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Convergence in myoelectric control: Between individual patterns of myoelectric learning

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ABSTRACT

Objective: To support the design of assistive devices and prostheses, we investigated the changes in upper-limb muscle synergies during the practice of a myoelectric controlled game using proportional-sequential control.
Methods: We evaluated 1) whether individual muscle synergies change in their structure; 2) variability; 3) distinctiveness; and 4) whether individuals become more similar with practice. Ten individuals practiced a myoelectric-controlled serious game for ten consecutive days (25 min/day) and one day after one week without training (retention).
Results: The results showed that individuals decreased the number of synergies employed and modified their flexor synergies structure, becoming more similar as a group with practice. Nevertheless, within-individual synergies' variability and distinctiveness did not change.
Conclusion: These results point out that individuals do not demonstrate muscle patterns less variable or differentiable after practice. However, participants increased performance and became more attuned to the task dynamics.
Significance: The present findings indicate that, depending on the task requirements, individuals converge to more similar muscle activation patterns – a feature that should be further explored in prosthetic design.

1. Introduction

Myoelectric control–the usage of surface electromyographic features (sEMG) to control a device–is considered to have potential for rehabilitating individuals with physical limitations. An exceptional case is the increased functionality offered to upper-limb amputees when controlling myoelectric prostheses [1,2]. These myoelectric prostheses can vary on how they extract features from sEMG to control the effectors: with applications varying from the amplitude-based signal from two EMG sensors to pattern recognition algorithms extracting user's intentionality from multi-channel EMG [1]. However, commercially available devices are mostly controlled by few electrodes and based on signal amplitude (but see CoApt COMPLETE CONTROL [3] and Otto Bock Myo Plus pattern recognition, for exceptions [4] that recently became commercially available). The application of advanced technologies is limited given issues on the human–machine interaction being demonstrated–independent of the control scheme used. Recent literature points to a limited matching between individuals' intention (intended command) and the device's actual performance (actual command performed) [5,6].

New developments in this area have tried to overcome these issues by creating control-schemes based on observed consistent muscle coactivation patterns (i.e., muscle synergies) [7–12]. There are different perspectives on muscle synergies; some suppose they have a neural origin [13–15], whereas others argue they reflect task constraints [16]. The current paper does not address these perspectives but uses the structure in muscle activation patterns (revealed by the techniques to assess muscle synergies) to examine changes in muscle synergies when learning a myoelectric control task. These synergies are observed through coactivation patterns between muscles. As some have demonstrated, muscle synergies are not rigid ([9,17–20], but see [21]). As pattern recognition control-schemes (including synergy-based ones) in

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myoelectric prostheses are based on stability of the extracted patterns (patterns learned in the training period of using the device), modifications from learning challenge the assumption of stability of synergies [22,23]. As current literature is limited to provide how synergies are modified through learning, such changes represent a challenge for myoelectric control.

The present study investigated muscle synergies changes in a myoelectric task, where two muscle sites control the task through proportional-sequential prosthetic control (see [1]). Although a two-site myoelectric task is straightforward, the activated muscles are embedded in a redundant muscle system (see [24]). Thus, if muscles are coordinated in muscle synergies, then changes in the activation of one muscle of a given synergy could lead to changes in how other muscles contribute to that same synergy.

There are several modifications in synergy control that can occur during motor learning. We addressed five potential aspects of such changes. The first was the number of synergies employed. One might expect that the number of participating synergies can increase–boosting flexibility in motor output (to show a large repertoire of behaviors – as to adapt to changing environment and/or unpredictable perturbations, see [25])–when learning to perform the task. Second, we measured how variability of muscle activation patterns within a synergy changed after learning. Third, we evaluated whether, and if so, how distinctiveness among synergies enlarged after learning. Fourth, we evaluated how synergies changed between the beginning and end of practice as an individual could have altered the muscle weightings within each synergy. Finally, we investigated whether such learning changes are similar between individuals.

The potential changes in synergies variability and distinctiveness for prosthesis user learning are highly relevant for developing pattern-recognition-based myoelectric prosthesis. A decrease in variability is generally expected during learning, while a larger distinction between synergies is supposed to decrease confounding errors in pattern recognition because of muscle activation pattern similarity. Both aspects would facilitate intention detection from the algorithm *if* activation variability and distinctiveness are easily learned. Additionally, convergence is desirable: *if* individuals converge during practice, then a single control-scheme would suffice for prosthetic usability for several individuals. However, current literature has provided sources to doubt convergence [26,27]. As shown, few are the cases in which convergence can actually be found [28–32].

