EXPLORING USER COMPLIANCE IN THE TRAINING OF REGRESSION-BASED MYOELECTRIC CONTROL

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ABSTRACT

Regression-based myoelectric control is promising because it could enable simultaneous independent control over multiple degrees of freedom. However, limitations in the robustness of online control and the added complexity of acquiring labelled training data have hindered its adoption. The scattered mix of prompting methods, visualization styles, and speeds used in the literature to collect labelled regression training data has obfuscated how these different prompting styles may affect the performance of regression-based myoelectric control. This work thus begins to investigate the potential effects that different visualizations may have on user behaviours and the quality of acquired training data for myoelectric control. Two distinct behaviours, referred to as *all or nothing* and *anticipation*, emerged when comparing the training data of three different prompting styles. Subsequently, 6 subjects were coached to emulate each of these behaviours during training and then completed a 10-trial Fitts' Law to assess the online usability of two different support vector regression (SVR) models. Results show that both user behaviours and the choice of regression model can have profound impacts on the usability of regression-based myoelectric control. Notably, real-time performance was severely degraded by the *anticipation* behaviour when using a linear kernel SVR, resulting in a 70% reduction in completion rate. These preliminary results motivate future work into how best to prompt users when training for supervised regression-based myoelectric control.

INTRODUCTION

Despite high levels of abandonment, many commercial upper-limb prostheses still employ decades-old control strategies [1]. Sophisticated coordination between the hand and wrist is needed for advanced tasks, yet even current prosthetic devices rely on sequential control schemes [1]. Regression-based control offers the potential of simultaneous independent control, but questions about the robustness of online regression control (e.g., challenges with quiescence, drift, susceptibility to confounds) and the increased complexity of acquiring labelled training data remain [1, 2].

A variety of training protocols have been used to acquire training data for regression-based systems, ranging from the use of force transducers, to limb kinematics tracking, to purely visual prompting styles [2–5]. Although the use of force and position mappings have been effective [3], they are not viable for users with upper limb differences, leading researchers to focus on visual prompts [2]. Unlike in classification tasks, however, the use of visual prompting in regression not only assumes that the user is performing the correct contraction, but also that they are tracking the amplitude of the degree of freedom closely over the entire progression. Given the likelihood of deviations in compliance and timing, however, this may not always be the case, potentially resulting in a discrepancy between the elicited contractions and the ground truth labels used to train the model. Furthermore, a variety of prompting methods, visualization styles, and speeds have been used in the literature, without clarity about how they may affect user behaviours or model training, or what role they may have on the online usability of regression-based myoelectric control [2, 4]. Consequently, this work describes an early exploration of the potential differences in user behaviours based on changes in prompting for regression-based myoelectric control.

METHODS

Data collection and preparation

Eight subjects participated in this exploratory pilot work (5 male, 3 female, 22 - 31 years old) as approved by the University of New Brunswick's Research Ethics Board (REB 2022-122). EMG data were collected from the forearm using the EMaGer cuff, a 64-channel high-density electromyography (HD-EMG) device comprised of a stretchable 4 x 16 array of EMG electrodes [6]. LibEMG, an open-source Python library for processing EMG, was used to facilitate data streaming, the creation of visual prompts, and real-time myoelectric control [7]. EMG data were bandpass filtered from 20-450 Hz to remove motion artefacts and notch filtered at 60, 120, 240, and 360 Hz to remove power-line interference. The filtered signals were then normalized to unit variance and zero mean to improve visualizations and standardize data for model training. The EMG time series were then enframed using 250ms windows with 50ms overlap, from which the Hudgins' Time Domain feature set were extracted [8].

