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Serious gaming to generate separated and consistent EMG patterns in pattern-recognition prosthesis control

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ABSTRACT

Pattern-Recognition (PR) control of upper-limb prosthetics has shown inconsistent results outside lab settings, which might be due to the inadequacy of users' electromyogram (EMG) patterns. To improve the separability and consistency of their EMG, users can receive training. Conventional training uses an internal focus of attention as prosthesis users focus on the muscle contractions of their (phantom) hand together with explicit learning processes facilitated by a coach guiding the user. In this study we investigated if an alternative training paradigm using an external focus of attention exploiting implicit learning processes based on serious gaming without a coach could lead to more separable and consistent EMG. Able-bodied participants (N = 25; mean age 22 years, 13 females) were recruited and followed conventional or game training for five days. In conventional training, participants performed the Motion Test thrice daily and received coaching on how to adapt their muscle contractions. In game training, participants controlled an avatar using a direct mapping from electrode to avatar direction. The participants utilized implicit learning processes, by exploring which muscle contractions made the avatar go in which directions. Performance in both groups was evaluated by using the Motion Test in a pre/post-test design. Training resulted in improved performance, with no differences between training paradigms. Participants who followed game training showed 51% more separated EMG patterns. EMG pattern consistency did not change over training. It was concluded that serious game training using an external focus of attention and implicit learning can be considered as a viable alternative to conventional training.

1. Introduction

Myoelectric prosthetic hands with multiple degrees of freedom (DoFs) are commercially available. Controlling several DoFs by Direct Control, as commonly done in clinical practice, has however been proved problematic [1] due to the unintuitive nature of the control commands that are used to switch between DoFs. Pattern Recognition (PR) control has been suggested as an alternative and more intuitive way to control multiple DoFs. PR control is based on a direct mapping between electromyography (EMG) patterns generated while performing muscle contractions (e.g. phantom movements) and the corresponding prosthetic DoFs. In controlled laboratory environments PR control has shown great promise, however evidence shows that outside the lab PR control is hardly faster or more intuitive than conventional Direct Control [2–5]. Research showed that PR lacked robustness primarily due to the misclassifications of intent based on EMG patterns [4,5]. The misclassifications occur because of either external disturbances to the EMG (e.g. electrode lift-off, sweat) or because the EMG patterns of the user was not of a sufficient quality. To avoid misclassifications, the EMG patterns need to meet two quality criteria: separability and consistency [6–8]. Separability is fulfilled if EMG patterns from different muscle contractions are located in areas in feature space that do not overlap. Consistency requires that EMG patterns from repetitions of the same muscle contractions should overlap in feature space.

To ensure separability and consistency of EMG patterns, user training has been suggested. Conventional user training as presented in the literature often consists of three major phases: exploration, evaluation and education. Before the exploration phase, the naïve system training is performed which will enable the control needed for the exploration phase. The exploration phase then allows the trainee to get some initial feeling for what the effect of muscle contractions is, through computer-generated or table mounted prosthesis using explorative activities such

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as bilateral mirroring without any specific goals [4,7,9–11]. The evaluation phase consists of computer-based tests such as the Motion Test [12] or the Target Achievement Control Test [13]. In these tests, the trainee must match a prompted prosthetic mode (e.g. prosthetic open hand) or prosthetic posture. Metrics such as completion rate and time are measured and presented to the trainee as feedback. In the education phase the trainee receives coaching by a researcher or a therapist and in some instances is told about the importance of EMG pattern separability and consistency [4,7,11]. The coach gives feedback on which EMG patterns were overlapping and/or inconsistent and on how muscular contractions should be adapted to ensure separability and consistency. A core component of conventional training is that the adaptation of the muscular contractions are given in terms of phantom movements. Furthermore, the adaptations often involve the use of "non-essential" parts of a (phantom) movement, e.g. while in a regular pinch the little finger is flexed it might now be extended to improve separability or consistency [4,7,11]. The coaching is based on the EMG patterns, which are sometimes shown to the trainee, but always under the guidance of the coach. After coaching, the classifier will be retrained and the trainee will go through the three phases again. The phases are repeated until the trainee reaches the desired level of control.

Conventional training has been promising, but has not yet led to robust control outside the lab [2–4]. This might partially be due to the effectiveness of the training in the education phase. The feedback provided in this phase induces an internal focus of attention, as the coaching focuses on muscular contractions and phantom movements and not on the actuation of the prosthesis resulting from said contractions/movements i.e. external focus of attention. An internal focus of attention has been shown to lead to worse performance (lower accuracy, lower speed) in a variety of motor tasks and to less automatized execution of tasks i.e. higher cognitive and neuromuscular effort [14,15] compared to an external focus of attention. Furthermore, coaching using an internal focus exploits explicit learning processes that rely on working memory. Explicit learners have reduced performance in stressful situations [16,17] and when performing secondary tasks [18,19] compared to implicit learners. A learning paradigm that uses an external focus of attention and exploiting implicit learning processes might therefore be beneficial for learning PR control.

In this work, we examine the efficacy of serious gaming for this purpose because a game has an external focus of attention and can be designed to promote implicit learning. Serious games are (computer) games where the main goal is to teach the player a new skill and they have successfully been used to give feedback on EMG for training Direct Control [20–23]. One of the main benefits of serious games is that feedback can be individually customized, which for persons with an upper limb deficiency might be important since the variability of EMG control and phantom sensations are high in this population. We suggest using a game inspired by the studies of Radhakrishnan et al. and Pistohl et al. [24,25]. In their studies, participants controlled a cursor in two DoFs using six surface electrodes placed on muscles in the hand and in the arm. The cursor was controlled using a direct mapping from each electrode to a direction of the cursor. With such a mapping, trainees use an external focus of attention because they focus on cursor movement and receive implicit feedback on the relation between muscle contractions and cursor movements. By employing a similar mapping in a game, trainees will learn to move a game avatar in different directions through different muscle contractions. Choosing a particular orientation of targets to which the avatar has to move, these muscle contractions should generate separable EMG patterns. By applying these muscle contractions when training a PR classifier should thus lead to fewer misclassifications than when using muscle contractions learned using conventional training.

In comparison with previous work [4,6,7,26–28] this work is the first investigating the involvement of serious games in user training for PR control and compare serious games with conventional training. Furthermore, this work extends the work of Bunderson & Kuiken [6] by exploring additional EMG metrics while using a similar acquisition, PR setup and evaluation paradigm.

In the current study it was investigated if training with a serious game controlled with a direct mapping from electrode to avatar movement will lead to better PR control than following conventional training. The objective of this study was to determine if EMG patterns and PR control performance were different when participants trained with a serious game, compared to conventional training. We hypothesized that training with a serious game will lead to 1) more separated EMG patterns, 2) more consistent EMG patterns and 3) better PR control than conventional training.

2. Methods

2.1. Participants

The inclusion criteria for participants were able-bodied adults, with no neuromuscular or joint disorders in the upper body and naïve to PR control. The study took place in the laboratories of the Department of Human Movement Sciences at the University Medical Center Groningen, the Netherlands. Prior to participation all participants signed a letter of informed consent. This study was approved by the local ethics committee (ECB/2017.01.12_1).

