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The Effect of Calibration Parameters on the Control of a Myoelectric Hand Prosthesis Using EMG Feedback

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Abstract

Objective: The implementation of somatosensory feedback in upper limb myoelectric prostheses is an important step towards the restoration of lost sensory-motor functions. EMG feedback is a recently proposed method for closing the control loop wherein the myoelectric signal that drives the prosthesis is also used to generate the feedback provided to the user. Therefore, the characteristics of the myoelectric signal (variability and sensitivity) are likely to significantly affect the ability of the subject to utilize this feedback for online control of the prosthesis. *Approach:* In the present study, we investigated how the cutoff frequency of the low-pass filter (0.5, 1 and 1.5 Hz) and normalization value (20, 40 and 60% of the maximum voluntary contraction), that are used for the generation of the myoelectric signal, affect the quality of closed-loop control with EMG feedback. Lower cutoff and normalization decrease the effect of the intrinsic variability of the EMG but also increase the time lag between the contraction and the feedback (cutoff) as well as the sensitivity of the myoelectric signal (normalization). Ten participants were asked to generate three grasp force levels with a myoelectric prosthetic hand, while receiving 5-level vibrotactile EMG feedback, over nine experimental runs (all parameter combinations). *Main Results:* The outcome measure was the success rate in achieving the appropriate level of myoelectric signal (primary outcome) and grasping force (secondary outcome). Overall, the experiments demonstrated that EMG feedback provided robust control across conditions. Nevertheless, the performance was significantly better for the lowest cutoff (0.5 Hz) and higher normalization (40 and 60%). The highest success rate for the EMG was 71.9%, achieved in the condition (40% MVC, 0.5 Hz), which was 24.1% higher than that in the condition (20% MVC, 1.5 Hz), which displayed the lowest performance. The success rate for the force followed a similar trend. *Significance:* This is the first study that systematically explored the parameter space for the calibration of EMG feedback, which is a critical step for the future of the clinical application of this approach.

Keywords: Closed-loop control, somatosensory feedback, EMG feedback, vibrotactile stimulation, prosthetic hand, grasping force control

1. Introduction

Loss of an upper limb is a traumatic event that significantly and lastingly disrupts the quality of life of the affected person [1]. The consequences are profound and varied, from hindering the execution of daily tasks [2], to long-lasting psychological challenges [1], [3], reduced social participation [1], [4] and significant difficulties in returning to the workplace after the injury [5]. In addition, substantial pain can be consistently present throughout the rehabilitation process [6]. Technological advances of the last few decades have enabled the development of sophisticated active upper-limb prosthetic devices integrating multiple degrees of freedom. Despite the ever-increasing complexity and capabilities of modern-day prostheses, abandonment rates remain high. The users often find controlling the prostheses hard and/or unintuitive and are unable to accept them as an integral part of their anatomy [7]–[9].

Myoelectric prostheses are controlled by recording muscle electrical activity to estimate the user's intention and translate it into commands for the device. In the simplest approach, known as direct proportional control, two EMG channels are used to activate a single degree of freedom in two directions (e.g. hand opening/closing), with the velocity of movement being proportional to the amplitude of the EMG. This is an intuitive approach to control, in the case of simple systems (e.g. single degree of freedom [DoF] grippers), however, the restoration of the lost functions is only partial, since contemporary prostheses do not transmit explicit feedback to the user. The provision of somatosensory feedback is often reported as an important requirement by prosthesis users [8]. However, only two commercial devices on the market (VINCENT Evolution [10]–[12] and Psyonic Ability Hand [13], [14]) are equipped with a feedback interface, but their clinical utility has yet to be demonstrated. Without explicit feedback, the users need to rely on vision and incidental information (such as auditory cues from the prosthesis motors). Although such implicit feedback can be useful for prosthesis control [12], [15], it requires the user to focus their full attention on the prosthesis, thereby increasing the cognitive load [10] to use the device.

Tactile feedback can be provided using invasive methods, by delivering subdermal electrical stimulation [16] or direct peripheral nerve stimulation [17]. Tactile sensations can also be elicited non-invasively, by mechanically or electrically stimulating the skin [18], [19]. One of the most widely used approaches is to generate vibrations tangentially or perpendicularly to the skin using coin motors [20] or tactors [21] respectively. Previous studies have demonstrated that the feedback can be beneficial to improving performance [7], promoting embodiment [10] and reducing phantom limb pain [22], [23]. Nevertheless, the development of an effective feedback system which improves performance in functional tasks remains a challenge [7].

A common approach to provide feedback is to read the data from the sensors embedded in the prosthesis (e.g. grasping force or joint angle) [21] and transmit this information to the user by modulating the intensity and/or the frequency of tactile stimulation [24]. Recently, a novel method to close the control loop was proposed, wherein instead of feeding back the prosthesis state (as estimated from the sensor data), the tactile stimulation transmits the value of the myoelectric signal controlling the prosthesis [25], [26]. As explained before, the prosthesis responds proportionally, with the amplitude of the myoelectric signal determining the prosthesis closing velocity and grasping force. Therefore, the subject can use the online feedback on the myoelectric signal to control the level of their muscle contraction while the prosthesis is closing and thereby the eventual amplitude of the grasping force that will be produced upon contact. The EMG feedback enables the user to control the force predictively and it has been shown to outperform the conventional force feedback [25], [26], facilitate the creation of internal models and improve prosthesis performance [27], [28].

The myoelectric signal is computed by full-wave rectifying, low-pass filtering and normalizing the recorded EMG, to obtain a smooth EMG envelope [29], [30]. The cutoff frequency of the low-pass filter controls the smoothness of the command signal, whereas the normalization to a percentage of the maximum voluntary contraction (MVC) determines the effort required to produce the maximum control input and, by extension, the maximum force. These two settings are typically selected heuristically. For instance, the normalization levels used in the literature vary from low (20% [31], [32]), to high (70% and over [21], [25]). Importantly, the effectiveness of EMG feedback depends on the ability of the subjects to modulate the myoelectric signal online by relying on the tactile stimulation. Both the cutoff frequency and the MVC calibration are likely to have a critical impact on this process.

The EMG is characterized by multiplicative signal dependent noise [33], which means that the myoelectric signal exhibits larger variance for stronger contractions. Thus, by decreasing the muscle activation range required to control the prosthesis by normalizing to a smaller percentage of the MVC, the myoelectric signals will be less variable and, thus, possibly easier to modulate reliably. However, this will cause the system to become more sensitive, since the same change in muscle contraction will generate a larger deflection in the myoelectric signal. Furthermore, the EMG arising from weaker muscle contractions is characterized by a lower signal-to-noise ratio [34], [35]. A similar trade off exists regarding the cutoff frequency. A lower cutoff will result in a smoother myoelectric signal but it will increase the delay in the response of the signal to a change in muscle contraction. The former is likely to be advantageous for online modulation (less variability), while the delay can have a detrimental effect on the control user's ability to timely exploit the EMG feedback.

