Möglichkeiten der Handprothesen-Kontrolle mittels Oberflächen-EMG
Possibilities of hand prosthesis control form suface EMG data

Dick F. Stegeman*, Sigrid S.G. Dupan, Ivan Vujaklija, Dario Farina
*Radboud University Medical Center Nijmegen, Donders Institute, Dept. of Neurology

State-of-the-art prosthetic hands allow separate control of all digits. Restoring natural hand use with these systems requires simultaneous and proportional control of all fingers. Regression algorithms might be able to predict any combination of degrees of freedom after training them separately. However, to the best of our knowledge, this has yet to be shown online. Twelve able-bodied participants were instructed to reach predefined target forces representing either single or combined finger presses, following a system training session consisting of only individual finger presses. Myoelectric control was implemented using linear ridge regression. The results demonstrated that myoelectric control allowed participants to reach both single finger, and combination targets, with hit rates of 88% and 54% respectively. These findings suggest that simultaneous control of multiple fingers is possible, even when these movements are not included in the training set.

I. INTRODUCTION

Regression techniques allow for the different degrees of freedom (DoFs) to be trained individually, after which these can be predicted simultaneously and proportionally [1]. This is especially interesting for finger control, where dexterous control of combined finger motions could be achieved even when the training is restricted to single finger movements, limiting the training time. Both Castellini and Koiva [2], and Krasoulis, Vijayakumar, and Nazarpour [3] showed that offline generalization to untrained finger movements is possible. They also illustrate that linear and non-linear regressors perform similarly when estimating unknown movements, even when the non-linear regressor outperforms the linear regressor on trained movements [3]. However, these results have yet to be corroborated in an online paradigm as it has been shown that online evaluation is far more relevant for the assessment of myoelectric controller performance [4]. Here, we conducted an online myoelectric control experiment, where single finger data were used in the training, and the participants were then asked to perform both single, and combined finger target hitting tasks.

II. METHODS

A. Subjects

Twelve able-bodied subjects participated in the study (age 26.5 ± 2.4, 6 male and 6 female). The study was approved by the Imperial College London Research Ethics Committee.

B. Experimental setup

The participants were seated with their index, middle, ring, and little finger resting on 4 individual force sensors (Fig. 1C; CZL635, Phidgets Inc, Canada). Forces were sampled at 10 Hz. Electromyography (EMG) was recorded using two high-density 8x8 monopolar surface electrode grids with a 10 mm inter-electrode distance (Fig. 1A,B; ELSCH064NM3, OT Bioelettronica, Italy). The signals were amplified (subject specific gain of 500 or 1000; OT Bioelettronica EMG-USB2 amplifier) and sampled at 2048 Hz with a resolution of 1.44 µV per least significant bit. Matlab 2016b (The Math Works Inc, USA) was used to develop custom software allowing for the real-time presentation of visual feedback.

C. Experimental protocol

Maximum voluntary contraction (MVC) trials were performed for all fingers, allowing subsequent measurements to be normalized. The training data for the regressor consisted of 3 repetitions of presses with each individual finger. The subjects were required to match a 15s trapezoidal cue with the plateau at 25% MVC.

The myoelectric controller used linear ridge regression of the EMG signals. Both for training and online application, the EMG signals were filtered (10-500 Hz bandpass filter, 4th order Butterworth; and 45-55 Hz bandstop filter, 2nd order Butterworth), and segmented into intervals of 200ms with an overlap of 100ms. EMG amplitude was calculated by taking the root mean square of each interval. Forces were normalized with respect to the MVC.

In the online EMG control session, subjects performed target reaching tasks in which the force bars on the screen were updated every 100ms based on the estimated forces calculated by the myoelectric controller. The session consisted of 5 repetitions of all single finger and combination tasks. The participants were instructed to reach a target force in the range of 20% to 30% MVC as fast as possible, while the forces of the non-instructed fingers remained below the threshold of 10% MVC. In order to complete the trial, the participants had to keep the force within the target window for 0.5s. Participants were timed out if they did not reach the target within 15s.

D. Data analysis

The Shapiro-Wilk test indicated that hit rate and completion time results for the EMG controlled trials were not normally distributed. As a result, the Kruskal-Wallis test was used in order to determine whether samples of different groups were derived from the same distributions. Post-hoc pair-wise comparisons were performed with the Wilcoxon signed rank test, using the Bonferroni error correction. The threshold for significance was set to 0.05. Statistical analysis was performed with IBM SPSS Statistics version 21 (IBM Corporation, USA).

III. RESULTS

Participants hit on average 88% of single finger targets, completing the trials in 4.2s (± 3.0s) (Fig. 2A). There was no statistically significant difference in hit rate for the different fingers ($p = 1$). The Kruskal-Wallis test showed a significant difference in completion time of the single finger trials ($p = 0.002$), with the little finger (3.7s ± 2.4s) reaching the targets faster than the index (4.2s ± 3.1s; $p = 0.003$), and the middle finger (4.7s ± 3.5s; $p = 0.01$). There were substantial differences between participants, with the single finger hit rate ranging from 65% to 100%, and the average completion time ranging from 2.1s ± 0.9s to 8.2s ± 4.8s ($p < 0.001$).

The combination targets (Fig. 2B) proved to be more challenging to reach, with an average hit rate of 54% over all participants. The average completion time was 7.2s (± 3.3s). The instructed finger combinations had no influence on hit rate ($p = 0.53$) or completion time ($p = 0.28$). The difference between participants increased for the combination trials, with the hit rate ranging from 10% to 97%, and the completion time ranging from 5.4s ± 1.6s to 10.6s ± 2.0s ($p = 0.001$).