2.2. Materials

2.2.1. EMG sampling

EMG was measured using eight active bi-polar electrodes (Otto Bock 13E200 = 50AC) placed equidistantly around the proximal part of the participants' non-dominant forearm. The electrodes were numbered and positioned at the same location between sessions. The band of electrodes was placed on the thickest part of the forearm with the electrodes oriented as shown in Fig. 1. A brace (Medical Specialties Wrist Lacer) was attached to the distal part of the same forearm and hand restricting movement of the wrist and thumb so participants produced isometric muscle contractions more alike those of an individual with an upper limb defect [29,30,50]. EMG was sampled at 1000 Hz. Arm dominance was determined using an adapted version of the Edinburgh inventory [31,32].

2.2.2. Game

A game called MyoBox was developed and implemented for the experiment. Myobox is an abstract game [33,34] inspired by games such as Labyrinth (BRIO, 1946), Marble Madness (Atari Games, 1984), and Neverball (Open source, conceived by R. Kooima, 2003). However, the game was purposefully kept as simple as possible to avoid overwhelming the player. In Myobox the player controls a ball, which functions as the avatar, in two dimensions, using EMG based control. The EMG was normalized per participant by having them perform maximum voluntary contractions (MVCs) of seven movements for three seconds each. The movements were pronation, supination, wrist flexion, wrist extension, hand open, key grip and fine pinch. The Root Mean Square (RMS) of the normalized EMG was calculated from 50 ms time windows. The RMS was mapped to control of the game avatar as depicted in Fig. 1. The goal of Myobox was to collect boxes positioned on the platforms the ball could move on, while avoiding falling off the platforms, see Fig. 2A. Boxes could be collected by moving through them, therefore, participants had to learn how different movements of their hand and fingers would make the ball move. By learning to control the ball, participants implicitly learned to consistently generate separated EMG patterns, as movement of the ball in different directions requires EMG patterns that are different from one another. The game had four recurring orientations of the platforms, with seven levels of difficulty reflected by narrower platforms and with three boxes in each orientation and level. Every time the player finished the fourth orientation the game restarted, but with narrower platforms, see Fig. 2B. In the beginning of the game when the

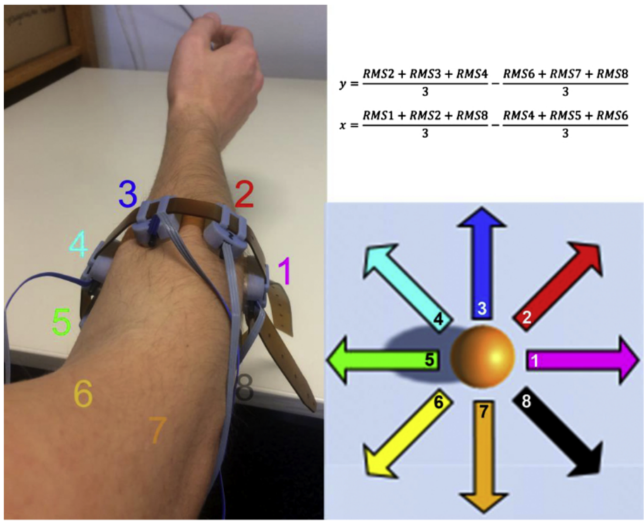

Fig. 1. Mapping of RMS to avatar control. Left: placement of electrodes on a right arm, with electrode 1 corresponding to RMS1, electrode 2 corresponding with RMS2 etc. For the left arm the electrodes are inverted so that electrode 1 is positioned on the volar side. Upper right: the y and x direction in 2D space was calculated as the mean RMS for three electrodes mapped to the positive y/x direction subtracted with the mean RMS for the three electrodes mapped to the negative y/x direction. Lower right: directions of the avatar. The color and the number inside of the arrows corresponds with the colored electrode number on the left-hand side of the figure.

platforms are wide, the player can complete the levels using two movements only. For instance, in Fig. 2A the user can subsequently activate electrode 3 and 5 to move the ball through all three boxes. However, as the platforms became narrower, the player was forced to learn all eight directions to play the game.

There are other games or game-like activities in the literature that are controlled using EMG and PR for phantom limb pain treatment [35] and for adapting control [36]. In these two examples the game is controlled using the output of a PR algorithm and these games were not specifically designed to train the user. Using the output of a PR algorithm, the user is constrained by the performance of the algorithm regarding which movements constitute a certain class. This requires the user to learn how to adapt to the algorithm and not how to make distinct patterns. In contrast, MyoBox is controlled without using a PR algorithm and was designed to train the user to generate distinct patterns. These distinct patterns can be used in the system training procedure and ensure that the classifier receives distinct patterns to optimize its performance. In MyoBox an exploratory game environment is provided where the user can explore all possible muscle contractions she/he can perform. The game helps the user to learn which movements are most distinct. These distinct muscle contractions can in turn be used to train the PR algorithm which might lead to better control of the prosthesis.

2.2.3. *Pattern recognition*

Pattern recognition control was based on classification using Linear Discriminant Analysis (LDA) [37]. LDA is widely used in the field and is available in open source platforms such as BioPatRec [38]. Many researchers are therefore familiar with LDA and can relate to the performance reported in this work. EMG was recorded in the system training procedure and features were extracted and used to train the classifier. The classifier was trained on four time-domain features of the EMG recorded at 30%, 60% and 90% MVC during system training (mean absolute value, waveform length, zero crossings and slope changes [39]). Features were extracted from 128 ms width windows with 32 ms overlap [40]. The features were classified into one of eight classes (7 recorded movements + rest).

2.2.4. *System training*

In the system training procedure, seven movements were recorded. In the pre-test these were: pronation, supination, wrist flexion, wrist extension, hand open, key grip and fine pinch. Before system training, these movements were first recorded at MVC to calibrate a visual cue presented as a trapezoid shape that participants had to follow during the system training to prescribe the produced force while performing the prompted movement. The height of the plateau of the trapezoid was set at the requested force level, varying over repetitions, based on the MVC recording. During the system training, the same seven movements were recorded three times for three seconds at 90%, 60% and 30% MVC, while following the visual cue on a screen.

2.3. *Pre-test*

Participants performed the pre-test before training to get baseline performance measures. The pre-test started with the system training procedure, in which data to train the PR classifier was collected. Following the system training, a Motion test [12] was conducted, which is a virtual test to assess control performance.

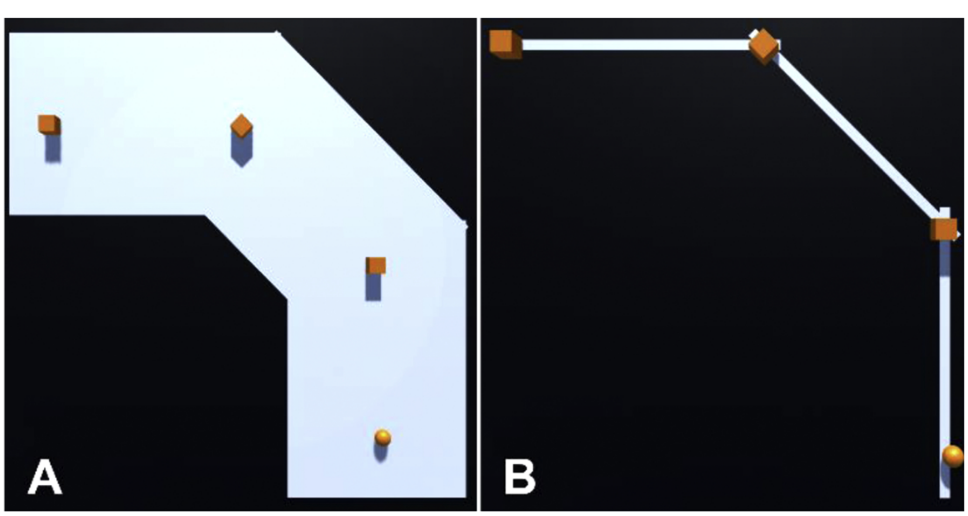

Fig. 2. A: First orientation of Myobox. The player controls the orange ball in the bottom and is tasked with collecting the three orange boxes while staying on the light blue platform. B: First orientation of Myobox with the smallest possible platform size in the game.

