

1 Estimating Speed-Accuracy Trade-offs to Evaluate and Understand 2 Closed-Loop Prosthesis Interfaces

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6 Abstract

7 **Objective:** Closed-loop prosthesis interfaces, combining electromyography (EMG)-based control with non-
8 invasive supplementary feedback, represent a promising direction to develop the next generation of user
9 prosthesis interfaces. However, we still lack an understanding of how users make use of these interfaces, and
10 how to evaluate competing interfaces. In this study we use the framework of speed accuracy trade-off functions
11 (SAF) to understand, evaluate and compare the performance afforded by two closed-loop user-prosthesis
12 interfaces.

13 **Approach:** Ten able-bodied participants and one amputee performed a force matching task in a functional
14 box-and-blocks setup at 3 different speeds. All participants were subject to both interfaces in a crossover
15 fashion with a one-week washout period. Importantly, both interfaces used (identical) direct proportional
16 control but differed in the feedback provided to the participant – EMG feedback vs force feedback. We thereby
17 estimated the SAFs afforded by the two interfaces, and additionally sought to understand how participants
18 planned and executed the task in the various conditions.

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

24 **Significance:** Overall, the results indicate that closed-loop prosthesis interfaces afford subjects to exhibit a
25 wide range of performance, which is affected both by the interface and the execution speed. Thereby, we argue
26 that it is important to consider the speed accuracy trade-offs to rigorously evaluate and compare (closed-loop)
27 user-prosthesis interfaces.

28 **Keywords:** Speed-accuracy trade-off, Myoelectric Prosthesis Control, EMG Biofeedback, Force Feedback,
29 Motor Skill, Closed-loop Interfaces

30

31 **Introduction**

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

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

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

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

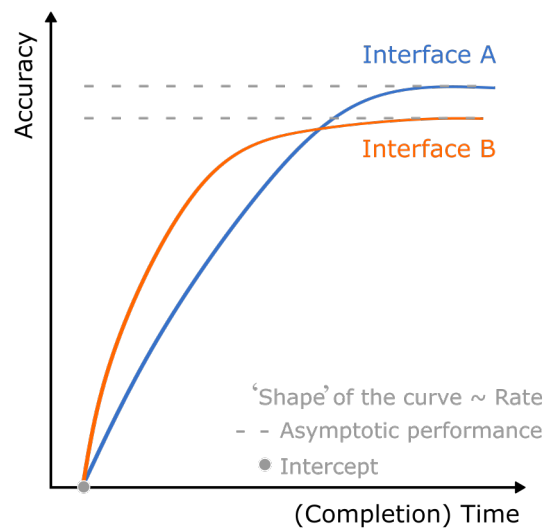


Figure 1: **Speed-Accuracy Trade-off.** A cartoon depicting the concept of speed-accuracy trade-offs as characterized by (1) intercept, (2) rate and (3) asymptotic performance, for two different interfaces.

64 measure and understand a participant's overall performance and motor ability [22], [24]. However, no current
65 user-prosthesis interface has been analyzed using this methodology.

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

83 these interfaces are difficult since the performance is sampled at a single, and possibly different, point along
84 the SAF.

85 In this experiment, we empirically study the SAF in closed-loop myoelectric control, using the prosthesis
86 force-matching paradigm in a functional task – the box and blocks test – to (1) show how SAF can be used to
87 evaluate (closed-loop) prosthesis interfaces and (2) thereby understand how they affect users’ ability to control
88 the prosthesis. Specifically, we compare two interfaces which both use direct proportional control to modulate
89 prosthesis velocity but differ in the feedback they provide to the subject – EMG feedback [28]–[30] vs force
90 feedback (see Table A1 in [3]). We use a prosthesis force-matching paradigm to understand how well the two
91 interfaces enable participants to achieve the same target force at three different speeds, ordinally defined as
92 fast, medium, and slow (see Methods: Experimental Design). Since the difficulty of the task itself and control
93 interface are fixed, the performance differences that arise from this experiment are a consequence of the
94 feedback interfaces. Having sampled the SAF at the three distinct speed requirements, we investigate how the
95 SAF differ for the two interfaces and analyze how the participants’ control policies change both across
96 interfaces and speeds. Finally, we investigated if the results extend to amputees, using a case study of a single
97 amputee.

