# Proportional Myoelectric Control of Robots: Muscle Synergy Development drives Performance Enhancement, Retainment, and Generalization

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Abstract-Proportional myoelectric control has been proposed for user-friendly interaction with prostheses, orthoses, and new human-machine interfaces. Recent research has stressed intuitive controls that mimic human intentions. However, these controls have limited accuracy and functionality, resulting in user-specific decoders with upper-bound constraints on performance. Thus, myoelectric controls have yet to realize their potential as a natural interface between humans and multifunctional robotic controls. This work supports a shift in myoelectric control schemes towards proportional simultaneous controls learned through development of unique muscle synergies. A multiple day study reveals natural emergence of a new muscle synergy space as subjects identify the system dynamics of a myoelectric interface. These synergies correlate with long-term learning, increasing performance over consecutive days. Synergies are maintained after one week, helping subjects retain efficient control and generalize performance to new tasks. The extension to robot control is also demonstrated with a robot arm performing reach-to-grasp tasks in a plane. The ability to enhance, retain, and generalize control, without needing to recalibrate or retrain the system, supports control schemes promoting synergy development, not necessarily user-specific decoders trained on a subset of existing synergies. for efficient myoelectric interfaces designed for long-term use.

Index Terms—Electromyography, human-robot interaction, motor learning, myoelectric control, real-time systems

# I. INTRODUCTION

**M**YOELECTRIC control of robots has been a research focus since the first implementation of myoelectric controlled interfaces over a half century ago. Proportional myoelectric interfaces, with output magnitudes directly proportional to neural inputs, provide user-friendly interaction [1]. Surface electromyography (EMG), with noninvasive access to muscle activity, creates a natural interface for controlling various robotic devices. As robotic applications trend toward compliant manipulation [2], [3] and haptic feedback [4], EMG brings potential to expand robotic operation to control force [5], [6] or stiffness [7], [8], as well as traditional position and velocity. EMG has contributed to advancements in prostheses [9], orthoses [10], [11], and select applications in teleoperation [12]–[15] and human-machine interfaces [16], [17]. Despite its potential, transient changes in EMG over time often limit the commercial viability of such applications [18].

## A. EMG Decoding

Recent research in myoelectric control has focused on accurately decoding user muscle activity into intuitive and desired limb motions. This approach trains decoders to adapt to a specific, supposed constant, motor system to produce desired output (see Fig. I-A). Intuitive control is often translated as a requirement for high system accuracy (i.e. realistic predictions of user kinematics). However, despite a decade of trained decoders consistently reporting accuracies and correlations above 90% in offline analysis [19], they have not necessarily translated to enhancements in commercial applications [20].

Post-processing is often necessary to incorporate proportional control outputs [21] and minimize misclassification effects [19]. Periodic training phases adapt trained models to transient changes in EMG signals [22], [23], which prevents generalization across a population [24], [25]. Moreover, Jiang et al. [26] demonstrated that offline and online performance is not correlated due to user adaptations through feedback, concluding that control schemes with poor association to kinematics are equally capable of achieving precise control as those with high offline accuracy. While pattern recognitionbased systems have seen some success in motivated users, the associated training systems and kinematic restrictions may not be necessary for efficient myoelectric control.

Farina et al. [27] suggested that robust, simultaneous and proportional controls are more likely to be achieved in abstract, or motor learning-based, controls which encourage learning and adaption. Such control methods are a more functional, simultaneous extension of the commonly implemented direct control approach, which sequentially controls multiple joints via two independent muscles and a switching technique [28].

#### B. Contribution

This paper supports a shift in closed-loop myoelectric control applications towards proportional controls that can be utilized to simultaneously control multiple degrees of freedom (DoFs) through refinement of unique muscle synergies. In this context, muscle synergies represent specific cross-muscle activation patterns used to achieve a behavioral goal [29]. Rather than training a decoder to a specific motor system (Fig. I-A) or calibrating EMG activity to define existing muscle synergies as control inputs [30]–[32], the proposed approach trains a motor system to develop new muscle synergies associated with system dynamics of a specific mapping function (Fig. 2). Users increase control efficiency simply by

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Fig. 1. Pattern recognition-based myoelectric interface interaction model. A decoder is trained to map EMG signals (m) to human arm motion (y). Once trained, the decoder is used in real-time to estimate arm motion (y') and map it to output (z) for an interface.