2.3.1. Motion test

In the Motion test, participants were prompted at random to perform one of the seven movements recorded during the system training at either 30% (±10), 60% (±15) or 90% (±20) MVC with a total of 21 movement trials (each movement is performed three times). A movement trial was successful if the participant could perform the prompted movement in such a way so that the classifier would correctly predict it for two seconds within a three second time-out within the given MVC margin. After the motion test, the number of successful movement trials and the online accuracy, denoting the percentage of time the classifier predicted the movement regardless of force level, was shown.

2.4. Procedure

Participants joined five training sessions on consecutive days which had a duration of either approximately 20 or 30 minutes, see Fig. 3. The pre-test was performed right before the first training session. To avoid fatigue, the first training session lasted 20 minutes. On days 2-4 training sessions were 30 minutes long. On day 5 the training session lasted 20 minutes and was followed by the post-test. See Fig. 3 for an overview.

2.5. Experimental groups

Before the pre-test, participants were randomly assigned to one of two experimental groups based on inclusion date; the first 12 participants were assigned to conventional training and the following 13 were assigned to game training.

2.5.1. Game training

During training sessions, the game training group played the Myobox game, that was designed for this study, for 20 minutes, except for day one where they played Myobox for 10 minutes, see Fig. 3. Before the first training session participants received instructions on how to control the game. For example, participants were asked to perform wrist flexion/extension and observe the corresponding movement of the avatar. Participants were then told that a sub-aim of the game is to learn the control of at least seven directions by exploring different movements of the hand and wrist. Participants were asked to use the movements that worked best for them and felt most natural. While playing Myobox, the experimenter annotated which movements the participants used to control the avatar for each direction. After playing Myobox, if the participants could control more than seven directions, they were asked to choose the best seven directions in terms of controllability. If the participant did not learn seven directions corresponding to seven movements, extra predefined movements would be added from a predefined set (see appendix) so the total number of movements was seven. The movements learned were recorded following the system training procedure. After system training, a classifier was trained using the recorded movements. Following classifier training, the participant conducted the Motion test to assess the performance of the movements in a classifier context.

2.5.2. Conventional training

The conventional training group followed a training scheme inspired from two studies [4], [7], see Fig. 3, in which the participants were guided by a personal coach who provided feedback, based on the coaching metrics (see Coching metrics for conventional training group):

1. System training was performed. The system training data was used to train the classifier.
2. Using the classifier, the Motion test was performed to assess control performance
3. The pair of patterns from different movements that was least separated was calculated using (3) and the participant was asked to adapt the corresponding movements following the principle from [26], see Fig. 4. A spider plot [11] was shown to the participant to help the participant to visualize the conflict and the effect of the change, see Fig. 4.
4. The pair of patterns from the same movement with the lowest consistency (i.e. least overlap over repetitions) was calculated using (6) and the user was asked to focus on the corresponding movement to make repetitions more alike.
5. The pattern with the highest variability was calculated using (7) and the user was asked to focus on the corresponding movement to decrease variability.

The steps took ~10 minutes and were repeated two or three times depending on the length of the training session being 20 or 30 minutes, as described in Fig. 3.

2.6. Post-test

The post-test was identical to the pre-test except that the game training group used movements learned in the game instead of the predefined movements used in the pre-test. This means the two groups were performing the same task, but used different movements (i.e. where the conventional group would use movements such as pronation or supination, the game group would use movements corresponding to moving the avatar up or down etc.).

2.7. Coaching metrics for conventional training group

Metrics on EMG pattern separability, consistency and variability were calculated and used by the experimenter to coach the participants in the conventional training group, for a schematic overview see Fig. 5.

2.7.1. Feedback on EMG pattern separability

To measure EMG pattern separability, the distance between EMG patterns of different movements was measured. We defined the separability metric Inter-class Distance Nearest Neighbor (IDNN) as the distance between two patterns defined as half the Mahalanobis distance in feature space between the centroids of movements i and j [28]:

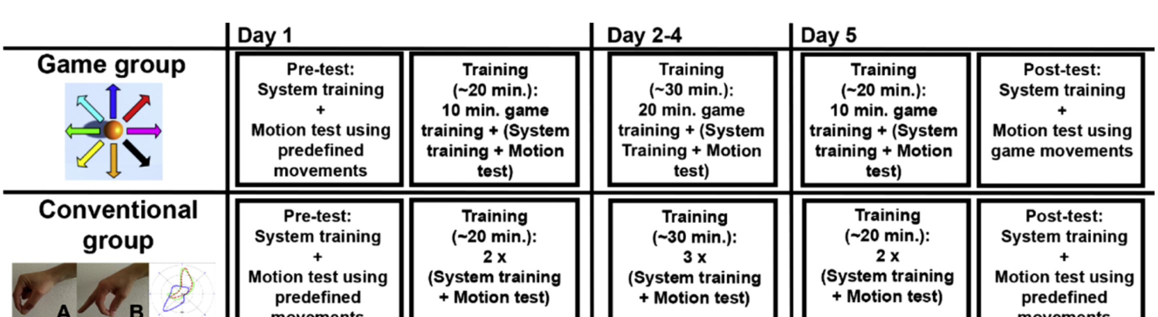

Fig. 3. Procedure for the two training groups (note that system training + motion test lasted about 10 minutes).

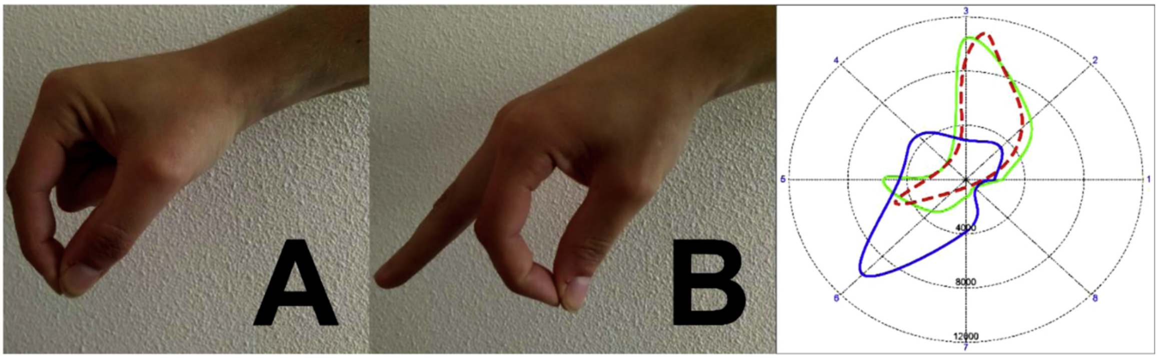

Fig. 4. Example of movement adaption and feedback given to the conventional training group. A: fine pinch grip with the non-essential fingers flexed. B: fine pinch grip with the non-essential fingers extended. Right: Example of spider plot with three movements plotted. The spider plot shows the root mean square of the EMG for each channel and serves as a simplified representation of the feature space with each movement represented by one coloured shape. Possible overlap can be visually perused and the experimenter can guide the participant to minimize it. The blue shape represents variation A of fine pinch and the green shape represents variation B of fine pinch. The red dotted shape represents an example movement that has considerable overlap with variation B of fine pinch. In this case, the experimenter would ask the participant to try variations of fine pinch such as variation A, to find the variation that causes the least overlap with the movement represented by the red dotted shape. Figure taken from [29].

