University of Groningen

Looking beyond proportional control

Heerschop, Anniek; van der Sluis, Corry K.; Otten, Egbert; Bongers, Raoul M.

Published in:
Biomedical signal processing and control

DOI:
[10.1016/j.bspc.2019.101647](https://doi.org/10.1016/j.bspc.2019.101647)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2020

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Heerschop, A., van der Sluis, C. K., Otten, E., & Bongers, R. M. (2020). Looking beyond proportional control: The relevance of mode switching in learning to operate multi-articulating myoelectric upper-limb prostheses. *Biomedical signal processing and control*, 55, [101647].
<https://doi.org/10.1016/j.bspc.2019.101647>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Looking beyond proportional control: The relevance of mode switching in learning to operate multi-articulating myoelectric upper-limb prostheses

Anniek Heerschop^{a,*}, Corry K. van der Sluis^b, Egbert Otten^a, Raoul M. Bongers^a

^a University of Groningen, University Medical Centre Groningen, Center for Human Movement Sciences, Groningen, the Netherlands

^b University of Groningen, University Medical Centre Groningen, Department of Rehabilitation Medicine, Groningen, the Netherlands

ARTICLE INFO

Article history:

Received 22 February 2019

Received in revised form 11 July 2019

Accepted 7 August 2019

Available online 29 August 2019

Keywords:

Electromyography

Motor learning

Myoelectric control

Perception-action

Prosthesis

ABSTRACT

Objective: Operating a multi-articulating myoelectric prosthetic hand requires both proportional control of surface electromyography (sEMG) signals and accurately producing triggers to switch between grip types. Proportional control, used for hand opening/closing, has been studied extensively but the grip-switching control far less so. Can switching be trained and if so, how early on can improvement be seen? And is the ability to produce precise switches related to proficiency in proportional control? We examined individual learning differences, monitored improvements in switching control, and assessed whether skilful proportional control predicts proficient switching.

Methods: Twenty-three unimpaired participants fitted with sEMG electrodes on the wrist flexors/extensors performed two 10-minute tasks: an adaptive virtual catching task (proportional control) and an sEMG-feedback-based switching task, with multiple performance measures being recorded and compared.

Results: Most outcome measures revealed large individual differences, with 47–87% of the participants showing improvement in switching and 14% deteriorating. As hypothesized, no correlations were found between mode-switching and proportional-control skills.

Conclusion: Learning to generate accurate grip-switching control proved difficult and might not be feasible for all individuals with upper-limb amputations. Unaffected participants showing proficient proportional control were not automatically good at producing well-tuned mode switches.

Significance: In rehabilitation, clients with good proportional control are often offered a multi-articulating hand prosthesis. Since we found no clear associations between the proficiency in proportional movements and mode switches, this rationale may warrant reconsideration. Rather, when selecting the most optimal prosthesis, an individual's skills in both control types should be examined separately.

© 2019 Published by Elsevier Ltd.

1. Introduction

In current rehabilitation practice most upper-limb prostheses are controlled with signals recorded using surface electromyography (sEMG), also called myosignals. In the last decade, several types of so-called myoelectric multi-articulating hands, i.e. hands of which thumb and fingers have multiple joints, have become commercially available. The increased number of articulating joints or degrees of freedom (DOFs), provides its user with a large range

of pre-programmed grip types and wrist motions, also defined as modes. Some prostheses offer up to 25 grip types [1], among which are grips such as power grip, precision grip, key grip and index pointing, etc. [2–5]. However, this wide variety of modes entails a challenge for the user: the available modes use a fixed number of electrodes that is smaller than the total number of modes available. So far, three main strategies to overcome this challenge have been experimentally tested; conventional control, pattern-recognition control, and simultaneous and proportional mapping [6]. Currently only the conventional control system is commercially widely available, while pattern recognition control has only recently been marketed and then mainly in the USA.

In this paper we accordingly focus on the conventional control strategy where DOFs are controlled in a sequential-proportional way using two surface electrodes to derive myosignals, usually

* Corresponding author at: University of Groningen, University Medical Centre Groningen, Centre for Human Movement Sciences, P.O. Box 196, 9700 AD Groningen, the Netherlands.

E-mail address: A.Heerschop@umcg.nl (A. Heerschop).

placed on the wrist flexors and extensors used to open or close the hand, respectively. The prosthesis user has to produce sequential-proportional control, which means that the hand first is switched in the appropriate mode after which this mode can be controlled proportionally (e.g., switching to power grip and then opening and closing the hand proportionally) [6,7]. Here the term proportional control indicates that the opening/closing speed of the hand is proportionally scaled to the amplitude of the myosignals. To perform such a mode switch, the user needs to generate 'triggers,' i.e. distinctive sEMG signals from either the flexors or the extensors, or from both muscle groups simultaneously. The most commonly used triggers are 1) co-contractions, created by briefly contracting the flexors and extensors simultaneously; 2) single pulses, consisting of a brief contraction of one of the muscle groups; and 3) hold signals, long contractions of one of the muscle groups [8]. In our study we looked at both aspects of sequential-proportional control by monitoring the user's ability to switch smoothly between two modes and the ability to generate proportional control.