Fig. 2. Embedded brain control for myoelectric interfaces. The brain learns a model of the plant (system dynamics identification) by comparing neural commands and output (z) of the interface. New synergies are developed based on the system identified, which are then utilized to adjust neural commands.

identifying the system dynamics relating neural activity to the task space. In this way, the user learns the control scheme as a new motor skill with a standard three stage learning process initially described by Fitts and Posner [33]. Subjects begin to learn a new motor skill with sporadic performance and heavy cognitive burden. However, as subjects enter the third stage of learning, the cognitive burden is reduced and tasks are performed consistently and nearly autonomously [33].

Previous studies related to motor learning have been done over a short time and often restrict the user to specific muscle activation patterns to complete a task. In contrast, this study examines long-term performance for simultaneous myoelectric control applications in which infinite muscle activation sequences can accomplish any particular task. Although the interface could potentially be controlled using only individual muscle activations, the paper hypothesizes that users learning to control a redundant task-space will continuously develop and refine a common set of muscle synergies as a natural consequence of understanding the system dynamics introduced by the specific choice of the control mapping function (see Fig. 2). Moreover, as subjects approach the third, autonomous, stage of learning [33], these new synergies are projected to be retained over periods of non-use so that users can retain similar performance on old tasks and efficiently perform new tasks.

## II. RELATED WORK

# A. Myoelectric Finite State Machines

As an alternative to pattern recognition-based control, a few applications have implemented finite state machines (FSM) [34], in which a sequence of input signals maps to a set of predefined commands and transition states for a given interface. Carrozza et al. [35] used FSM to open and close a prosthetic hand using forearm flexor and extensor muscles. Moon et al. [36] operate a wheelchair based on EMG signals from muscle groups of each shoulder. Felzer and Freisleben [37] also operate a hands free wheelchair using EMG signals from the forehead. Nilas et al. [38] created Morse code-like commands using EMG signals of two antagonistic muscles to represent dots and dashes corresponding to primitive movements on a robot. Cipriani et al. [39] also used two antagonistic muscles to concoct higher level commands dictating a reaching, shaping, and grasping sequence on a prosthetic hand.

These methods mostly remove the constraint on userspecificity and have a small learning curve for successful performance in the given applications. However, the commands are limited to simple task-specific applications with minimal user interaction. Moreover, the lack of proportional outputs places upper limits on control efficiency and performance.

#### B. Motor Learning through Myoelectric Control

Many studies support the human motor system naturally learning a novel inverse map relating the effect of motor commands on task-relevant variables when interacting with applications involving motor control inputs [40]. Chase et. al [41] compared user performance of brain-computer interfaces involving the motor cortex, showing significant differences between two unique decoding algorithms in open-loop control tasks, but less difference when feedback is present. Radhakrishnan et al. [42] demonstrated the effect of human motor learning for both intuitive (mapping related to limb movements) and non-intuitive (random mapping) decoders mapping EMG signal amplitude from six muscles to 2D cursor position. Antuvan et. al [43] evaluated user performance over two myoelectric interfaces utilizing four distinct mapping functions. Non-intuitive mappings had higher initial learning curves, but also provided higher learning rates and better performance over time compared to intuitive mappings.

Liu et al. [44] show that continuous visual feedback helps subjects learn to generalize control to new tasks, indicating proper learning of the inverse model. Héliot et al. [45] model this learning process with a simulated algorithm depicting the brain as an adaptive controller which modifies neural signals and uses output error to develop an inverse model.

Pistohl et al. [46] demonstrate motor learning in robot control by comparing subject performance for two different myoelectrically controlled tasks. The first task is a standard cursor control task, similar to [42]. The second uses a similar mapping function to operate individual fingers of a robotic hand. The results show similar performance trends when given visual feedback, indicating that these control systems can be trivially extended to other forms of robotic control.