The aim of this study was, therefore, to systematically assess the effect of these two parameters on prosthesis control using EMG feedback. To that end, the task for the subjects was to use EMG feedback provided through vibrotactile stimulation to close the prosthesis and reach several levels of prosthesis grasping force for each combination of three MVC calibration and three cutoff values (nine conditions in total). The performance in reaching the correct level of the myoelectric signal and grasping force upon contact was measured and compared across the conditions.

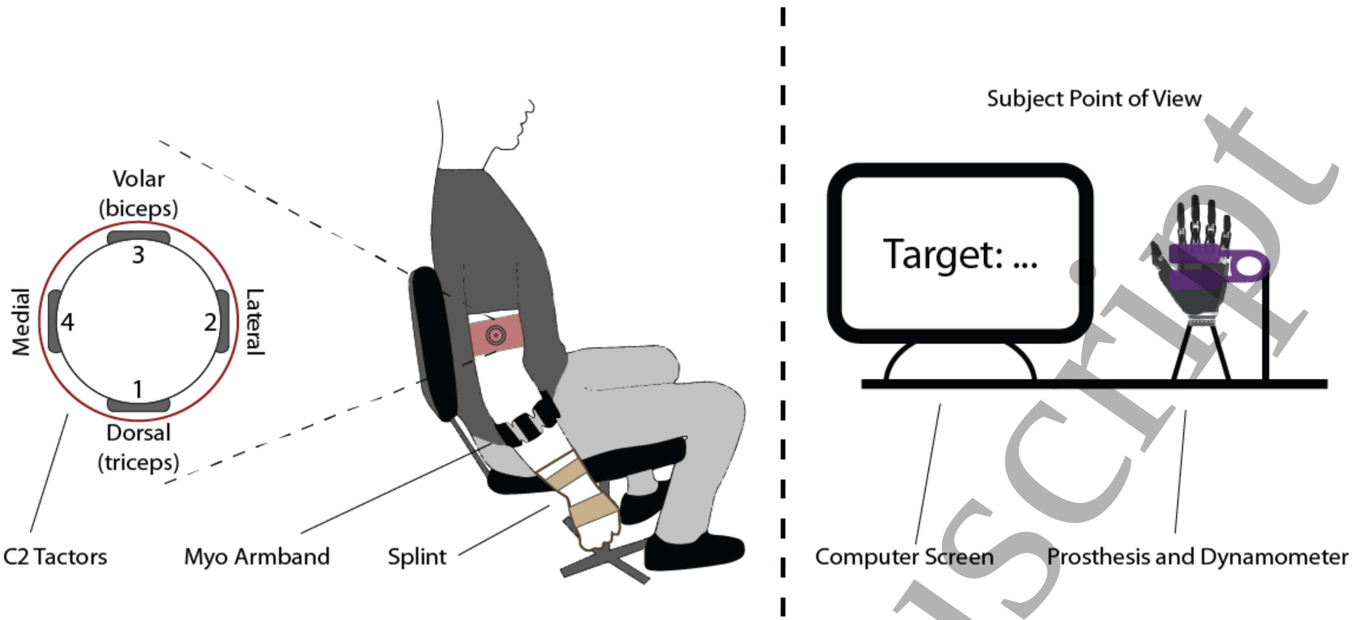

Figure 1: The experimental setup. The left panel shows the subject, wearing an orthopaedic splint, Myo Armband and C2 tactors underneath an elastic band. The C2 tactors were placed circumferentially and equidistantly around the upper arm. The right panel depicts the view from the perspective of the subject, looking at a computer monitor displaying the target force level, the RoboLimb and the hand dynamometer

2. Materials and Methods

2.1. Subjects

Ten healthy able-bodied subjects (28.9±2.5 years), with no prior experience in myoelectric control, participated in this study. Before commencing the experiment, the subjects signed an informed consent form. The experimental protocol was approved by the Research Ethics Committee of the Nordjylland Region (approval number N-20 190 036).

2.2. Experimental Setup

The experimental setup (Fig. 1) comprised the following components: 1) a 6-degree-of-freedom dexterous prosthetic hand (RoboLimb from TouchBionics, UK), 2) four C2 vibrotactors and their control unit (Engineering Acoustics Inc., US) to provide feedback, 3) a DTS Scientific Handgrip Dynamometer (Noraxxon, US) to measure the grasping force of the prosthetic hand, 4) a data acquisition board (NI USB-6229 BNC, National Instruments, US) to sample the analog output of the dynamometer, 5) a Myo Armband (Thalmic Labs, US) to record EMG, 5) a splint to immobilize the wrist and enforce isometric contractions and 6) a standard laptop (Lenovo ThinkPad 52, Intel Core i7 @2.60GHz, 32GB RAM) running Windows 10 and an 18" computer monitor. The prosthesis, tactor control unit and acquisition board were connected to the laptop via USB, while the Myo Armband was connected via Bluetooth. The program for closed-loop prosthesis control using EMG feedback, which acquired the EMG data, sent commands to the prosthesis and the tactors and sampled the produced grasping force was implemented in MATLAB Simulink 9.3, using the closed-loop toolbox for human-manual control [36].

The Myo Armband was placed on the subject's right forearm, approximately 10 cm distal to the elbow, taking care not to place any of the channels directly over the ulnar bone. Only one out of eight available EMG channels, sampled at 200 Hz, was used in this experiment, as explained below. The Myo Armband implements onboard high-pass filtering of the raw sEMG, to remove movement artifacts.

The C2 tactors produce vibrations perpendicular to the skin, with adjustable gain and frequency. In the present study, the vibration frequency was set at 230 Hz, which lies within the range of maximum sensitivity of the Pacinian corpuscles [37]. Four C2 tactors were placed circumferentially and equidistantly around the subject's upper arm, 5 cm proximally with respect to the elbow, and held in place by an elastic band. The gain of the tactors was adjusted individually for each subject, based on their sensation threshold (see section Experimental Protocol). The C2 tactors emit a loud noise when they vibrate; therefore, to block this sound, the subjects wore a pair of Sony (WH-CH700N) noise cancelling headphones playing white noise.

