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# Adapting Proportional Myoelectric-Controlled Interfaces for Prosthetic Hands

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***Abstract*—Powered hand prostheses with many degrees of freedom are moving from research into the market for prosthetics. In order to make use of the prostheses' full functionality, it is essential to find efficient ways to control their multiple actuators. Human subjects can rapidly learn to employ electromyographic (EMG) activity of several hand and arm muscles to control the position of a cursor on a computer screen, even if the muscle-cursor map contradicts directions in which the muscles would act naturally. We investigated whether a similar control scheme, using signals from four hand muscles, could be adopted for real-time operation of a dexterous robotic hand. Despite different mapping strategies, learning to control the robotic hand over time was surprisingly similar to the learning of two-dimensional cursor control.**

## I. Introduction

Improvements in robotics have advanced the design of hand prostheses with multiple degrees of freedom. But because measurement of reliable and sufficiently independent surface electromyography (EMG) from several muscles is difficult in amputees, current commercial implementations of hand prostheses usually employ only one or two electromyographic channels and an on-off control mechanism to switch between different modes of operation or grasp types.

However, if the limitation of myoelectric sources can be overcome, humans are well able to use multiple muscles for myoelectric control, as has been demonstrated in healthy subjects: Radhakrishnan et al. [1] showed that humans could learn to control a cursor in two dimensions on a computer screen with their EMG activity, using isometric contractions of multiple muscles: Six vectors, pointing in different directions, scaled with the magnitude of EMG from six sites on hand and arm determined the position of a cursor. While initially subjects found it easier to control interfaces that mimic movement directions of natural limb function (*biomimetic interface*), with sufficient training, they also learned to operate interfaces that were entirely unintuitive (*abstract interface*), with comparable accuracy of cursor control achieved with abstract and biomimetic interfaces. In addition it has been shown that control of hand muscles is sufficiently flexible to form unnatural synergies appropriate for a multitude of complex abstract functions [2, 3]. This supports our view that experiments of myoelectric cursor control can answer questions relevant to the control of prosthetic hands.

With this study, we offer a proof of concept that compares a direct posture control of an advanced hand prosthesis with myoelectric position control of a cursor on a screen with respect to training time and accuracy. We hypothesized that, with training, the human motor cortex could internalize and apply the new control schemes in both cases. We used a proportional control mechanism that affords its user a high level of flexibility and has access to a continuum of possible hand postures.

## II. Methods

### A. Participants

Eight right-handed subjects, two female, six male, aged between 23 and 36 years (median: 28 years), participated in this study. They were free of any neurological or motor disorders and gave informed consent. The study was approved by the local ethics committee at Newcastle University.

### B. Experimental Setup

Participants had their left hand restrained inside a glove, fixed to a horizontal board, and their forearm strapped to an armrest (Fig 1a). EMG was recorded from four intrinsic hand muscles of the left hand: the abductor pollicis brevis (APB), the first dorsal interosseous (1DI), the third dorsal interosseus (3DI) and the abductor digiti minimi (ADM). Subjects controlled the myoelectric interface with isometric muscle contractions.

EMG was measured using pairs of stick-on electrodes (Bio-logic, Natus Medical Inc., Mundelein, IL, USA) positioned on the belly of the hand muscle and an adjacent knuckle. An in-house fabricated (Newcastle University), battery-powered portable device was used to amplify the EMG signals between 0.1K and 5K and signals were band-pass filtered between 30 Hz and 2 kHz. A data acquisition card (NI USB-6229, BNC, National Instruments, Austin, TX, USA) digitized the signals at a 5 kHz sampling frequency and made them available to the computer for recording and real-time processing. Data recording, online processing

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and graphical user-interface were handled by Python-based software, developed to implement these experiments.

For each subject, we recorded calibration data to assess resting levels $y_r$ and comfortable contraction levels $y_c$ for each EMG channel. Comfortable contractions reflected muscle activity that could easily be repeated several hundred times. During the experiment, resulting calibration levels of EMG signals were used to normalize the muscle activation levels $y$ extracted from raw EMG measurement (see Section II-C) to compute $y_n = (y - y_r) / (y_c - y_r)$.