Nazarpour et al. [47] analyze motor learning in the context of muscle synergies. They define tasks requiring simultaneous control of a pair of muscles, and test subjects on combinations of biomechanically independent and antagonistic muscles. They showed that users learned flexible control through the formation of dynamic, task-dependent muscle synergies. De Rugy et al. [48] found that the synergies are not as flexible in biomechanically dependent muscles of the forearm, concluding that low-level synergy constraints prevent fast adaptations.

#### C. Muscle Synergies in Myoelectric Controls

Muscle synergies are considered the underlying coordination principles used in myoelectric control, and are described via multiple metrics in the literature. Direct synergy metrics specifically evaluate EMG activation patterns. D'Avella et al. [49] use a time-variant measure to describe task-specific synergies. Ting and Chvatal [50] highlight time-invariant measures for comparing muscle synergies across different tasks. They cite the most common methods as principal component analysis (PCA) and non-negative matrix factorization (NMF).

PCA describes the major direction of activations without imposing restrictions within the space defined by these components. Castellini and van der Smagt [51] use PCA to describe natural muscle synergies during grasping in humans. PCA is also commonly used to give muscle synergies as inputs to myoelectric interfaces [18]. Hargrove et. al [52] use PCA to extract synergies from EMG signals of small muscles to improve classification accuracy. Artemiadis et al. simplify a trianed model mapping low-dimensional synergies from nine muscles to control a robot in 3D.

NMF prescribes an activation subspace restricting expressible data points to these combinations [50]. With relaxed constraints on orthogonality and statistical independence, NMF often describes specific muscle synergies associated with a given task [53]–[55]. Ajiboye et al. [56] use NMF to predict hand configurations by identifying synergies, while other methods use NMF to calibrate existing synergies as input to intuitive simultaneous and proportional control schemes [30]–[32].

Indirect muscle synergy metrics are also inferred by evaluating correlations between control outputs. Nazarpour et al. [47] quantify synergies in terms of inferred muscle correlation structure from variance in cursor position. They evaluate evolution of these synergies over time with a regression model.

# **III.** METHODS

The experiments performed in this study are designed to evaluate the development and retention of muscle synergies and their relation to performance as subjects learn to control a myoelectric interface with novel system dynamics. Five healthy subjects (all male, 19-28 years old) participated in the primary experiment consisting of a multi-day learning phase followed by a retention testing phase one week later. Two additional healthy subjects (1 male age 24, 1 female age 27) participated in a secondary three week-long experiment to evaluate learning and retention in a sample robotic application. All subjects gave informed consent according to procedures approved by the ASU IRB (Protocol: #1201007252).

# A. Experimental Setup

Wireless surface EMG electrodes (Delsys Trigno Wireless, Delsys Inc) were placed on four upper limb muscles of a

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(a) Experiment 1: Competitive Visual Interface



(b) Experiment 2: Robot Interface

Fig. 3. Experiment setup including the EMG system, the DAQ, and interface. (a) Subjects compete by moving their helicopter to the displayed helipad as quickly as possible. (b) Subjects move the KUKA Light Weight Robot 4 (LWR 4) and attached Touch Bionics iLIMB Ultra bionic hand along the 2D plane and touch the palm of the hand to the target object.

human subject. Each subject chose a preferred arm to use throughout the experiment. In accordance with [47] and [48], Biceps Brachii (BB), Triceps Brachii (TB), Flexor Carpi Ulnaris (FCU), and Extensor Carpi Ulnaris (ECU) were chosen as biomechanically independent pairs of antagonistic muscles to enhance the potential for new synergy development. EMG signals from each muscle are digitized at 2kHz by a multifunction data acquisition card (DAQ) (USB-6343X, National Instruments) for input to the myoelectric interface. The interface is a customized program written in C++ using OpenGL API [57]. The EMG signals are converted to control variables that depict the velocity of a virtual helicopter (Fig. 3(a)) or robotic hand (Fig. 3(b)), with a refresh rate of 100Hz.