The subject sat comfortably in front of a desk, with their right arm relaxed vertically by the side of the body. The RoboLimb was placed on the desk, approximately 50 cm from the subject and next to the computer screen. The prosthesis supports velocity control over its six DoFs (five fingers and thumb abduction), where each digit can be individually commanded to close or open at seven different velocities. In this study, all fingers moved at the same velocity, performing

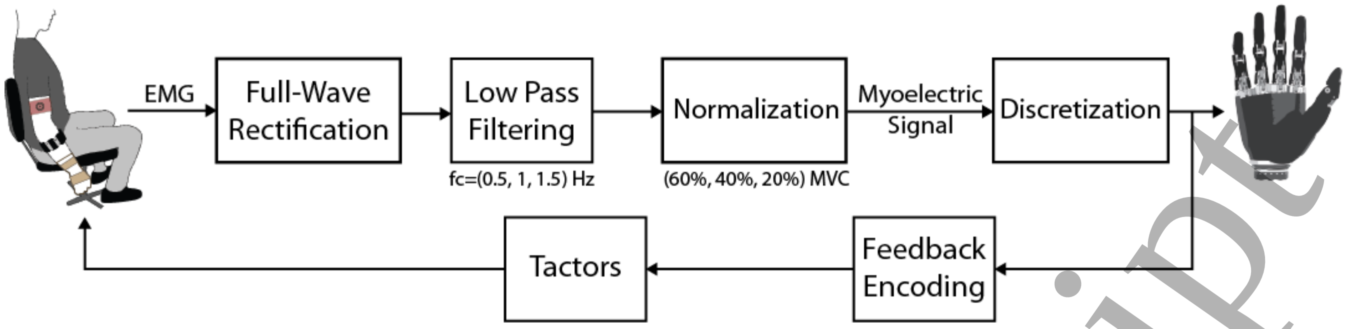

Figure 2: The block diagram of the control scheme. The recorded EMG was full-wave rectified, low-pass filtered and normalized to a percentage of the MVC. Three different values were tested for the cutoff frequency of the low-pass filter and %MVC in the normalization block (nine combinations in total). The myoelectric signal was discretized and sent to the prosthesis as a closing velocity command, as well as back to the user through the vibrotactile feedback. The term "EMG" denotes the preprocessed EMG transmitted by the Myo Armband to the setup PC.

a palmar grasp (with the thumb at opposition) closing around the handle of the hand dynamometer. A higher closing velocity generated a higher grasping force. Only five out of seven velocity levels were used in this experiment, since they produced distinct grasping forces. The force measurements were normalized to the maximum force produced by closing the hand at the highest velocity.

2.3. Closed Loop Prosthesis Control

The pipeline for the closed-loop prosthesis control using EMG feedback is shown in Fig. 2. The EMG was processed following a standard approach for direct and proportional control of prosthesis closing velocity and grasping force [29]. The EMG was full-wave rectified, low-pass filtered using a 2nd order Butterworth filter, normalized to a percentage of the MVC and finally discretized into 5 levels using the thresholds indicated in Fig. 3. The EMG levels {1, 2, 3, 4, 5} were mapped to the closing velocities {1, 2, 4, 6, 7} of the prosthetic hand and, at the same time, communicated to the user via vibrotactile feedback (see Fig. 3B). Each EMG level corresponded to a different spatial activation of the tactors. Levels 1 to 4 were indicated by activating one of the four tactors, while level 5 was communicated by the simultaneous activation of all four tactors. Therefore, as the subject increased the strength of their muscle contraction, they felt vibrations that moved from the dorsal to lateral, volar and medial side of the upper arm (levels 1 to 4) and, finally, all around the upper arm (level 5). This pattern was selected since it was easy for the subject to perceive and interpret the spatially coded feedback after only a brief familiarization. The feedback transmitted discrete levels because the prosthesis implemented discrete control, as explained in the previous section. It is important to note that this is not a limitation, since it has been shown in the literature that discrete feedback can indeed be effective [7], [12], [20], [21], [26]. When discretizing the myoelectric signal, levels 2, 3 and 4 were mapped to ranges of increasing width, to account for the expected larger signal during stronger contractions (Fig. 3A). The threshold values for the discretization were selected heuristically, based on pilot tests.

Fig. 3C demonstrates the prosthesis control using EMG feedback. To achieve a specific grasping force level (e.g. level 3), the subject increased their muscle contraction until they felt the corresponding tactor (tactor on the volar aspect of the upper arm in this example) vibrating. This was an indication that the myoelectric signal was within the appropriate level. If the signal remained at that level when the prosthesis contacted the object, the correct force (level 3) would be generated. The subject, therefore, maintained the contraction level while the hand closed and if they were successful (the same tactor still vibrating while the hand closed around the dynamometer), the desired grasping force was indeed generated.

2.4. Experimental Protocol

First, the baseline EMG signal was recorded by asking the subjects to keep their arm completely relaxed for 5 seconds. The average of the rectified measurements of each of the Myo Armband channels was calculated and subtracted from the following EMG measurements. The subjects were then asked to maximally flex their wrist against the splint for 5 seconds and this was repeated 3 times. A 1-second window starting at the third second of each recorded myoelectric signal (obtained by rectifying and low-pass filtering at 3 Hz) was segmented out and the mean value within each window was calculated. The measurement was repeated three times and the MVC was defined as the mean of the three repetitions. The channel that yielded the largest value during the MVC recording was selected and used for prosthesis control during the rest of the experiment.

Next, the sensation threshold (ST) for the vibrotactile stimulation was determined using the method of limits [38]. For each C2 tactor, the vibration intensity was manually increased in small steps (2-3% in the normalized scale) and the subjects reported when they felt the stimulation for the first time. The intensity of each tactor was then set to $ST + 0.4 \times DR$, where DR is the dynamic range defined as the