For skilful prosthesis use, appropriate and sophisticated myosignals are required. Previous papers have indicated that producing adequate signals for proportional control of the hand can be a challenge [e.g. 2,9–12], but that signal quality can improve with training [3,13–15]. The importance of training is also underlined by the fact that a lack thereof has been identified as one of the reasons for device abandonment [3]. Another huge challenge in arm-prosthesis training is how to determine individual skill levels both before and after training, essential for deciding on the course of the rehabilitation process, progress monitoring, and the choice of prosthetic components, such as the type of hand and the option of adding a movable wrist. In rehabilitation practice, a client's proportional-control proficiency is often used to decide whether (s)he is a candidate for a multi-articulating prosthesis, requiring sequential control. This is also one of the reasons that previous studies on this topic have primarily focused on different aspects of proportional control [3,15,16], while grip or mode switching has received hardly any attention [7].

Moreover, the studies on proportional control report large individual differences: some participants showed quite skilful proportional control whereas others could open and close the hand at only one, mostly high, speed [3,15,16]. Considering these large differences in this aspect of motor control, the first aim of our study was to look whether these differences would also occur in participants learning to produce mode switches. Our second aim was to assess whether mode-switching ability would improve with training. Since in proportional-control studies improvement was seen after a relatively short training duration, we also decided on a brief training period [15,17–19]. Our third aim was to explore the relationship between an individual's performance level in proportional control and their skill in mode switching. This latter relationship may have practical relevance given that the choice of hand prostheses is currently mainly based on a client's proportional control skills while we have hardly any knowledge about whether their capacity to produce accurate myosignals has any implications for their ability to switch between grips. Because previous studies revealed a lack of correlation between performance on different proportionally controlled tasks [20], we did not expect to find a strong correlation between the two types of control. If confirmed, this may have consequences for rehabilitation practices, in that, when looking for the most optimal hand prosthesis, proportional and switching control should be examined separately.

2. Materials and methods

All participants performed two tasks: a switching task, more specifically, a visual sEMG-based feedback task (EF), and a proportional myoelectric control task, i.e. an adaptive virtual catching (AC)

task. Both tasks were controlled using the same two sets of muscles: the flexors and extensors of the wrist. In the EF task participants were asked to produce as many co-contractions as possible within a 1-minute time frame while their myoelectric signals were presented to them on a computer screen. Here a co-contraction is a signal generated by a simultaneous, short contraction of the flexors and extensors of the wrist. During the AC task participants had to play a serious game in which falling objects had to be caught with a virtual grabber. The sEMG signal of the extensors was used to open the grabber, the sEMG signal of the flexors to close the grabber.

2.1. Participants

Participants were all unimpaired adults (18 years or older), mostly university students. All were right handed, had normal or corrected to normal vision, were free of any (history of) of arm and upper-body disorders, and had no prior experience in using a myoelectric device. The experiment was performed at the Centre for Human Movement Sciences of the University Medical Centre Groningen, The Netherlands, approved by the local ethics committee and included in the Dutch Trial Register (NTR5876). Written informed consent was obtained from all participants prior to the start of the experiment.

2.2. Materials

During both tasks participants were seated in front of a computer screen wearing 2 sEMG electrodes (13E200 electrodes, MyoBock, Otto Bock Healthcare products, Austria) placed on the most prominent muscle bellies of the flexors and extensors of the right wrist. In order to keep the delay between the muscle contraction, the collection and processing of the myoelectric signals, and the action of the end effector identical, the same electrodes were used in both tasks.

In the EF task the electrodes were connected to a MyRio (National Instruments, USA), on which custom-built LabView software (National Instruments Corporation, USA) was used to digitally filter (band filter, cut-off frequency 10 Hz; low-pass filter, cut-off frequency 35 Hz) and normalize (between 0 and 1, see Procedure) the signals. The normalized signal was fed from the MyRio to a laptop computer via wireless UDP at 200 Hz. The custom-built software on the MyRio also detected whether a correct co-contraction was made. In Fig. 1 (left panel) the black and blue lines show the sEMG of the extensors and flexors of the wrist, respectively. Only when both signals passed the threshold amplitude of 0.3 at the same time and descended below this threshold again within a pre-fixed time of 350 ms, did the software identify this as a co-contraction. For purposes of illustration, this moment is indicated by a red, vertical line. The participants received on-screen feedback (Fig. 1, right panel), where a black rectangle superimposed on the signals indicated successfully made co-contractions.

In the AC task the electrodes were connected to a desktop computer via a Porti-5 data acquisition device (TMS International, The Netherlands, sample rate 500 Hz). The same custom-built LabView software as in the EF task (see EF task description) was applied to digitally filter the signals. The filtered signal was calibrated to the highest value and scaled between 0 and 1 (see Procedure) after which the scaled signal was fed at 100 Hz from the desktop computer to a laptop computer via UDP.

The design of the AC task can be seen in Fig. 2. The opening and closing speed of the grabber was proportionally related to the amplitudes of the normalized sEMG signals to simulate the functioning of a real prosthesis. In this adaptive game, participants also received on-screen feedback (see Procedure), enabling them to adapt their catching strategies on the basis of this information.

Fig. 1. Left; Example of a correct co-contraction detection in the sEMG-feedback (EF) task. The two lines represent the sEMG signals of the extensors (black) and flexors (blue). Correctly generated co-contractions are indicated by the red vertical line. Right; Example of the visual feedback provided. The two lines represent the sEMG signals of the extensors (green) and flexors (red). Correctly generated co-contractions are indicated by a superimposed black rectangle.