98

99 **Methods**

100 **Participants**

101 Ten healthy, able-bodied participants (7 male and 3 females with a mean age of 28 ± 2 years) and one
102 transradial amputee (female, 49 years old, 10 years since traumatic amputation of non-dominant hand, limited
103 daily use of a single DoF myoelectric prosthesis) were recruited. All participants signed an informed consent
104 form before the start of the experiment. The experimental protocol was approved by the Research Ethics
105 Committee of the Nordjylland Region (approval number N-20190036).

106 **Experimental Setup**

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

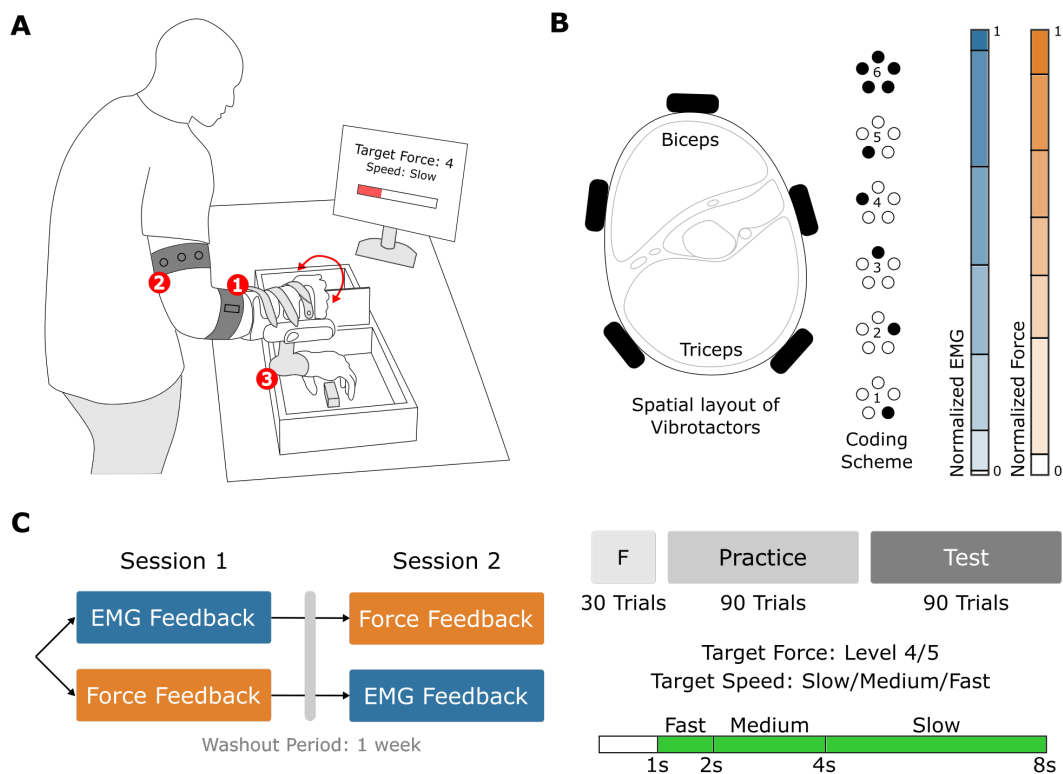


Figure 2: **Experimental setup and protocol.** (A) Sketch of the experimental setup showing 1. Two dry EMG electrodes placed on the forearm, 2. Vibrotactor array for delivering feedback placed on the upper arm and 3. The Michelangelo prosthesis. (B) Vibrotactor array arrangement and coding scheme used 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.

115 on a computer screen placed at a comfortable viewing angle and distance. The prosthesis was connected to a
 116 standard laptop PC through a Bluetooth link, while the vibrotactors were connected through a USB port. The
 117 control loop for the experiment was implemented in MATLAB Simulink using a toolbox for testing human-
 118 in-the-loop control systems [31] and operated on the host PC in real time at 100Hz through the Simulink
 119 Desktop Real Time toolbox.

120 EMG Control

121 Participants used near-isometric wrist flexion and proportional control to generate velocity commands to close
 122 the prosthesis. Opening the prosthesis was triggered by a strong contraction (see below) of the wrist extensors,
 123 instead of proportional control, since fine control of the opening was not relevant for the study. Two electrodes,
 124 placed on the flexors and extensors as explained above, were used to record the root mean square of the
 125 windowed (100 ms) EMG signal at 100Hz through the embedded prosthesis controller. The signals were

126 subsequently filtered digitally using a second order Butterworth low-pass filter with a 0.5 Hz cutoff. The EMG
127 envelope from each of the electrodes was normalized to 50% of the maximum voluntary contraction (MVC).
128 For the flexor EMG, this corresponded to the maximum closing velocity of the prosthesis. A piecewise linear
129 mapping between EMG amplitude and closing velocity was used to design the proportional controller, to
130 compensate for the higher variability in the EMG signal at higher amplitudes (stronger contractions). The
131 breakpoints for the mapping were defined as follows: $EMG = \{0.01, 0.1, 0.27, 0.47, 0.69, 0.95, 1\}$, $velocity =$
132 $\{0, 0.25, 0.42, 0.59, 0.76, 0.9, 1\}$. For the extensor however, participants simply needed to reach 0.4 on the
133 normalized range (corresponding to 20% MVC) to trigger hand opening.

