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Comparison of Hand and Forearm Muscle Pairs in Controlling of a Novel Myoelectric Interface

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Abstract—With commercial prosthetic hands, executing some everyday movements, for example, concurrent grasp and bending of the wrist to pick up an object from a high shelf, is very challenging. We hypothesised that after the loss of the hand, the flexibility of the nervous system enables prosthesis users to bypass the innate biomechanical constraints on upper-limb muscles and joints. We show that users are able to learn to operate a myoelectric-controlled interface by flexibly contracting pairs of hand and forearm muscles. The use of these novel activity patterns can have a transformative effect on the control of future prosthetic hands.

I. Introduction

An artificial arm, or prosthesis, is an example of technology that can be used to help somebody perform essential activities of daily living after a serious injury that results in the loss of their arm or a congenital deficit. Such activities might include eating, washing, opening doors, or shaking hands with a friend. Prosthetic arms are often controlled by sensing the electrical activity, the surface electromyogram (sEMG), of the muscles of the remaining arm to which the prosthesis is attached.

The on-off 1-degree of freedom control paradigm that Reinhold Reiter proposed in 1948 [1] is still used widely for prosthesis control. As early as 1967, Finley and Wirta [2] showed that on-off control does not offer enough flexibility to the user and proposed the use of pattern recognition to estimate the prosthesis user's movement intention by processing and pattern recognition of sEMG signals. Pattern recognition of sEMG has recently been adopted in a commercial myoelectric control application allowing the control of wrist movements: pronation, supination, flexion, and extension and hand opening and closing in real-time [3]. However, almost half a century since Finley and Wirta proposed the use of pattern recognition, and despite remarkable laboratory demonstrations, it has not been feasible to *widely* commercialise the approach. This shortcoming may be due to three core issues [4]–[6]:

- It is often difficult for amputees to generate distinct activity patterns for different movement classes. This can lead to overlapping class distributions in the feature space.
- During non-clinical prosthesis use, feature spaces are non-stationary, and typically move due to electrode displacement or movement of the residual limb.

- The combined effect of dynamic factors, e.g. forearm orientation and muscular force, can be nonlinear.

Therefore, one major challenge for next-generation prosthetic systems is the ability to design a proportional control scheme [7] that allows for the control of a number of degrees-of-freedom (DOF). Towards this vision, many research studies have demonstrated the ability to reconstruct both wrist [8], [9] as well as finger movement trajectories [10]–[13] by using regression rather than classification. These regression based methods have not yet translated to clinical practice, perhaps because accurate tracking of joints typically requires that many electrodes be placed on the forearm.

The nervous system constrains movements such that our diverse actions can be constructed with a few innate building blocks called muscle synergies [14], [15], e.g. hand postures [16], [17]. Intrinsic and abstract muscle synergies have been used for myoelectric control in recent years [18]–[20]. In general, muscle synergies are extracted using unsupervised learning methods and are subsequently used to predict kinematic variables or grasp shapes. For instance, Jiang et al. [7] used a muscle synergy model to decode wrist kinematics during real-time experiments with amputee participants. The concept of muscle synergies has also been used in EMG signal classification for prosthesis control [18]. However, because of the problems mentioned earlier, it has not been possible to extend the synergy classification approach to identify patterns of simultaneous movements.

We previously showed that the human nervous system can learn to overwrite innate muscle synergies to achieve specific motor goals [21]. This can be achieved by grouping and activating muscles that do not naturally belong in a synergy. These new groups were termed abstract muscle synergies. Moreover, we showed that it is feasible to control a desktop robotic hand via an arbitrary mapping between hand muscles and prosthetic joints, e.g. controlling the prosthetic thumb with muscles in the little finger [19].

In this paper, we develop a proof of concept experiment to enable quantification of how well humans can learn to activate their upper-limb muscles in novel groups and to use these new groups to control a novel myoelectric-controlled interface. Importantly, we do not use pattern recognition. Instead, we utilise simple robust methods to directly link muscle activity to visual feedback and leverage participant's adaptive behaviour. Our approach sidesteps the core problems associated with non-clinical use of pattern recognition. We believe these methods have the potential to enable simultaneous multi-joint control of prosthetic hands.

II. Method

A. Participants

Twelve participants took part in this experiment: all were able-bodied, right-handed and free from neurological or motor disorder. Approval was granted by the local ethics committee at Newcastle University. All participants had informed written consent before participation.

