportional controller), or when one is required to change grips by co-contractions, it becomes crucial to understand the intercept as well. Finally, this framework can be extended to multidimensional task spaces, for example, to characterize the trade-offs in prehension (posture matching with prostheses) combined with force matching to create better interfaces for current state-of-the-art commercial prostheses.

Conclusion

In this study, we empirically derived the SAF for prosthesis force control using a functional box-and-blocks task. We demonstrated that two closed-loop myoelectric interfaces that differed only in the variable provided as feedback to the participants – EMG vs. Force– exhibited different SAFs. EMG feedback afforded better performance throughout, but especially at medium speeds, and enabled the participants to develop stronger feedback control. We argue that the methodological advancement provided here is a valuable step forward in evaluating and understanding (closed-loop) user-prosthesis interfaces.

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