### C. Muscle activation estimators

Our control algorithm consisted of a muscle activation estimator and a mapping strategy that linked muscle activation to the effectors. Mapping procedures differed between the two parts of the experiment and are described in Section II-E. After removing a possible signal offset from the EMG recordings, we used either of two methods to extract muscle activation levels from the raw EMG: (1) A linear filter that, in each update step, averaged the rectified EMG signal from each channel over the preceding 750 ms. (2) Or a Bayesian estimator using a recursive filter algorithm, proposed by T. D. Sanger [4]. This method modelled a desired neural drive signal as a combined diffusion and jump process. The posterior probability density of the instantaneous neural drive was updated with every new sample of EMG.

### D. Robotic Hand

For part B of the experiment, subjects interacted with an improved version of the SmartHand [5], a bio-inspired hand prosthesis in which five motors independently actuate thumb abduction, thumb flexion, index finger flexion, middle finger flexion and a combined flexion of ring and little finger. Four of those motors were controlled by subjects in this study, whereas thumb abduction stayed at a constant level throughout the experiment. Bidirectional communication between prosthesis and computer was established over a serial RS232 communication protocol, using high level commands, built into the hand's controller, to repeatedly update levels of finger flexion and monitor actual finger positions.

### E. Experimental Procedure

Our experiment was conducted in two parts (A and B). Each part consisted of 320 trials, arranged in two consecutive blocks of 160 trials, each of which took about 12 minutes to complete. All subjects participated in both parts, with half of them starting with part A and the other half with part B. Subjects sat with their left hand immobilized in a horizontally fixed glove and controlled the task through isometric muscle contractions. They were not told which muscle activation resulted in which action and the association was designed to be non-intuitive, that is, unrelated to natural hand function, but equal for all subjects.

#### 1) Part A: cursor control

For the cursor control task, subjects sat in front of a laptop computer screen and controlled the position of a circular, yellow cursor. Targets were indicated by larger, green circles (Fig. 1b/d). Relaxing all muscles brought the cursor to the centre of the screen, whereas contraction of each single muscle drove the cursor away from the centre, along its direction of action (DoA, see Fig. 1b). The 2D cursor position $x$ was determined by the sum over all four DoA vectors scaled by the normalized muscle activation level $y_n$ of each corresponding muscle:

$$x = \sum_{i=1}^{4} y_{n,i} \; DoA_i \; .$$

Eight peripheral targets were presented in a pseudo-random order, with each target appearing once in a set of eight consecutive trials. Four targets could be reached by activation of a single muscle at a level corresponding to 75% of comfortable contraction; the remaining four required the activation of at least two muscles simultaneously, albeit at a lower level.

At the start of a new trial, subjects were required to relax their muscles in order to match a central target for a time of 500 ms, after which a new peripheral target appeared, accompanied by an auditory cue (660 Hz frequency). This in-