134 **Vibrotactile Feedback Interfaces**

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

145 **EMG Feedback**

146 In this interface, the participants were provided feedback about the EMG signal that they generated using their
147 flexor muscles to control the closing velocity of the prosthesis. The six discrete levels were defined using the
148 breakpoints of the piece-wise linear mapping described in section “Methods: EMG Control.” Therefore, as
149 soon as the participants started contracting their wrist flexors, they received feedback about the EMG level (1-
150 6) they were generating, thereby enabling them to predictively modulate to the target level. The breakpoints
151 of the piecewise mapping were designed in such a way that if the participants reached a particular level of
152 EMG (with the object contact established and stable), they will have applied the same level of force on the
153 object. For instance, if a participant would generate and maintain EMG level 2, the prosthesis would close
154 around the object and exert the level 2 of the grasping force (level boundaries defined in the next section).

155 **Force Feedback**

156 The force applied on the blocks was measured by a sensor embedded within the prosthesis. The measured
157 force, sampled at 100Hz by the embedded controller, was normalized and divided into six discrete ranges
158 (levels) with boundaries at $\{0.05, 0.31, 0.45, 0.58, 0.73, 0.9 \text{ and } 1\}$ on the normalized scale. With this feedback

159 interface, the participants received feedback on the level of force (1-6) applied on the object. Contrary to EMG
160 feedback, where vibrotactile stimulation was delivered as soon as the myoelectric signal crossed the threshold
161 of the dead-zone (e.g., when the prosthesis started closing), in the case of force feedback, the stimulation was
162 delivered only after contact was established with the object.

163 **Experimental Design**

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

172 To adequately sample the SAF, participants were required to perform the task in three speed conditions – slow,
173 medium, and fast, where each condition specified the time window for task completion. During the Slow
174 condition, trials had to be completed within 4 – 8s, while for the Medium and Fast conditions the speed/time
175 requirements were 2 – 4s and 1 – 2s, respectively. The time windows have been defined to capture the relevant
176 domains of the SAF curve. Previous studies suggest that participants in a fast routine grasping task spend
177 around 2s to achieve required force while they attain close to 100% accuracy at around the 6s mark [10]. In
178 effect, we used a time-band methodology to derive the SAF [24]. While there exist several methodologies to
179 obtain the SAF [11], [24], we believe that this approach reduced inter-subject variability in learning feedback
180 control. This would not have been the case in, e.g., a deadlines-based methodology, where participants may
181 have no incentive to perform the task at a slower speed if they were satisfied with their accuracy while using
182 faster speeds.

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

185 **Experimental Protocol**

186 Initially, all equipment (EMG electrodes, vibrotactors, wrist immobilization splint and the prosthesis) were
187 placed on the participant. Then a brief calibration and familiarization followed in both sessions. During the
188 EMG calibration phase, three 5-second-long maximum voluntary contractions (MVC) for both the flexors and
189 extensors were recorded to calibrate the control interface. The MVC measurements were recorded in the same
190 posture that the participants would use to perform the box and blocks task (similar to [32]), to address the
191 effect of arm posture and prosthesis weight on the recorded EMG. Next, the participants were familiarized

192 with the interface and were guided to explore how their flexor EMG signal affected the prosthesis closing
193 velocity and how their extensor EMG signal triggered hand opening. Finally, they were familiarized with the
194 vibrotactile feedback (common across both feedback interfaces) by performing a spatial discrimination task
195 where they were presented with two sets of 18 stimulation patterns (3 repetitions x 6 levels, Figure 2B) and
196 asked to identify the patterns. The experiment proceeded after ensuring that the participants achieved at least
197 95% success in the discrimination task, which normally took less than 5 mins.