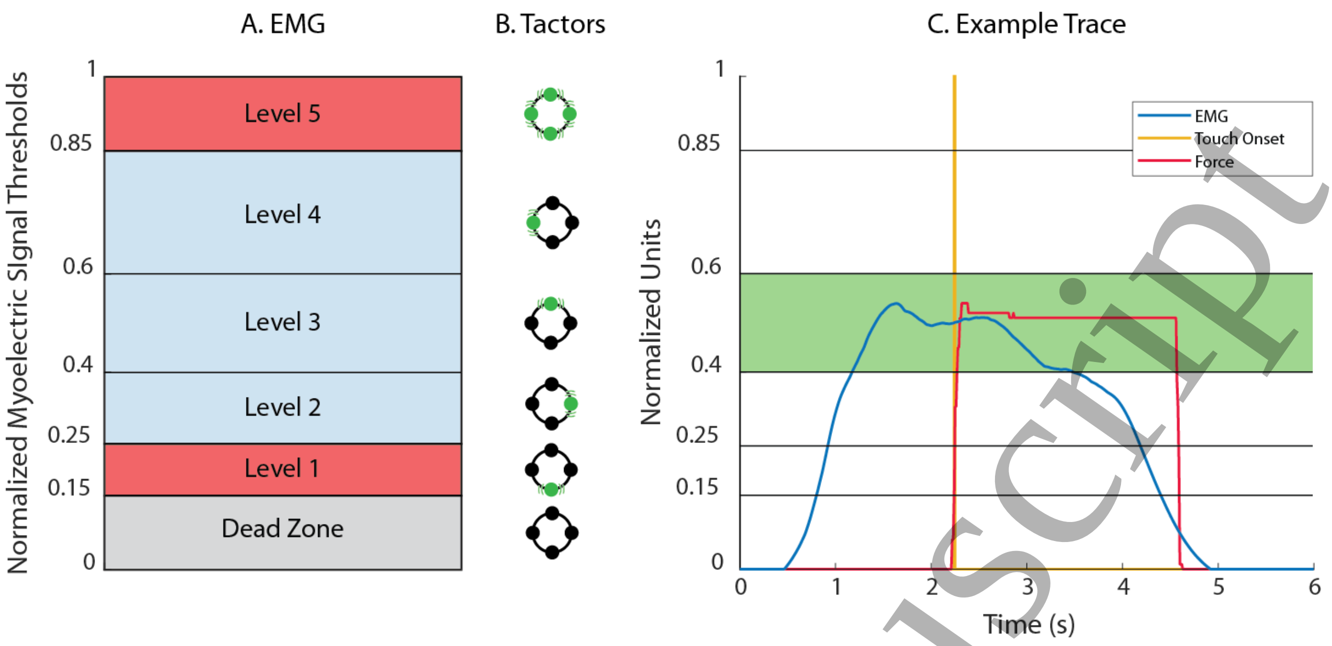

Figure 3: The control scheme implemented in this study. Each EMG level (A) corresponded to a specific spatial tactor activation pattern (B) and to a specific hand closing velocity/grasping force. The EMG feedback allows the subject to adjust the muscle contraction to the appropriate level during hand closing (C). In the visual representation of the tactors, green and black indicate active and inactive tactors respectively. The orientation of the tactors corresponds to the one shown in Figure 1

difference between the maximum vibration intensity and the sensation threshold. This value was selected to generate clearly perceivable, localized vibrations, which were also not too intrusive.

Following the calibration of the tactors, the subjects received a session of reinforced learning, to familiarize with the vibrotactile feedback. First, the tactors were activated in sequence, from 1 to 4 and then all together (level 5), while the experimenter verbally reported the level that each stimulation pattern represented. Then, the stimulation patterns 1 to 4 were activated in a random order (10 times per pattern) and the subject was asked to identify which level was being transmitted by the feedback. The experimenter indicated if the answer was correct or asked the subjects to try again until they identified the correct pattern. Finally, this test was repeated, but this time without verbal feedback from the experimenter (validation phase). If the correct identification rate was above 90%, the experiment continued. Otherwise, the procedure was repeated. All the subjects reached a success rate of over 90% after the first repetition, indicating that the selected feedback coding scheme was indeed easy to perceive and interpret.

Next, the subjects carried out the main experimental task, in which they controlled the prosthesis by relying on the vibrotactile feedback to modulate their muscle contraction to the correct level. Three values were selected for the MVC calibration (60, 40 and 20%) and the cutoff frequency (0.5, 1 and 1.5 Hz), resulting in nine different conditions. The parameter values were selected based on pilot tests and reflect values commonly used in literature [26], [39]–[42]. The effect of the different values of MVC calibration is visualized in Fig.

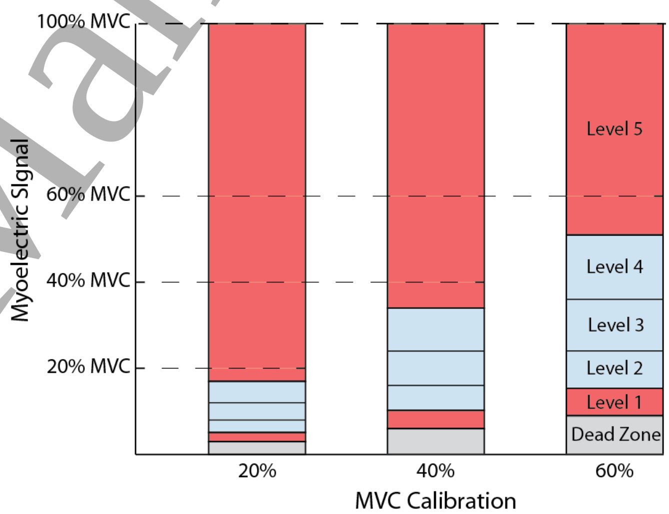

Figure 4: Illustration of different MVC calibration values (dashed lines at 20, 40 and 60%). The levels defined in Fig. 3 (normalized myoelectric signal) are mapped to different ranges of muscle contraction strength (myoelectric signal before normalization)

4. Each condition can be regarded as a different scaling of the levels shown in Fig. 3 into a percentage of the myoelectric signal range. The discretization of the normalized myoelectric signal into levels defined in Fig. 3 was the same in all conditions. These levels were mapped into vibrotactile feedback patterns and prosthesis closing velocity, as described in Section 2.3. On the other hand, as shown in Fig. 4, the normalization parameters (MVC calibration value) determine the correspondence between the levels defined in Fig. 3 and the muscle contraction strength, where 100% is the strongest

contraction the subject can produce. Therefore, the smaller the MVC calibration, the narrower the EMG levels. A lower MVC calibration required the subjects to perform weaker muscle contractions to reach a specific level and vice versa. They also had to maintain the contraction within a smaller range while the prosthesis closed. For instance, a normalized signal of e.g. 0.5 always corresponded to level 3, which activated the top tactor (as seen in Fig. 3) and commanded the hand to close at velocity 3 (see Section 2.3). However, for a condition with a lower MVC calibration (e.g. 20% versus 60%), a weaker muscle contraction was required to produce the same value (0.5) of the normalized signal.

The subjects were introduced to the EMG feedback using 40% MVC for the calibration and 1 Hz for the cutoff frequency. First, the subjects were allowed to freely contract their forearm muscles, while receiving vibrotactile EMG feedback. The myoelectric signal and the current contraction level were also shown on the screen, so that the subjects could easily associate the muscle activation level shown visually to the vibrotactile feedback. Next, the prosthesis was also activated and the subjects were instructed to close it and grasp the dynamometer. The generated force level was displayed on the screen. The experimenter explained that the EMG level the subjects generated, as indicated by visual and vibrotactile feedback, corresponded to a specific closing velocity, which, in turn, produced the same force level once the prosthesis closed around the dynamometer (e.g. level 2 of EMG resulted in force level 2).