All the investigated changes were also evaluated in terms of a week-after retention test to guarantee that the observed changes were relatively permanent in the individuals' motor repertoire.

2. Methods

2.1. Participants

Ten non-disabled individuals (23 to 35 years of age, 4 females) volunteered to participate in the study. All of them signed an informed consent form approved by the Institutional Review Board of the University of São Paulo–School of Physical Education and Sport of Ribeirão Preto. All individuals had no history of neurological or musculoskeletal injuries that would limit their capacity to perform the task. All participants had normal or corrected-to-normal vision.

2.2. Apparatus, task and design

Participants practiced a myoelectric controlled virtual game (*The Falling of Momo*, [31]) for 10 days (from Monday to Friday twice, subsequent weeks), 25 min per day. Additionally, they performed a retention test 7 days after the last practice day. The task was to move the avatar through obstacles and rising platforms to avoid being trapped at the top of the screen (see [31,32] for more information). The task's goal was not to touch the ceiling for as long as possible while the velocity of the rising platform and difficulty of the obstacles increased.

For both practice and retention tests, participants practiced the task for at least 25 min for as many trials as required; participants finished the session only when they failed in a trial after completing 25 min (median 26.79, interquartile range = 7.21 min per day). For all trials, the participant started the practice at the level corresponding to half of the achieved level of the last trial. In this way, the difficulty and motivation were maintained throughout practice. Only in the first trial of the retention test did participants start again from level 1.

The myoelectric game was designed originally to work using two electrodes from a specific myoelectric bracelet, the MyoBand. To increase the sampling rate and improve spatial specificity, we modified the software to allow the data to be collected with the Delsys Trigno Electromyography (EMG) sensors (sampling frequency of 1 kHz). Thus, to control the avatar, EMG sensors were placed on the skin of the dominant arm in 2 muscles: flexor carpi radialis (FCR) and extensor carpi radialis longus and brevis (ECR). We also placed sensors on other 7 muscles: biceps brachii (BB), triceps brachii (long head) (TB), brachioradialis (BR), flexor digitorium superficialis (FDS), flexor carpi ulnaris (FCU), extensor carpi ulnaris (ECU), and extensor digitorium communis (EDC). The placement location followed [33,34] (also see [35]).

After placing the sensors, the individuals were instructed to perform one gentle wrist flexion and one gentle wrist extension to calibrate the system. The calibration was performed directly on the game wizard that provided a suitable gain for each signal based on the signal properties. The co-contraction signal was defined as 70% of both muscles' gentle contraction. The calibration details followed the guidelines available in the accompanying calibration guide [31].

The game has a control-scheme similar to the proportional-sequential prosthetic control (see (1)). It was developed to stimulate the practice of controlling the sEMG signal prior to prosthesis use [31,32]. The motion velocity of the avatar in each direction was proportional to the magnitude of the signal from the respective electrode placed in the forearm. Co-contraction made the avatar "jump" on the screen.

Participants were seated in an adjustable-height chair in front of a monitor with its center at eye-level. Their arm was supported at the wrist by a wooden support covered with polyethylene foam. The chair-height was adjusted to have the individuals' arm with a 90° flexion at the elbow, forearm in neutral position, and upper arm positioned at the side of the trunk.

2.3. Data analysis

The Momo game software provides three different score measures: levels (i.e., how many platforms the avatar passed through), number of coins (i.e., the number of coins that the avatar collected in the game), and a composite score. There is the possibility of different strategies in the game. For instance, some individuals might be more conservative and try to go through levels without collecting coins. Avoiding interfering with the nature of the game and how individuals chose to practice it, we analyzed all three scores.

The EMG data was first visually inspected to detect artifacts. Large spikes (saturation of the signal) in data were observed in few moments probably due to the proximity and touching of the EMG sensors depending on the movements. These artifacts (large spikes in data) were deleted by removing a small window encompassing the artifact for all 9 time-series. This procedure eliminated 9.33% of the data (this referred to only 4 participants – likely with smaller arm sizes). The resulting EMG data was band-pass filtered (4th order Butterworth filter, 20–500 Hz), rectified, and low-pass filtered (4th order Butterworth filter, 10 Hz) to determine the linear envelope of the EMG signal (following [36]).

