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Continuous Versus Discrete Simultaneous Control of Prosthetic Fingers

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***Abstract*— Modern, commercially available hand prostheses offer the potential of individual digit control. However, this feature is often not utilized due to the lack of a robust scheme for finger motion estimation from surface electromyographic (EMG) measurements. Regression methods have been proposed to achieve closed-loop finger position, velocity, or force control. In this paper, we propose an alternative approach, based on open-loop action-based control, which could be achieved through simultaneous finger motion classification. We compare the efficacy of continuous closed-loop and discrete open-loop control on the task of controlling the five degrees of actuation (DOAs) of a dexterous robotic hand. Eight normally-limbed subjects were instructed to teleoperate the hand using a data glove and the two control schemes under investigation in order to match target postures presented to them on a screen as closely as possible. Results indicate that, firstly, the performance of the two control methods is comparable and, secondly, that experience can lead to significant performance improvement over time, regardless of the method used. These results suggest that prosthetic finger control in a continuous space can be potentially achieved by means of myoelectric classification and discrete, action-based control and hence encourage further research in this direction.**

I. INTRODUCTION

Arguably, the holy grail of machine learning-based myoelectric control of multi-articulated prosthetic hands is a robust scheme for simultaneous and independent control of multiple digits. Many research groups have thus concentrated their efforts toward this goal and provided proof-of-concept results by carrying out offline analyses [1–4] and real-time myoelectric control experiments [5–9]. Nevertheless, the clinical impact of such approaches has been rather limited, possibly due to the lack of robustness under real-life conditions [10].

One of the intrinsic difficulties of pattern recognition-based individual digit control is that it relies on regression strategies [11]; that is, a continuous variable (e.g. joint angle, velocity, or digit force) has to be estimated from non-invasive measurements, typically recorded with surface electromyography (EMG) or, as has been recently proposed, force myography (FMG) [12]. On the other hand, methods based on classification of surface EMG signals have been proven more robust [13–15], as is to be expected given the smaller set of possible predictions/actions.

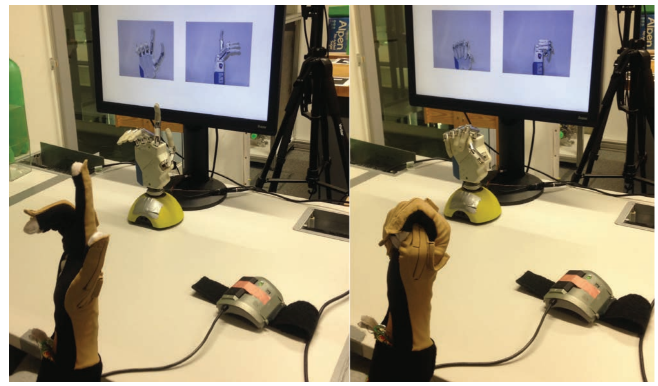

Fig. 1. Experimental setup. A participant is controlling the 5 DOAs of the IH2 Azzurra robotic hand using a CyberGlove II data glove. The goal is to match the posture of the robotic hand to the one displayed on the screen as closely as possible.

One possible way to increase the robustness of individual digit control that has not been explored is through multi-label classification [16], that is, simultaneous finger motion classification. With this approach, each label corresponds to a possible discrete action, namely, open, close, and stall, for a single digit. This scheme has the potential of providing the user with control over a multidimensional continuous space of movement, albeit using in its core a discrete control mechanism. This method, however, is likely to feel less intuitive initially and therefore its efficacy may rely on user adaptation through learning. There is evidence that humans are particularly good at learning to use muscle co-activation patterns, even non-intuitive ones, when these are required to achieve certain tasks, such as cursor position control [6, 17, 18], robotic finger control [6], and high-dimensional prosthetic arm control [19, 20].

The purpose of this study is to provide a preliminary investigation into the potential of an open-loop discrete control scheme for individual fingers of multi-articulated prostheses. We demonstrate that such control scheme is feasible, in principle, and can achieve comparable performance to that attained with direct closed-loop finger position control. We finally investigate the learning curves associated with controlling multiple degrees of actuation (DOAs) of a prosthetic hand.