198 After familiarization with the control and feedback, the participants performed 30 trials (10 per speed
199 condition) of the modified box and blocks test to practice the time-constrained force-matching task. Each trial
200 began by displaying the force and speed targets. The participants then had to modulate their muscle contraction
201 and use the feedback interface to successfully complete the trial. Once the participant felt they successfully
202 reached (or overshot) the target, they were instructed to extend their wrist to trigger hand opening. Immediately
203 after the trial ended, the participants received knowledge of performance, which indicated if they achieved,
204 overshot, or undershot the target force and target speed. During the practice trials, the participants were
205 explained how to modulate their muscle contraction to control the closing velocity of the prosthesis. They were
206 also clearly instructed to avoid eccentric behavior, e.g., in the slow condition they were instructed against
207 holding their contraction at a low level until 4 s and then quickly correcting upwards, hence inadvertently
208 making a fast/medium condition trial.

209 After the initial practice trials, the participants performed 90 training and 90 test trials with a break after every
210 30 trials. In each such block of 30 trials, the target speeds (slow, medium, and fast) remained the same for 10
211 trials, while the target forces (4, 5) were presented 5 times each in a random order. In addition, during the first
212 60 training trials, the speed targets were presented in a specific order – slow, medium, and fast – while during
213 the remaining trials, this was also randomized.

214 **Outcome Measures**

215 During each trial, the EMG commands and force measurements were recorded and processed to obtain the
216 primary outcome measures – reach time and trial success. from when the participant started generating the
217 EMG input (above the dead-zone) to the time point where the maximum force was reached during the trial. A
218 successful trial was therefore one where the reach time satisfied the speed requirement (1 – 2s for fast, 2 – 4s
219 for medium and 4 – 8s for the slow speed), and the reached force was within the corresponding force interval
220 (target level). The trials were aggregated per speed condition to obtain percent success rates (S). Subsequently,
221 we computed the rate of trade-off in success rate (ΔS per second) during fast-to-medium and medium-to-slow
222 conditions to evaluate how quickly the participants traded speed for accuracy. For each participant, we
223 computed the rate of trade-off as the difference in success rates (ΔS) between successive speed conditions
224 divided by the difference in the corresponding reach times. For example, the rate of trade-off for participant p