Fig. 2. Overview of the adaptive catching (AC) task. Objects drop from the top of the screen and have to be caught with the grabber shown at the bottom of the screen. Closing the hand too fast results in the object being crushed (bottom left corner). Opening the grabber too wide results in the grabber being broken (bottom right corner).

2.3. Procedure

Prior to starting the task the most prominent muscle bellies of the extensors and flexors of the wrist were palpated, after which one electrode was placed onto the extensors and the other on the flexors using an elastic sweatband. Normalization of the sEMG signals was similar for both tasks: participants were asked to first flex and then extend their wrist slowly until they reached their maximum force to thus determine the maximum amplitudes of the sEMG signals for both the extensors and the flexors, which were then normalized between 0 and 1. When changing from AC to EF or vice versa the electrodes remained on the arm, preventing deviations due to position changes.

During the EF task the scaled sEMG was shown on the screen and participants were instructed to produce co-contractions by finding

a way to get both signals to rise quickly and simultaneously to the top of the screen and to subsequently make them decline again to the bottom of the screen together as fast as possible. They were told they would receive visual feedback, where a black rectangle superimposed over the signals would indicate that they had performed the co-contraction correctly and a grey rectangle would appear if a single pulse from the extensor was detected, but that these could be ignored since they were irrelevant for the current experiment.

For the AC task the maximum opening/closing speed of the grabber matched the maximum amplitude of the scaled sEMG signals. After calibration, participants were told how to play the game. The goal was to catch randomly sized objects (with a fixed minimum and maximum size) that would come falling down in a straight line from the middle of the top of the screen using the grabber displayed in the middle of the bottom of the screen. The game

Table 1
Definitions of the outcome measures.

Measure	Category	Task	Description	Aim
Amplitude	SC	EF	The height of the generated trigger [20]. In order for the algorithm to recognize a correct trigger, a threshold of 0.3 (normalized signal) has to be surpassed. This measure is calculated for both sEMG signals separately and is averaged across the two. A higher amplitude indicates better performance.	1/2
Amplitude Difference	SC	EF	The difference in the amplitudes of the two sEMG signals. Both signals need to surpass a threshold before the algorithm recognizes a correct trigger. Large differences between the amplitudes can therefore prevent a successful trigger. A smaller Amplitude Difference indicates better performance.	1/2
Width	SC	EF	The duration between the onset and conclusion of a trigger command [20]. The duration needs to remain below a 300 ms threshold in order for the algorithm to recognize it as a trigger. Shorter trigger duration reduces the likelihood for the algorithm to interpret the signal as an opening or closing command of the hand and thus reduces the chances of unintentional movement of the hand. Width is calculated based on the rise of the first signal and the fall of the last signal. A smaller Width reflects better performance.	1/2
Phasing	SC	EF	The time difference between the peak amplitudes of both sEMG signals [20]. Since, ideally, the peaks occur simultaneously, a smaller Phasing represents better performance.	1/2
Time Between Switches (TBS)	PM	EF	The time between two correctly performed switches as defined by the detected end times of the two correct switches. The smaller this measure, the better the performance.	1/2/3
Switching Accuracy (SA)	PM	EF	The percentage of switch attempts that was performed correctly. The number of attempts is determined by detecting when one or both sEMG signals surpassed a threshold set at 10% of the maximum sEMG amplitude as reached during the calibration phase. The number of correctly performed switches was stored in the collected data. The higher the Switching Accuracy, the better the performance.	1/2/3
Aperture Gap	PM	AC	The difference between the maximum aperture in a trial and the size of the falling object. The mean Aperture Gap per five minutes was computed. The two means for the two 5-minute training sessions were averaged. A small Aperture Gap indicates better performance.	3
Catching Accuracy (CA)	PM	AC	The percentage of fallen objects that were caught correctly (i.e., without being crushed). Calculated per completed level and averaged over the 10 minute duration of the task. The higher the Catching Accuracy, the better the performance.	3

Note: SC = switch characteristics, PM = performance measures, EF = EMG feedback task, AC = adaptive catching task.

displayed feedback about the width of the opening of the grabber relative to the object size and the grabber's closing speed. The objects to be caught came in three different shapes (diamond, square, and ellipse) and three different colours (red, light blue, or blue) that indicated the three levels of breakability (easy, medium or hard, respectively). Feedback was given on the grabber's aperture; if the aperture exceeded 1.5 times the diameter of the falling object, the grabber would visually start to vibrate and give off sparks (Fig. 2), while opening the grabber more than 1.7 times the object's diameter would cause it to close rapidly, making it impossible to catch the object. These values were based on results published by van Dijk et al. [21]. The participants were briefed to avoid crushing the objects by closing the grabber at both the appropriate time and speed. They were also explicitly instructed to scale their hand opening to the objects. Training with the embedded augmented feedback has been shown to ensure transfer of the learned behaviour from the game to actual prosthesis use [18].

2.4. Design

Participants performed both the EF and the AC task on the same day, each task lasting ten minutes divided into two 5-minute blocks. In the EF task the 5-minute periods were subdivided into five 1-minute blocks separated by 30-second breaks. During the two 5-minute sessions of the AC task, participants played levels that always comprised 25 falling objects, with 30-second breaks between completed levels.