Synergy Extraction. For each day analyzed (first and tenth days of practice and retention day), we concatenated all trials to extract the muscle synergies performed on that given day. For each set of sEMG (9 time-series of 25 min of data), we used the Non-Negative Matrix

Factorization (NNMF) [37,38] to identify the synergies observed. This algorithm runs an optimization-iterative procedure to fit two initially random matrices to the observed EMG set: a weighting matrix (W_{SxN}) and a time-varying signal (C_{NxT}) where N is the number of muscles, S is the number of synergies, and T is the time-length. The weighting matrix was normalized to have the maximum weight per synergy with a value of 1 [39]. To calculate the appropriate number of synergies, we followed [40]. We ran the algorithm iteratively varying the number of synergies from 1 to 9 and calculating the variance accounted for (VAF) of the reconstructed set. Through a bootstrapping procedure (250 samples with replacement) we selected the number of synergies that showed VAF significantly higher than (95% confidence interval) 90%.

Synergy Change. To understand the nature of synergy change, we compared synergy composition and three synergy indexes (number of synergies, within-subject variability, and distinctiveness) between days of practice and retention. Synergy change analysis was performed comparing all possible pairs of synergies between days with the normalized dot product [15]. From the NNMF decomposition, we have the vector (weighting) that describes the coactivation pattern of the muscles of a given synergy. The normalized dot product measures the projection of a given vector onto another, normalized by their magnitudes. With this, we got a measure of the difference between a synergy at a given moment of practice and that same synergy observed at another moment. A normalized dot product of one [1] demonstrates perfect equality of vectors, while a normalized dot product of zero (0) shows perfectly orthogonal synergies (no relation).

We evaluated whether individuals used the same synergy for the same function between the first and last days of practice and retention. We categorized the resultant synergies into flexor, extensor, or non-specific. We considered synergies that had only flexors (FCR, FCU, FDS) with weights above 0.6, but no extensors (ECR, ECU, EDC), as flexor synergies and vice versa. Those who were mixed or had only non-specific muscles (BB, TB, BR) with weights above 0.6 were considered non-specific synergies. We compared, using the normalized dot product, within each category and between days, whether individuals maintained the same synergy (dot product above 0.9, see [15]).

Synergy Variability and Distinctiveness. To investigate whether within-subject variability and distinctiveness changed, we calculated the dispersion of each synergy with bootstrap procedures and calculated the centroid distance between synergy's distributions (following [40]). The dataset for each day and subject was resampled 100 times, selecting 80% of the data set randomly. For each sample, an NNMF was performed using the number of synergies extracted from the original data, and a *k-means* clustering algorithm was used to group similar synergies. For each group, the activation patterns of the muscles within the synergy represent a sphere in muscle space (9 dimensions). The within-subject variability of the synergies of the day was measured as the radius of the *n*-sphere (9 dimensions) comprising 95% of each grouping. The within-subject variability of each grouping was averaged per day. Distinctiveness was measured as the average distance between each *n*-sphere.

Synergy Convergence. To investigate whether individuals converged to more similar synergies during practice, we evaluated the dispersion of flexor and extensor synergies in the first, tenth and retention days. For this, we took the average flexor and extensor synergy for each individual per day and, using a bootstrap procedure (400 samples), calculated the radius and the confidence interval of the *n*-sphere (9 dimensions) comprising 90% of all subjects' synergies of the given day (between-subject variability). Also, we compared, using the dot product, the centroid of the group's synergies between days.

2.4. Statistical analysis

The analysis of performance (levels, coins, and composite score), and the changes in the number of synergies, within-subjects variability and distinctiveness between days (first and tenth day of practice and retention day) followed the same procedure. We performed Friedman's ANOVA with post hoc analyses using pairwise Wilcoxon tests corrected by the Bonferroni sequential procedure [41]. All tests were performed with its exact 1-tailed significance value, and the *r* effect sizes were calculated using the conversion of the χ^2 *p*-values to *z*-scores and dividing it to the square root of the sample size [42]. The pairwise comparisons are described detailing the median and interquartile range (IQR). The significance level was set at $p < .05$.

3. Results

3.1. Performance

Fig. 1 shows the performance measures of the group and participants over the 10 days of practice and retention tests.

Friedman's ANOVAs for all three performance measures were significant (levels: χ^2[2] = 9.60; p = .007; r = 0.78; coins: χ^2[2] = 10.40; p = .003; r = 0.87; score: χ^2[2] = 11.40; p = .002; r = 0.91). Pairwise comparisons showed that participants increased levels achieved from 33.08 (IQR = 12.81) on the first day to 63.00 (IQR = 22.81) on the tenth day (Z = 2.70; p = .002) and 61.91 (IQR = 22.50) on the retention test (Z = 2.70; p = .002). There was no difference in levels achieved between the tenth day and retention test (p = .385). Participants increased number of coins collected from 80.63 (IQR = 78.50) on the first day to