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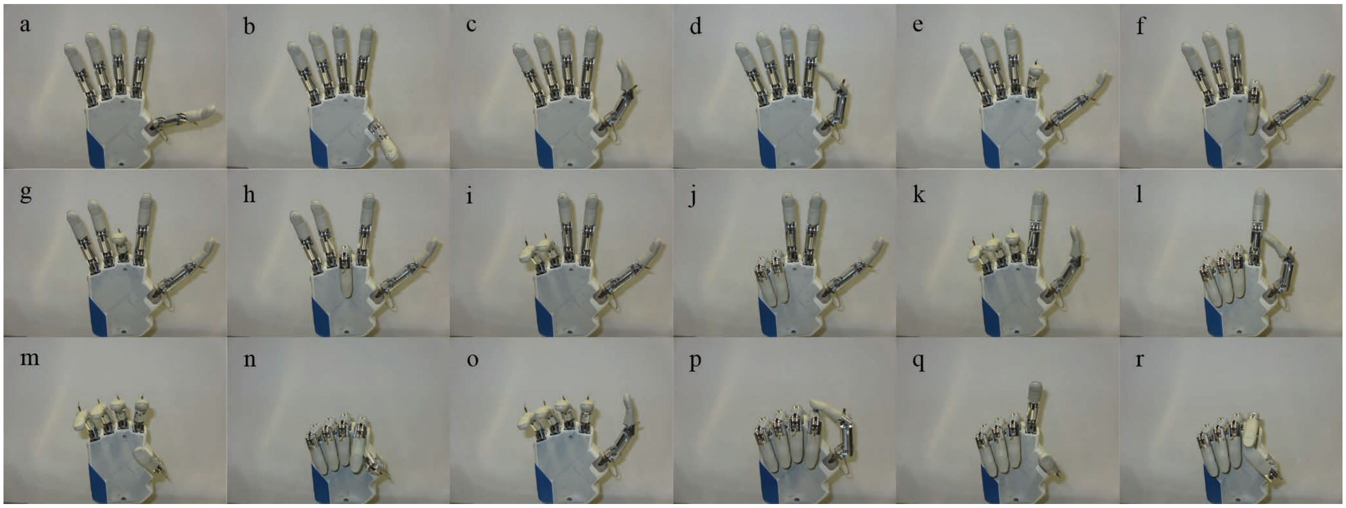

Fig. 2. Target poses. (a) thumb abduction (half); (b) thumb abduction (full); (c) thumb flexion (half); (d) thumb flexion (full); (e) index flexion (half); (f) index flexion (full); (g) middle flexion (half); (h) middle flexion (full); (i) ring/little flexion (half); (j) ring/little flexion (full); (k) index pointer (half); (l) index pointer (full); (m) cylindrical grip (half); (n) cylindrical grip (full); (o) lateral grip (half); (p) lateral grip (full); (q) tripod grip (half); (r) tripod grip (full).

II. METHODS

A. Participant recruitment

Eight healthy, right-handed male volunteers (median age 28 years) were recruited for this study. All experiments were approved by the local Ethics Committee of the School of Informatics, University of Edinburgh. Prior to the experiments, all subjects read a participant information sheet and signed a consent form. Upon completion, participants were required to answer a short questionnaire (Section II-G).

B. Hardware

A right-hand, 18-degree of freedom (DOF) CyberGlove II[1] data glove was used to record hand kinematic data. The glove was calibrated using dedicated software provided by the manufacturer. Finger motion data recorded with the glove were used to control the five DOAs (thumb abduction/adduction, thumb flexion/extension, index flexion/extension, middle flexion/extension, combined ring/little flexion/extension) of a Prensilia[2] IH2 Azzurra robotic hand. Calibrated glove sensor measurements were transformed into hand digit positions using a linear mapping.

C. Control schemes

Participants were instructed to teleoperate the robotic hand using the data glove. Two distinct control schemes were used, namely, continuous *position control*, in which the calibrated glove measurements directly controlled the five joint positions of the hand DOAs (flexion/extension of four digits and thumb rotation); and discrete *action control*, whereby differences in two consecutive measurements were compared to a fixed threshold and subsequently translated into one of the following three commands: open, close, or stall. All five DOAs were controlled simultaneously using this paradigm and the respective data glove measurements. The speed of opening/closing for all digits, as well as thumb rotation, was set a priori and kept fixed throughout; however, the duration of digit movement varied across DOAs, so that complex gestures were feasible to perform.