$$dist_j^i = \frac{1}{2}\sqrt{\left(\mu_{Ti}-\mu_{Tj}\right)^T * {S_{Ti}}^{-1} * \left(\mu_{Ti}-\mu_{Tj}\right)} \tag{1}$$

$$dist_i^j = \frac{1}{2}\sqrt{\left(\mu_{Tj}-\mu_{Ti}\right)^T * {S_{Tj}}^{-1} * \left(\mu_{Tj}-\mu_{Ti}\right)} \tag{2}$$

$$IDNN_i = \min_{i=1,\ldots j-1,j+1,\ldots 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \tag{3}$$

Where μ_{Ti} and μ_{Tj} denote the feature vector centroids of the training data from movement i and j, respectively. S_{Ti} and S_{Tj} are the covariance of the training data from movement i and j, respectively.

2.7.2. Feedback on EMG pattern consistency

To measure EMG pattern consistency, we measured the distance between EMG patterns from repetitions of the same movement. We defined the consistency measure Within-class Distance (WD) as the distance between two patterns defined as half the Mahalanobis distance in feature space between repetition r and k of movement j [28]:

$$dist_{kj}^{rj} = \frac{1}{2}\sqrt{\left(\mu_{Trj}-\mu_{Tkj}\right)^T * {S_{Trj}}^{-1} * \left(\mu_{Trj}-\mu_{Tkj}\right)} \tag{4}$$

$$dist_{rj}^{kj} = \frac{1}{2}\sqrt{\left(\mu_{Tkj}-\mu_{Trj}\right)^T * {S_{Tkj}}^{-1} * \left(\mu_{Tkj}-\mu_{Trj}\right)} \tag{5}$$

$$WD_j = \sum_{k=1}^{3} \frac{dist_{kj}^{rj} * dist_{rj}^{kj}}{dist_{kj}^{rj} + dist_{rj}^{kj}} \tag{6}$$

2.7.3. Feedback on EMG pattern variability

To measure EMG pattern variability, we measured the size of the EMG patterns for each movement using the Mean Semi-principal Axis (MSA) measure defined by (6):

$$MSA_j = \left(\prod_{k=1}^{32} a_k\right)^{\frac{1}{32}} \tag{7}$$

Where a_k is the geometric mean of the semi-principal axes of the 32-dimensional hyperellipsoid.

2.8. Outcome variables

The outcome variables used in this study measure EMG separability, EMG consistency and control performance. EMG variability was not used as an outcome measure even though it was used as feedback for the conventional training group. We used EMG variability as feedback since it has been used in previous research [6], [26]. However, no evidence has been found that it relates to performance which is why we did not formulate a research question and a hypothesis related to EMG variability.

2.8.1. Differences in separability of EMG patterns

To assess the differences in separability of EMG patterns, we measured EMG pattern separability between the two training groups. We defined three measures for pattern separability; Inter-class Distance Nearest Neighbor Total ($IDNN_{Total}$), Inter-class Distance All Neighbours (IDAN) and Most Separable Dimension (MSD) [28]. Notation of (8), (9) and (10) follows that of (1) and (2).

$$IDNN_{Total} = \frac{1}{7}\sum_{j=1}^{7} IDNN_i \tag{8}$$

$$IDAN = \frac{1}{7}\sum_{j=1}^{7}\left(\frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j}\right) \tag{9}$$

$$MSD = \frac{1}{7}\sum_{j=1}^{7} \max_{d=1,\ldots,32}\left(\min_{i=1,\ldots j-1,j+1,\ldots 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j}\right) \tag{10}$$

For MSD the feature vectors of dist (μ_{Ti} and μ_{Tj} in (1) and (2)) are calculated for each of the 32 dimensions (4 features times 8 channels, d = 1,…,32) and the dimension where the distance is the largest (max) is then used to calculate MSD

2.8.2. Differences in consistency of EMG patterns

To assess differences in consistency of EMG patterns, we measured EMG pattern consistency by measuring the WD over all movements and taking the mean. We define WD_{Total} as:

$$WD_{Total} = \frac{1}{7}\sum_{j=1}^{7} WD_j \tag{11}$$

2.8.3. Differences in PR control

To assess differences in PR control, we computed the online accuracy from the Motion Test. The online accuracy was defined as the percentage of time during which the participants performed the movement so that the classifier could correctly identify whether such movement was (or was not) performed with the level of force required. Online accuracy was chosen as it is the most used metric for measuring control performance when performing screen-based tests [38].