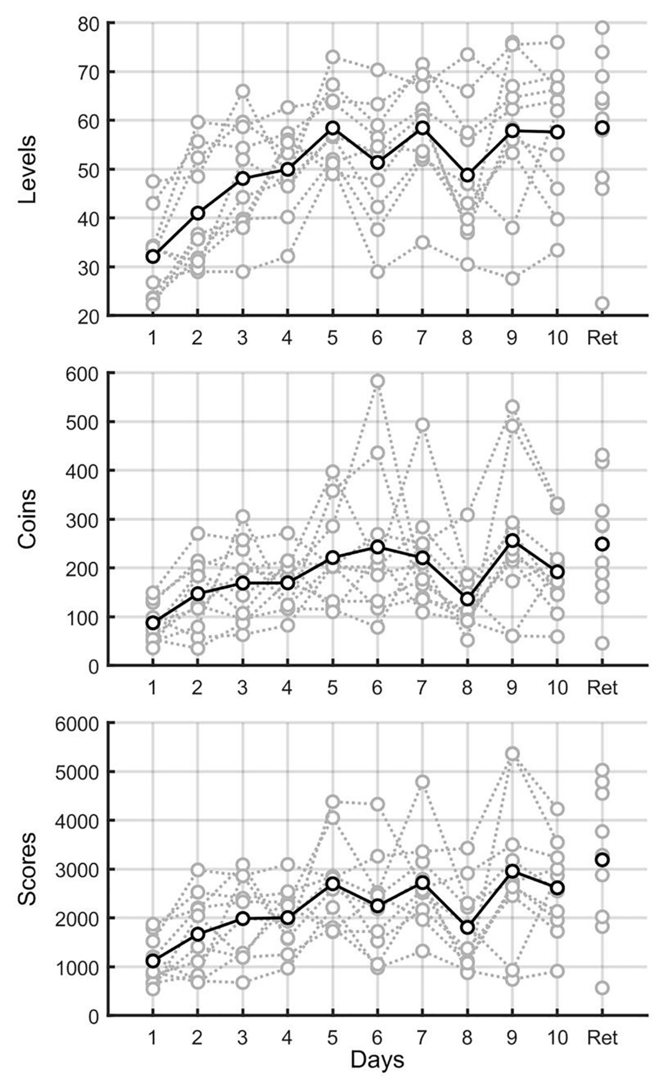

Fig. 1. Performance measures as a function of days. Gray lines represent each participant and the black line represents the group average.

188.67 (IQR = 109.17) on the tenth day ($Z = 2.50$; $p = .005$) and 248.67 (IQR = 182.94) on the retention test ($Z = 2.70$; $p = .002$). They also increased from the tenth day to the retention test ($Z = 1.89$; $p = .032$). Finally, participants increased their scores from 1035 (IQR = 919) on the first day to 2711 (IQR = 1416) on the tenth day ($Z = 2.70$; $p = .002$) and 3240 (IQR = 2636) on the retention test ($Z = 2.70$; $p = .002$). There was no difference in scores between the tenth day and retention test ($p = .053$).

3.2. Synergies

Fig. 2 shows the changes in synergy indexes. Friedman's ANOVA on the number of synergies revealed significant changes between the first and tenth days of practice and retention (χ^2[2] = 5.83; $p = .045$; $r = 0.53$). Pairwise comparisons showed that participants decreased the number of synergies from 3.00 (IQR = 0.25) on the first day to 2.50 (IQR = 1.00) on the retention day ($Z = 2.45$; $p = .016$). The tenth day (3.00, IQR = 1.10) did not differ from any other day (p's > 0.156).

Friedman's ANOVAs on synergy within-subject variability and distinctiveness failed to reach significance (within-subject variability: χ^2[2] = 2.40; $p = .368$; $r = 0.11$; distinctiveness: χ^2[2] = 3.80; $p = .187$; $r = 0.28$).[1]

3.3. Individuality in learning

Fig. 3 shows two exemplary participants: one that maintained the synergy structure almost intact between the first and last day of training (participant 4) and one who showed large changes in flexor synergies between these days (participant 10).

Tables 1 and 2 present the synergy similarity (normalized dot product) between days for extensors and flexors, respectively.

As can be observed, all participants maintained the same synergies for extensors (only participant 9 showed a value of 0.89 between the first day and the tenth day, which can be disregarded given high values between all other days). This observation was not the case for flexors. Participants 6 (all comparisons), participant 7 (D1 → Ret), participant 8 (all comparisons), participant 9 (D10 → Ret), and participant 10 (D1 → D10, D1 → Ret) showed large differences in the composition of their muscle synergies.