Prompting styles

Three different prompting approaches were explored, based on their prevalence in the literature [4, 9, 10] and as distinct presentation styles. Contractions corresponding to two degrees of freedom (DOF), hand open/close and forearm

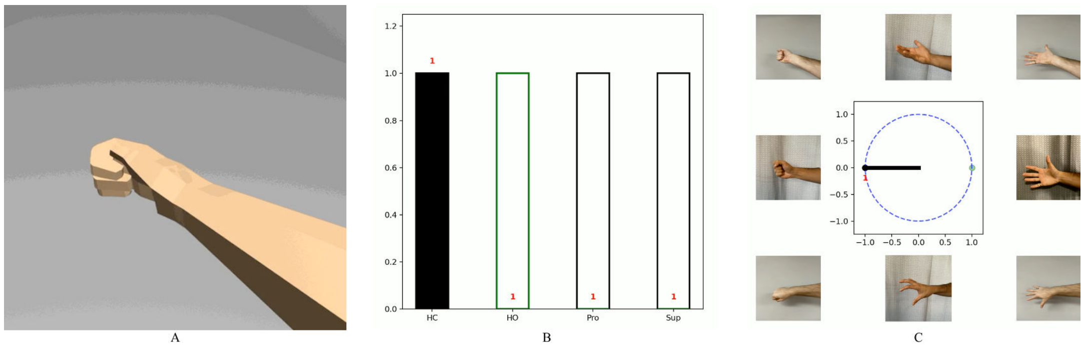

Fig. 1: Example of the Anthropomorphic (A), Bar plot (B), and Cartesian (C) visualizations used for prompting the user during training. For the Bar plot and Cartesian visualizations, countdowns were shown in red during periods of constant amplitude and the next destination of the target was shown in green.

pro/supination, were prompted as shown in Fig. 1. Briefly, the anthropomorphic approach (A) involved following a moving virtual limb, displayed from the user's perspective [10]. The bar plot (B) displayed the desired activation level and direction of a given direction DOF (similar to the prompting of classification based approaches, but with a target intensity [9]). Finally, the Cartesian approach (C) denoted the desired contraction and intensity via mappings to spatial locations, as often done in Fitts' Law testing [4].

Five subjects participated in this portion of the study, completing 5 repetitions of each DOF for each prompting style. Each repetition comprised of the sequence: no motion, to DOF -ve direction (e.g., pronation), to DOF +ve direction (e.g., supination), to no motion, to DOF +ve direction, to DOF -ve direction, to no motion. Every movement segment involved a ramp up (2 seconds), steady state (2 seconds), and a ramp down (2 seconds) and periods of no motion lasted 3 seconds. The order of visualizations was randomized for each participant. In all cases, users were asked to map the intensity of their contractions to the corresponding position of the prompt.

User behaviours

After analyzing the data from the prompting styles described above, a second pilot study was performed. Six subjects completed a training session emulating specific behaviours that had been observed consistently across subjects (anecdotally), followed by an online usability study. The goal of this portion was therefore not to evaluate the specific prompting styles, but to assess the impact of observed behaviours on the usability of the trained regression models. Subjects were coached to elicit two distinct behaviours; *all or nothing* and *anticipation*(explained below in *Results - Prompting styles*), and a baseline case, where they were asked to follow the prompt to the best of their ability. The order of these three cases was randomized for each participant, and 5 repetitions of each DOF were collected in each case. A Cartesian-style prompt was used in this phase due to its prevalence in the literature and similarity to the downstream task [4]. After each round of training, participants performed a 10-trial Fitts' Law-style target acquisition test, as provided by LibEMG [7], to assess the usability of the resulting regression model. To probe the impact of model linearity, three subjects used a support vector regressor (SVR) with a linear kernel, whereas the other three used a SVR with a non-linear radial basis function (RBF) kernel. A *deadzone* threshold of 0.25 was used for both models to reduce inadvertent activation (i.e., predictions with magnitude less than 0.25 did not elicit movement of the cursor) [2]. Online usability was assessed using effective throughput, path efficiency, and the number of target overshoots [11]).

RESULTS

Prompting styles

Fig. 2 shows a representation of how users reacted to the different prompting styles, using trends in the observed mean absolute value (MAV) of their EMG signals. The median MAV across channels was used to approximate the strength of the contraction for a given window and the median value across subjects was used to observe the consistency of user behaviours.