The experimental task was then explained to the subjects. In each trial, the target level of grasping force was displayed on the computer screen. Only levels 2, 3 and 4 were tested (light blue in Fig. 3 and 4). The lowest and highest levels were not considered as they could be easily produced by the subjects by generating a minimal contraction that would move the prosthesis (level 1) and by maximally activating the muscles to saturate the myoelectric signal (level 5). The subjects were instructed on how to use EMG feedback, i.e. to increase the muscle contraction until the desired level is reached and then maintain this activation, waiting for the hand to close and completely grasp the dynamometer. The subjects then relaxed their muscles and the hand opened automatically, signaling the beginning of a new trial.

The sequence of parameter settings was randomized for each subject, to eliminate the possibility of bias due to training and familiarization. Each of the nine conditions was tested as follows: first, the subjects went through two training runs of 15 trials each, during which they could see the entire user interface (trial number, target force level, myoelectric signal and level, generated force level). Then, they performed the assessment block that comprised 45 trials, during which the subjects could only see the target level and the trial number. The target levels were presented to the subjects in groups of five trials of the same target in both the training and assessment blocks.

2.5. Data Analysis

The main aim of the present study was to assess how the calibration parameters affected the ability of the subjects to modulate the myoelectric signal online, using EMG feedback. Therefore, the primary outcome measure was the success rate in achieving the correct EMG level. The trial was deemed successful if the EMG level at the moment of contact between the hand and the gripper was equal to the target level. The role of the prosthesis in this setup was mainly to impose the timing constraint, as the subject needed to reach the target EMG level ideally before the moment of contact. Nevertheless, the success rate in generating the target force was also computed as a secondary outcome measure. The generated force was regarded as successful if the maximum force level produced during a trial was equal to the target level. Both EMG and force success rates were calculated as the number of successful trials over the total number of trials in the assessment block.

The data was tested for normality using the Shapiro-Wilk test. A repeated measures ANOVA or Friedman test was performed depending on the outcome of the normality test, while the post-hoc multiple comparisons were corrected using the Dunn-Sidak and Tukey-Kramer methods. IBM SPSS Statistics 25 and Mathworks Matlab 2019a were used for the statistical analysis. The average success rates were computed for each of the main factors (MVC calibration, cutoff frequency and target level) and compared between the factor levels. For instance, for each MVC calibration a success rate was determined for each subject considering all trials performed with that specific normalization (regardless of the cutoff frequency and target level). Then, the overall average success rate was computed across subjects. The other factors were treated in the same manner. Finally, the performance (Success Rate) was compared between cutoff frequencies for the given MVC calibration and vice versa. The threshold for statistical significance was set at $p<0.05$. The results in the text are reported as median {interquartile range}.

3. Results

Figure 5 depicts superimposed myoelectric signals, generated by a representative subject when reaching for each of the target force levels (2, 3 and 4), in two conditions: calibration at 40% MVC and 0.5 Hz cutoff frequency (Fig. 5A) and 20% and 1.5 Hz (Fig. 5B). The difference in the morphology of the generated myoelectric signals in these two conditions is substantial. The signals for the higher cutoff and lower calibration (Fig. 5B) were substantially more variable. The EMG was difficult to maintain within the target level (indicated as a green patch), it exhibited frequent under- and overshoots, as well as saturations to the maximum value,

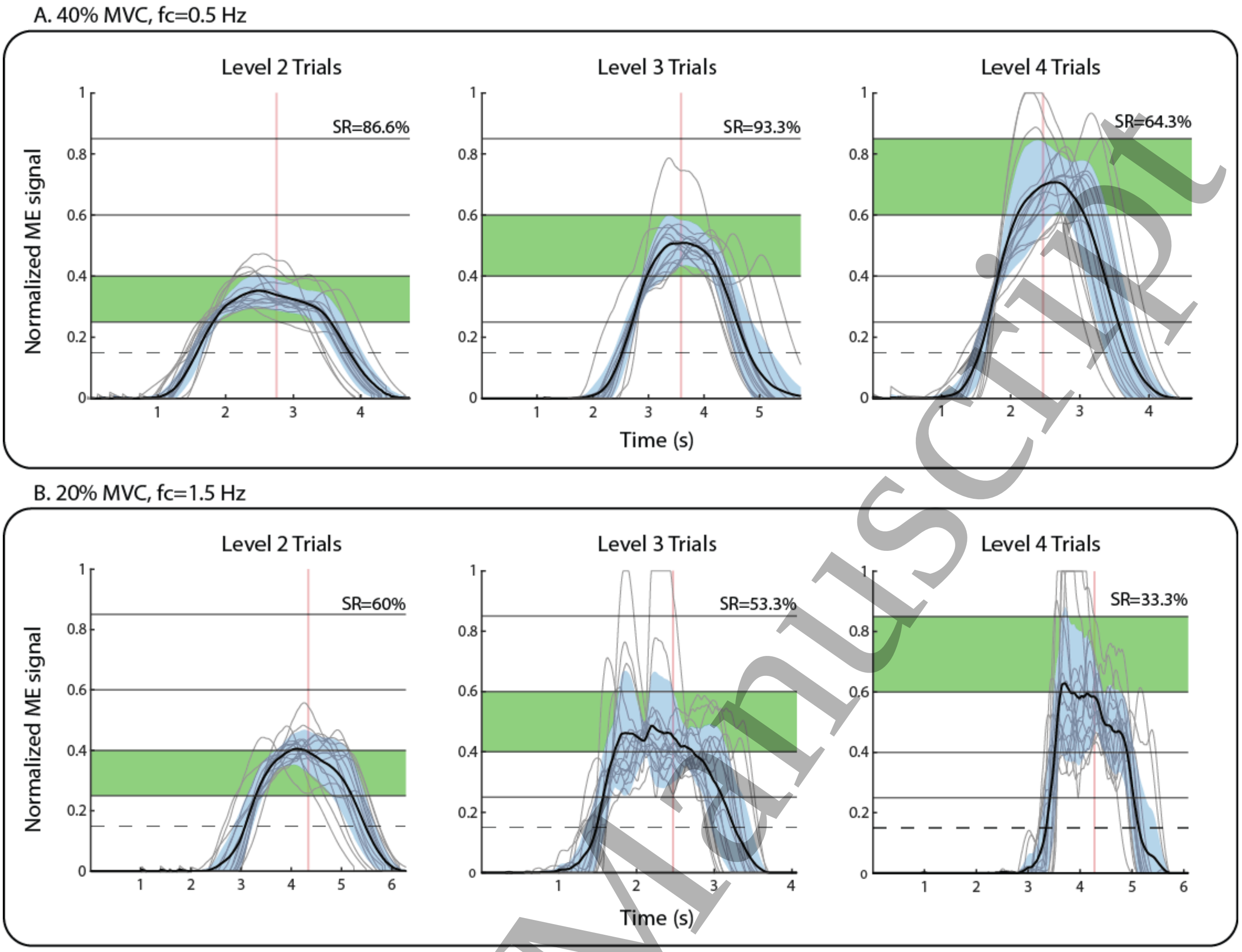

Figure 5: Myoelectric signal traces (grey) for the three levels in two parameter settings. The success rate (SR) is denoted in each case. The red vertical line denotes the moment of contact. The mean and standard deviation of the traces are denoted with the black line and blue highlighted area in each plot. The dashed horizontal line is the threshold of the dead zone, while the black solid horizontal lines are the thresholds of the higher levels. Note the difference in the morphology of the myoelectric signal between the two settings, as well as the higher signal variability for stronger muscle contractions in both conditions