Participants were randomly divided into two groups, performing the tasks either in the order EF – AC – AC – EF, or AC – EF – EF – AC, for which we had opted (i) to make sure that underlying learning effects were evenly spread across conditions while also avoiding that one condition was only performed in the early learn-

ing phase and the other only in the late learning phase, and (ii) to reduce time delays and the chance of failures due to electrode connector changes and signal recalibration. When preparing participants for the second task, the electrode connectors had to be changed and signals recalibrated for the new task, affording the participants a 2-minute break (approximation), while they also had two minutes between the two EF and AC sessions. Thus, for each task, sessions lasted 20 min including breaks and several minutes for task preparations.

2.5. Outcome measures

Customized Matlab (2015b, The Mathworks Inc., USA) scripts were used to analyse the data of the eight outcome measures, which were divided into two categories: 1) switch characteristics (SC, Table 1, 4 upper rows), and 2) performance measures (PM, Table 1, 4 lower rows). The SCs were either identical to or derived from the parameters described by Tabor et al. [22] and were only calculated for correctly performed switches. The 'Aperture Gap' PM was taken from Bouwsema et al. [14,23], who showed it to be a reliable indicator of the functional use of a prosthesis, with aperture gaps being correlated with the Southampton Hand Assessment Procedure (SHAP) scores [24] of experienced prosthesis users.

2.5.1. Data analysis

As to our first aim, assessing individual differences in switching abilities, means, standard deviations, medians, and interquartile ranges were calculated for all EF measures.

Regarding our second aim, monitoring changes in switching control during and after training, all of the EF measures described in Table 1 were calculated per minute. The Pearson correlation coefficient (r) of the least square line between the per minute outcomes

Fig. 3. Normalized spread for all 6 outcome measures of the EF task shown on the x-axis. Per outcome measure a boxplot shows the median (red) with interquartile ranges (blue) and the mean (X). The normalized outcome per participant is shown next to each boxplot (filled circles). Outliers are indicated by a +.

across the 10-minute period was computed for each individual outcome measure, where r can vary between -1 and 1 . For Amplitude and Switching Accuracy (SA) an increase over time indicated improvement with a positive value of r indicating improvement and a negative r value indicating deterioration. For the other outcome measures (Amplitude Difference, Width, Phasing, and Time between switches (TBS)) a decrease over time indicated improvement, reflected in a negative r value. P-values smaller than 0.05 were considered to be statistically significant.

To assess associations between proportional and switching control skills, our third goal, participants were ranked per task based on their individual performance data. Kendall rank correlation coefficients (τ) were computed to analyse agreements in scores between the participant's performance on the two tasks. EF and AC task performance was compared as follows. First, for the EF task participants' were ranked based on TBS mean times, while for the AC task rankings were based on the Aperture Gaps (where both measures reflect the participants' skill in the respective task). Second, Switching Accuracy (SA, EF task) and Catching Accuracy (CA; AC task) were compared. For all comparisons, correlations with P-values smaller than 0.05 were considered statistically significant.

3. Results

Twenty-four participants were included. One participant was unable to complete the AC task due to technical malfunctions in the experimental set-up and was therefore excluded. The 23 remaining participants performing both tasks had a mean age of 22.7 years (SD 3.2) and six were male.

3.1. Individual differences in switching (aim1)

Fig. 3 shows the boxplots of the normalized values of the outcome measures for the EF task. Individual differences in co-contractions were quite large, with most measures showing a wide distribution. Furthermore the plot reveals a few outliers for three outcome measures and several outliers for one outcome measure (TBS). The actual values of the outcome measures and their distribution, the mean (SD) and the median (IQR) of the non-normalized

Table 2

Means, standard deviations, medians, and interquartile ranges for all outcome measures of the EF task.

	Mean	SD	Median	IQR
Amplitude	90.65	28.93	78.95	37.72
Amplitude Difference	48.30	35.72	35.36	40.69
Width	47.47	4.81	47.88	4.04
Phasing	4.96	1.69	4.69	1.23
Time Between Switches (TBS)	9.52	11.12	4.27	7.88
Switching Accuracy (SA)	26.60	15.62	27.40	25.51

values, listed in Table 2 show the same large variations among the individuals.

3.2. Change in switching control after training (aim 2)

To determine the effects of the 10 min-training sessions, correlations were calculated for all six EF outcome measures for each participant (Fig. 4). TBS and SA were the measures for which most participants showed improvement, but this was not significant for all participants, while some even showed a mild deterioration. The data of four of the six measures indicated both (significant) improvement and (significant) deterioration over training. Table 3 shows results per outcome measure. Although on average 64.5% of the participants showed improvement, the change was only significant for 25.4% of the participants. Of the 35.5% showing a decline in their performance, this was significant in 14.5%.

3.3. Agreement between proportional and switching control abilities (aim 3)

The rankings for Aperture Gap and TBS did not correlate ($\tau = -0.05$, $p = 0.75$, left panels Fig. 5), nor was this the case for SA and CA ($\tau = -0.01$, $p = 0.96$, right panels Fig. 5). Fig. 5 further shows that the individual differences in performance were quite large for all of the outcome measures (TBS: mean 6.53 (SD 9.96), Aperture Gap: mean 0.21 (SD 0.21), SA: mean 27.17 (SD 16.04), CA: mean 23.57 (SD 12.04).