IV. DISCUSSION

In order for myoelectric control to be applicable for clinical translation, the amount of time necessary to train the controller should be limited. Therefore, regression strategies, which allow for the controlling combination of DoFs while training only of on single DoFs [1], are a viable candidate for myoelectric finger control. We demonstrated the feasibility of online simultaneous myoelectric finger control, even when the myoelectric controller was trained based on single finger data. Our training set was limited to twelve trials, resulting in a short setup. The differences in hit rate between participants suggest that generalization in myoelectric control is for the most part depending on the ability of the user to adapt to the control. Future research should investigate if participants that show a low hit rate initially are able to adapt to the control when given more time.

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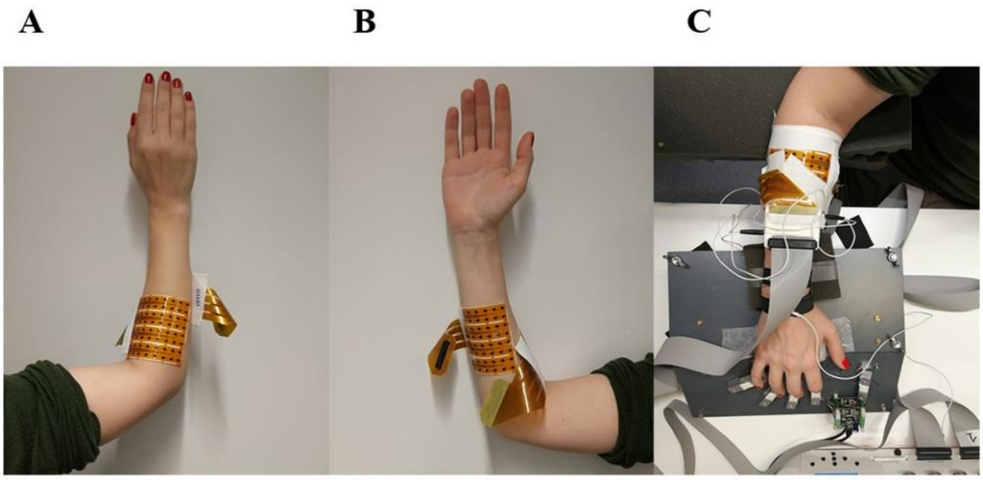

Fig. 1. Experimental setup. (A) Placement of HD-EMG grid on extensor, and (B) flexor muscles of the lower arm. (C) Custom made force device.

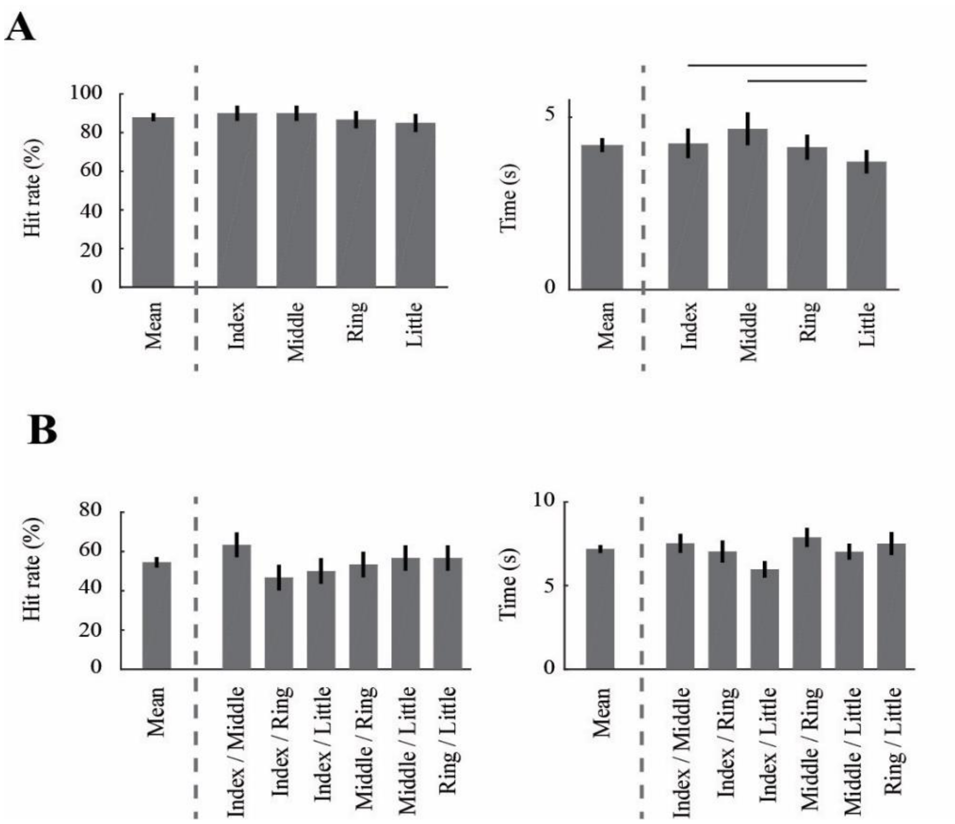

Fig. 2. Online performance of (A) single finger, and (B) combined finger control. The horizontal lines indicate statistical differences between instructed fingers.