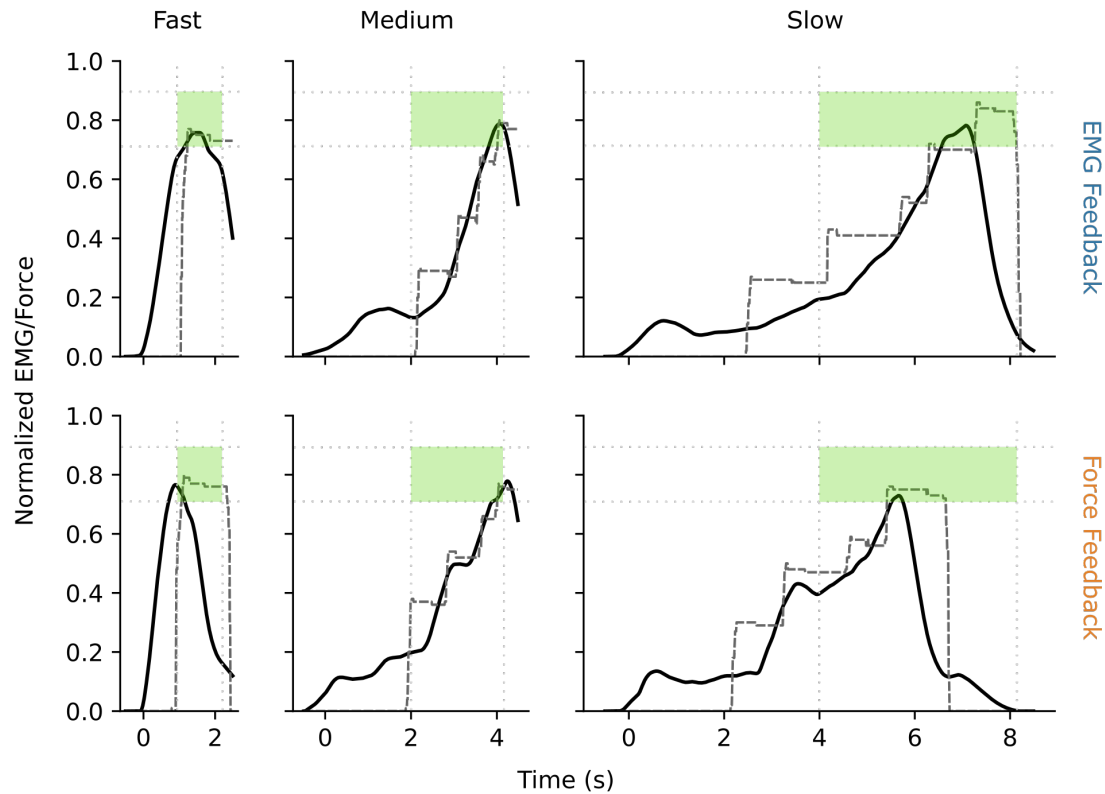


Figure 3: **Representative Trials.** Six representative trials (EMG commands in solid black, prosthesis force in dark gray) as performed by the amputee subject using the two different interfaces, at the three required speeds for target force Level 5. Faint dotted vertical and horizontal lines indicate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

225 for fast-to-medium transition was computed as $(S_{p|med} - S_{p|fast}) / (T_{p|med} - T_{p|fast})$, where $S_{p|cond}$ is success
 226 rate and $T_{p|cond}$ is the average reach time in the condition *cond*.

227 Further, to understand how the participants planned and executed the task in the different speed and feedback
 228 conditions we computed three behavioral metrics. Firstly, we calculated the number of force corrections in
 229 each trial that the participants made, by counting the number of distinct plateaus (longer than 250ms) in the
 230 force trajectory [10]. For example, during the slow condition with EMG feedback the amputee subject made 4
 231 force corrections in the trial shown in Figure 3. Then, we analyzed the generated EMG commands, to
 232 understand if one feedback type could enable the participants to generate (1) smoother and (2) more repeatable
 233 EMG commands. To evaluate smoothness, we calculated the integrated squared jerk of each trajectory,
 234 normalized to the reach time. To measure the repeatability, we computed the trial-by-trial variability of the
 235 generated EMG commands. We first normalized all EMG trajectories to 200 time points between the start of

236 the trial and reach time, then measured the standard deviation at each of the 200 time points. As the final
237 measure of variability, we computed the median of the standard deviations across the time points since the
238 distribution of the standard deviations was found to be often skewed.

239 **Statistical Analysis**

240 Statistical analysis was performed on outcomes obtained during the 90 test trials. 3-factor mixed ANOVAs
241 were fitted each for success rate, rate of trade-off and the behavioral metrics as the outcome, with two within-
242 subjects factors – feedback interface and speed condition – and one between-subjects factor “order”, which
243 denotes the order in which the participants were exposed to the feedback interfaces. We interpreted the main
244 effect of order as an interaction between feedback interface and session, while the interaction effect between
245 order and feedback interface was interpreted as the main effect of session, as is common in cross-over designs
246 [33]. The assumptions of Normality, homogeneity of variance and sphericity were verified using Shapiro-
247 Wilk’s, Levene’s and Mauchly’s tests, respectively.

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

252

253 **Results**

254 **Representative Trials**

255 Figure 3 shows representative trials of the amputee subject in all target speeds, with level 5 as the force target.
256 Firstly, we can notice that both feedback types allowed the subject to flexibly control the prosthesis at different
257 speeds and still succeed in the task, i.e., reaching the target grasping force within the given time window. Then,
258 we can notice that the subject was slightly faster when using Force feedback than EMG feedback (especially
259 noticeable in the slow trials), a feature that also holds across participants (see Figure 4A). Secondly, we can
260 observe a difference in the “quality” of the generated EMG commands across the feedback conditions. While
261 the EMG commands produced during the fast condition is largely similar between the feedback types, the
262 EMG signal generated during both medium and slow trials is smoother during EMG feedback as opposed to
263 Force feedback, where the EMG commands exhibit distinct “jumps”.