especially at the higher target levels (3 and 4). Thus, the success rates were substantially lower, compared to the condition of lower cutoff and higher calibration. Nevertheless, even in this case, the signals concentrated around the target area (notice the mean profile, given as a black line). The myoelectric traces for the lower cutoff and higher calibration were smoother and more stable (Fig 5A) than those for a higher cutoff and lower calibration (Fig. 5B). In most cases, the subjects reached the target level (green patch) before contact (red line) and easily maintained the signals within that level. In contrast to the previous condition, where the mean profiles (black lines) concentrate close to the bottom/top of the target areas, the mean profiles are not positioned "safely" in the middle of their respective areas. Shortly after contact, they relaxed the muscle and the prosthesis opened. The higher levels (3 and 4) were more challenging to reach and maintain in this condition as well. The success rates for levels 2 and 3 were close to 90%, while it dropped to 64% for level 4 (note also two cases of saturation).

The summary results for all subjects are shown in Fig 6. The figure confirms that the task performance depended on the processing parameters of the myoelectric control pipeline. Specifically, the performance was better for the higher calibration values (Fig 6A). The success rate in achieving the target EMG level for the calibration at 60% (66.9% {4.7}) and 40% (63.9% {11.3}) was significantly higher compared to that obtained at 20% MVC (58.9% {7.3}). Regarding the filtering (Fig 6B), the median success rate was the highest with a cutoff frequency of 0.5 Hz (68% {4.7}), but the difference was significant only compared to the cutoff of 1.5 Hz, (58.2% {7.2}). Finally, Fig 6C shows that it was more difficult to successfully reach level 4, since the success rate decreased significantly to 55.7% {6.6} in this level, compared to the

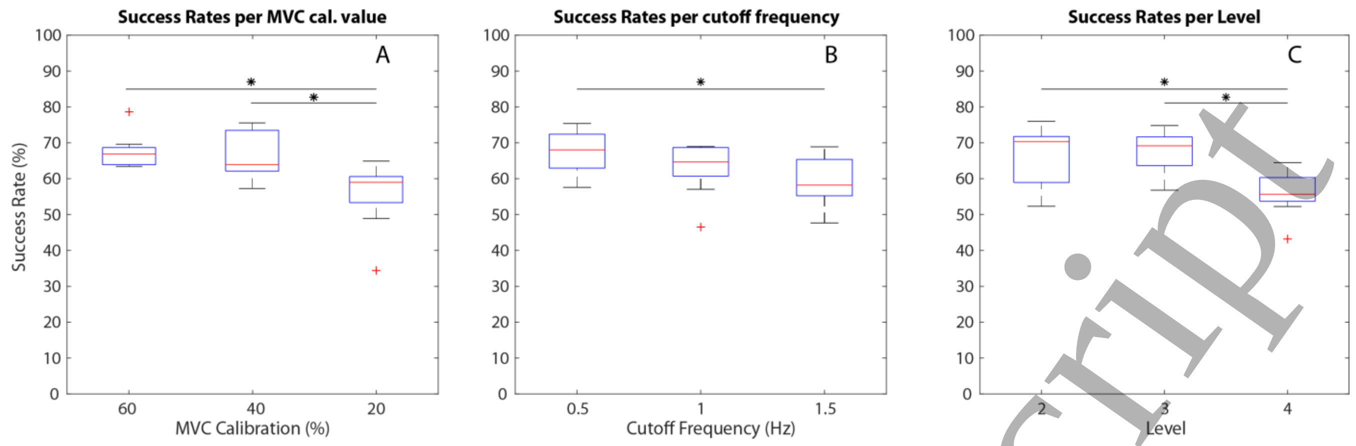

Figure 6: Summary results (box plots) of EMG success rates across different MVC calibration values (A), cutoff frequencies (B) and target levels (C). The performance was better for the higher calibration, lower cutoff and levels. The red line is median, boxes indicate interquartile ranges, whiskers represent min/max values and crosses are outliers. The horizontal bars denote statistically significant differences (*, $p < 0.05$).