Fig. 4. Each panel shows a different outcome measure, with the dots representing individual participants. The red line indicates the threshold for significance, values between 0.05 and 0.1 are interpreted as trends towards significance. The x-axis shows the correlation-coefficient (r). Depending on the outcome measure, positive or negative r values represent improvement or deterioration, as indicated per outcome measure. Participants with P -values larger than 0.1 are indicated by (+) at their r -values at the top of the panels. The number of participants with $P < 0.05$ for improvement and deterioration and those above 0.05 are represented with (N=...). Gray shading reflects deterioration in all panels.

Table 3
Improvement per outcome measure.

	% improvement	% significant improvement	% deterioration	% significant deterioration
Amplitude	56.5	26.1	43.5	26.1
Amplitude Difference	47.8	13.0	52.2	34.8
Width	60.9	26.1	39.1	13.0
Phasing	65.2	8.7	34.8	13.0
Time Between Switches (TBS)	87.0	34.8	13.0	0.0
Switching Accuracy (SA)	69.6	43.5	30.4	0.0

4. Discussion

We compared performance of 23 unaffected adults on two myoelectrically controlled tasks, one requiring switching control (EF task) and the second requiring proportional control (AC task). Both tasks were controlled using the sEMG of the same set of forearm muscles. As anticipated, we found large individual differences in the EF task on multiple outcome measures. Furthermore, after training there was no outcome measure on which all participants improved. Depending on the outcome measure, we found both significant improvement and significant deterioration in switching skills, with improvement rates being generally higher. Lastly, we did not find any correlations between the performance on the two tasks.

4.1. Large individual differences in switching-control (aim1)

A note has to be made about the variation found in the participants' performance in relation to the methods used to calculate the outcomes measures and the algorithm that detects the correct switches. The detection algorithm applied thresholds to both the signal amplitude and duration. The amplitude threshold needed to be surpassed while the maximum duration should not. As a result, for Amplitude and Amplitude Difference, all signals above the threshold were correct, leaving room for rather large variations. Note that as long as the threshold is passed, this variability does not affect performance. For Width and Phasing, which are dependent

on the duration threshold, less variation is possible, automatically resulting in less individual variability. Note that this remark only holds for the switch characteristics (SC) outcome measures and not for the performance measures (PM) measures since the latter are not directly derived from the sEMG signal.

That we found large variations in all switching outcomes, is a novel finding. Although there are few studies comparing conventional control with pattern-recognition control of multi-articulating prostheses [8,22], none of the available studies focused explicitly on individual differences and the effects of initial learning when generating triggers for switches as we did in the current study. It is, however, plausible that these individual differences will diminish with further training. We were unable to examine this within the scope of this study but in future research we hope to look into this possibility, with more extended training preferably spread over several days, with other switch commands also being studied.

From clinical practice we already know that making co-contractions is hard for many individuals with an amputation and for some it is even impossible. When looking from the perspective of Ecological Task Analysis (ETA) [25] this can be explained by the fact that all types of actions emerge from the interaction between the individual, the environment, and the task. Emphasizing the role of the task, the environment, and the individual for understanding emergent behaviour is not new (cf. Burton & Davis [25]; Davis & Burton [26]; Newell [27,28]; Vaz [29]) but it has only recently been

Fig. 5. The bar graphs depict the participants' performance rankings for the switching (EF) task (black) and the proportional control (AC) task (grey). The top half of this figure shows the raw values (y-axis) per participant, the bottom half of the figure shows the same outcome measures but as the ranking (y-axis) per participant. The rankings are ordered based on the performance on the EF task. Left; the Time Between Switches (EF) versus the Aperture Gap (AC). Right; Switching Accuracy (EF) versus the Catching Accuracy (AC).

applied to prosthesis use [21]. Here ETA implies that executing a task with a prosthetic hand does not only depend on the (type of) prosthesis but also on the goal of the task, the environment in which it has to be executed and the abilities of the individual handling the prosthesis. Translated to our study, all motions need to be generated by the person producing the myosignals (the individual) in a certain experimental environment (the environment) to achieve a certain goal (the task). Although the EF task and the environment in which it was performed were kept constant as much as possible, the individuals who performed the task did differ with respect to gender, body composition, control over their muscles, strength, motivation to perform the task, and other aspects. These individual differences were reflected in their individual performance. Our findings in this myoelectrically controlled task then support the notion that individual differences need to be taken into account when training and assessing switching capability in prosthesis use (see also next paragraph), which is in line with the current trend in global healthcare to invest in personalized care/medicine [30–32]. This also entails that patients are classified based on their current abilities to thus provide better-targeted treatment and promote treatment adherence [33].

4.2. Effects of training (aim 2)

Overall, almost two-thirds of our participants showed improvement in switching after the 10-minute training, with a quarter (statistically) significantly so, demonstrating that participants were able to learn how to produce better co-contractions. Even participants who already started with a relatively high SA and a short TBS, showed further improvement. However, 14.5% showed a significant deterioration over time. As to causes, two seemed most plausible: fatigue, resulting in poorer performance, and insufficient training duration which might result in sub-optimal performance. Having opted for 10 min of training to minimize the effects of fatigue, we learned from informal inquiries after the experiment that the EF task was still experienced as tiring for the forearm muscles. We therefore propose using shorter training sessions with long(er) pauses during sessions, with sessions being offered over the course of a longer period (e.g. several weeks).

Another explanation for the observed deterioration may lie in the way some of the measures were computed. Amplitude Difference and Amplitude showed the most deterioration meaning that the amplitudes of the correctly made switches dropped over time.