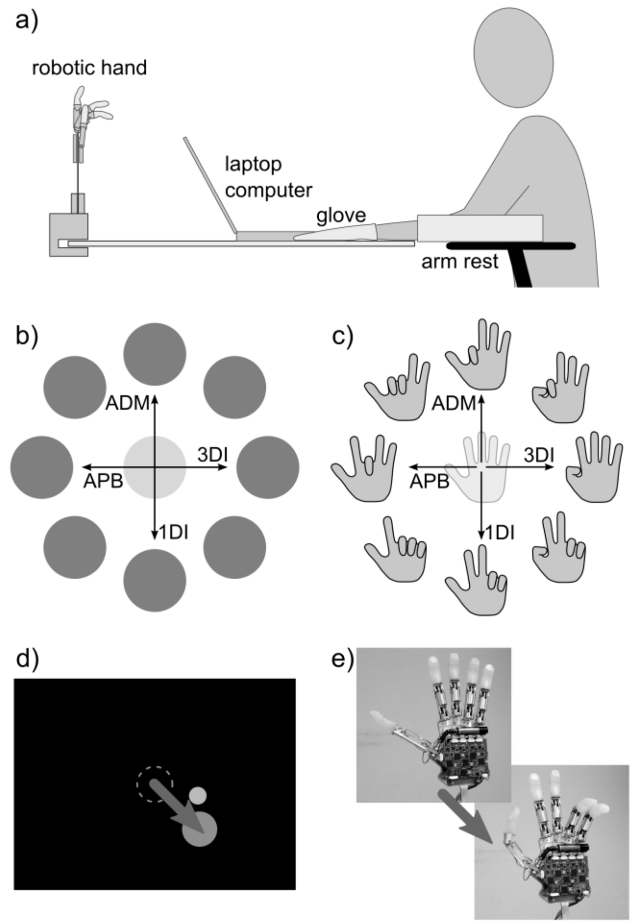


Figure 1: Layout of the experiment. (a) Experimental setup. (b) Mapping of EMG activity for the centre-out task. Each muscle controlled movements in one direction of action (DoA), the linear sum of which determined the two-dimensional position of a cursor. (c) Target postures for robotic hand control. The activation levels of each muscle proportionally controlled the flexion level of one robotic finger. Four target hand shapes could be achieved by activation of a single muscle, four others (on the diagonals) with two muscles. (d) Cursor movement to a target on the computer screen. Only the current cursor and target positions (solid circles) were visible. (e) Starting and sample target postures of the robotic hand.

dicated the start of a movement period, lasting 2 s. A second auditory cue (880 Hz) signalled the start of a hold period, 1 s long. Subjects were instructed to move and hold the cursor as close to the centre of the target as possible.

*2) Part B: robotic hand control*

In the robotic hand control task, subjects manipulated flexion levels of four fingers on the robotic hand: thumb, index finger, middle finger and ring/little finger; ring and little finger being coupled in their movement. Each one of these parameters was individually controlled by the activation level of one muscle. Relaxing all muscles opened the hand, which was used as a starting position. Targets in 2D space were replaced by target postures, appearing in a pseudo-random order, like the positional targets of part A. In analogy to the cursor task, four target postures could be achieved with activation of a single muscle at 90% of comfortable contraction, whereas the other four required simultaneous activation of two muscles at a lower level (Fig. 1c). Starting posture (open hand) and target postures were instructed by photographs of the posture on the laptop screen. The robotic hand was mounted about 40 cm behind the screen, so that subjects could comfortably observe both (Fig. 1a). Trial structure matched this of part A.

*3) Performance measure*

At the end of each trial, following the hold-period, in both experiments 1A and B subjects were presented a score between 0 and 100, reflecting their performance during the last trial. We measured Euclidean distance of either the cursor or the current hand posture (in its four-dimensional space of finger flexions) to their respective targets. To achieve a score greater than zero, subjects had to get closer to the target. Thus, the impact of large errors on the score was limited:

$$score = \begin{cases} 100 - [d(C,T)/d(S,T)] \times 100, & d(C,T) \leq d(S,T) \\ 0, & d(C,T) > d(S,T) \end{cases},$$

where $d(C,T)$ is the Euclidean distance, averaged over the hold-period, between the two-dimensional cursor and target positions (part A) or between current and target hand postures, as represented by vectors of four flexion levels (part B). $d(S,T)$ denotes the Euclidean distance between starting and target position or posture.

## III. Results

Offline analysis was done using MATLAB (MathWorks, Natick, MA, USA).

### *A. Cursor control vs. robotic hand control*

We evaluated learning of cursor and hand control task over time. Fig. 2 shows average learning curves over two consecutive blocks (160 trials each) for both parts of the experiment. Markers indicate score averages over sets of 32 trials, pooling all scores from all subjects.

During the first block, a steady improvement in task performance could be observed for both task conditions, cursor and robotic hand control. At the end of the second block, however, scores of the cursor control task deviated significantly from those in hand control, where task performance peaked at a somewhat lower level.

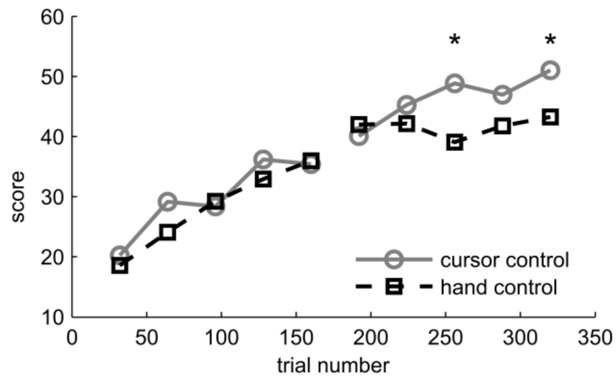

Figure 2: Myoelectric control learning curves. Average scores, indicative of task performance, based on Euclidean distance to target position (cursor control, grey circles) or target posture (hand control, black squares), over two consecutive blocks of 160 trials each. Averages are computed over 32 consecutive trials for each subject. Asterisks mark significant differences between measures for cursor and hand control tasks within a set of 32 trials (unpaired t-test, $p < 0.05$, corrected for multiple comparisons).