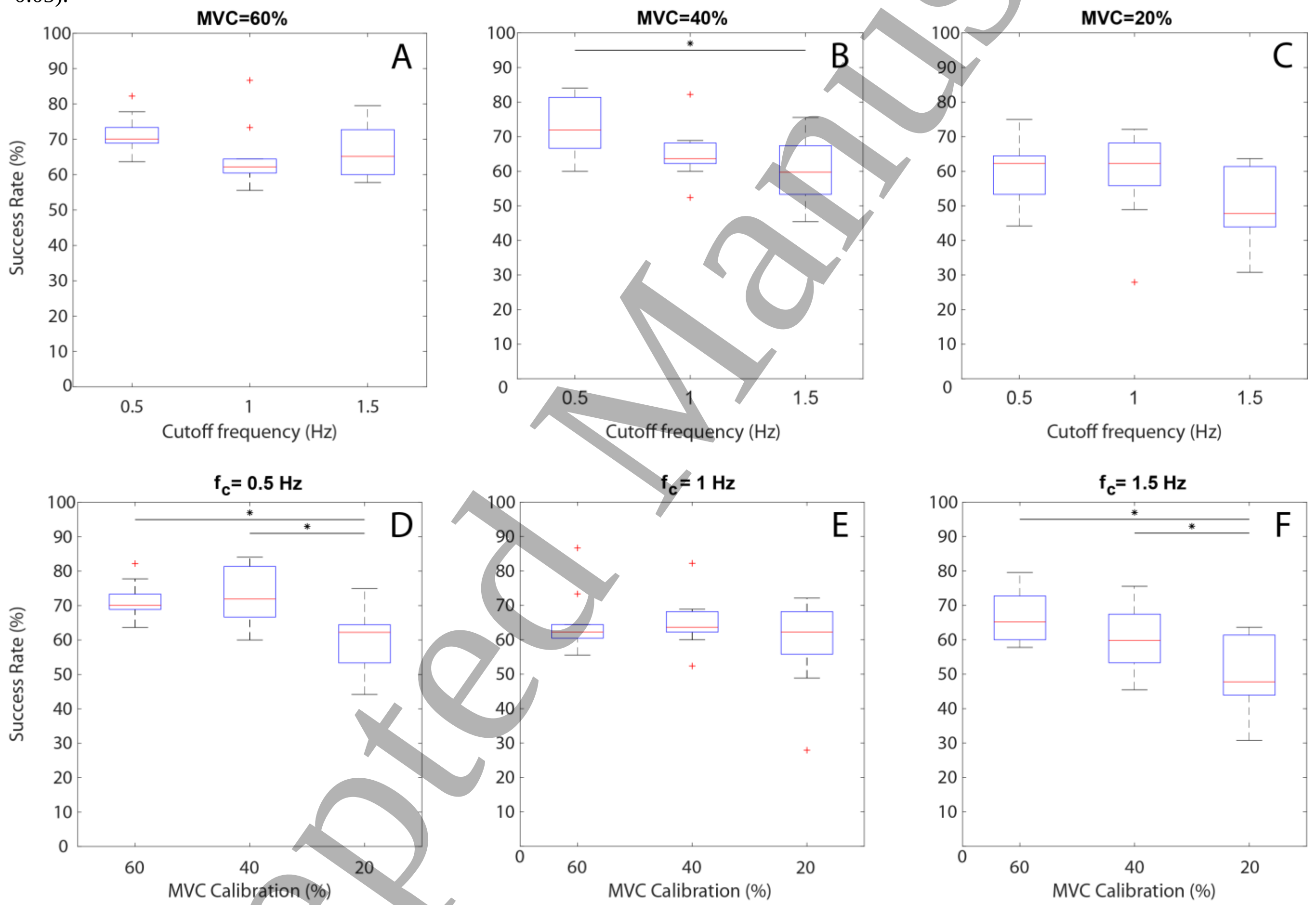

Figure 7: Summary results (box plots) of EMG success rates in each of the nine tested conditions, grouped by MVC calibration values (A, B, C) and cutoff frequencies (D, E, F). Note that a low cutoff (0.5 Hz) and higher calibration (40 and 60%) resulted in the highest success rates. The red line is the median, the boxes indicate interquartile ranges, whiskers represent min/max values and crosses are outliers. The horizontal bars denote statistically significant differences (*, $p < 0.05$).)

other two levels; 70.3% {12.8} for level 2 and 69.2% {8.0} for level 3.

Figure 7 shows the performance for each combination of the cutoff and calibration. In panels A-C, the success rates are grouped per MVC calibration value, whereas the panels D-F show the same boxplots, but grouped per cutoff frequency. For the cutoff frequencies of 0.5 and 1.5 Hz (Fig 7D and 7F), there was a statistically significant drop in performance for 20%

MVC, compared to 60% (p=0.0054) and 40% (p=0.0019). For a given MVC calibration, the median success rate for 0.5 Hz was higher compared to that of 1.5 Hz, however the difference in performance was statistically significant only at 40% MVC (Fig. 7B, p=0.0001). The overall highest success rates of 70.1% {4.4} and 71.9% {14.7} were achieved in the conditions (60%, 0.5 Hz) and (40%, 0.5 Hz), while the overall lowest result (47.8% {17.5}) was obtained for (20%, 1.5 Hz).

In general, the success rate for the force showed similar trends as for the EMG (Fig. 8). Specifically, the performance for the calibration of 60% (63.2% {6.4}) was similar to that at 40% (63.4% {8.1}) and significantly better than 20% (56.8% {3.5}) (Fig 8A). The success rate for the cutoff frequency of 1.5 Hz was 55.4% {7.8}, and this was significantly lower compared to that achieved for 0.5 Hz (62.8% {8.5}) and 1 Hz (63.5% {8.9}).

4. Discussion

The present study explored the impact of EMG processing parameters on closed-loop control of myoelectric signals and prosthesis force using EMG feedback. In this approach the myoelectric signals controlling the prosthesis are also transmitted as feedback to the user. The EMG feedback was already employed for myoelectric prosthesis control [25], [26], but different configurations have not been compared before. Therefore, the present study is the first step towards establishing objective guidelines for the implementation of EMG feedback. More specifically, we have systematically investigated the effect of the cutoff frequency of the low-pass filter and the percentage of MVC that are used to obtain and normalize the myoelectric signal respectively. The results demonstrated that it is preferable to use a higher MVC calibration value and a lower cutoff frequency, as these values resulted in better myoelectric and force control performance.

Overall, the EMG feedback allowed a robust online control of EMG contraction levels across the tested conditions. Despite a clear preference towards using a larger MVC calibration and a lower cutoff frequency, the median success rates differed at most 12% between the conditions, with the exception of a particularly low performance for 20% MVC and 1.5 Hz (Fig. 7). Importantly, the EMG feedback encoded five levels, while only three “internal” levels were investigated in the present study, since the first and last levels (1 and 5) could be easily attained by the subjects, as explained in the Methods section. The effective success rates for all 5 levels would be, therefore, higher, which is an important implication for the future clinical application. The present study also demonstrated that EMG feedback enabled successful force control in a prosthesis that is not sensorized. RoboLimb is not equipped with an embedded force sensor and the hand dynamometer was not a part of the control loop but was only used for assessing the generated grasping force.

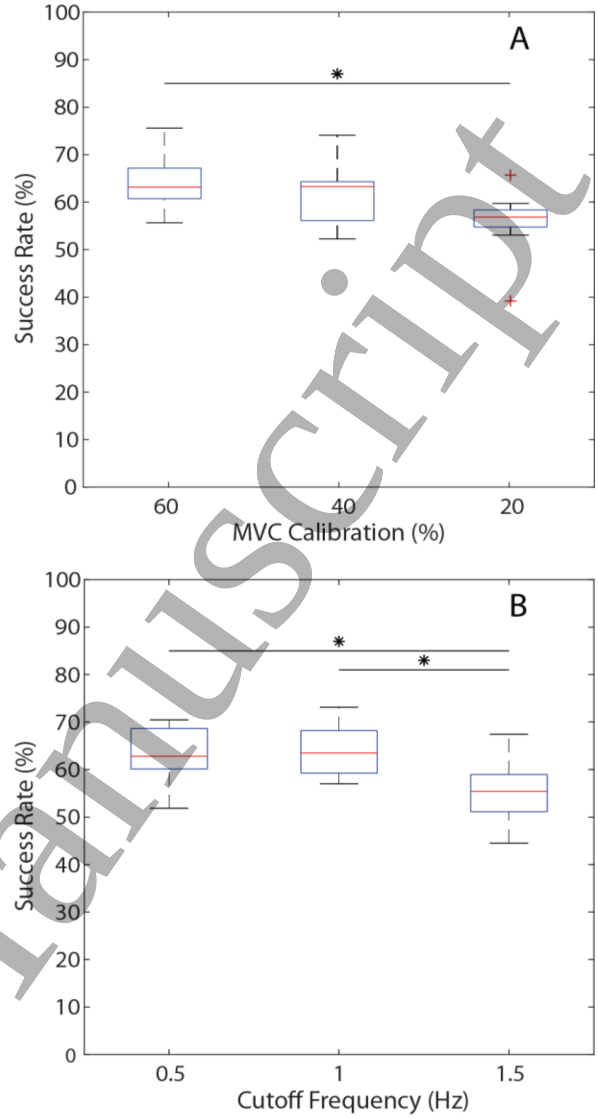

Figure 8: Summary results (box plots) of force success rates across different MVC calibration values (A) and cutoff frequencies (B). The red line is median, boxes indicate interquartile ranges, whiskers represent min/max values and crosses are outliers. The horizontal bars denote statistically significant differences (*, p < 0.05).

