ADAPTIVE EMG PATTERN RECOGNITION REDUCES FREQUENCY AND IMPROVES QUALITY OF AT-HOME PROSTHESIS TRAINING FOR UPPER LIMB MYOELECTRIC PROSTHESIS WEARERS

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ABSTRACT

Upper limb myoelectric pattern recognition-controlled prostheses use machine learning algorithms to identify a wearer's intended movement from their muscle activity patterns. However, many factors can contribute to changes in the characteristics of the EMG input signals (electrode shift, muscle fatigue, limb position etc.) during everyday prosthesis use which can diminish controller performance. Multiple in-lab studies have demonstrated promising results towards improving controller performance by employing advanced algorithms, none of which have been tested clinically, that can adapt to these changes. This paper presents the implementation of a supervised-adaptation algorithm on a commercially available pattern recognition control system that makes use of historical EMG data collected during previous user-initiated calibration routines to update the existing classification model. In an at-home clinical study, we evaluated whether real-world use of adaptive classification reduces how often upper limb prosthesis wearers need to recalibrate their pattern recognition system.

INTRODUCTION

Pattern recognition style of myoelectric prosthesis control has benefitted many individuals since commercialization in 2013. Using machine learning techniques to decode complex muscle activity patterns recorded from electromyographic (EMG) sensors, a pattern recognition controller can provide wearers natural and intuitive control of their powered prosthesis [1]. A key feature of pattern recognition is that is needs to learn the wearer's unique EMG patterns corresponding to each type of prosthesis motion they want to control. This is achieved by inputting representative data during system training (i.e., calibration). The inability of a control system to classify the user's EMG inputs significantly affects user control of their prosthesis device. This often leads to frequent recalibration which can be quite time-consuming and burdensome for many pattern recognition wearers.

Effective EMG pattern recognition requires wearers to make repeatable, consistent muscle contractions [2]. Studies have shown that it is possible for control algorithms to achieve accuracies greater than 90% under ideal laboratory conditions [3], [4]. However, classification accuracies deteriorate significantly under more realistic usage scenarios such as when electrodes shift positions [5], when the user changes the posture/position of their residual limb [6], or when modulating the force of their contraction. To address these deteriorations, the most effective method might be to collect additional algorithm training data that is representative of these conditions. After representative data is collected, the control system may be adapted to incorporate this new data.

The default behaviour of many existing pattern recognition systems is to clear the existing classification model from memory each time the user initiates a calibration. Studies have shown that an alternative solution, which instead modifies the existing classifier using EMG input data recorded upon recalibration, has the potential to improve pattern recognition control. In lab-based studies, Vidovic et al. found that classification accuracy improved from 75% to above 92% [7] and Cummins et al. found that classification error rates significantly decrease across multiple days of training data [8] when utilizing such adaptive calibration strategy. These promising results point to the need for clinical implementation; yet, no studies have evaluated the effectiveness of using pattern recognition adaptation under realistic use conditions – i.e., while prosthesis wearers use their device at-home in their own environment. Here, we present preliminary results from an at-home study where upper limb myoelectric pattern recognition wearers used a supervised adaptation calibration paradigm. Our primary hypothesis is that using adaptation reduces the frequency at which recalibration is needed. In a randomized, cross-over study design, we compared everyday wearers' calibration frequency and the quality of their EMG input data between their prosthesis use with and without the adaptive classification algorithm.

METHODS

Participants:

Five individuals with upper limb difference/absence (three at the transradial level and two at the transhumeral level) have completed the at-home study. Two additional individuals are currently enrolled, and two others withdrew their study participation. All participants provided informed consent in accordance with the Institutional Review Board and Human Research Protection Office.

Apparatus:

Participants used their existing Coapt Complete Control Gen2® pattern recognition control system to control their motorized arm components. The number and type of prosthesis motions participants had enabled varied depending on the type of powered devices connected (hand, wrist or elbow combination). Gen2 system users are able to train their EMG pattern recognition controller by performing either a prosthesis-guided or software-guided motion calibration sequence using the Complete ControlRoom software application [9]. The classification algorithm of the control system is linear discriminant analysis (LDA) [10] which, when enabled, clears the existing classifier from memory upon a user-initiated motion calibration sequence. Effectively, new EMG input data recorded during a calibration replaces the existing data and only this data is used to create a new LDA classifier.

