ACTION MYOELECTRIC CONTROL FOR ADVANCED HAND PROSTHESES VIA MULTI-LABEL CLASSIFICATION

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ABSTRACT

We propose action control, a novel approach for myoelectric independent digit control based on multi-label classification. At each time step, the decoder classifies movement for each controllable degree-of-freedom (DOF) into one of three categories: open, close or stall (i.e., no movement). The user employs continuous feedback information to estimate and minimise the mismatch between target and current digit positions. We implemented the proposed action controller and evaluated its real-time performance with 3 transradial amputee—two bilateral, one unilateral—, whilst they controlled a six-dimensional computer interface with surface electromyography (EMG) signals. We benchmarked the performance of the algorithm against the state-of-the-art in myoelectric digit control, that is, position control using multi-output regression. We found that action control consistently and substantially outperformed position control. Furthermore, all participants rated action higher than position control in a series of questions in a post-experimental survey and expressed and overall preference for the former. The proposed algorithm warrants further investigation in the future by transferring the control space from a computer display onto a real prosthesis and evaluating performance during activities of daily living.

INTRODUCTION

The holy grail of upper-limb myoelectric prostheses is individual control of digits in a continuous space [1]. Several teams have previously attempted to use regression algorithms to map electromyography (EMG) features onto digit positions/velocities offline [2-5]. Only a few studies, however, have demonstrated real-time digit position control in amputees [6-8]. Furthermore, the feasibility of using this paradigm to enable the user to perform object manipulation and activities of daily living in an unconstrained environment yet remains to be demonstrated.

We propose *action control*, a novel approach for individual digit control with EMG signals. In the heart of the control algorithm lies a multi-label classifier, which decodes movement intent for each controllable degree-of-freedom (DOF) into one of three classes: open, close or stall (i.e., no movement). We implement our proposed algorithm in real-time and evaluate its performance with three transradial (i.e., below-elbow) amputee participants using a six-dimensional control interface. We show that action control can systematically and substantially outperform the state-of-the-art for myoelectric digit control, which is based on position control via multi-output regression.

METHODS

Participant recruitment

We recruited three transradial amputee volunteers. Two of the participants had bilateral and one had unilateral amputation. Participant 2 performed two experimental sessions with alternate sides, thus the total number of sessions was $n = 4$. Experimental procedures were in accordance with the Declaration of Helsinki and approved by the local ethics committee at Newcastle University. Participants gave written informed consent prior to the experiments.

EMG recording system

We recorded surface EMG activity with 16 Delsys® Trigno™ sensors placed around the forearm in two rows of eight equidistant electrodes. Prior to sensor placement, we cleansed participants' skin using 70% isopropyl alcohol swabs. We visually inspected the quality of all EMG channels and used adhesive tape to secure sensor positions. The EMG sampling rate was fixed at 2 kHz.

Signal pre-processing and feature extraction

We processed EMG data using a sliding window with overlap. The length of the window was set to 128 ms and the overlap to 50%. Two features were extracted from each EMG channel, namely, waveform length and log-variance.

Prosthetic hand

We used the Robo-limb™ hand to demonstrate target postures to participants. The hand is similar to the Össur® i-Limb® Ultra hand and comprises six motors controlling thumb rotation and flexion/extension of all digits. The hand was powered by an external power supply unit (7.4 V/7 A) and operated by a laptop computer via a CAN bus connection.

Training data collection

We instructed participants to perform imaginary movements with their phantom limb, which were instructed on the prosthesis. The following single-digit and grip exercises were included: thumb opposition/reposition; thumb, index, middle, ring and little finger flexion/extension; cylindrical and lateral grip opening/closing. Participants performed 12 repetitions for each exercise and myoelectric data were recorded and stored on disk.

Control schemes and decoder training

During the interval between training data collection and real-time control, two types of decoders were trained: 1) a multi-output regression mapping EMG features onto digit positions (*position control*); and 2) a multi-label classifier decoding EMG features onto one of three classes: open, close or stall (i.e., no movement) (*action control*). In both cases, the target vector was six-dimensional, that is, the number of controllable DOFs.

Real-time control task

Participants were instructed to use their muscles to control a six-dimensional bar interface on a computer display. Prior to the start of the trial, the target posture was demonstrated on the prosthesis. Upon completion, a cue sound initiated the start of the *preparation phase* of the trial and six pairs of bars appeared on the screen. For each DOF, a fixed red bar indicated the target position and a blue bar showed the position that was controlled by the participant. Participants were given 5 s to match the blue bars to the red ones as closely as possible. A second cue sound initiated the start of the *evaluation phase* of the trial, which lasted for 1 s. Ten target postures were included, which comprised both single-digit and full-hand grip patterns: thumb opposition; thumb, index, middle, ring and little finger flexion; cylindrical, lateral and tripod grips; and index pointer. Note that not all exercises were included in the training set. Participants performed 10 blocks of trials for each control condition. Every target posture was included exactly once within each block in a pseudo-randomised order.

Evaluation

At the end of each trial, participants received a score characterising their performance during the evaluation part of the trial. The score was based on the median absolute error between the target and controlled positions and was normalised between 0% and 100%.