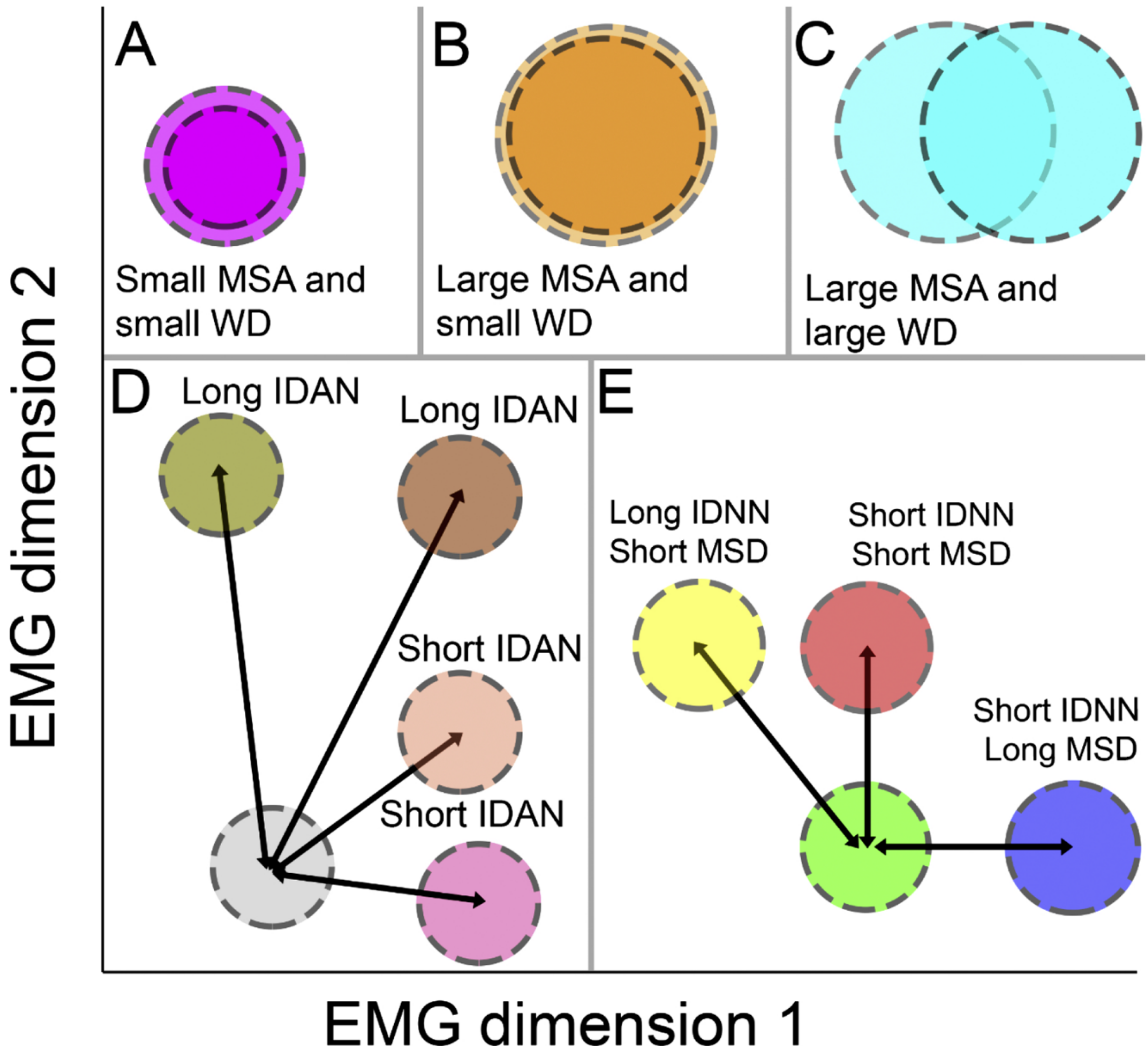

Fig. 5. Schematic overview over all coaching metrics and EMG-based outcome variables. Each shape represents an EMG pattern and the colour of the pattern determines the movement it belongs to. A: Example of small Mean Semi-principal Axis (MSA) and small Within-class Distance (WD). B: Example of Large MSA and small WD. C: Example of large MSA and large WD. MSA measures variance and can be depicted as the size of an EMG cluster. WD measures pattern consistency between repetitions of the same movement. D: Example of long (top, dark green and brown) and short (right side, beige and pink) Inter-class Distance All Neighbours (IDAN) measured from the grey example class. E: Example of Inter-class Distance Nearest Neighbour (IDNN) and Most Separable Dimension (MSD) measured from the green example class. E, top left: long IDNN and short MSD (yellow). E top: Short IDNN and short MSD (red). E right: short IDNN and long MSD (blue). IDAN, IDNN and MSD all measure pattern separability. IDAN measures the average distance to all neighbours. IDNN measures the distance to the nearest neighbour. MSD measures the length of the most separable dimension.

2.9. *Data analysis*

Differences in age and gender distribution between the groups were analysed using Chi-Square tests. All outcome variables $IDNN_{Total}$, IDAN, MSD, WD_{Total} and online accuracy were analysed using repeated measures ANCOVAs using pre-test values of number of successful movement trials as the covariate (see section “Motion test”). The within-subjects factor was test (pre-test vs post-test), and group (game vs conventional) was the between-subjects factor. Post-hoc testing was done using T-tests with Bonferroni correction and was performed when the results of the ANCOVAs were significant. The level of significance was set at $\alpha < 0.05$. Results are reported using mean ± standard error of the mean (SEM).

3. Results

Twenty-five people participated in the study (Game: N = 13, 6 women and 7 men, age = 21.3 ± 0.44 (mean ± SEM); Conventional: N = 12, 7 women and 5 men, age = 22.33 ± 1.06). No significant differences in the age or the gender distribution of the participants were found between groups. At the post-test, all participants in the game group used movements learned in Myobox.

3.1. *Differences in separability of EMG patterns*

The covariate, number of successful movement trials in the pretest, was not significantly related to $IDNN_{Total}$, IDAN and MSD. No significant effects were found for $IDNN_{Total}$. The analysis on IDAN revealed no significant main effects. Interestingly it showed a significant interaction effect for test and group ($F(1,22) = 9.165$; $p = .006$). Post-hoc testing revealed that participants in the game group increased their IDAN significantly ($t(12) = -5{,}086$; $p > .001$, $r = .82$), while the conventional training group did not ($p = .135$). See Fig. 6. No significant effects were found for MSD.

3.2. Differences in consistency of EMG patterns

The covariate, number of successful movement trials, was not significantly related to WD_{Total}. No significant effects were found for WD_{Total}, see Fig. 7.

3.3. Differences in PR control

The covariate, number of completed movements, was significantly related to online accuracy ($F(1,22) = 17.52$, $p > .001$, $\eta p2 = .443$). The analysis on online accuracy revealed a significant main effect of test ($F(1,22) = 8.03$; $p = .01$, $\eta p2 = .267$) with an increase between pre- and post-test (62% ± 2.27%; 78% ± 3%, Fig. 8). The main effect of group and the interaction effect were not significant. However, as can be seen in Fig. 8, the conventional group appears to reach a skill ceiling at the second session and do not appear to improve much in the following sessions. The game group on the other hand show some improvement over all sessions especially for the worst performers. Furthermore, at the post-test the worst performer in the game group had an online accuracy that was more than 40% lower than the best performer in the game group.

4. Discussion

The results showed, in line with our hypothesis, that participants who trained with a serious game generated EMG patterns that were significantly more separable than those of participants who underwent conventional training. However, participants in the game group did not achieve more consistent patterns nor better control of the classifier output, as measured by online accuracy, compared to those in the conventional group. This is surprising, as previous research has identified the separability of EMG patterns as the metric that explained the superior performance of those skilled in PR control compared to novices [6].

4.1. Serious games can be used to train PR control

Participants in the game group improved control of the classifier output to the same extent as participants in the conventional training group. This shows that game-based training with an external focus of attention exploiting implicit learning processes can be used to train PR control. However, some participants were having difficulties to transfer their skills from the game to the test. While the results for the game group are promising, some improvements are still needed if game training should replace conventional training. If skill transfer can be

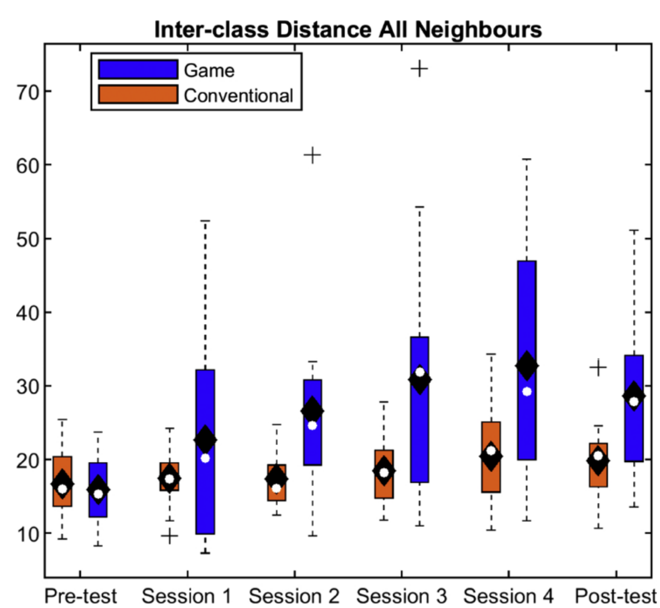

Fig. 6. Inter-class Distance All Neighbours (IDAN) for each session for all participants (N = 25). For the conventional training group data from the last system training is shown per session. The bottom and top box edges denote the 25th and 75th percentile respectively. The white dot denotes the median and the black diamond the mean. Outliers are marked with black plus signs. Abbreviations: Conventional (Conventional training), Game (Game training).