These changes could have occurred given individuals converged to a single solution. The analysis of the *n*-sphere centroid changes for the first, tenth and retention days showed that, for both extensors and flexors, the group remained around the same region. The normalized dot product was ≈ 1.00 and > 0.97 for extensors and flexors, respectively, for all days.

The analysis of group dispersion (the group *n*-sphere radius, between-subject variability) showed, for extensors, an increase from the first day (17.02, $CI_{95\%} = 0.18$) to the tenth day (28.18, $CI_{95\%} = 0.27$) and to retention (19.52, $CI_{95\%} = 0.11$). The dispersion decreased from the tenth day to retention. For flexion, we found the opposite trend: individuals decreased their dispersion from the first day (72.04, $CI_{95\%} = 1.54$) to the tenth day (69.57, $CI_{95\%} = 1.39$) and then, to retention (36.33, $CI_{95\%} = 1.64$). Fig. 4 shows the distribution between individuals on flexor synergies. It is clear that the distribution largely decreases between non-specific (BB, TB, BR) and extensors muscles (ECR, ECU).

4. Discussion

We investigated the dynamics of muscle synergies when practicing a myoelectric-controlled game using proportional-sequential prosthetic control. We observed that individuals – using the game as a source of feedback – modified their behavior, decreasing the number of muscle synergies employed. The synergies employed did not decrease within-subject variability or increase within-subject differentiation. The synergies, however, showed modifications between the first and last days of practice, which led to remarkable similarities between individuals. Importantly, our retention test demonstrated that these changes were permanent–the new skill was preserved. The present study extended the concerns on whether performance in such tasks improves (as previously performed, see 32) to explain *how* this improvement occurs and to *whom*. These results are promising to the area of multi-site EMG-based prosthetic design in directing how individuals can improve muscle control in terms of the task (and prosthetic) requirements.

A first result is that the number of synergies decreased over time. Despite the fact that this decrease was only significant for the retention, it is not uncommon that many processes (such as mental and physical fatigue, memory consolidation) can modify how individuals behave from the end of practice to a retention test (see [43]). However, the fact that the number of synergies decreased seems to disagree with the literature on muscle synergies that relates more synergies to increased behavioral flexibility and, consequently, better performance in a range of tasks [44,45]. Nevertheless, such literature disregards how the task requirements interact with behavioral changes in practice. These task constraints [46] are determinant in guiding how individuals change behavior in a task [47,48]. It could be said that flexibility is not required in a task such as this, but it is perfectly adaptive to reduce the number of synergies through practice.

It might be that the task constraints determined to a large extent the pattern of change (and the non-changes for that matter) in the synergies. In the current task, only two muscles were used to control the avatar in the game. Moreover, these muscles were antagonistic and there were no restrictions on hand movements otherwise. This aspect implies that only the activations of those two muscles determined the task's performance. Learning to produce the proper myosignal in these two muscles could be done by changing the activation patterns of the different synergies that these muscles are involved in or selecting the most appropriate synergies for activating those two muscles. The tendency observed, more synergies at first and less at the end of practice, seems to imply that individuals *selected* the most appropriate synergies from a range of potential candidates – the idea of selection from variation defended in other fields [49,50].

Nevertheless, we also observed that individuals *modified* the employed synergies [18–20]. This observation is contrary to the view that synergies are fixed motor modules that cannot be modified with practice [13,21], and in line to a more function-driven organization of synergies [9,51]. This is not to say that consistent muscle activation patterns are not observed, as the literature shows repeatedly (e.g., [13–15,52]). It is just that these synergies can be tuned to the task demands. The pathway of learning here was starting with more synergies and extra effort (coactivation of non-required muscles) with later selective activation of only the relevant muscles to perform the task.

However, changes in the synergy structure occurred only for the flexors. This finding might relate to anatomical and functional aspects of the task. We found clearer signals from the extensors of the wrist compared to flexors. We speculate that this comes from between-individual variability on fat tissue located at the forearm region. This characteristic would induce variation between individuals in the signal amplitude and then, the effort to generate the same motion of the avatar. This increased effort could be seen as increased activation of non-

[1] As can be observed in Fig. 2.B and 2.C, there is a single outlier individual in the last day of practice for both variability and distinctiveness. Despite the fact that Friedman's ANOVA is a non-parametric test (which would be robust for such deviation in distribution), we performed two other statistical analysis to sustain the mentioned results: Friedman's ANOVA without the outlier and robust repeated measured ANOVA (Wilcox, 2017). For variability, both the Exact Friedman's ANOVA and robust RM ANOVA did not reach significance (p's = 0.154 and 0.103). For distinctiveness, the Exact Friedman's ANOVA just reached significance ($p = .048$) while robust RM ANOVA did not ($p = .175$). Considering these results, we refrain from inferring that some change actually occurred.