Although in our operationalization of these measures the decrease in amplitude is taken as deterioration, it is important to realize that a lower amplitude that still reaches the required thresholds is not necessarily a deterioration but may also be a sign of more efficient switching. The same could be the case for Amplitude Difference. This improved efficiency might be better reflected in other performance measures such as TBS and SA. This means there is a discrepancy between the outcome measures describing the switch characteristics (SC) and the performance measures (PM). In order to further improve the assessment of switching capacity, we hence recommend to always employ a combination of both switch characteristics and performance measures.

4.3. Relationship between proportional and switching-control abilities (aim 3)

Our participants also differed in how and to what extent their switching and proportional-control skills were related. Here the tight coupling between task, environment, and the individual, as posited in the ETA model [25] may also help to interpret this finding. In our EF task myocontrol was needed to switch between grip types, while the proportional (AC) task required the control over opening and closing motions of the hand using sEMG, mimicking the control of a multi-articulated myoelectric hand prosthesis. The actor now remains the same but the environment in which the two tasks are performed and even more so, the tasks themselves, differ. Producing switches requires different coordination between muscles compared to the coordination needed to exert proportional control. In ETA terms this would mean that the coupling between the action needed to achieve a goal and the information perceived during that action (i.e. the action-perception coupling) of the EF task differs from the action-perception coupling of the AC task (cf. Bootsma [34]; van Dijk et al. [21]; Warren [35]), which will inevitably lead to low correlations between outcomes on these two tasks.

Although it needs to be noted that the myocontrol tasks we used differ from the tasks of myocontrol an actual prosthesis user is engaged in, the absence of a correlation between proportional and switch control may have implications for clinical practices as the differences we found in the participants' control abilities most likely also hold for prosthesis use. Currently, mainly prosthesis users with good to excellent proportional control over their simpler hand prosthesis (affording a single grip type) are selected to try a sequentially-proportionally controlled multi-DoF prosthesis. Given that performance on proportional control was not related to performance on switching control, our study suggests, however, that being proficient at opening and closing a 1-DoF hand does not automatically mean that someone will also be able to accurately produce triggers to switch between the modes of a multi-DoF prosthesis. Professionals involved in the treatment and rehabilitation of individuals with an amputation then need to take into account these differences in control skills when clients express a desire for a more sophisticated, complex prosthesis, which is not common practice today. Multi-articulating hand prostheses require skill in both types of control, necessitating adequate assessments and (new) ways to determine and describe the quality of switching abilities at the individual level. Given that we found large differences in the effects of our brief training, rehabilitation training also needs to be tailored to the individual, both in intensity, duration, and content, with all types of switches (e.g. single pulse or longer-pulse switches such as 'hold-open triggers') being practised, which will help determine individual learning curves and prospects of success.

4.4. Limitations

Acknowledging that we only investigated one type of switching (co-contraction) in an experimental task with a relatively short

training program and the fact that we measured unimpaired participants, we are aware that generalization of the results and the conclusions to individuals with an amputation should therefore be handled with caution. Since, to our knowledge, switching behaviour has not been thoroughly studied, and the population of people with an arm amputation is relatively small, we chose to first test our ideas in adults without an impairment. But, given that the use of prosthesis simulators has yielded performance outcomes and kinematic profiles that are comparable with those obtained using real prostheses [14], we expect to see similar results in prosthesis users. Of course, our results first need to be replicated and validated in individuals with an amputation or congenital limb deficiencies.

The EF and AC tasks we used in our study are no functional tasks such as the SHAP [24], box and block test [36], refined clothes-pin test [37], or Cubbies task [8]. Because ours is the first study on switching behaviour in this context, we were primarily interested in basic results, which is why we opted for a simple switching task. Future experiments should be extended to more functional tasks.

Even though both tasks in our study were carefully chosen, results are limited to these two tasks generalizing the conclusions to other tasks should be done carefully. Since the task, the environment, and the actor are all relevant factors, it is well possible that a different set of tasks may show different outcomes and correlations. Also, as alluded to above, both tasks were trained for 10 min only, nowhere near the training that individuals with an amputation would receive when they are fitted with a prosthesis. Even though our participants still showed improvement in both tasks, a longer, differently scheduled training period might have yielded further progress. In future investigations, the effects of the duration, frequency, and intensity of training, and the type of tasks being trained are important topics for consideration.

5. Conclusion

We found large individual differences in the participants' proportional and switching-control abilities in the early stages of training. The majority showed improvement but some showed deterioration in their performance, underscoring the importance of an individual approach to the rehabilitation of persons with an arm prosthesis. Moreover, proportional and switching control skills were not related, indicating that the two types of motor control should always be assessed and monitored separately in clinical practice.

Authors' contribution statement

For this paper the first author designed and set up the study, gathered, analysed, and interpreted the data, and drafted the manuscript. The second and fourth authors also contributed greatly to the study design and set-up, the interpretation of the data, and the writing, and the third author contributed to the writing. All authors have read and approved the final manuscript.

Acknowledgments

This study was conducted within the framework of a research project funded by the University Campus Fryslan (UCF13 032.2013.1011) and Revalidatiefonds Nederland (R2014073).

We gratefully acknowledge Hylke van Dijk (NHL, Leeuwarden, The Netherlands) for his help with developing the serious game, Wim Kaan for developing the LabView switch-detection software and for his technical assistance and Morten Bak Kristoffersen for his constructive contributions. Furthermore we thank Hanneke Meulenbroek-van der Meulen for her linguistic contributions.