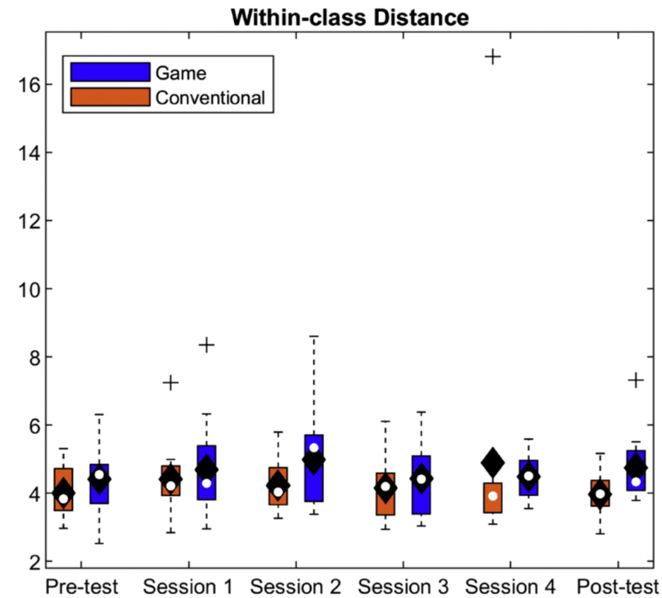

Fig. 7. Within-class (WD) for each session for all participants (N = 25). For the conventional training group data from the last system training is shown per session. The bottom and top box edges denote the 25th and 75th percentile, respectively. The white dot denotes the median and the black diamond the mean. Outliers are marked with black plus signs. Abbreviations: Conventional (Conventional training), Game (Game training).

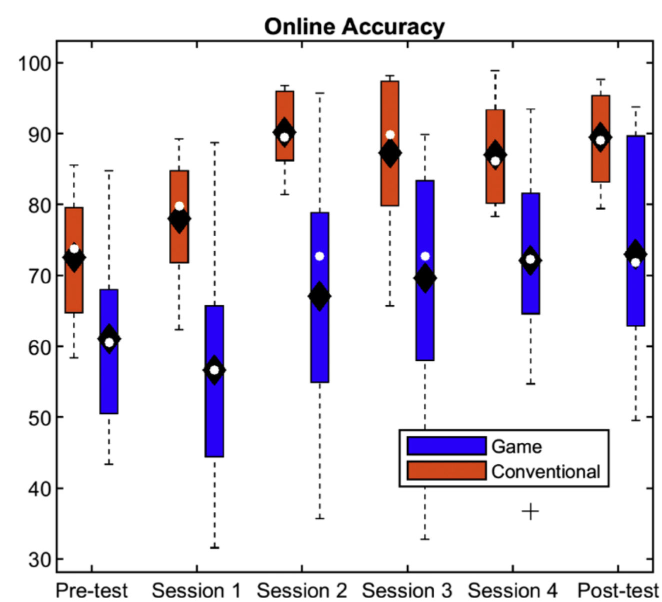

Fig. 8. Online accuracy for each session for all participants (N = 25). For the conventional training group data from the last system training is shown per session. The boxes show data from all participants, where the bottom and top edges denote the 25th and 75th percentile, respectively. The white dot denotes the median and the black diamond the mean. Outliers are marked with black plus signs. Abbreviations: Conventional (Conventional training), Game (Game training).

improved, there is a great potential using games like MyoBox for user training for PR control, as the generated EMG patterns are on average almost 50% more separable and for the best performers more than twice as separable compared to the best performers in the conventional training group.

That serious games show potential for user training for PR control might benefit users if transfer has been improved. A major benefit of using games with an external focus of attention and implicit learning is that the training exploits stages of motor control that are presumed to require less cognitive effort [41], which might be beneficial as prosthesis users have reported that PR control takes a lot of cognitive effort during training [42] and use [4,43]. In addition, game-based training can offer individualized feedback that is tailored to the participants skills and learning goals and can be done at home without additional clinical resources. Furthermore game based training can result into higher training exposure, as training is more motivating [44]. The motivational aspect can be further improved by using commercial games for training by applying the continuous RMS control scheme used in Myobox. Commercial games provide entertainment beyond what can be developed in clinical practice and users can play a game of their favourite genre. These games are also more likely to make the trainee reach the flow state [45], in which an appropriate challenge makes the trainee completely focused on the task at hand. The learning rate is improved when trainees are in the flow state [46,47]. However, care should be taken so that the commercial games still require that the user controls the avatar in all directions as to promote the generation of separated EMG patterns. Moreover, transfer of abilities in those games need to be explicitly tested [20,21].

4.2. More separated patterns do not lead to better control

While participants in the game group had more separable EMG patterns, their control performance, as measured by the online accuracy, was not better than that in the conventional training group. This relation was suggested by Bunderson and Kuiken [6], but very few studies have investigated if it holds true. We suggest that future research investigates the relation between EMG pattern separability and online accuracy and whether there are other metrics that correlate with online accuracy.

However, that higher EMG pattern separability does not necessarily translate to higher online accuracy does not mean that there is no relation between more separated patterns and control, as they both increased significantly from pre- to post-test. It might be the case that beyond a certain threshold, more separated patterns do not lead to better control, e.g. if patterns do not overlap, it might not improve control to separate them further. Nevertheless, this is speculation as our data cannot confirm this. Another possible reason why the game group did not perform better than the conventional training group is that the conventional training group had more training in performing the Motion test since the training and test platform were the same. A question for future research is which type of training will have the best skill-transfer if the test in the pre- and post-test will be different from the test used during training. Especially, if the task involves functional prosthesis use where non-stationarity effects such as limb position and weight will have a greater impact on control. In such a task, more separated patterns might eventually lead to better control.

4.3. (Dis)advantages of conventional versus game training

PR control is often described as being intuitive, because this control is based on (phantom) movements that match the actuation of the prosthesis. One of the aims of conventional training is to adapt the intuitive muscle contractions to make them more separable from one another. A downside of this approach is that the more the intuitive muscle contractions are adapted, the less intuitive they become [4]. We argue that these adaptions and the way they are being taught is one of the main reasons that PR control achieves comparable performance to conventional myoelectric prosthetics [2,4] or lower [3,11,5]. Game based training instead utilizes the adaptability of people and let them define their own muscular contractions that they can use for control. One of the benefits with game-based training is that an external focus of attention and implicit learning processes can be exploited.

A disadvantage of the control scheme used in the game is that movements that generate symmetrical patterns, e.g. EMG activity on both sides of the arm, will not lead to avatar movement and thus might not be used even though they are separated from other patterns. This means that some separated patterns might go unused, which might limit the number of DoFs a user can control. From our experiences such EMG patterns might come from a co-contraction or a (phantom) fist. We suggest that if game training fails to provide the number of desired DoFs, muscle contractions that result in symmetrical EMG patterns should be added under the supervision of a therapist during system training. In this way, the therapist can verify that the added muscle contraction does not interfere with the trained muscle contractions. For the same reason, we included “fist” as the first muscle contraction to be added in case the participant did not learn enough muscle contractions while playing Myobox. It should be noted however, that all participants in the game group used muscle contractions learned while playing Myobox at the post-test, i.e. that the fist muscle contractions never had to be manually added in this fashion.