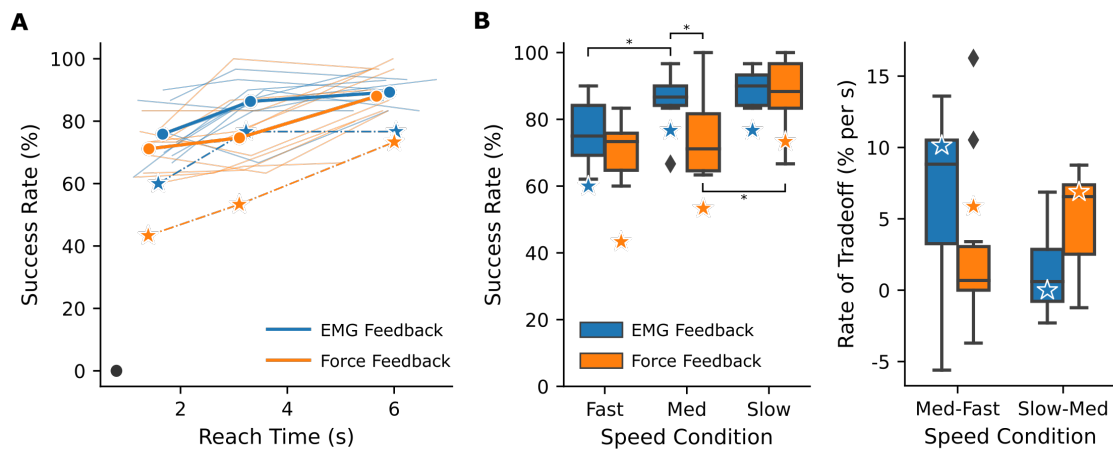


Figure 4: **Speed-Accuracy trade-offs in prosthesis force control.** (A) Individual speed-accuracy trade-off curves are plotted for each participant (faint lines), group means (bold lines) and the amputee subject (dashed lines and stars). Bold diamond indicates the time (X-intercept) when success is 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. Colored stars represent results of the amputee subject.

264 Speed-Accuracy Trade-offs

265 The participants' speed-accuracy trade-off curves showed a general tendency to be monotonic (14 out of 22,
266 Figure 4A), and when they were not monotonic, they were only off due to a few trials (1 – 3 trials), while the
267 mean SAF across participants were monotonic. This was true for both feedback interfaces. Next, we fit a 3-
268 factor ANOVA by treating the speed condition as categorical to analyze the effect of feedback interface and
269 speed condition on success rate. We observed a significant effect of feedback interface ($p=0.006$), and speed
270 condition ($p=2.3 \times 10^{-6}$) on success rate as well as a significant effect of session (feedback interface x feedback
271 order interaction effect, $p=0.003$).

272 We then analyzed if feedback interface affected performance at each of the speed conditions. In the Fast
273 condition, we did not observe a significant effect of feedback interface (EMG: $75.8 \pm 9.4\%$, Force: $71.1 \pm$
274 7.4% see Figure 4B), while in the Medium condition, we observed that participants performed significantly
275 better using EMG feedback than Force feedback (EMG: $86.3 \pm 8\%$, Force: $74.6 \pm 12.2\%$, $p\text{-adj}=0.022$). In the
276 Slow condition (asymptotic performance), as expected, we observed that the interface had no significant effect
277 on performance (EMG: $89.2 \pm 4.8\%$, Force $88 \pm 10.2\%$). Taken together, we see that while the feedback
278 interface had a significant effect on success rate overall, it was in the Medium speed condition that this
279 difference originated from. Further, EMG feedback enabled participants to reach asymptotic performance
280 sooner, with participants significantly improving their performance between Fast and Medium conditions (p -

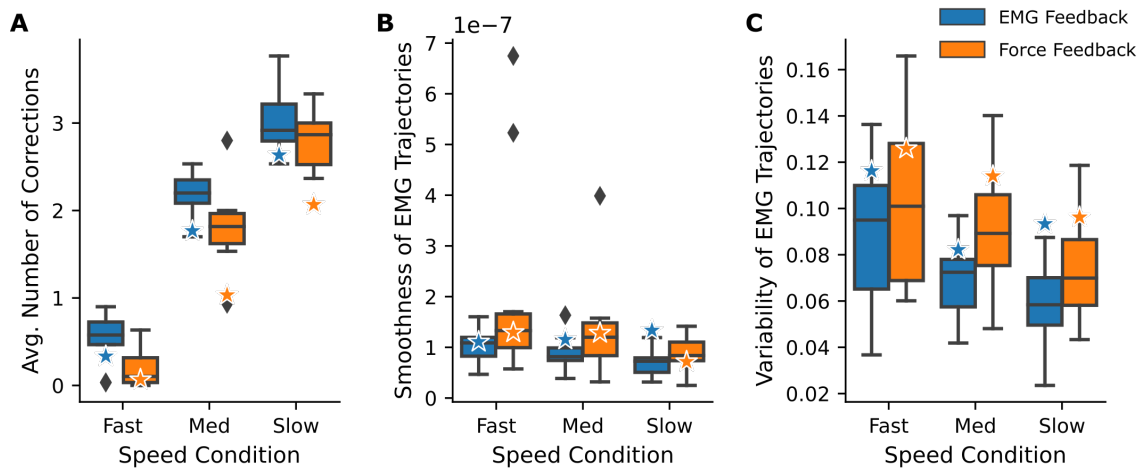


Figure 5: **Behavioral metrics for both interfaces, across participants.** (A) Average number of force corrections (distinct force plateaus) per trial. (B) Smoothness of EMG trajectories (commands) generated by the participants, computed as integrated squared jerk of the normalized EMG amplitude. (C)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