Declaration of Competing Interest

The authors report no conflicts of interests.

References

- [1] i-limb ultra revolution OT manual.7.24.14.pdf [Internet]. [cited 27 May 2016]. Available: <http://www.touchbionics.com/sites/default/files/files/i-limb%20ultra%20revolution%20OT%20manual.7.24.14.pdf>.
- [2] C. Behrend, W. Reizner, J.A. Marchessault, W.C. Hammert, Update on advances in upper extremity prosthetics, *J. Hand Surg.* 36 (2011) 1711–1717, <http://dx.doi.org/10.1016/j.jhbsa.2011.07.024>.
- [3] K. Østlie, I.M. Lesjø, R.J. Franklin, B. Garfelt, O.H. Skjeldal, P. Magnus, Prosthesis use in adult acquired major upper-limb amputees: patterns of wear, prosthetic skills and the actual use of prostheses in activities of daily life, *Disabil. Rehabil. Assist. Technol.* 7 (2012) 479–493, <http://dx.doi.org/10.3109/17483107.2011.653296>.
- [4] J.T. Belter, J.L. Segil, A.M. Dollar, R.F. Weir, Mechanical design and performance specifications of anthropomorphic prosthetic hands: a review, *J. Rehabil. Res. Dev.* 50 (2013) 599, <http://dx.doi.org/10.1682/JRRD.2011.10.0188>.
- [5] M. Atzori, H. Müller, Control capabilities of myoelectric robotic prostheses by hand amputees: a scientific research and market overview, *Front. Syst. Neurosci.* 9 (2015), <http://dx.doi.org/10.3389/fnsys.2015.00162>.
- [6] D. Farina, Ning Jiang, H. Rehbaum, A. Holobar, B. Graimann, H. Dietl, et al., The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges, *IEEE Trans. Neural Syst. Rehabil. Eng.* 22 (2014) 797–809, <http://dx.doi.org/10.1109/TNSRE.2014.2305111>.
- [7] M. Vilarino, J. Moon, K.R. Pool, J. Varghese, T. Ryan, N.V. Thakor, et al., Outcomes and perception of a conventional and alternative myoelectric control strategy: a study of experienced and new multiarticulating hand users, *J. Prosthet. Orthot.* 27 (2015) 10.
- [8] T.A. Kuiken, L.A. Miller, K. Turner, L.J. Hargrove, A comparison of pattern recognition control and direct control of a multiple degree-of-freedom transradial prosthesis, *IEEE J. Transl. Eng. Health Med.* 4 (2016) 1–8, <http://dx.doi.org/10.1109/JTEHM.2016.2616123>.
- [9] E. Biddiss, T. Chau, Upper-limb prosthetics: critical factors in device abandonment, *Am. J. Phys. Med. Rehabil.* 86 (2007) 977–987, <http://dx.doi.org/10.1097/PHM.0b013e3181587f6c>.
- [10] L.V. McFarland, S.L.H. Winkler, A.W. Heinemann, M. Jones, A. Esquenazi, Unilateral upper-limb loss: satisfaction and prosthetic-device use in veterans and servicemembers from Vietnam and OIF/OEF conflicts, *J. Rehabil. Res. Dev.* 47 (2010) 299, <http://dx.doi.org/10.1682/JRRD.2009.03.0027>.
- [11] S.M. Engdahl, B.P. Christie, B. Kelly, A. Davis, C.A. Chestek, D.H. Gates, Surveying the interest of individuals with upper limb loss in novel prosthetic control techniques, *J. NeuroEng. Rehabil.* 12 (2015), <http://dx.doi.org/10.1186/s12984-015-0044-2>.
- [12] E. Biddiss, D. Beaton, T. Chau, Consumer design priorities for upper limb prosthetics, *Disabil. Rehabil. Assist. Technol.* 2 (2007) 346–357, <http://dx.doi.org/10.1080/17483100701714733>.
- [13] H. Bouwsema, C.K. van der Sluis, R.M. Bongers, Effect of feedback during virtual training of grip force control with a myoelectric prosthesis, *Lytton WW, editor, PLoS One* 9 (2014), e98301, <http://dx.doi.org/10.1371/journal.pone.0098301>.
- [14] H. Bouwsema, C.K. van der Sluis, R.M. Bongers, Changes in performance over time while learning to use a myoelectric prosthesis, *J. Neuroeng. Rehabil.* 11 (2014) 1.
- [15] H. Bouwsema, C.K. van der Sluis, R.M. Bongers, Learning to control opening and closing a myoelectric hand, *Arch. Phys. Med. Rehabil.* 91 (2010) 1442–1446, <http://dx.doi.org/10.1016/j.apmr.2010.06.025>.
- [16] E.A. Biddiss, T.T. Chau, Upper limb prosthesis use and abandonment: a survey of the last 25 years, *Prosthet. Orthot. Int.* 31 (2007) 236–257, <http://dx.doi.org/10.1080/03093640600994581>.
- [17] L. van Dijk, C.K. van der Sluis, H.W. van Dijk, R.M. Bongers, Learning an EMG controlled game: task-specific adaptations and transfer, *PLoS One* 11 (2016), e0160817.
- [18] Dijk L. van, C.K. van der Sluis, H.W. van Dijk, R.M. Bongers, Task-oriented gaming for transfer to prosthesis use, *IEEE Trans. Neural Syst. Rehabil. Eng.* 24 (2016) 1384–1394, <http://dx.doi.org/10.1109/TNSRE.2015.2502424>.