Changing the control system to the adaptive classification algorithm can be easily done by accessing the controller settings in the software. This classification model uses covariate shift adaptation to update the class means and pooled covariance matrices of an existing LDA model using the new EMG input data recorded during each subsequent user-initiated calibration. The control system retains memory of the existing LDA classifier which does not clear until the user manually performs a full system reset. A full derivation of the adaptive algorithm can be found in [7]. It is important to note that the default classification algorithm employed by the Complete Control Gen2 system for all new and existing wearers is the adaptive algorithm, thus study participants were not naïve.

Following each calibration, the EMG input and classifier data is analyzed by the Control Coach® [11]. The Control Coach® uses artificial intelligence to detect calibration issues and to evaluate the quality of the calibration data. In addition to providing feedback messages (up to two per motion) to users on how to improve calibration quality, the software tool provides a star rating for each enabled prosthesis motion relating to the potential severity of any calibration data quality issues detected (1 star = most severe, 5 stars = least severe). The overall calibration quality is determined by computing the average star rating across all motions. The Gen2 system hardware also has data logging capabilities to monitor at-home prosthesis use including prosthesis wear-time, calibration frequency, commanded motion frequency and device output speeds, electrode liftoff frequency and Control Coach® data.

Procedures:

Participants were asked to use their prosthesis at-home for a total of 16-weeks. Each participant was randomly assigned to one of two study groups. For the first 8-weeks, participants used their Gen2 system with the adaptive classification algorithm either ON or OFF, and for the second 8-weeks, the opposite classification algorithm was enabled. Only research personnel had access to the controller settings to enable or disable the adaptive algorithm at the beginning of each 8-week period so that participants were blind to the classification algorithm enabled on their system throughout the experiment. At the beginning of each 8-week period, research personnel manually performed a full control system reset to clear out any existing calibration data. Participants were then asked to complete an initial motion calibration sequence. At the end of the study, participants completed a questionnaire asking about their preferences towards the type of classification algorithm used in both 8-week periods in terms of their perceived prosthesis control efficiency and controller performance.

RESULTS

Our primary outcome measure was calibration frequency which we defined as the ratio between the number of times users initiate a calibration sequence and the number of times the user powers on their prosthesis. This calibration frequency metric accommodates for differences in user wear-time and number of calibration events. We compared calibration frequency during each 8-week period in which the adaptive algorithm was either ON or OFF for each user (Fig. 1, left). Preliminary results reveal a trend towards a reduction in calibration frequency among participants with the adaptive algorithm ON. Three out of the five participants reduced their calibration frequency on average by 43% while one participant showed a marginal increase and another participant nearly doubled calibration

frequency with the adaptive algorithm ON. Our preliminary analysis also shows a trend towards increased prosthesis wear-time per calibration (Fig. 1, middle) as four out of five participants demonstrated an increase in how many hours (on average, 2.7 more hours) they used their prosthesis with the same classifier before recalibrating. Four out of the five participants also showed improvements in the quality of their calibration data, as measured by the Control Coach® star ratings, with the adaptive algorithm ON (Fig. 1, right).