281 adj=0.03) but not between Medium and Slow conditions. On the contrary, participants exhibited significant
282 improvement between Medium and Slow conditions (p -adj=0.004) while using Force feedback. The two
283 feedback types are therefore characterized by SAFs that are qualitatively different, while still allowing similar
284 asymptotic performance.

285 Therefore, we analyzed if the observed rate of trade-off in success rate (% per s) for the Fast to Medium, and
286 Medium to Slow transitions were significantly different between EMG and Force feedback (see Figure 4B,
287 right). Visually, there appears to be a difference in both cases, with the higher rate of trade-off for EMG
288 feedback during Fast to Medium ($6.6 \pm 6.3\%$ vs $2.7 \pm 6.1\%$ per second) and opposite for Medium to Slow
289 transition ($1.3 \pm 2.8\%$ vs $5.1 \pm 3.5\%$ per second). However, the difference was not statistically significant.

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

294 Behavioral Analyses

295 We sought to understand the behavioral differences between the feedback types, i.e., how the different
296 interfaces allowed participants to plan and execute movements (Figure 5). First, we investigated if participants
297 developed different strategies during the different speed targets. We found that both feedback interface

298 (p=0.005) and speed condition (p<1e-15) had a significant effect on the number of corrections made by the
299 participants (Figure 5A), and the feedback and session exhibited significant interaction (p=0.02). Therefore,
300 the participants were able to flexibly modify their control policies by using the available feedback, especially
301 during the Medium (2.2 ± 0.3 , 1.8 ± 0.5 corrections per trial) and Slow conditions (3 ± 0.4 , 2.8 ± 0.3 corr.
302 p/trial) compared to the Fast condition (0.5 ± 0.3 , 0.2 ± 0.2 corr. p/trial).

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

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

311

312 **Discussion**

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

325 **SAF to Evaluate Closed-Loop Interfaces**

326 Evaluation and comparison of user-prosthesis interfaces is challenging and multi-faceted. Despite rapid
327 development of promising control and feedback interfaces [25], [26], their comparison has received less
328 attention, barring a few exceptions [29], [34]. While it is a difficult undertaking due to various reasons such as
329 incomparable experimental setups and tasks, here we showed that it is additionally compounded by measuring

330 the performance only at a single speed (sampling at a single point on the SAF). For example, if we had only
331 measured performance in the Fast condition in this study, we would infer that both interfaces enable similar
332 performance, while they are in fact significantly different when used at the Medium speed. We argue therefore,
333 that it is valuable to compare interfaces at more than a single point on the SAF especially since the shape of
334 the SAF afforded by different interfaces is unknown.

335 Here, we used the SAF framework to rigorously compare two closed-loop interfaces in a functional force-
336 matching task. By enforcing task execution at different speeds, we elicited a range of success rates that were
337 significantly affected by the feedback interface used. We expected that EMG feedback would enable better
338 success rates during the Fast condition, since it promotes predictive control [28], [29], but that was not the
339 case. We believe that this is likely due to two reasons. First, Fast condition might have been too restrictive,
340 with a short 2 s window, for the participants to exploit the EMG feedback effectively for online adjustment of
341 control commands. Second, the task included only 2 force levels and the participants received training before
342 performing the test trials. The training might have enabled participants to acquire a reliable internal model and
343 achieve a good performance when using Force feedback despite the short time window (which basically
344 precluded the use of force feedback to drive the corrections). However, we noticed a large difference in success
345 rates between the two interfaces in the Medium condition. Therefore, the results demonstrate that the expected
346 advantage of EMG feedback over Force feedback occurs in this range of movement speeds, where the former
347 allows users to predictively modulate their contractions to reach the target level as opposed to ‘reactively’
348 jump between levels. Finally, the feedback interfaces resulted in similarly high performance in the Slow
349 condition, as the participants had enough time to reach the goal by focusing on either of the two feedback
350 signals. The present study therefore demonstrates that SAF allows identifying the time interval in which
351 feedback (Force or EMG) becomes an important factor for the effectiveness of the control loop.