These behaviours were consistent enough across subjects that two distinct, anomalous behaviours emerged. The first behaviour, here called anticipation, is exemplified by a preemptive increase in MAV prior to reaching the 0 point of the Cartesian visualization in Fig. 2, and as later simulated in Fig. 3. The anticipation behaviour occurs when the user transitions from one end of the DOF to the other too early, meaning that they begin ramping up the other end of the DOF (e.g., hand close) while the prompt (and thus labels) indicate they should be still be ramping down from the previous end of the DOF (e.g., hand open). This occurred more often when the participants travelled from one extreme of the DOF to the other than when beginning from the rest position. This mismatch between behaviour and prompt, particularly around the rest position, may cause model confusion at low amplitudes and thus problems with quiescence.

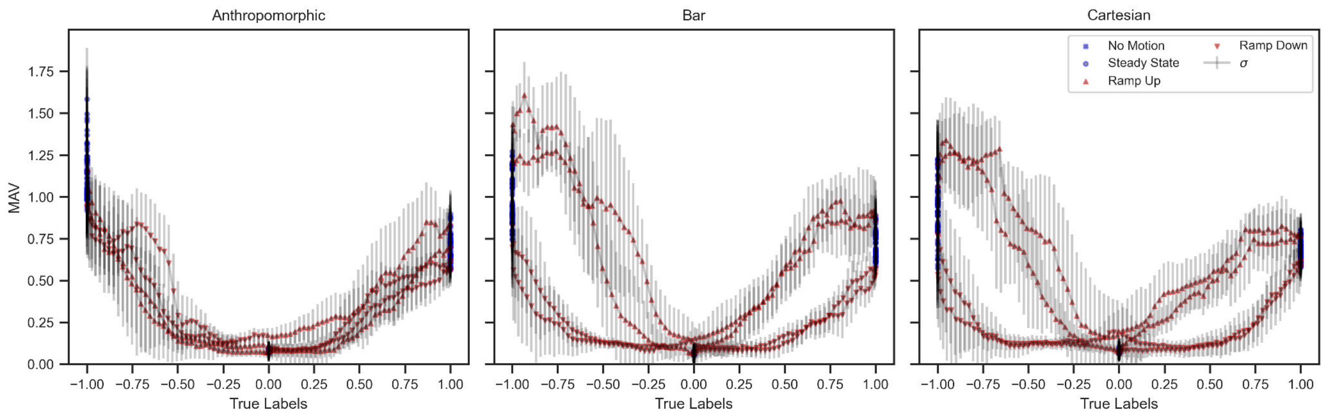

Fig. 2: Scatter plot of the strength of elicited contraction across subjects as prompting varied for each visualization style during collection of the hand open / close DOF. Each point represents the median MAV across channels and subjects for a single window. The segment of the movement (e.g., ramp up) is determined based on the ground truth labels at that window.

The second behaviour, here called *all or nothing*, is exemplified in Fig. 2 in the Anthromorphic and Bar visualizations, and later simulated in Fig. 3. From the Anthromorphic case, we see a wide band around 0 where there is no real activation. In the Bar plot case, we see cases where the users goes from rest very quickly to high levels of activation. These combined behaviours represent a lack of gradual modulation from low to high, or high to low. The all or nothing behaviour, in contrast to linearly increasing or decreasing prompts, may lead to poor model fitting and problems with proportional control.

User behaviours

Based on the previous observations, we explored how these two distinct behaviours may affect the training and usability of the resulting models. To emphasize their effect in this small pilot set, subjects were coached to elicit the identified behaviours, as shown in Fig. 3. The emulated behaviours exhibited by participants were purposely exaggerated to observe the potential effects of these behaviours on online performance in extreme cases. The MAV trends shown in Fig. 3 highlight these behaviours, described previously as observed more subtly in *Prompting styles*, including a wider deadzone during the all or nothing emulated behaviour and early ramping up during the anticipation emulated behaviour.