B. Experimental Setup

Participants sat with their right hand open and pronated inside a glove. Participant's wrists were strapped to a fixed horizontal board, attached to the armrest of an experimental chair. EMGs were recorded from three groups of intrinsic hand muscles: the thenar (abductor pollicis brevis (APB)), hypothenar (abductor digiti minimi (ADM)) and the first dorsal interossei (1DI), as well as two forearm muscles: flexor carpi radialis (FCR) and extensor carpi radialis (ECR).

EMGs were measured using disposable snap electrodes (Nicolet® and TECA®, Care Fusion, Middleton, WI, USA). Myoelectric signals were amplified (D360 Amplifier, Digitimer, Hertfordshire, UK) with a gain of 5k and band-pass filtered between 30 Hz and 1000 Hz. The acquired signals were digitised and sampled at 5000 Hz using a data acquisition card (NI USB-6212 BNC, National Instruments). A Python-based system was used for data acquisition, real time processing and presentation of stimuli.

Before the start of the experiment, we recorded signal offsets as well as the amplitude of the measured signal during rest and comfortable contraction for each EMG channel separately. To determine comfortable contraction levels, participants were instructed to contract each muscle at a level that could be comfortably maintained and repeated several hundred times without fatigue. In previous studies with similar myoelectric interfaces, this level corresponded to an activity between 10-20% of the maximum voluntary contraction [21]–[23]. Any encountered offset was subtracted from each channel as the first pre-processing stage. The sEMG signal was rectified and smoothed by a window of approximately 750 ms.

C. Experimental Protocol

Participants used isometric muscle contractions to operate a myoelectric user interface. The contraction of two paired muscles determined the position and movement of the 2-D cursor. Figure 1A shows the 2-D myoelectric user interface control space. Participants were instructed to move the cursor to the target area and hold it there for the trial duration.

Three pairs of muscles were used to control the cursor: APB (thumb abduction) and ADM (little finger abduction), 1DI (index finger abduction) and APB (thumb abduction), and ECR (wrist extension) and FCR (wrist flexion). Pair APB–ADM are muscles that do not co-contract naturally (independent), 1DI–APB represents a synergistic muscle pair, and FCR–ECR are an antagonist muscle pair. Participants were informed as to which pair of muscles to use prior to each experimental condition, but were not told how muscle activations related to cursor direction.
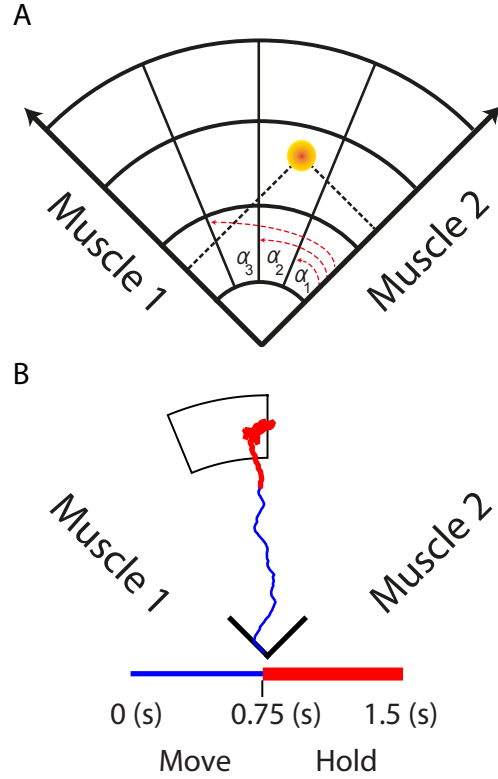

Fig. 1. A) A 2-dimensional myoelectric interface control space. Participants use muscle contractions to move the virtual cursor towards the target. B) A representative cursor trajectory in the task space. The thin blue and thick traces show the trajectories during movement and hold periods.

For each muscle pair participants performed eight blocks of 72 trials for two target area conditions. Trials contained three feedback conditions: visual feedback fully available (48 of 72), visual feedback partly available (12 of 72), and visual feedback not available (12 of 72). Feedback conditions were pseudo-randomised throughout the 72 trial blocks.