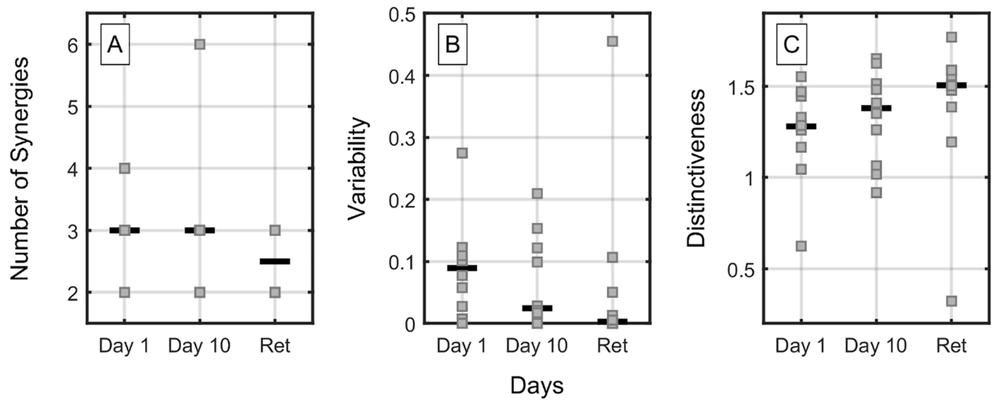

Fig. 2. Synergy indexes as a function of days. Panel A: number of synergies; Panel B: Within-individual variability; Panel C: distinctiveness. The black line represents the median and the squares represent each individual.

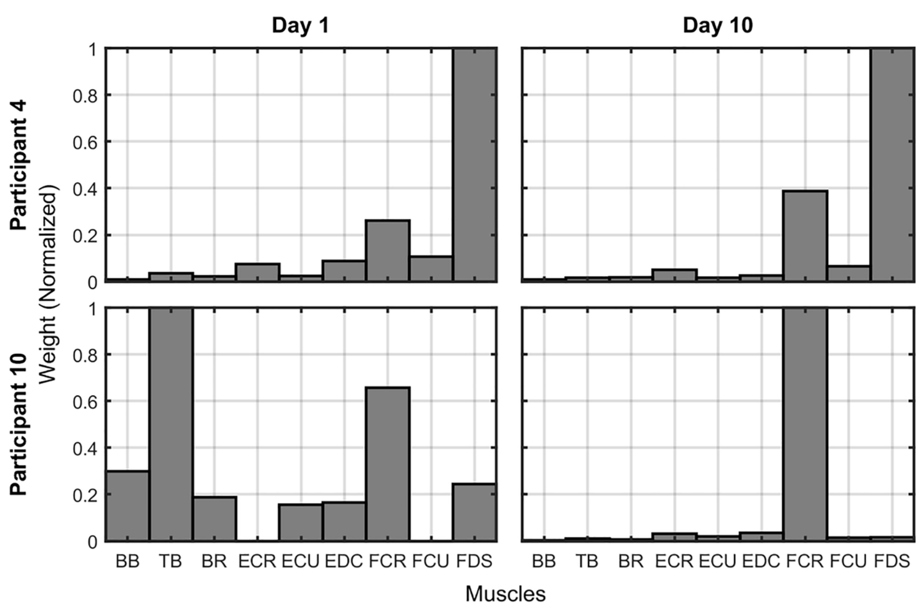

Fig. 3. Flexor synergy weights for participants 4 and 10 on the first and tenth day of practice. BB: Biceps Brachii; TB: Triceps Brachii; BR: Brachioradialis; ECR: Extensor Carpi Radialis; ECU: Extensor Carpi Ulnaris; EDC: Extensor Digitorium Communis; FCR: Flexor Carpi Radialis; FCU: Flexor Carpi Ulnaris; FDS: Flexor Digitorium Superficialis.

Table 1
Synergy similarity for extensors between days 1, 10 and retention.

Participant	D1 → D10	D1 → Ret	D10 → Ret
1	0.91	0.94	0.93
2	0.94	0.96	0.96
3	0.95	0.90	0.98
4	0.98	0.93	0.98
5	0.98	0.96	0.99
6	0.97	0.99	0.99
7	0.91	0.99	0.93
8	0.95	0.98	0.97
9	0.89	0.98	0.94
10	0.96	1.00	0.97

Table 2
Synergy similarity for flexors between days 1, 10 and retention.