From a hardware control perspective, the first method is a closed-loop paradigm that uses a proportional integral derivative (PID) controller embedded in the robotic hand. Conversely, the latter is a discrete, open-loop control scheme, which heavily relies on user error correction using visual feedback about the current state of the digits. In our experiments, such visual information was available during both control schemes.

D. Experimental paradigm

Participants sat comfortably in an office chair and wore the data glove in their right hand. They were then instructed to move their fingers in order to drive the robotic hand into target postures presented to them on a computer monitor (Fig. 1). There were 18 target poses in total, which comprised individual finger movements as well as three grips (cylindrical, lateral, and tripod) requiring simultaneous movement of all DOAs (Fig. 2). One trial corresponded to the execution of a single posture and a block of trials comprised the execution of all 18 postures in a pseudo-randomized order. Each participant performed six blocks of trials with each of the two conditions, that is, the two control modes introduced in Section II-C. The condition presentation order was counter-balanced across participants to account for the human adaptation effect occurring during the course of the experiment, regardless of the condition used.

An audio cue initiated the start of each trial and simultaneously two pictures were displayed on the monitor showing a front and a side view of the target posture, respectively. The

[1] `http://www.cyberglovesystems.com`
[2] `https://www.prensilia.com`

participants were then given 5 s (*preparation phase*) to match the posture of the robotic hand to the one displayed on the screen as closely as possible. At the end of the preparation phase, a second audio cue signalled the initiation of the *evaluation phase* that lasted for 1.5 s. When participants were satisfied with the level of match between the target and executed postures, they were instructed to hold the latter during the evaluation phase; otherwise, they were instructed to perform compensatory movements to improve their performance. At the end of each trial, participants received a score characterizing their performance (see Section II-E) during the evaluation phase only, that is, during the last 1.5 s of the trial.

E. Performance evaluation

Two metrics were used to quantify user performance, namely, the median of the *L_1 distance* between the target and performed postures, defined with

$$L_1 = \left|\left|\boldsymbol{y} - \hat{\boldsymbol{y}}\right|\right|_1 = \sum_{j=1}^{K} \left|y_j - \hat{y}_j\right|, \qquad (1)$$

where y_i and $\hat{y}_i$ denote, respectively, the target and true positions of the j$^{\text{th}}$ DOA, and $K = 5$ is the total number of DOAs; and a normalized version of the same metric defined in the range 0%-100% that was used to provide the participants with an intuitive performance *score* at the end of each trial. Normalization constants were computed using simulated random predictions, such that a randomly performed posture corresponded on average to a 0% score, whereas a perfect reconstruction of the target posture corresponded to a 100% score.

F. Statistical analysis

Normality tests showed that performance scores and L_1 distances did not follow normal distributions; therefore, statistical comparisons were performed using the non-parametric Wilcoxon signed-rank test.

G. Questionnaire

At the end of the experimental sessions, participants answered a short questionnaire asking them to report whether they had noticed the presence of two experimental conditions, express their preference, if any, and compare the ease and naturalness of the two paradigms.

III. RESULTS

Eight participants completed six blocks of trials for each control scheme. The overall results are presented in Fig. 3 in terms of L_1 distances between target and performed postures and normalized scores. The average performance of the position control scheme was slightly superior to that of action control (median score 78.23 and 76.35; median L_1 distance 0.42 and 0.45, respectively). Nonetheless, differences in performance were not statistically significant ($p > 0.05$ for both metrics).

Fig. 4 illustrates average participant performance against the experimental block number. It is clear from this graph

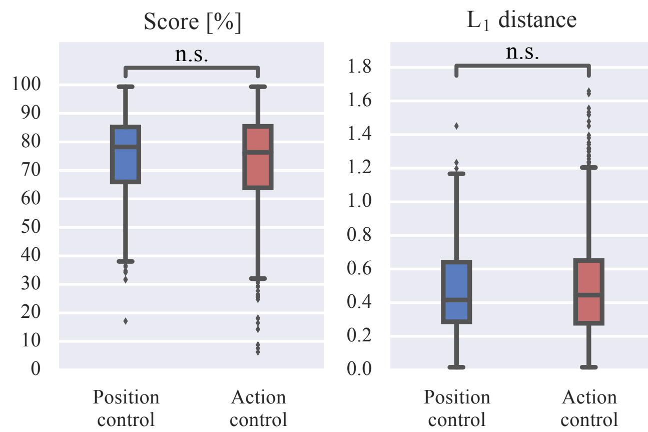

Fig. 3. Results summary. Normalized performance scores and L_1 distances are shown for the two different control schemes. Straight lines, medians; solid boxes, interquartile ranges; whiskers, overall ranges of non-outlier data (1.5 IQR); diamonds, outliers; n.s., non-significant difference ($p > 0.05$, Wilcoxon signed-rank test).