### *B. Muscle Tuning*

Muscle tuning functions describe the relation between task goals and muscle activation. In our case they revealed how subjects' behaviour was following the relationship of myoelectric activity and the control output imposed in the experiment. Fig. 3 shows median muscle activation levels, as a percentage of the level equivalent to target distance, plotted as a function of target. Targets were ordered according to direction for cursor control (part A) or an equivalent order of postures (cf. Fig. 1c) for hand control (part B). To average over tuning functions for different muscles, they were shifted so that a muscle's DoA (part A) or the equivalent posture (part B) corresponded to 0° or posture 0, respectively.

During the early learning phase (Fig. 3a), tuning functions for cursor control (grey circles) were broad, had an elevated baseline and EMG levels showed high variability for targets far from the muscles' DoA. In the early stages of hand control (black squares) variability in the control signals for finger flexions, unrelated to the target posture (relative posture indices < -2 or > +2), was better contained.

At the end of the both parts of the experiment (Fig. 3b), median muscle tuning was close to a minimal activation pattern (light grey line) that only employed muscles essential for task success. Tuning functions for cursor and hand control were almost identical, with little variability in EMGs that were not relevant for task success.

## IV. Discussion

We translated a paradigm for myoelectric cursor control to direct proportional control of a multi-fingered hand prosthesis. The four-muscle control scheme of the two-dimensional cursor task transferred well to real-time control of a robotic hand with similar dynamics of subjects' learning and similar initial levels of accuracy for both cursor control (experiment 1A) and robotic hand control (experiment B).

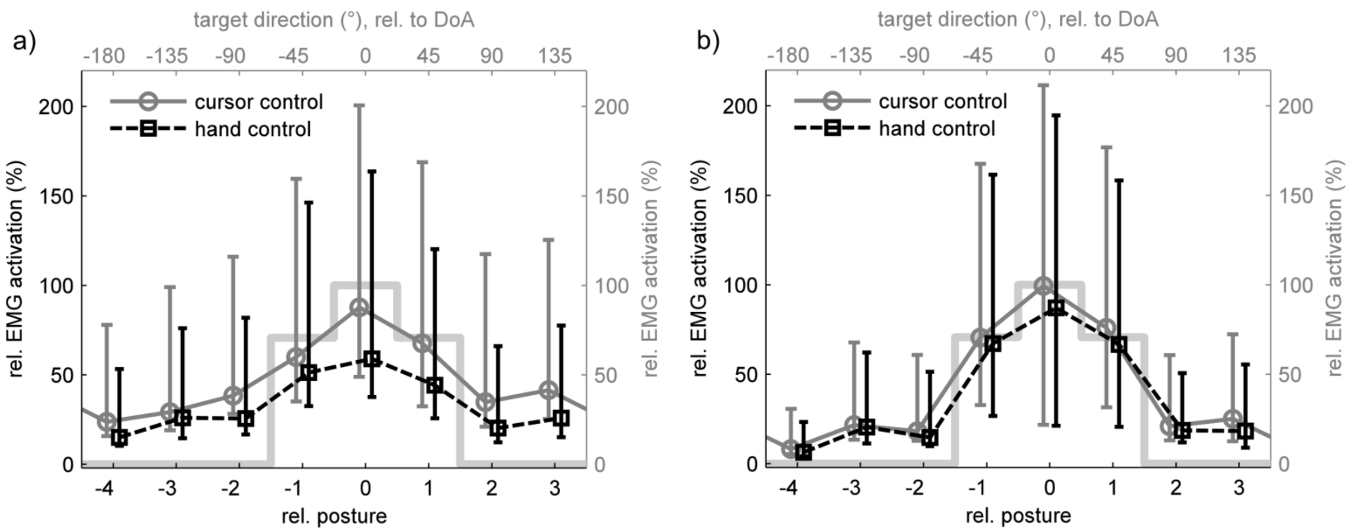


Figure 3: Tuning functions. (a) First 80 trials, (b) last 80 trials of a total 320 trials in experiment 1. Relative EMG activation levels during the hold period over different target positions/postures. Medians were calculated over all muscles and subjects; error bars display $25^{th}$ and $75^{th}$ percentiles. Targets are given as directions relative to a muscle's DoA (cursor control; grey circles) or as an equivalent relative posture according to the arrangement in Fig. 1c (hand control; black squares). The light grey step function indicates the minimal activation pattern of muscles that could achieve perfect performance.