Participant	D1 → D10	D1 → Ret	D10 → Ret
1	0.96	0.96	0.98
2	0.91	0.97	0.97
3	0.91	0.96	0.97
4	0.99	0.98	0.96
5	0.96	0.95	0.98
6	0.15	0.83	0.50
7	0.90	0.88	0.94
8	0.80	0.84	0.81
9	0.97	0.91	0.87
10	0.53	0.60	0.94

relevant muscles (e.g., biceps, triceps), as observed here.

Also, individuals modified the wrist flexion during practice to improve control. At first, we observed some individuals performing a slow flexion up to the joint range limit and acting against this limit to generate a higher EMG output. In some cases, such strategy increased the contraction of other muscles. More commonly, we observed an increase in BB and TB activation; in other cases, activation of the antagonists would occur, and a jump would be observed on the screen. Later in practice, individuals performed fast flexion of the wrist, which would be enough to provide large EMG signals with no further need for acting against the joint range limit or coactivate other muscles.

Considering the initial differences in strategy and the possible influence of fat tissue on EMG signal, the reason for individuals' convergence seems to be the interaction of a task with achievable

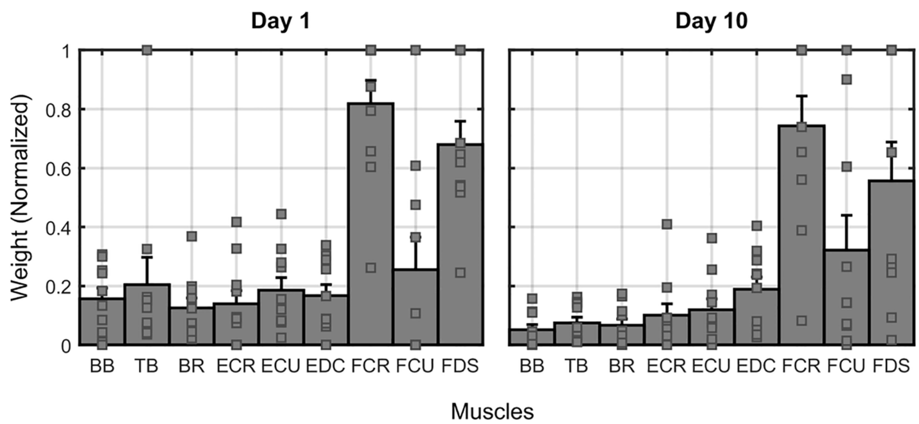

Fig. 4. Between-participant mean flexor synergy weights (bars and error bars) and participants' distribution (squares) on the first and tenth day of practice. The error bars refer to the standard error. BB: Biceps Brachii; TB: Triceps Brachii; BR: Brachioradialis; ECR: Extensor Carpi Radialis; ECU: Extensor Carpi Ulnaris; EDC: Extensor Digitorium Communis; FCR: Flexor Carpi Radialis; FCU: Flexor Carpi Ulnaris; FDS: Flexor Digitorium Superficialis.

requirements, but constraining, and the capacity that individuals have to accommodate such requirements. It is important to note that such convergence is rarely the case in motor learning [53,54]. In general, motor learning, different initial repertoire, ways of encompassing the task requirements and redundant task requirements lead to different solutions that can be equally functional [28,29]. It could be that the present task is sufficiently constraining to, considering biomechanical similarities, leads individuals to converge [30]. Further, it is important to understand that individuals converged to better solutions, as the performance curves demonstrate (see Fig. 1). Convergence in behavior is a powerful attribute for prosthetic design: if the requirements of the task (prosthesis control requirements) are within the capacity of the system to learn, individuals will converge to these requirements (i.e., a motor learning-based control [7,55]) with few days of practice, decreasing the need for training-algorithms.

However, some individuals improved much less than others. This was independent of the measure of performance utilized (correlations between measures were all high; levels and coins: Spearman's $\rho = 0.77$; coins and score: $\rho = 0.93$; levels and score: $\rho = 0.92$). Thus, it was not a matter of "preference" in how to play the game. We used a game that is readily available to increase the contextual validity of the study but this limited analysis of the in-game performance in a more detailed way. These individual differences warrant further research. Previous research on motor learning pointed out that individuals search for solutions in their motor repertoire differently, which facilitates/hinders improvement in the task [27,54,56]. An appropriate design for studying such search within the space of muscle synergies is, thus, highly relevant for the field.