#### B. Proportional Control

Both the helicopter and hand are moved using proportional control of its velocity. The raw EMG signals are pre-processed to compute the linear envelope for reliable inputs [58]. The linear envelope captures signal energy through full-wave rectification and a low pass filter (2nd order Butterworth, cut-off frequency of 8Hz). The decoder is implemented as a randomized linear mapping between a  $4 \times 1$  vector **e** of EMG amplitudes and a  $2 \times 1$  vector **u** of control outputs:

$$\mathbf{u} = g \mathbf{W} \left[ (\mathbf{e} - \sigma) \circ u(\mathbf{e} - \sigma) \right], \\ \mathbf{W} = \begin{bmatrix} -0.5537 & -0.5404 & 0.0941 & 1.0000 \\ -0.5214 & 0.0142 & 1.0000 & -0.4929 \end{bmatrix}$$
(1)

where  $\circ$  is element-wise matrix multiplication, u(x) is the unit step function,  $\sigma$  is the muscle activation threshold, and g is the output gain. In a preliminary evaluation with separate subjects,  $\sigma = 0.002mV$  and g = 2 provided a user-friendly environment with no output at rest and appropriate sensitivity providing control without muscle fatigue.



Fig. 4. Visual representation of W converting unit input EMG amplitudes to unitless control outputs as defined in (1). The four vectors represent the proportional contribution of each muscle activation level to the control outputs. Redundancy is caused by four muscles controlling two Cartesian velocities.

The decoder transforms EMG amplitudes to control variables corresponding to the velocity of the helicopter and hand along the x and y directions in screen space and end effector space, respectively. W is an arbitrary matrix created as follows: 1) Random weights are generated for each element. 2) Each row is shifted to have zero mean. 3) Each row is normalized by the maximum weight in the row. As a result, W contains redundancies such that only three muscles are needed to reach the entire task space (see Fig. 4).

In contrast to other studies using cursor position control [42], [46]–[48] the subject's arm was *not* constrained in this experiment, and the EMG signals were *not* normalized with respect to each muscle's maximum voluntary contraction. Liu et al. [59] showed that deciphered inverse models appear invariant to scaling changes within a decoder during the learning process. Therefore, it was expected that subjects would quickly adjust activation levels to the desired outcome in task-space despite potential sensitivity changes that come with small changes in sensor placement each day.

# C. Experimental Protocol

1) Experiment 1: This experiment presented a visual interface to subjects as they learn to control a virtual helicopter towards target helipads in common center-to-reach-out tasks. A single trial required a subject to move the helicopter to the given helipad using EMG signals (see Fig. 3(a)). The trial ends once the helicopter covers the helipad. The helicopter resets to the center of the screen, and a new helipad appears for the next trial after five seconds to prevent muscle fatigue.

The experiment was divided into a learning and testing phase, separated by one week. In the learning phase, subjects performed the task in pairs to create a competitive environment encouraging fast task completion. Four target helipads were created at random offsets from the four corners of the screen. The targets were presented in cycles, with the four targets randomly arranged each cycle. Each task set ran for 25 cycles, a total of 100 trials. Each subject performed 12 sets over 3-5 consecutive days with 1-4 sets per day according to subject availability. Subjects were given approximately 30 minutes of rest between sets performed on the same day.

The retention testing phase occurred one week after completing the learning phase. Subjects were asked to perform the same task, but this time individually. As in the learning phase, subjects were not given any practice time. Targets were again presented in cycles, with the exception that every other cycle used a different set of targets. The new target set was shifted  $45^{\circ}$  with small random offsets from the original set. Subjects were not informed of the new targets so that performance was indicative of generalizing to new tasks.

2) Experiment 2: This experiment demonstrated a sample myoelectric-controlled robotic application with a learning protocol which might be used in a practical setting. Subjects learned to use the system by interacting with the robot for two 25 minute sessions once a week for three weeks. A Touch Bionics iLIMB Ultra bionic hand was attached to a KUKA Light Weight Robot (LWR 4) to simulate reach-to-grasp tasks (see Fig. 3(b)). The LWR 4 restricted motion to a 2D plane, and fixed the iLIMB to a constant orientation via Cartesian impedance control. Subjects were asked to reach out and touch a cylindrical object with the palm of the iLIMB without knocking the object off its stand (see Fig. 5). A single trial consisted of a subject moving the iLIMB along a controlled path to approach the object from a specific trajectory. The trial ended once the palm of the iLIMB was touching the object without having knocked the object off its stand. The iLIMB moved back to its starting position, and the object was moved for the next trial after five seconds to prevent muscle fatigue.