Post-experimental questionnaire

At the end of the experimental session, participants were asked to rate the two control schemes, namely, position and action control, based on the following three questions: 1) the interface was easy; 2) the interface was intuitive; 3) I found it easy to adapt to the interface. Ratings ranged from 1 (strongly disagree) to 5 (strongly agree) and half scores (e.g., 3.5) were also allowed. Participants were finally asked to indicate their overall preference. Participant 2 answered the questionnaire twice, once after each session, and respective scores were averaged.

Statistical analysis

For each participant, the target presentation order was the same for the two conditions (i.e., paired measurements). To compare performance between the two algorithms, we used two-sided Wilcoxon signed-rank tests with Holm-Bonferroni correction to account for multiple comparisons. The condition order was counter-balanced across participants.

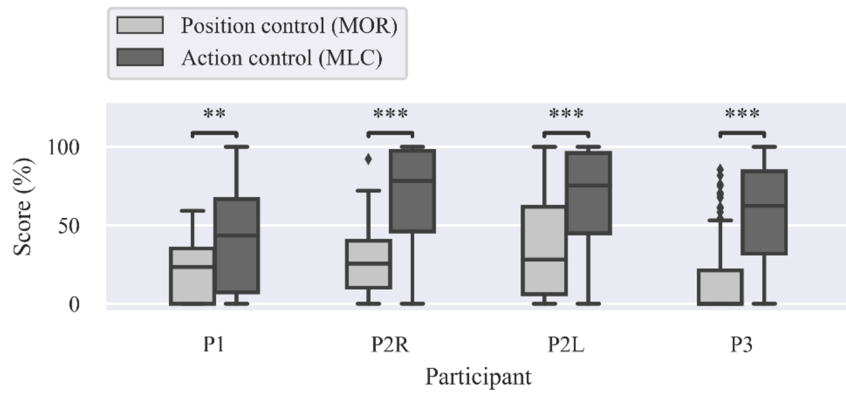

Figure 1: Performance comparison between position (i.e., multi-output regression) and action (i.e., multi-label classification) control. The performance score characterised the match between target and controlled positions during the evaluation phase of the trial. Higher values indicate better performance. Solid lines, medians; solid boxes, interquartile ranges; whiskers, overall ranges of non-outlier data; diamonds, outliers; double asterisk, $p < 0.01$; triple asterisk, $p < 0.001$.

Table 1: Post-experimental questionnaire

Range: 1 (strongly disagree) to 5 (strongly agree); PC, position control; AC, action control

Participant	**Question**						
	Interface was easy		**Interface was intuitive**		**I found it easy to adapt to the interface**		**Overall preference**
	PC	***AC***	***PC***	***AC***	***PC***	***AC***	
P1	2	4	1	4	3	5	AC
P2	2	3.5	3	4	2.5	3.5	AC
P3	3	4.5	2	4.5	2	4	AC

RESULTS

The performance results from the real-time control experiment are presented in Figure 1. The scores achieved by each participant with the two conditions (i.e., position and action control) are summarised using box plots. For all four sessions, action control (i.e., multi-label classification) significantly outperformed position control (i.e., multi-output regression). The differences in median performance were as follows: P1, $MD = 20.14$, $p < 10^{-2}$; P2R, $MD = 52.63$, $p < 10^{-13}$; P2L, $MD = 47.23$, $p < 10^{-10}$; P3, $MD = 62.32$, $p < 10^{-13}$.

The outcomes of the post-experimental questionnaire are presented in Table 1. All participants rated action higher than position control in all three questions. Furthermore, all three participants expressed an overall preference for action control.

DISCUSSION

We have introduced a novel paradigm for myoelectric digit control. At each time step, the algorithm decodes movement for each controllable DOF in one of three categories: open, close or stall. To reach a desired position, the user has to utilise the available feedback information—in our experiment visual from the computer display—to estimate the mismatch (i.e., error) between the target and current position(s) and take appropriate action(s) to minimise it. The controller can be viewed as an extreme, discretised case of velocity control; the velocity has a fixed value and is, thus, only parametrised by its direction. Using this approach, we can employ a multi-label classifier as the decoder, rather than a multi-output regression algorithm. One caveat of regression-based approaches is that noise in the input (i.e., EMG) space is propagated to the output, hence resulting in unstable control. To address this issue, it is common to smooth the output using a low-pass filter. Nevertheless, a large amount of smoothing is typically required to achieve a satisfactory outcome, which translates into a noticeable control delay. Classification, on the other hand, does not suffer from this limitation due to its discrete nature. Thus, by replacing the regression algorithm by a classifier we can achieve more stable digit control. Action control has an additional advantage. As opposed to position control, whereby a user has to hold a muscle contraction to retain a specific posture, with action control the user can completely relax once the target posture has been reached. This can result in more effortless control for the user.

We have previously shown that position and action control can yield comparable performance in a robotic hand tele-operation task with a data glove [9]. Here, we have provided a real-time myoelectric implementation of the two algorithms and have shown that action control can systematically outperform position control, which is considered as the state-of-the-art for prosthetic digit control. Moreover, all participants rated action higher than position control in a series of questions and expressed an overall preference for the former. As a future direction, we will compare the performance of the two algorithms using additional metrics. Finally, we will further evaluate action control by transferring the control space from a computer interface onto a real prosthesis.

CONCLUSION

We have proposed and evaluated a novel paradigm for myoelectric individual digit control based on multi-label classification. We have shown that it can systematically outperform the state-of-the-art position control approach based on multi-output regression. In the future, we shall further validate the algorithm by transferring the control space from a computer interface onto a real prosthesis.

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