4.4. Transfer

In the current study, training was similar to the Motion test that was used to assess the training effect. However, the requirements for good functional prosthesis use, which is the ultimate end-goal of training, are quite different from the Motion test. Good functional prosthesis use requires matching the aperture of the hand to the size of the object being grasped [48] and fine control of the speed of the hand (proportional control) [49]. The Motion test contains none of these requirements. Therefore, it is not certain that a high performance in the Motion test leads to a high performance when controlling a PR controlled prosthetic hand. This also means, that training as presented in this study might not lead to an improved functional prosthesis use. The reason that we used the Motion test for both training and testing was because this study investigated changes at the EMG level and not at the functional level. Therefore, transfer effects were not investigated. To increase the chance that there will be transfer of training to functional prosthesis use, we do have some suggestions on what training should entail. First, training should require the user to adjust an aperture to match objects. Second, training should require the user to adjust the speed when adjusting an aperture. A game using augmented feedback i.e. feedback on the procedural aspects of the task demands, to reinforce these constraints has shown promising results training able-bodied participants to operate a one DoF prosthetic simulator [20]. We suggest implementing these recommendations in future versions of Myobox to improve transfer.

4.5. Limitations

This study had some limitations. Participants were able-bodied and the outcome measures did not measure functional prosthetic use. We recruited able-bodied participants to measure the effect of game training in a homogenous population before moving on to a heterogeneous patient population. In this way, we can ensure that game training might have an effect before spending resources recruiting patients. However, this still means that our results cannot be directly applied to prosthetic control for individuals with upper limb absence. In addition, the training and test platform was the same for the conventional training group and partly so for the game group. As a consequence, participants might have improved during testing. However, considering that all training was performed between the two tests we believe this had a very minor influence on the results as exposure to the test was low compared to the training.

5. Conclusion

A serious game with an external focus of attention using implicit learning can be used by PR control trainees to generate EMG patterns more separated than those learned from conventional training. Participants training using the game reached similar consistency in generating EMG patterns and similar control of the PR classifier output as participants who followed conventional training even though they did not receive coaching. Serious game training therefore appears to be a viable alternative to conventional training schemes.

CRediT authorship contribution statement

Morten B. Kristoffersen: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Andreas W. Franzke:** Conceptualization, Methodology, Investigation, Data curation, Writing - review & editing. **Corry K. van der Sluis:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition. **Alessio Murgia:** Conceptualization, Writing - review & editing, Funding acquisition. **Raoul M. Bongers:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Extra predefined movements for game group:

1. Fist
2. Stretch fingers
3. Wrist flexion
4. Wrist extension
5. Flex pinky finger
6. Key grip
7. Fine pinch
8. Pronation
9. Supination

References

[1] E. Biddiss, T. Chau, Upper-limb prosthetics: critical factors in device abandonment, Am. J. Phys. Med. Rehabil. 86 (12) (2007) 977–987, https://doi.org/10.1097/PHM.0b013e3181587f6c.

[2] T.A. Kuiken, L.A. Miller, K. Turner, L. Hargrove, A comparison of pattern recognition control and direct control of a multiple degree-of-freedom transradial prosthesis, IEEE J. Transl. Eng. Heal. Med. 4 (2016) 1–8, https://doi.org/10.1109/JTEHM.2016.2616123.

[3] I. Vujaklija, S. Amsuess, A.D. Roche, D. Farina, O.C. Aszmann, Clinical evaluation of a socket-ready naturally controlled multichannel upper limb prosthetic system, Biosyst. Biorobotics 16 (2017) 3–7.

[4] L. Resnik, H.H. Huang, A. Winslow, D.L. Crouch, F. Zhang, N. Wolk, Evaluation of EMG pattern recognition for upper limb prosthesis control: a case study in comparison with direct myoelectric control, J. Neuroeng. Rehabil. 15 (1) (2018) 23, https://doi.org/10.1186/s12984-018-0361-3.

[5] E. Mastinu, J. Ahlberg, E. Lendaro, L. Hermansson, B. Håkansson, M. Ortiz-Catalan, An alternative myoelectric pattern recognition approach for the control of hand prostheses: A case study of use in daily life by a dysmelia subject, IEEE J. Transl. Eng. Heal. Med. 6 (2600112) (2018), https://doi.org/10.1109/JTEHM.2018.2811458.

[6] N.E. Bunderson, T.A. Kuiken, Quantification of feature space changes with experience during electromyogram pattern recognition control, IEEE Trans. Neural Syst. Rehabil. Eng. 20 (3) (2012) 239–246, https://doi.org/10.1109/TNSRE.2011.2182525.

[7] M.A. Powell, R.R. Kaliki, N.V. Thakor, User training for pattern recognition-based myoelectric prostheses: Improving phantom limb movement consistency and distinguishability, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (3) (2014) 522–532, https://doi.org/10.1109/TNSRE.2013.2279737.

[8] N. Nilsson, B. Håkansson, M. Ortiz-Catalan, Classification complexity in myoelectric pattern recognition, J. Neuroeng. Rehabil. 14 (July (1)) (2017) 68, https://doi.org/10.1186/s12984-017-0283-5.

[9] A.M. Simon, B.A. Lock, K.A. Stubblefield, Patient training for functional use of pattern recognition-controlled prostheses, J. Prosthet. Orthot. 24 (2) (2012) 56–64, https://doi.org/10.1097/JPO.0b013e3182515437.

[10] T. Kuiken, L. Miller, K. Turner, L. Hargrove, A comparison of pattern recognition control and direct control of a multiple degree-of-freedom transradial prosthesis, IEEE J. Transl. Eng. Heal. Med. 2372 (c) (2016), https://doi.org/10.1109/JTEHM.2016.2616123, pp. 1–1.

[11] A.D. Roche, et al., A structured rehabilitation protocol for improved multifunctional prosthetic control: a case study, J. Vis. Exp. (105) (2015) e52968, https://doi.org/10.3791/52968.

[12] T.A. Kuiken, B.A. Lock, R.D. Lipschutz, L.A. Miller, K.A. Stubblefield, K. B. Englehart, Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms, JAMA 301 (6) (2009) 619–628, https://doi.org/10.1001/jama.2009.116.

[13] A.M. Simon, L.J. Hargrove, B.A. Lock, T.A. Kuiken, Target achievement control test: evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses, J. Rehabil. Res. Dev. 48 (6) (2011) 619–628, https://doi.org/10.1682/JRRD.2010.08.0149.

[14] G. Wulf, R. Lewthwaite, Effortless motor learning?: An external focus of attention enhances movement effectiveness and efficiency. Effortless Attention: A New Perspective in the Cognitive Science of Attention and Action, 2010, pp. 75–101.

[15] J. Vance, G. Wulf, T. Töllner, N. McNevin, J. Mercer, EMG activity as a function of the performer's focus of attention, J. Mot. Behav. 36 (4) (2004) 450–459, https://doi.org/10.3200/JMBR.36.4.450-459.

[16] L. Hardy, R. Mullen, G. Jones, Knowledge and conscious control of motor actions under stress, Br. J. Psychol. 87 (4) (1996) 621–636, https://doi.org/10.1111/j.2044-8295.1996.tb02612.x.

[17] R.C. Jackson, K.J. Ashford, G. Norsworthy, Attentional focus, dispositional reinvestment, and skilled motor performance under pressure, J. Sport Exerc. Psychol. 28 (1) (2006) 49–68, https://doi.org/10.1123/jsep.28.1.49.

[18] J.P. Maxwell, R.S.W. Masters, E. Kerr, E. Weedon, The implicit benefit of learning without errors, Q. J. Exp. Psychol. A 54 (4) (2001) 1049–1068, https://doi.org/10.1080/02724980143000073.