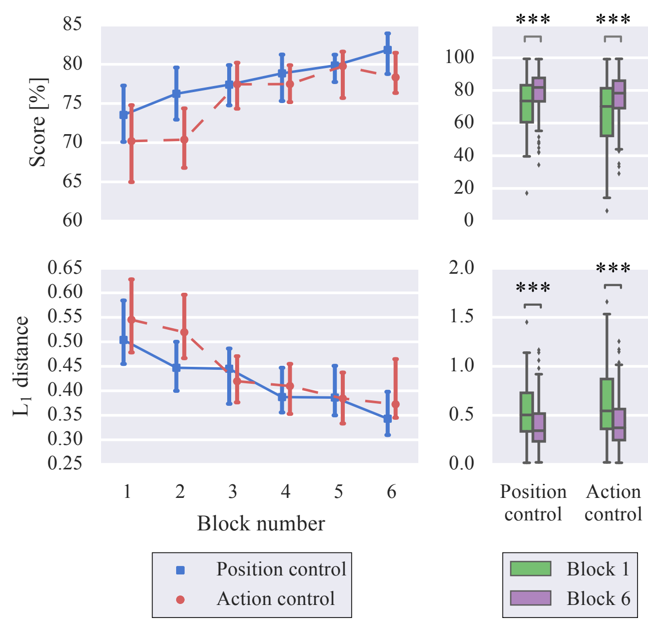

Fig. 4. Learning curves. (Left) normalized performance scores (top row) and L_1 distances (bottom row) are plotted against the experimental block number for the two control schemes. Points, medians; error bars, 95% confidence intervals estimated via bootstrapping (1000 iterations). (Right) comparison between first and last blocks for position and action control modes. ***, $p < 10^{-3}$.

that user experience resulted in a considerable increase in performance; both metrics improved significantly between the first and last block of trials ($p < 10^{-3}$ for both metrics and control schemes).

Finally, it is worth stressing that all participants noticed the existence of two different controllers. Seven out of eight subjects expressed a preference for position control, whereas all participants reported that this paradigm felt more natural than action control. Despite this preference, however, the performance of the two methods was found to be comparable (Fig. 3 and 4).

IV. DISCUSSION

The goal of this study was to investigate whether a discrete open-loop scheme can be used for simultaneous independent control of multiple fingers of a dexterous robotic hand. The results presented here provide evidence in support of this hypothesis, since it has been shown that a discrete control scheme with only three possible actions for each DOA (open, close, and stall) can achieve comparable performance to that of direct, closed-loop joint angle control. The open-loop approach relies on visual information being fed back to the user for error correction and, therefore, its performance is expected to deteriorate when sensory feedback is not available or limited. Nevertheless, this approach may be promising in that it can potentially allow for dexterous prosthetic finger control over a continuous space of movement using classification rather than regression methods. This paradigm can be seen as an extreme case of joint velocity control, albeit with a constant velocity that is only parametrized by its direction.

It was found that performance improved with experience for both control schemes. This increase in performance should not be surprising for the action control scheme, since this paradigm may be regarded as not entirely intuitive for the user initially, and thus require time and experience for its potential to be fully exploited. On the contrary, such improvement was less expected for the direct finger position control scheme, since the latter approach is fully biomimetic. This finding may be mainly attributed to two factors: firstly, it is likely that participants were able to develop strategies allowing them to improve their performance in the executed task due to the score that was fed back to them at the end of each trial; and secondly, it is possible that the mapping between glove measurements and robotic hand DOAs was also slightly unnatural. For example, the joint angle of each finger was estimated as a weighted sum of the activation of the metacarpophalangeal (MCP) and proximal interphalangeal (PIP) glove DOFs. It is thus possible that participants learnt such associations during the course of the experiment, which gradually helped them improve their performance.

As a future direction, we aim to compare the performance of the two schemes within the context of myoelectric prosthetic control, by carrying out real-time experiments with able-bodied participants as well as people with limb difference.

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