The object was moved along eight target locations equally arranged around a semi-circle. The targets were presented in cycles, with the eight targets randomly arranged each cycle. Each session ran for two 25-minute sets, a total of 50 minutes of interaction. Each subject performs 3 sessions, one session per consecutive week. Subjects were given approximately 10 minutes of rest between sets performed on the same day.

The third session tested both retention and generalization. The first set measured retention through four cycles, or 32 total trials. The second set analyzed generalization by rotating the robot hand  $180^{\circ}$  (see Fig. 6). This required the subject to control different paths while reaching the same target location, indicating how well the subject has learned the controls.

# D. Data Analysis

Experiment 1 learning and retention phases collected trial data from the EMG inputs, helicopter path, and completion time. These components are analyzed to see the effects of learning the system dynamics with regards to efficient control, synergy development, and performance retention and generalization after the learning phase is completed. Experiment 2 task completion times further demonstrated performance retention and generalization.

1) Learning Efficient Control: Learning phase performance is evaluated according to two metrics: completion time and path efficiency [19]. Completion time,  $c_t$ , is the time from







Fig. 6. iLIMB hand configuration during tasks. Left: normal configuration for beginning sets. Right: rotated configuration for the last set.

the start of the trial to successfully reaching the target. Path efficiency,  $p_e$  is the shortest path to the target over the actual path taken to reach the target [60]. Both metrics are modeled as learning curves dependent on trial number t. Due to the non-intuitive decoder, both metrics are assumed to contain an initial "fast" learning followed by a "slower" learning rate. The slow learning rate is of most interest in this study, as it would reveal long-term continuous learning. Therefore, both learning curves are fitted to a sum of exponential decays:

$$c_t(t) = \tau_c e^{-\alpha_c t} + \kappa_c e^{-\beta_c t} \tag{2}$$

$$p_e(t) = 1 - \tau_p e^{-\alpha_p t} - \kappa_p e^{-\beta_p t} \tag{3}$$

where t represents trial number,  $\tau$  and  $\alpha$  represent an initial "fast" learning component, and  $\kappa$  and  $\beta$  represent a "slower" long-term learning component.  $\alpha$  and  $\beta$  represent the learning rate for each component, respectively. To confirm significant long-term learning, (2) and (3) are linearized with respect to the long-term component and fit to the data, where a positive  $\beta$  indicates a significant long-term learning component:

$$c_{t_{lin}}(t) = \tau_{cl} e^{-\alpha_{cl} t} + (\kappa_{cl} - \beta_{cl} t)$$
(4)

$$p_{e_{lin}}(t) = 1 - \tau_{pl} e^{-\alpha_{pl}t} - (\kappa_{pl} - \beta_{pl}t)$$
(5)

2) Synergy Development: Synergies have been described via multiple metrics in the literature (see Section II-C). Fitting a model to path efficiency evolution in (3) is similar to the inferred muscle correlation structure described in [47].

A more direct evaluation of synergy development was done with PCA to depict the evolution of continuous synergy space used as input to the interface as subjects learn better control of the system. PCA is performed on filtered EMG inputs over each completed cycle in the learning phase. The principal eigenvectors, or components, contributing to the explained variance indicate the entire input-space used by subjects to complete all tasks. By including the entire population of data for each cycle, the components indicate any population-wide development of time-invariant muscle synergies. Trends in the explained variance of each component reveal potential optimizations with regards to the input-space used by the subjects, and is used to determine the relevant number of components to use in the synergy analysis. Finally, the mean angle between principal eigenvectors applied to each individual subject are compared via cosine similarities:

$$\varphi(p,q,c) = \frac{\sum_{i}^{N} \arccos(\frac{\mathbf{p}_{i}^{\mathbf{c}} \cdot \mathbf{q}_{i}^{\mathbf{c}}}{\|\mathbf{p}_{i}^{\mathbf{c}}\|_{2} \|\mathbf{q}_{i}^{\mathbf{c}}\|_{2}})}{N} \tag{6}$$

where  $\mathbf{p}^{\mathbf{c}}$  and  $\mathbf{q}^{\mathbf{c}}$  are  $4 \times N$  matrices of N principal eigenvectors (sorted by descending eigenvalue) from subjects p and q at cycle c, and N is the number of components considered relevant according to the cumulative explained variance. The mean angle between PCA components for all subject pairs is analyzed as a function of cycle number. A negative linear correlation would suggest all subjects converging to the same set of population-wide synergies.