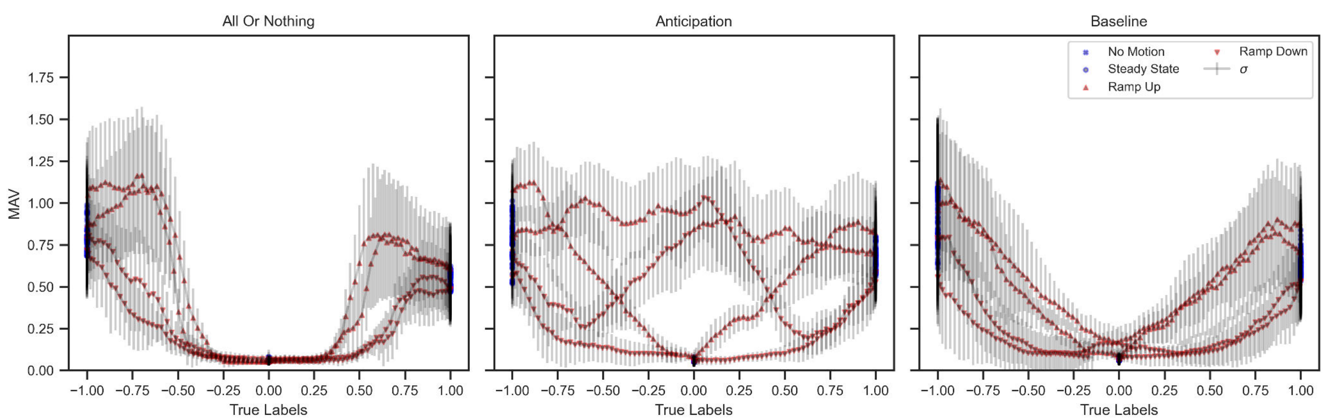

Fig. 3: Scatter plot of the simulated (and emphasized) behaviours illustrating the strength of contraction across subjects as prompting varied for each observed behaviour during data collection along the hand open / close DOF.

The results of the Fitts' Law testing for each of the behaviours are shown in Fig. 4. The anticipation behaviour was found to destroy the performance of the linear SVR model, as indicated by the fact that 24 of the 30 total trials could not be completed before the 30 second timeout. Because, the other performance metrics reported in Fig. 4 cannot be computed unless a trial is completed, this model cannot be fairly compared to those of the other behaviours / models. The linear SVR model also degraded when facing the all or nothing behaviour, though not nearly as badly. Contrarily, the non-linear RBF SVR appeared to be quite resilient to the anticipation and all or nothing behaviours.

DISCUSSION

This work describes the early pilot results of an ongoing study. Despite modest numbers of subjects, empirical evidence of the impact of prompting style on contraction behaviours was found. Anticipatory behaviours were seen that caused

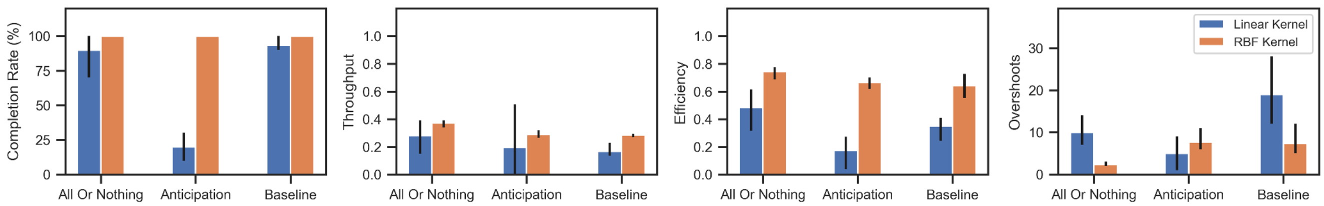

Fig. 4: Comparison of usability metrics captured via Fitts' Law test across user behaviours. Each bar represents the mean across subjects, error bars indicate the minimum and maximum values across subjects.

misalignment between the EMG and the given prompts. The observed all or nothing behaviours suggest user difficulties in slowly modulating DOF-specific contraction intensities in alignment with the prompts. The three prompting styles also tended to elicit different behaviours. For example, the clear spatial mapping of the Cartesian case, combined with the green "next destination" hint, caused more of the anticipatory behaviour. The limb position information implied by the Anthropomorphic style may have encouraged more of a position control behaviour leading to the all or nothing patterns of EMG. However, in addition to the impact of different prompting styles, many other factors could influence user behaviours, such as the speed at which contractions are prompted, the use of "next motion" hints, and the potential use of real-time feedback to help users better align. Although these results should not be taken as conclusive, they motivate further work on how to best to prompt users when training for regression-based myoelectric control.