An important result was that individuals did not decrease variability or differentiation between synergies despite the increment in performance. Note that, given that individuals could increase performance without decreasing synergy variability might indicate that the task was not appropriate to elicit such a change–in the same vein as the task constraints discussed above. Other studies provided mixed results on these measures. Allen et al. [17] showed that, after an intervention, individuals with Parkinson showed more consistent and distinct muscle synergies in walking than before the intervention. Also, Sawers et al. [57] showed differences between experts and novices on a beam walking task. Nevertheless, Allen et al. [40], comparing stroke and healthy individuals on gait, did not find any differences in these measures. It is questionable whether decreased variability and increased distinctiveness is a natural consequence of practice.

If we follow the literature on motor learning, variability, in many cases, is not restricted to decrease and might even increase [47,58]. The means-end relation in the task goal and movement possibilities will define whether variability is allowed, desirable or undesirable. Also, individuals converged to motor solutions that are in line with the requirements of the task (i.e., followed the task dynamics) without much concern with the reproducibility of the patterns. Researchers at the forefront of prosthesis design should recognize that control schemes externally imposed–with no reference to actual possibilities of myocontrol learning–will inevitably fail given the tendency to attend to task dynamics or even exploit features not anticipated by the designer [59]. That is, requiring consistent (and distinct) EMG patterns for recognition-based control schemes seem to be not in line with how EMG signals emerge (see [60]).

These results can have several implications for the realm of prosthesis design. First, considering proportional-sequential control, we found no requirement for multiple muscles to be recorded–both for control and training–as the motor system approaches improved control on the designated control muscles. Second, even though our experiment did not employ pattern recognition directly, our results follow the discussions of Ison and Artemiadis [7] in that prosthesis design could take large advantage of the fact that individuals converge to similar synergies in given tasks, being robust to sEMG artifacts [8].

Ghassemi et al. [61,62] did not find healthy individuals modifying the coactivation pattern of the muscle synergies to improve performance in their body-machine interface. In their papers, they extracted principal components from the EMG signals of their participants performing several gestures. These principal components were used to control a virtual cursor in many virtual reaching/tracking tasks. Note, Ghassemi created the body-machine interaction *in terms* of the repertoire already demonstrated by the individual before the task. Thus, we expect that their participants could perform the task by just modulating overall activation before altering the structure. The motor behavior literature considers a possible hierarchy of changes in motor behavior–one would first try to accommodate the task demands in terms of parameterizing the coordinative structure (i.e., synergy) before modifying the covariation patterns of coordination structure [63,64]. Additionally, Ghassemi et al. used group averages to investigate whether individuals did conform to the task requirements. Here, we based ourselves on the learners' differences to understand whether they were diverging or, as we saw, converging. Learner's status is also a form of constraint; this cannot be forgotten if we are to understand motor behavior [27,65].

The present study has a few limitations that are worth mentioning. First, despite our main intention to understand muscle synergy control to elucidate good practices for technology design, we evaluated health and young individuals who are, at least currently, the least similar to target populations. This approach has been a common practice in the literature, and we believe that the insights gathered here can be generalized as the principles of learning are, potentially, the same. We refrain, however, from stating that despite similarities in principles will maintain patterns of change qualitatively the same between different populations. The second point of consideration is that we did not record the actual arm movements that individuals explored to perform the task. It might have been that the individual differences revealed originated from differences in the arm movements (although informal observations during the experiment did not point in that direction). One of our considerations heavily relied on such differences and, despite that actual amputees will not provide such information, this might be a valuable source of information. Finally, we did not assess anthropometric measures such as body fat percentage or body mass index. These, as we inferred, might be relevant in explaining differences between individuals.

5. Conclusion

In the present paper, we investigated the dynamics of change in muscle synergies when practicing a myoelectric-controlled game. The findings highlight the variable nature of motor behavior and point to aspects that prosthetic design should consider. We strongly suggest that a systemic approach to technology design will succeed if they consider the marvelous capacity of the human system to adapt to different task demands. Nevertheless, one should further understand the biomechanical and functional constraints of the individual to not restrict the requirements to patterns incompatible with the own nature of human motor behavior (i.e., rigid control). Current views on prosthetic control, we believe, are in line with our considerations and suggestions [59,66].

CRediT authorship contribution statement

Matheus M. Pacheco: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing – original draft, Writing - review & editing. **Renato Moraes:** Resources, Supervision, Writing – original draft, Writing - review & editing. **Tenysson W. Lemos:** Software. **Raoul M. Bongers:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing - review & editing. **Go Tani:** Funding acquisition, Supervision.

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.

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