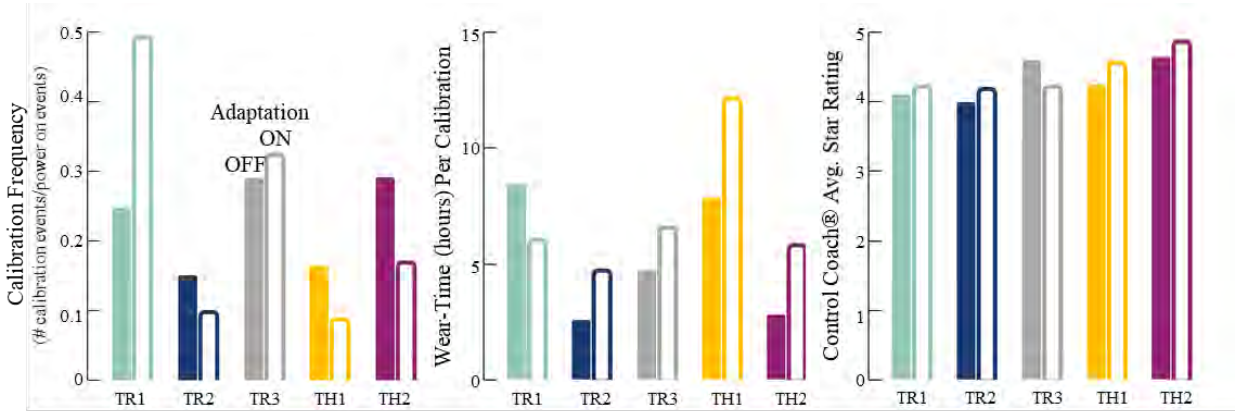

Figure 1: Differences in individual participant logged prosthesis use data including (left) calibration frequency (middle) wear-time per calibration (right) average calibration quality star-ratings when the adaptation classification algorithm was enabled or disabled on their pattern recognition control system.

DISCUSSION

We presented preliminary results of an at-home study to determine whether an adaptive classification algorithm for upper limb myoelectric prosthesis wearers reduces how often users choose to recalibrate their pattern recognition controller when using their prosthetic device within their home environment. By adding new data to the pattern recognition classifier rather than completely clearing the existing classifier, we implemented an adaptive algorithm that affords the controller the opportunity to generalize to more movements, prosthesis use conditions and a larger set of EMG input data. Our preliminary analysis reveals a trend towards a reduction in calibration frequency and an increase in how much time elapses before users choose to recalibrate their device when the adaptation algorithm was enabled. Interestingly, four of the five participants reported, in a Post-Study Questionnaire, that they felt they achieved better control performance during the 8-week period when the adaptive algorithm was enabled on their device. The implementation of supervised controller adaptation on a commercial pattern recognition system that decreases the need for recalibration, and even improves home-use performance can have a far-reaching clinical impact on prosthesis wearers.

An adaptive classification strategy may provide a means not only to reduce the frequency of user recalibration, but also to improve their functional prosthesis control. Another main finding of our preliminary results was that users improved their calibration quality when the adaptive algorithm was enabled. This result provides preliminary evidence that adding additional EMG input data can improve calibration quality which may translate to enhanced user control of their prosthetic device. Further analysis of participants' usage logs and virtual game data collected during each 8-week period is needed to determine the correlation between the quality of their calibrations and their control efficiency within both a virtual environment and their home environment.

While the adaptation algorithm implemented on the control system can generalize over a broader set of EMG calibration inputs, it is unable to account for EMG signal noise recorded during regular prosthesis use. EMG signal quality is a significant factor in users being able to consistently achieve adequate control of their device. While there are several physiological and engineering factors that can affect EMG signal quality (including external noise, muscle fatigue, electrode-skin impedance), myoelectric prostheses require that the electrodes maintain contact with the skin surface to ensure proper user function. The Complete Control System can detect such electrode liftoff events which can be used to monitor signal quality issues. Interestingly, the two users who had higher a calibration frequency when the adaptive algorithm was off also had a high frequency of electrode liftoff events. Currently, the

only way for users to counteract frequent electrode liftoff is by disabling the electrode channels with a noticeably high occurrence of liftoff events.

Participants in this study were required to perform a full motion calibration sequence to either replace or update their control system's classifier during both 8-week periods. However, one of the added features of the adaptative calibration algorithm is the ability to add EMG input data to a single motion rather than completing the entire motion sequence. This feature provides users a convenient way to update and improve their classifier for a single motion if they feel that their control efficiency for that motion has deteriorated or if there are prosthesis use conditions where they want to train with that specific motion. Since participants in this study were existing Complete Control system wearers and the adaptive classification algorithm is the default behaviour of the system, many who normally rely on the "Single Motion Add Data" feature to improve their prosthesis control did not have access to it. In fact, one of the participants who withdrew from the study reported that the inability to use the "Single Motion Add Data" feature as the primary reason for withdrawing from the study.

DISCLOSURES

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Coapt, LLC is the manufacturer of the FDA-cleared Class II medical device, called the Complete Control System, used in this study. Wright, as Research Principal Investigator, is an employee of Coapt, LLC. Lock, as CEO, has financial interest in Coapt, LLC.

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