A complementary indirect measure of synergy development is normalized mutual information (NMI), a general measure of dependencies between time-series based on information theory [61]. In this analysis, NMI confirms the adaptation of all subjects to a common synergy space, ensuring that the synergies described by PCA are not dominated by a single subject. NMI is found between all subject pairs for each trial t of a given target. A positive correlation between NMI and t for a target indicates the emergence of similarities in timevarying control strategies as subjects learn better control of the task, and infers development of task-dependent, time-variant synergies described in [49].

3) Performance Retention and Generalization: The experiment 1 testing phase evaluates performance retention and generalization by comparing completion time distributions between sets of the learning phase and retention phase, for both old and new targets. Corresponding synergy retention is evaluated by comparing the population-wide PCA components with respect to the development seen in the learning phase. Experiment 2 similarly analyses changes in completion time distributions both after a week between sets, and after rotating the iLIMB during the last set.

# **IV. RESULTS**

At the end of both experiments, all subjects felt they had achieved good control of the tasks such that they no longer had to consciously think about how to control their device, but could "just direct it in the appropriate direction." This is



Fig. 7. Completion time as a function of trial number for all subjects in the learning phase. Box plots indicate distributions for all subjects over each set. The grey (dashed) line represents the median performance for all subjects in each trial, and the red (solid) curve represents the best fit curve over all data points with both a fast and slow learning component:  $c_t(t) = 19.9e^{-2.05 \times 10^{-2}t} + 5.83e^{-9.68 \times 10^{-4}}$ .

indicative of subjects entering the autonomous learning stage and forming a good understanding of the system dynamics, which is hypothesized as the catalyst for synergy development.

#### A. Learning Efficient Control

In the learning phase, subjects initially showed poor performance in both completion time and path efficiency, but significantly improved both metrics over time. All completion times were fit to (2), revealing significant fast and slow learning components ( $R^2 = 0.990$ ):

$$\begin{aligned} \alpha_c &= 2.05 \times 10^{-2} \ (95\% \ CI \ [2.01 \times 10^{-2}, \ 2.10 \times 10^{-2}]) \\ \beta_c &= 9.68 \times 10^{-4} \ (95\% \ CI \ [9.38 \times 10^{-4}, \ 9.98 \times 10^{-4}]) \end{aligned}$$

Figure 7 shows  $c_t$  closely following the median, with box plots indicating the distribution for all subjects within each set. The data is also fit to the linearized model in (4) to reaffirm significance of the long-term learning component ( $R^2 = 0.669$ ,  $\tau_{cl} = 20.0$ ,  $\alpha_{cl} = 1.76 \times 10^{-2}$ ,  $\kappa_{cl} = 5.05$ ):

$$\beta_{cl} = 2.77 \times 10^{-3} \ (95\% \ CI \left[ 2.25 \times 10^{-3}, \ 3.29 \times 10^{-3} \right] \right)$$

This confirms that subjects continuously improved performance with increased exposure to the interface.

All path efficiencies were fit to (3), also indicating significant fast and slow learning components ( $R^2 = 0.156$ ):

$$\alpha_p = 1.81 \times 10^{-2} (95\% CI [1.31 \times 10^{-2}, 2.30 \times 10^{-2}])$$
  
$$\beta_p = 5.74 \times 10^{-3} (95\% CI [5.16 \times 10^{-4}, 6.33 \times 10^{-4}])$$

Figure 8 shows  $p_e$  following the median despite the low correlation and high variance. The competitive environment caused subjects to focus on completion time, resulting in occasional overshoot. Variance is more sensitive in higher efficiencies, and thus small overshoots in optimal paths contribute to variance equally as larger motions in indirect paths. The data is also fit to the linearized model in (5) to confirm the significant long-term learning component ( $R^2 = 0.155 \tau_{cl} = 0.363$ ,  $\alpha_{cl} = 1.60 \times 10^{-2}$ ,  $\kappa_{cl} = 0.531$ ):

$$\beta_{pl} = 2.19 \times 10^{-4} \ (95\% \ CI \left[ 1.96 \times 10^{-4}, \ 2.41 \times 10^{-4} \right] )$$

Interpreting this metric similarly to [47], the significant increase in path efficiency represents the formation of dynamic, task-specific muscle synergies, despite the experiment not placing emphasis on path strategies.