[19] R.S.W. Masters, J.M. Poolton, J.P. Maxwell, M. Raab, Implicit motor learning and complex decision making in time-constrained environments, J. Mot. Behav. 40 (1) (2008) 71–79, https://doi.org/10.3200/JMBR.40.1.71-80.

[20] L. Van Dijk, 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 (12) (2016) 1384–1394, https://doi.org/10.1109/TNSRE.2015.2502424.

[21] 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 (8) (2016) 1–14, https://doi.org/10.1371/journal.pone.0160817.

[22] A. Tabor, S. Bateman, E. Scheme, Evaluation of myoelectric control learning using multi-session game-based training, IEEE Trans. Neural Syst. Rehabil. Eng. PP (c) (2018), https://doi.org/10.1109/TNSRE.2018.2855561, pp. 1–1.

[23] C. Prahm, F. Kayali, A. Sturma, O. Aszmann, PlayBionic: game-based interventions to encourage patient engagement and performance in prosthetic motor rehabilitation, PM&R 10 (11) (2019) 1252–1260, https://doi.org/10.1016/j.pmrj.2018.09.027.

[24] S.M. Radhakrishnan, S.N. Baker, A. Jackson, Learning a novel myoelectric-controlled interface task, J. Neurophysiol. 100 (4) (2008) 2397–2408, https://doi.org/10.1152/jn.90614.2008.

[25] T. Pistohl, C. Cipriani, A. Jackson, K. Nazarpour, Abstract and proportional myoelectric control for multi-fingered hand prostheses, Ann. Biomed. Eng. 41 (December (12)) (2013) 2687–2698, https://doi.org/10.1007/s10439-013-0876-5.

[26] M.A. Powell, N.V. Thakor, A training strategy for learning pattern recognition control for myoelectric prostheses, J. Prosthet. Orthot. 25 (1) (2013) 30–41, https://doi.org/10.1097/JPO.0b013e31827af7c1.

[27] T.A. Kuiken, S. Member, L.A. Miller, S. Member, K. Turner, A comparison of pattern recognition control and direct control of a multiple degree-of-freedom transradial prosthesis, IEEE J. Trans. Eng. Health Med. 2372 (c) (2016), https://doi.org/10.1109/JTEHM.2016.2616123.

[28] M.B. Kristoffersen, A.W. Franzke, C.K. van der Sluis, A. Murgia, R.M. Bongers, The effect of feedback during training sessions on learning pattern-recognition-based prosthesis control, IEEE Trans. Neural Syst. Rehabil. Eng. 27 (10) (2019) 2087–2096, https://doi.org/10.1109/TNSRE.2019.2929917.

[29] A.L. Fougner, Ø. Stavdahl, P.J. Kyberd, System training and assessment in simultaneous proportional myoelectric prosthesis control, J. Neuroeng. Rehabil. 11 (1) (2014) 1–13, https://doi.org/10.1186/1743-0003-11-75.
[30] L.H. Smith, T.A. Kuiken, L.J. Hargrove, Myoelectric control system and task-specific characteristics affect voluntary use sof simultaneous control, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (1) (2016) 109–116, https://doi.org/10.1109/TNSRE.2015.2410755.
[31] M.S. Cohen, "Brain Mapping, Handedness Questionnaire," Handedness Questionnaire, 2008 http://www.brainmapping.org/shared/Edinburgh.php. (Accessed 3 July 2018).
[32] R.C. Oldfield, The assessment and analysis of handedness: The Edinburgh inventory, Neuropsychologia 9 (1) (1971) 97–113, https://doi.org/10.1016/0028-3932(71)90067-4.
[33] K. Salen, E. Zimmerman, Rules of Play: Game Design Fundamentals, MIT Press, 2004.
[34] J. Begy, Experiential metaphors in abstract games, Trans. Digit. Games Res. Assoc. 1 (April (1)) (2013), https://doi.org/10.26503/todigra.v1i1.3.
[35] M. Ortiz-Catalan, et al., Phantom motor execution facilitated by machine learning and augmented reality as treatment for phantom limb pain: a single group, clinical trial in patients with chronic intractable phantom limb pain, Lancet 388 (10062) (2016) 2885–2894, https://doi.org/10.1016/S0140-6736(16)31598-7.
[36] R.B. Woodward, L.J. Hargrove, Adapting myoelectric control in real-time using a virtual environment, J. Neuroeng. Rehabil. 16 (December (1)) (2019) 11, https://doi.org/10.1186/s12984-019-0480-5.
[37] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, 2nd Edition, John Wiley, New York, 2001. Section.
[38] M. Ortiz-Catalan, R. Brånemark, B. Håkansson, BioPatRec: a modular research platform for the control of artificial limbs based on pattern recognition algorithms, Source Code Biol. Med. 8 (11) (2013), https://doi.org/10.1186/1751-0473-8-11.
[39] B. Hudgins, P. Parker, R.N. Scott, A new strategy for multifunction myoelectric control, IEEE Trans. Biomed. Eng. 40 (1) (1993) 82–94, https://doi.org/10.1109/10.204774.
[40] S. Amsuess, et al., Context-dependent upper limb prosthesis control for natural and robust use, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (7) (2015) 744–753, https://doi.org/10.1109/TNSRE.2015.2454240.
[41] E.C. Kal, J. Van Der Kamp, H. Houdijk, External attentional focus enhances movement automatization: a comprehensive test of the constrained action hypothesis, Hum. Mov. Sci. 32 (4) (2013) 527–539, https://doi.org/10.1016/j.humov.2013.04.001.
[42] A.W. Franzke, et al., Users' and therapists' perceptions of myoelectric multi-function upper limb prostheses with conventional and pattern recognition control, PLoS One 14 (8) (2019) 1–13, https://doi.org/10.1371/journal.pone.0220899.
[43] C. Moran, et al., Modular prosthetic limb control by an individual with congenital upper-limb amputation: a case report, J. Prosthet. Orthot. 31 (3) (2019).
[44] K. Lohse, N. Shirzad, A. Verster, N. Hodges, H.F.M. Van der Loos, Video games and rehabilitation, J. Neurol. Phys. Ther. 37 (4) (2013) 166–175, https://doi.org/10.1097/NPT.0000000000000017.
[45] M. Csikszentmihalyi, Flow: The Psychology of Optimal Experience, 1990.
[46] J. Vervaeke, L. Ferraro, A. Herrera-Bennett, Flow as spontaneous thought: Insight and implicit learning, June, 2018.
[47] G. Wulf, R. Lewthwaite, Optimizing performance through intrinsic motivation and attention for learning: The OPTIMAL theory of motor learning, Psychon. Bull. Rev. (2016) 1382–1414, https://doi.org/10.3758/s13423-015-0999-9.
[48] H. Bouwsema, C. K. va. der Sluis, R.M. Bongers, Movement characteristics of upper extremity prostheses during basic goal-directed tasks, Clin. Biomech. 25 (6) (2010) 523–529, https://doi.org/10.1016/j.clinbiomech.2010.02.011.
[49] 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 (1) (2014) 1–15, https://doi.org/10.1186/1743-0003-11-16.
[50] M.B. Kristoffersen, A.W. Franzke, C.K. van der Sluis, R.M. Bongers, A. Murgia, Should hands be restricted when measuring able-bodied participants to evaluate machine learning controlled prosthetic hands? IEEE Trans. Neural Syst. Rehabil. Eng. (2020) https://doi.org/10.1109/TNSRE.2020.3007803.