This implies that control mechanisms, relevant to the use in prosthetic hands, can be studied in the well-established and easily implementable framework of centre-out cursor movements. We further believe, a myoelectric-controlled cursor task could be a valuable and inexpensive tool to familiarize patients with myoelectric control and identify the most promising sets of muscles, prior to the fitting of a myoelectric prosthesis. In this line, virtual reality tasks have already been suggested to train patients in the control of myoelectric prostheses using a classification approach [6]. However, the continuous feedback, offered by a proportional controller may lend itself better to biofeedback training.

During hand control (part B of the experiment), target postures could only be matched by exactly one combination of muscle activities, while deviations from this were always detrimental to task performance. This might explain, why, at an early stage, activation of non-relevant muscles was better suppressed than in cursor control (part A). Redundancy inherent to the mapping scheme of cursor control, on the other hand, could be exploited so that the suboptimal behaviour would not overly reduce success in the cursor task [1]. This could be achieved by partial co-activation of muscles with opposite DoAs or even muscles with perpendicular DoAs. Exploiting this redundant mapping in part A gave cursor control a possible advantage over part B. The possibility to match cursor and target directly on the screen may have further contributed to a higher accuracy in cursor control towards the end of the experiment.

A one-to-one mapping of muscles to actuators of a robotic hand, as demonstrated in our study, may not be viable for prosthetic hands with many degrees of freedom, if only few muscles are available for stable recordings. A large number of controlling muscles also may increase necessary training time and cognitive effort. Hence, for real-life prosthetic applications, a more promising path of action might try to reduce the dimensionality in the prosthesis' control space for common hand movements [7]. In spite of the reduced complexity, this can still allow the access of a continuum of relevant hand postures: Matrone et al. used principal component analysis over 50 different grasps of a prosthetic hand to identify two components that were sufficient to grasp a large variety of objects [8, 9]. This approach can further constrain hand configurations so that unfavourable postures e.g., paths of different fingers crossing each other, will be avoided.

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## REFERENCES

[1] S. M. Radhakrishnan, S. N. Baker, and A. Jackson, "Learning a novel myoelectric-controlled interface task," *J Neurophysiol,* vol. 100, pp. 2397-408, Oct 2008.

[2] M. H. Schieber and M. Santello, "Hand function: peripheral and central constraints on performance," *J Appl Physiol,* vol. 96, pp. 2293-300, Jun 2004.

[3] K. Nazarpour, Barnard, A., Jackson, A., "Flexible cortical control of task-specific muscle synergies," *J Neurosci,* vol. 32, pp. 12349-12360, 2012.

[4] T. D. Sanger, "Bayesian filtering of myoelectric signals," *J Neurophysiol,* vol. 97, pp. 1839-45, Feb 2007.

[5] C. Cipriani, M. Controzzi, and M. C. Carrozza, "The SmartHand transradial prosthesis," *J Neuroeng Rehabil,* vol. 8, p. 29, 2011.

[6] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Target Achievement Control Test: evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses," *J Rehabil Res Dev,* vol. 48, pp. 619-27, 2011.

[7] C. Pesyna, K. Pundi, and M. Flanders, "Coordination of hand shape," *J Neurosci,* vol. 31, pp. 3757-65, Mar 9 2011.

[8] G. C. Matrone, C. Cipriani, M. C. Carrozza, and G. Magenes, "Real-time myoelectric control of a multi-fingered hand prosthesis using principal components analysis," *J Neuroeng Rehabil,* vol. 9, p. 40, 2012.

[9] G. C. Matrone, C. Cipriani, E. L. Secco, G. Magenes, and M. C. Carrozza, "Principal components analysis based control of a multi-DoF underactuated prosthetic hand," *J Neuroeng Rehabil,* vol. 7, p. 16, 2010.