Fig. 8. Path efficiency as a function of trial number for all subjects in the learning phase. Box plots indicate distributions for all subjects over each set (100 trials). The grey (dashed) line represents the median performance for all subjects in each trial, and the red (solid) curve represents the best fit curve over all data points with both a fast and slow learning component:  $p_e(t) = 1 - 0.338e^{-1.81 \times 10^{-2}t} - 0.559e^{-5.74 \times 10^{-4}}$ .



Fig. 9. Cumulative explained variance for the first three PCA components with respect to cycle number. Box plots show distributions from each set.

#### B. Synergy Development

PCA projection on the entire population of EMG inputs for each cycle reveals the evolution of time-invariant synergies. Figure 9 shows the evolution with respect to cumulative explained variance of each eigenvector, in descending order of eigenvalues. The first two components (red) showed a strong positive correlation to cycle number ( $R^2 = 0.622$ ), explaining 85% of the variance by the end of the learning phase. Figure 10 shows the evolution of these two components, which form principal planes in the muscle domain, for each cycle in each set. The initial high variability and alignment with input axes represents individual muscle activations as subjects explore how to control the task-space. As the subjects better identify the system dynamics, the synergy space rotates toward a specific muscle combination forming a consistent plane.

PCA is also projected on single subject EMG inputs for each cycle c. The mean angle between the first two principal eigenvectors of all subject pairs is calculated via (6) and fit to a line  $\varphi_{p,q}(c) = mc + b$ , revealing a significant subjectindependent synergy convergence ( $R^2 = 0.524$ ):

$$m = -6.37 \times 10^{-2} (95\% CI \left[ -6.81 \times 10^{-2}, -5.93 \times 10^{-2} \right])$$

Time-varying synergy convergence is verified with NMI trends between all subject pairs with respect to trial t and target  $k = \{1, 2, 3, 4\}$ :  $NMI_{p,q,k}(t) = m_k t + b_k$ . Each target had a significant synergy convergence despite initial NMI values indicating near-random strategies (see Table I).



Fig. 10. Evolution of the synergy space formed by the first two components of PCA projection during the learning and testing phase. The first three rows show the evolution of the synergy space throughout the 12 sets in the learning phase, while the bottom two rows show the synergy space used during each of the five cycles in the testing phase, for both old (4th row) and new (5th row) targets. The principal plane, as identified from the PCA, is shown on the 4-dimensional EMG input space. This plane contains between 70% and 90% of the explained variance while performing the tasks. Each axis represents a corresponding muscle input, and the color represents the fourth dimension. The evolution during the learning phase shows a clear convergence and rotation to a more steady plane that represents a unique synergy space for the given task-space. The fourth row displays the synergy retention while performing the same tasks, while the bottom row shows initial uncertainty when introduced to new targets followed by a fast convergence to a plane similar in orientation to the original targets (3rd row). This convergence occurs much more quickly than the learning phase.

TABLE I NMI LINEAR FIT FOR EACH TARGET





Fig. 11. Completion time distribution comparison between learning phase and testing phase. Error bars represent 95% confidence intervals. Asterisks over the learning phase indicate significant performance differences between a particular set in the learning phase compared the old (red) or new targets (green) during the testing phase (Welch's t-test, p < 0.05).