The start of each trial required participants to relax their hand and forearm, so that the cursor returned to the starting area. The trial did not begin until the cursor was inside the start area. Each trial was 1.5 s, divided into two 750 ms periods for movement (Figure1B: blue phase) and hold (Figure1B: red phase). During the experiments participants did not see the traces. An audio tone cued the start of the movement and hold periods. At the end of the trial a percentage score was presented. The percentage score reflected the duration of time that the cursor was in direct contact with and/or was held within the target are during the hold period.

The order of the muscle pairs and the order of the target area conditions were counter-balanced between participants.

D. Myoelectric Interface

The mean absolute value of sEMG in a controlling muscle over the previous 750 ms determined the cursor position on the relevant dimension of the interface. Interface cursor values were normalised such that a comfortable contraction, as recorded prior to experimentation, resulted in the cursor reaching the periphery of the interface.
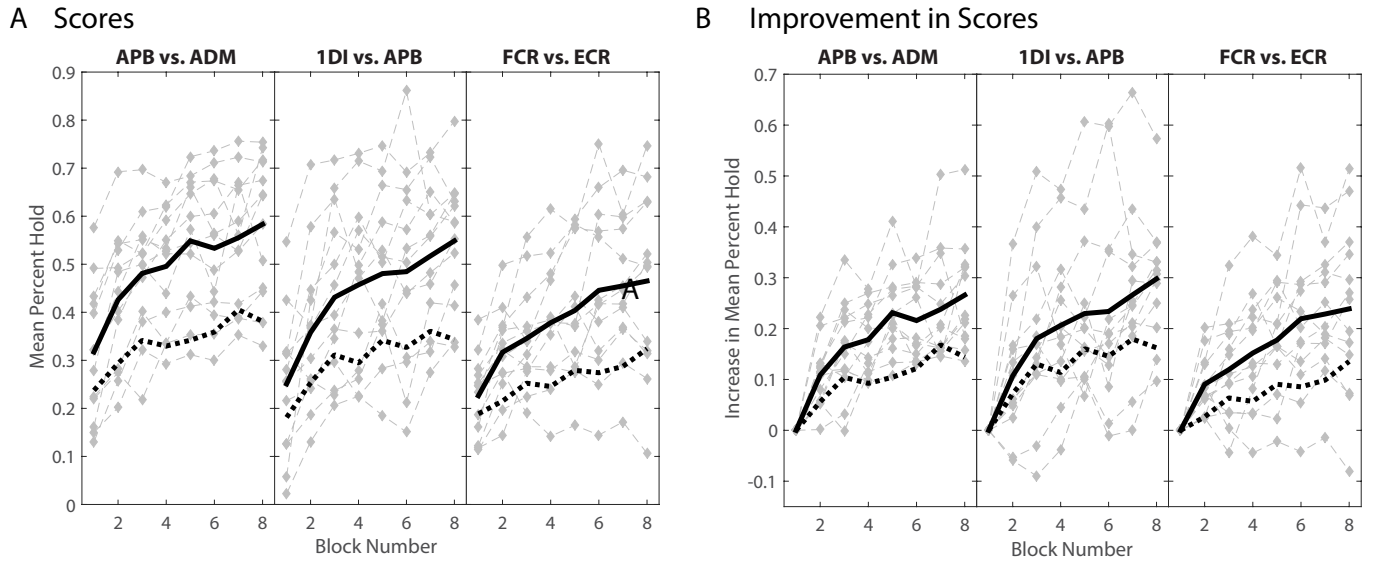
Fig. 2. Analysis of performance score: A) Average percent hold score by block number and B) Improvement in average score for the three muscle pairs achieved by participants. In all insets the solid black trace indicates trials with visual feedback and the dotted black trace shows trials without visual feedback. The grey traces indicate the score performance for individual participants.
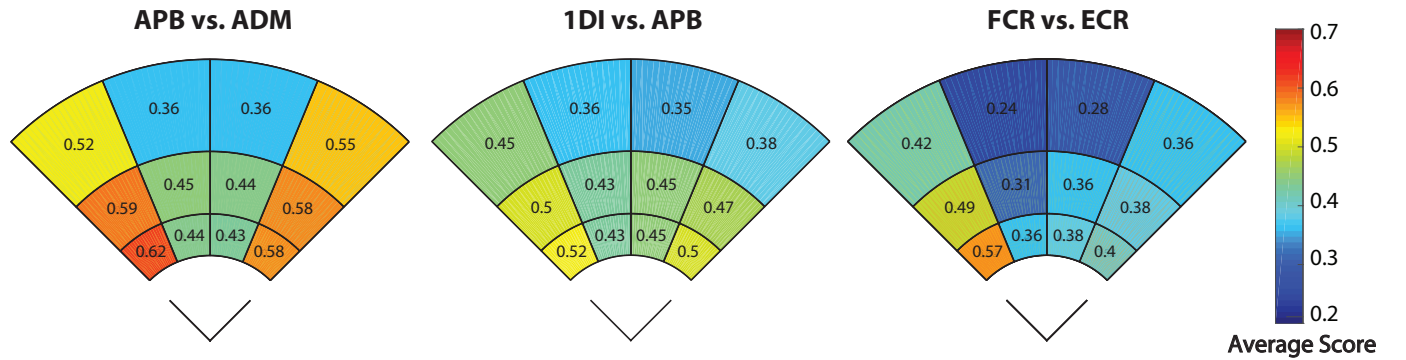