352 Taken together, we found that the asymptotic performance for both interfaces was similar, while EMG
353 feedback allowed participants to approach the asymptotic performance sooner. Note that this important
354 characterization of the two feedback types is derived from the trade-off itself and could not be obtained if the
355 performance was assessed in a single point. More generally, SAF provides a way to estimate the expected
356 completion time to guarantee a given (e.g., 90%) performance in a task, and therefore can be a relevant
357 instrument for meta-analytic comparison of interfaces across studies. Moreover, we believe that determining
358 SAF will be advantageous for person-based approaches to designing prosthesis interfaces [35], by e.g.,
359 determining the appropriate user-prosthesis interface for the amputee based on their inherent speed preferences
360 (see Figure 1). Thereby, in the present study, we provided a holistic comparison of the performance afforded
361 by two established interfaces in a functional task and added to a pool of methods that have been recently
362 developed to assess the performance as well as behavior of the users of closed loop prostheses [15], [36].

363 **SAF to Understand Closed-Loop Interfaces**

364 Closed-loop user-prosthesis interfaces are a promising technology likely to translate into clinical applications,
365 but currently still facing several conceptual and implementational barriers [1], [27], [37]. A key prerequisite
366 for designing better closed-loop interfaces is to understand the complex interplay between feedforward and
367 feedback control processes of the users, and how different interfaces facilitate it [3], [6], [10]. We believe that
368 studying the SAF, as described here, is an effective instrument to approach this point as it enables us to
369 understand how users interact and exploit different interfaces to achieve specific (time bound) goals.

370 Here, in addition to measuring performance, we used SAF to understand how participants planned and
371 executed movements in a functional prosthesis task. We found that both closed-loop interfaces enabled users
372 to develop flexible control policies. That is, participants were able to incorporate feedback to varying extents
373 to guide their behavior during the different speed conditions, as reflected in the number of force corrections
374 they made. Then, we found that EMG commands generated when participants used EMG feedback were
375 smoother than when they used Force feedback. Interestingly, this suggests that even though participants
376 received discretized feedback, they could exploit EMG feedback to predictively guide their contractions to
377 generate an overall smooth control input. Combined with the low trial-by-trial variability across speed
378 conditions, EMG feedback effectively reduced the uncertainty in generating prosthesis commands, a central
379 aim of implementing supplementary feedback [6], [35]. Our results therefore add to a body of evidence which
380 underscores the promise of some form of predictive feedback, about users' own intention [5], [28], [29].

381 Together, the flexibility, smoothness and repeatability measures which are hallmarks of skilled behavior, help
382 us understand how participants incorporate supplementary feedback in their control policies. And investigating
383 the SAF provides a suitable framework for such an analysis. Finally, we also found that all outcome measures
384 had similar trends in the amputee experiment. We believe that this is an encouraging result, albeit expected
385 since motor planning and execution should remain comparable across able-bodied participants and amputees,
386 especially when using a simple command interface (direct proportional control).

387 **Limitations and Outlook**

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

393 Measuring the SAF can be an instrument for assessment of prosthesis control with rather general applicability.
394 Future studies should be therefore conducted to investigate how the control interface (direct control, pattern
395 recognition etc.) of the user-prosthesis loop affects the SAF, relative to the effects of feedback interface as

396 explored here. In addition, this approach could be used to compare feedback interfaces which differ only in
397 their encoding schemes (e.g., discrete vs continuous), while the feedback variable remains the same. The
398 intercept (see Figure 1), which characterizes the minimum time required to have any chance of success, did
399 not play a role in our current setup since the control interface was always the same (direct proportional control).
400 However, in case one wishes to compare interfaces that allow different maximum velocities (e.g., due to
401 different sensitivities for the proportional controller), or when one is required to change grips by co-
402 contractions, it becomes crucial to understand the intercept as well. Finally, this framework can be extended
403 to multi-dimensional task spaces, for example to characterize the trade-offs in prehension (posture matching
404 with prostheses) combined with force-matching, to create better interfaces for current state-of-the-art
405 commercial prostheses.

406

407 **Conclusion**

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

414

415 **Acknowledgements**

416 We expressly thank Shima Gholinezhad for her help in organizing and conducting the experiments with the
417 amputee subject. We thank Ana Sofia Santos Cardoso for their help in making Figure 1(A). This work has
418 been supported by the projects 8022-00243A (ROBIN) and 8022-00226B funded by the Independent Research
419 Fund Denmark.

420

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