# C. Performance Retention and Generalization

1) Experiment 1: Subjects returned a week after completing the learning phase, using the same controls to reach the original four targets as well as the four new targets. Completion times are divided between the old and new targets and compared to the performance curve shown in the learning phase (see Fig. 11). Subjects reached the original targets significantly faster than the new targets (Welch's t-test, p < 0.05). Compared to the learning phase, subjects reached the original targets significantly faster than during the initial six sets in the learning phase, similar to sets 7, 8, and 9, and significantly slower than the last three sets (Welch's t-test, p < 0.05). Subjects reached the new targets significantly faster than during the initial four sets in the learning phase, similar to sets 5 and 6, and significantly slower than the last six sets (Welch's t-test, p < 0.05). Despite one week between sets and no practice time to adjust to sensitivity changes, subjects only regressed slightly and generalized control to new targets without requiring the initial learning curve.

Figure 10 (bottom two rows) shows synergy-space retention in the testing phase. The original target set shows consistent synergy spaces for all 5 cycles (4th row), similar to the end of the learning phase (3rd row), indicating synergy retention. The new target set (bottom row) is initially different but quickly converges towards a similar space given by the original targets, indicating generalization.

2) Experiment 2: Subjects control the robot once a week for three weeks, demonstrating retention at the beginning of the second and third session. Generalization is tested by rotating the hand during the last set of the third session. Despite a week between each session, there are no significant degradations between session 1 and 2 (Welch's t-test, p = 0.397) or



Fig. 12. Completion time distribution comparison between sessions during robot interaction. Error bars represent 95% confidence intervals. The testing session shows subject performance for both the original hand configuration (red) and rotated hand (green). Asterisks under the first two sessions represent significant performance differences between adjacent sets (blue) or a particular set in the learning phase and either retention (red) or generalization (green) performance during the testing phase (Welch's t-test, p < 0.05).

between session 2 and 3 (Welch's t-test, p = 0.2185) (see Fig. 12). Rotating the hand slightly increases completion times compared to the retention test (Welch's t-test, p = 0.09). However, both tasks showed significantly better completion times than were achieved after up to 75 minutes of total training time (Welch's t-test, p < 0.05). This shows that learning the controls does not require a long, intensive training session, but can be split up over time due to learning retention and generalization while interacting with the device.

## V. CONCLUSION

This study supports a shift in closed-loop myoelectric control applications towards proportional and simultaneous controls which can be learned through development and refinement of unique muscle synergies. Such control naturally provides real-time myoelectric interfaces without regard for anthropomorphic constraints. The study contributes evidence for this shift through the revelation of a long-term learning component robust to some transient changes in EMG signal within and across sessions that often result in constant recalibration, retraining, and potential system failures in patternrecognition models [62]. The learning component is associated with improved performance during periodic operation of a myoelectric interface with an arbitrary decoder. The learning correlates with natural development of a unique populationwide synergy space that is refined over time and retained both after a week of non-use and with the introduction of new tasks.

The findings are obtained using biomechanically independent and antagonistic muscles to facilitate synergy development while minimizing the constraints of potential low-level synergies. Unlike other studies evaluating motor learning, this interface was not dependent on a specific synergy formation. Multiple solutions were available for reaching a given target within the space, including individual muscle activations. Therefore, the common population-wide synergy development is a natural result of effectively identifying system dynamics of the interface, resulting in enhanced control of the interface. These results suggest that myoelectric controls can be learned similarly to new motor skills, allowing users to enter an autonomous control stage [33] even for non-intuitive mapping functions. Although the current study only evaluates healthy subjects, this concept has potential implications on myoelectric interfaces designed for assistive and rehabilitation robotics, particularly for individuals who may not have voluntary control over muscles needed for intuitive and/or pattern recognition-based controls. This may be a viable option for amputees undergoing Targeted Muscle Reinnervation surgery [63] to learn new mappings between reinnervated muscles and commands to operate a prosthetic device, as well as individuals suffering from multiple sclerosis, who can control myoelectric devices despite severely atrophied muscles [14]. Both populations will be the focus for future research.

In addition to continual and long-term performance enhancements, the method naturally provides a user-independent interface that has not yet been achieved through training decoders. Although motivation is needed to overcome the initial learning curve and start developing synergies, the ability to both retain these unique synergies and utilize them to generalize control supports the use of synergy development, not necessarily trained decoders, for efficient myoelectric interfaces designed for long-term use. Thus, myoelectric motor learning may open doors for significant expansion and enhancement of myoelectric controlled applications.

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