Fig. 3. Spatial distribution of scores for the three pairs. Colors code the success. Most successful targets were side targets and the least successful the far middle target. The score are reported for trials in which visual feedback was fully available during the hold period.

III. RESULTS

In this paper data recorded during the two target area conditions were combined. Moreover, trials in which visual feedback was partly or not available at all were merged.

Percentage hold was used as the primary performance measure for all muscle pairs in the work. All data analysis was performed using MATLAB.

A. Scores and Learning Rates

We evaluated learning of the myoelectric control user interface using the percent hold score over time for each muscle pair, shown in Figure 2A. The mean percent scores show consistent improvement for all muscle pairs, even in the absence of visual feedback, although scores were considerably lower for trials in which visual feedback was not complete. These results confirm that participants were able to *learn* to activate the muscles pairs in new ways for control of the myoelectric cursor.

Figure 2B compares the improvement in average scores across the three muscle pairs. Improvement was calculated relative to scores on the initial run. Mean improvement in score with all muscles pairs were ~25% and ~15% in trials with and without visual feedback, respectively.

B. Spatial distribution of success

We then investigated the spatial distribution of scores across different targets for the three muscle pairs when visual feedback was fully available during the hold period. The heat maps in Figure 3 show that for all pairs the highest scores are achieved when targets are on the side targets. Moreover the lowest scores were observed in the farthest middle targets when new synergistic contractions was required.

Scores suggest that the APB–ADM (independent pair) and 1DI–APB (synergist pair) lead to comparable levels that were higher that the score achieved with the FCR–ECR (antagonist) pair.

IV. Concluding remarks

We showed that able-bodied participants can learn to use their hand and forearm muscle pairs to flexibly control the position of a myoelectric cursor in a 2-D task environment. Our results suggest it is easier for participants to control the task with muscle pairs that comprise intrinsic hand muscles when compared to wrist flexor and extensor muscles. Importantly however, a comparison of the rate of learning between hand and forearm muscle pairs suggested that the development of novel co-contraction patterns, or muscle synergies, may be equally easy. In addition, analysis of score distribution maps corroborated that the muscle pairs that we selected behave in very similar ways, that is, middle targets are less successful that side targets. This observation is consistent with the predictions of signal dependent noise when two effectors control the cursor position [24].

Studies of flexibility of upper-limb muscles in generating novel and abstract have resulted in the exciting notion of biofeedback or direct control of upper-limb prostheses [14], [25], [26]. In fact, direct control has its conceptual roots in the biofeedback experiments of the early 1960s that demonstrated that the relationship between cell activity and behaviour can be altered with operant conditioning [27]. It was shown previously that is possible to control a desktop prosthesis hand with arbitrary mappings between upper-limb muscles and active joints of prosthetic hands [19], [28].

Future work will include investigating whether amputee users can control a prosthetic hand with a controller based on the proposed task environment. In this setting, each sector in the task was $\frac{\pi}{4}$ wide. It would be very interesting to quantify if the size to the two middle targets would need to be adjusted automatically or adaptively according to users' performance [29]. Finally, it would be informative to test whether a cursor velocity controller [30], in which quiescent muscle activity leads to a stationary cursor, is more appropriate than our cursor position control.

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