- [19] S. Romkema, R.M. Bongers, C.K. van der Sluis, Intermanual transfer in training with an upper-limb myoelectric prosthesis simulator: a mechanistic, randomized, pretest-posttest study, *Phys. Ther.* 93 (2013) 22–31, <http://dx.doi.org/10.2522/ptj.20120058>.
- [20] A. Heerschop, C.K. van der Sluis, R.M. Bongers, Developing a test to determine quality of proportional control over a myoelectric prosthetic [abstract], in: International Society for Prosthetics and Orthotics United Kingdom Member Society “Advances in our Understanding” The Compendium, 2016 Sept 26–Oct 1; Glasgow, UK, 2016 [Internet]. [cited 26 Oct 2017]. Available: <http://www.ispo.org.uk/pdf/TIPSIPO2016%20-%20Final%20Compendium%20Web%20print.pdf>.
- [21] L. Van Dijk, A. Heerschop, C.K. Van der Sluis, R.M. Bongers, The anatomy of action systems: task differentiation when learning an EMG controlled game, *Front. Psychol.* 7 (2016), Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5156961/>.
- [22] A. Tabor, S. Bateman, E. Scheme, Evaluation of myoelectric control learning using multi-session game-based training, *IEEE Trans. Neural Syst. Rehabil. Eng.* 26 (2018) 1680–1689, <http://dx.doi.org/10.1109/TNSRE.2018.2855561>.
- [23] H. Bouwsema, P.J. Kyberd, W. Hill, C.K. van der Sluis, R.M. Bongers, Determining skill level in myoelectric prosthesis use with multiple outcome measures, *J. Rehabil. Res. Dev.* 49 (2012) 1331, <http://dx.doi.org/10.1682/JRRD.2011.09.0179>.
- [24] C.M. Light, P.H. Chappell, P.J. Kyberd, Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: normative data, reliability, and validity, *Arch. Phys. Med. Rehabil.* 83 (2002) 776–783, <http://dx.doi.org/10.1053/apmr.2002.32737>.
- [25] A.W. Burton, W.E. Davis, Ecological task analysis utilizing intrinsic measures in research and practice, *Hum. Mov. Sci.* 15 (1996) 285–314, [http://dx.doi.org/10.1016/0167-9457\(95\)00047-X](http://dx.doi.org/10.1016/0167-9457(95)00047-X).
- [26] W.E. Davis, A.W. Burton, Ecological task analysis: translating movement behavior theory into practice, *Adapt. Phys. Activ. Q.* 8 (1991) 154–177, <http://dx.doi.org/10.1123/apaq.8.2.154>.
- [27] K.M. Newell, Constraints on the development of coordination, in: M.G. Wade, H.T.A. Withing (Eds.), *Motor Skills Acquisition*, Martinus Nijhoff, Dordrecht, 2019, pp. 341–360.
- [28] K.M. Newell, Change in movement and skill: learning, retention, and transfer, in: M.L. Latash, M.T. Turvey, N.A. Bernstein (Eds.), *Dexterity and Its Development*, 2019, pp. 431–451.
- [29] D.V. Vaz, P.L. Silva, M.C. Mancini, C. Carello, J. Kinsella-Shaw, Towards an ecologically grounded functional practice in rehabilitation, *Hum. Mov. Sci.* 52 (2017) 117–132, <http://dx.doi.org/10.1016/j.humov.2017.01.010>.
- [30] B. Li, X. He, W. Jia, H. Li, Novel applications of metabolomics in personalized medicine: a mini-review, *Molecules* 22 (2017) 1173, <http://dx.doi.org/10.3390/molecules22071173>.
- [31] S. Sirotti, E. Generali, A. Ceribelli, N. Isailovic, M. De Santis, C. Selmi, Personalized medicine in rheumatology: the paradigm of serum autoantibodies, *Autoimmun. Highlights* 8 (2017), <http://dx.doi.org/10.1007/s13317-017-0098-1>.
- [32] C.C.Y. Poon, M.D. Wang, P. Bonato, D.A. Fenstermacher, Editorial: special issue on health informatics and personalized medicine, *IEEE Trans. Biomed. Eng.* 60 (2013) 143–146, <http://dx.doi.org/10.1109/TBME.2012.2233593>.
- [33] Personalized Medicine Coalition, Academy of Medical Sciences, 2014, May 2015 [Internet]. [cited 23 Jun 2017]. Available: http://www.personalizedmedicinecoalition.org/Userfiles/PMC-Corporate/file/pmc_case_for_personalized_medicine.pdf.
- [34] R.J. Bootsma, Ecological movement principles and how much information matters, *Models Hum. Mov. Sci.* (1998) 51–63.
- [35] W.H. Warren, The dynamics of perception and action, *Psychol. Rev.* 113 (2006) 358–389, <http://dx.doi.org/10.1037/0033-295X.113.2.358>.
- [36] V. Mathiowetz, G. Volland, N. Kashman, K. Weber, Adult norms for the Box and Block Test of manual dexterity, *Am. J. Occup. Ther.* 39 (1985) 386–391.
- [37] A. Hussaini, P. Kyberd, Refined clothespin relocation test and assessment of motion, *Prosthet. Orthot. Int.* 41 (2017) 294–302.