Calibrating to a lower MVC value (e.g. 20% MVC) theoretically makes the myoelectric signal easier to control by decreasing its variability. However, it seems that higher control sensitivity due to smaller ranges allocated to each EMG level (Fig. 4) , as well as lower SNR for weaker contractions [34] were in this case more influential factors leading to overall worse performance. As shown in some studies [35], [43] although the absolute variability decreases with weaker contractions, the variability expressed relative to the mean level that the subject tries to achieve and maintain is, in fact, likely to increase. Therefore, the recommendation would be to choose higher calibration levels (40 and 60%). Nevertheless, normalizing to a lower MVC percentage can also delay the development of muscle fatigue. Therefore, calibrating to 40% might be an appropriate compromise, leading to better control, while also requiring less effort from the user.

Regarding the filtering, the lowest cutoff seems to be the best overall. A lower value for the cutoff frequency results in a smoother myoelectric signal, but potentially introduces a lag between the muscle contraction and the generated myoelectric signal, especially for the lowest frequency (0.5 Hz). The obtained results, however, demonstrate that this delay did not negatively affect the ability of the subjects to exploit the feedback and modulate the signal online. It is important to note that the subjects were instructed to gradually increase their contraction to the target level, thereby avoiding rapid changes in the muscle activation, which likely decreased the impact of the delay. Finally, this could also explain the good performance in the low cutoff frequency and higher calibration conditions (40 and 60% with 0.5 Hz). In this case, the strong filtering compensates for the increased variability of the myoelectric signals arising from the stronger contractions required in these conditions. As the results demonstrate, the subjects can easily adapt to the time delay, while, at the same time, they can enjoy lower sensitivity (larger EMG ranges allocated to each level, see Fig. 4).

The success rate in achieving the target force exhibited a similar (but not identical) trend to that observed for EMG (Fig. 8 versus Fig. 6). In principle, the “translation” from the EMG level to the force level is not an ideal process. For instance, if the subject reaches the target EMG level too close to the contact event or changes the level after contact, the produced force might not correspond to the EMG at the moment of contact. In addition, we noticed some variability in the measured force depending on the exact closure of the hand around the dynamometer. This indicates that the properties of a specific prosthesis need to be considered when implementing EMG feedback. Importantly, the focus of the present study was on the online EMG modulation, which sets the baseline performance of this approach and is independent from the actual prosthesis used. The role of the prosthesis was to impose a time constraint as the subjects were instructed to reach the desired level before the prosthesis contacted the dynamometer. Nevertheless, closed-loop control with EMG feedback has been successfully applied to the Michelangelo hand [25], which differs substantially from the RoboLimb, used in this experiment.

Another consistent finding is that the subjects found it harder to reach the highest target level (level 4). This behavior was observed even though the levels had been designed to accommodate the higher EMG variance observed in stronger muscle contractions (Fig 3). It is possible that a redesign of the thresholds for the EMG levels, for instance a further widening of level 4, could enhance the performance in that level. However, this would mean that the width of other levels would need to decrease, which might worsen the performance at those levels. A comprehensive study into the optimization of the threshold values as well as the optimal number of levels is an important future goal.

The present experiment was performed on able-bodied subjects. However, we believe that this is not a significant limitation, considering the aim, experimental setup and scope of the study. Namely, the control was simple, as the subjects were asked to modulate a single EMG signal, which would be feasible for most amputees. The aim of the study was not a direct clinical translation but a general investigation of the calibration parameters and their effect on performance of EMG feedback. Although the performance in amputee subjects could be different compared to an able-bodied population, especially in case of experienced users, the relative performance between the conditions is likely to remain the same.

Due to space limitations, the C2 tactors could not be placed on the forearm but were instead positioned on the upper arm. In clinical applications, the tactors will be fitted into the socket, to obtain a self-contained system. Importantly, the feedback scheme in the present study is purposefully designed to be easy to perceive and simple to interpret. Therefore, the placement of the tactors (forearm versus upper arm) is unlikely to significantly affect the performance.

The next step in this research is to assess the EMG feedback calibrated using the values recommended in the present study during prosthesis control in a functional task. Mounting the prosthesis to the limb might affect the quality of the sensations, while the focus on the task could have an impact on the ability to perceive and interpret the dynamic EMG feedback. Therefore, a functional assessment is the necessary next step towards the envisioned clinical application.

Subjective experience and preference is another factor and can be considered when choosing the calibration parameters. However, the present study did not investigate the user experience when controlling the prosthesis in different conditions, but rather focused on objective performance measures. Importantly, the EMG feedback was designed to assist the subject in producing force levels across the full force range of a given prosthesis, as the normalized EMG levels were mapped to a full range of closing velocities. In a clinical application, the user will have to determine, through training and experience, which force level is appropriate for which task in their daily lives. If a different prosthesis is used, generating the same levels of muscle activation (normalized to a percentage of their MVC), will still create the same normalized force levels, but those levels will now produce a grasping force of different magnitude. Nevertheless, even this parameter may be further adjusted by mapping the EMG to a subrange of closing velocities and thereby a subrange of the full force range of a given prosthesis.

The present study is the first effort to investigate how the calibration parameters of the myoelectric processing pipeline affect the quality of closed-loop control using EMG feedback. The low-pass cutoff frequency and the normalization level determine the signal sensitivity and variability. The value selection for these parameters have tradeoffs (e.g., lower variability but higher time lag and/or sensitivity). Overall, the present study has shown that the EMG feedback provides robust control across parameter combinations. The results have, nevertheless, shown that there is a clear preference towards a higher percentage of MVC calibration and a lower cutoff, since these values resulted in significantly better control for both EMG and force. This is an important outcome for the clinical application of EMG feedback for the control of a myoelectric prosthesis during functional tasks.

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5. References

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