The broader goal of this work is to explore the quality of training data and the impact that varying degrees of compliance has on regression performance. To wit, the behaviours that emerged from the prompting investigation led to notable differences in control when evaluated in an online Fitts-style test. Based on these preliminary results, some interesting observations emerged. The non-linear RBF SVR yielded better results than the linear model in general, and may thus be a more resilient solution in accounting for imperfection in training. The large number of timeouts of the linear SVR model with anticipation support this, but also highlight the interplay between model and behaviour. Paradoxically, it appears that the all or nothing behaviour actually led to better usability than the baseline behaviours. It was anticipated that this behaviour may result in a "skating" behaviour wherein the user is unable to stop. However, it is worth noting that a 25% activation threshold was employed across all models in this work, below which the controller would not move. While this was determined empirically to be necessary for usability (as in previous studies [2]), this may have masked the effects of the all or nothing behaviours.

Finally, it is important to acknowledge that this work represents only an initial examination of these effects. The user behaviours were emulated and exaggerated to better evaluated their effects for the small sample size. It also appears that user behaviours may have model-dependent impacts on usability. Consequently, this work serves mostly to highlight the potential implications of training compliance on model development, robustness, and usability, and warrants further examination.

REFERENCES

[1] A. D. Roche, H. Rehbaum, D. Farina, Oskar, and C. Aszmann, "Prosthetic Myoelectric Control Strategies: A Clinical Perspective," *Current Surgery Reports 2014 2:3*, vol. 2, no. 3, pp. 1–11, jan 2014.

[2] A. Ameri, E. N. Kamavuako, E. J. Scheme, K. B. Englehart, and P. A. Parker, "Support vector regression for improved real-time, simultaneous myoelectric control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 6, pp. 1198–1209, nov 2014.

[3] A. Ameri, E. J. Scheme, E. N. Kamavuako, K. B. Englehart, and P. A. Parker, "Real-time, simultaneous myoelectric control using force and position-based training paradigms," *IEEE Transactions on Biomedical Engineering*, vol. 61, pp. 279–287, 2 2014.

[4] J. M. Hahne, F. Bießmann, N. Jiang, H. Rehbaum, D. Farina, F. C. Meinecke, K. R. Muller, and L. C. Parra, "Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 2, pp. 269–279, 2014.

[5] G. Hajian, E. Campbell, M. Ansari, E. Morin, A. Etemad, K. Englehart, and E. Scheme, "Generalizing upper limb force modeling with transfer learning: A multimodal approach using EMG and IMU for new users and conditions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024.

[6] F. Chamberland, É. Buteau, S. Tam, E. Campbell, A. Mortazavi, E. Scheme, P. Fortier, M. Boukadoum, A. Campeau-Lecours, and B. Gosselin, "Novel wearable hd-emg sensor with shift-robust gesture recognition using deep learning," *IEEE Transactions on Biomedical Circuits and Systems*, 2023.

[7] E. Eddy, E. Campbell, A. Phinyomark, S. Bateman, and E. Scheme, "LibEMG: An Open Source Library to Facilitate the Exploration of Myoelectric Control," *IEEE Access*, vol. 11, pp. 87 380–87 397, 2023.

[8] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 40, pp. 82–94, 1993, this is the reference for the HTD feature set.

[9] M. Barsotti, S. Dupan, I. Vujaklija, S. Došen, A. Frisoli, and D. Farina, "Online finger control using high-density EMG and minimal training data for robotic applications," *IEEE Robotics and Automation Letters*, vol. 4, pp. 217–223, 4 2019.

[10] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "The target achievement control test: Evaluating real-time myoelectric pattern recognition control of a multifunctional upper-limb prosthesis," *Journal of rehabilitation research and development*, vol. 48, p. 619, 2011.

[11] E. J. Scheme and K. B. Englehart, "Validation of a selective ensemble-based classification scheme for myoelectric control using a three-dimensional Fitts' law test," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, pp. 616–623, 2013.