MACHINE LEARNING TO IMPROVE PATTERN RECOGNITION CONTROL OF UPPER-LIMB MYOELECTRIC PROSTHESES

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ABSTRACT

The clinical application of machine learning to prosthesis control is becoming better understood and more widely accepted. Commercially available pattern recognition systems employ machine learning algorithms to allow users to control their powered prostheses more intuitively, using their unique patterns of electromyography (EMG) signals. As users wear their devices more, the EMG signals they elicit for device control become more consistent [1]. There are factors, however, that can lead to changes in the characteristics of the EMG signals, which serve as inputs to the pattern recognition controller, such as electrode shift, muscle fatigue, et cetera. Currently, no commercially available pattern recognition system makes use of machine learning, supervised-adaptation algorithms to improve control via the utilization of historical EMG data collected during previous calibration routines. This paper introduces clinically relevant approaches and implementations of adaptive machine learning for control of prosthetic and orthotic devices.

INTRODUCTION

More than 11,000 amputations at the wrist disarticulation or higher-level occurred in the US between 2005 and 2013 [2] – with many more occurring worldwide. Pattern recognition control for myoelectric prostheses has benefitted many individuals with upper limb loss and limb difference since commercialization in late 2013 [3]. Described as "the single biggest breakthrough in [Pattern Recognition] in decades" [4], prosthesis-guided calibration played a significant role in the commercialization of pattern recognition control [5-8]. Researchers, clinicians, and users alike have expressed appreciation for the on-the-go recalibration feature, which puts the user in control of calibrating (i.e., updating) the pattern recognition system whenever and wherever desired – and without the need for a computer. However, despite the accessibility of the calibration scheme, it remains somewhat rigid: requiring the user to perform a sequence of all available prosthesis movements for each calibration.

All human-computer interfaces inherently involve two systems capable of adaptation: the human and the computer (i.e., the algorithm), with both systems affecting performance [1]. He et al. found a statistically significant trend of improved muscle contraction repeatability across days of use with a training paradigm that did not employ any external feedback. As the electrode locations and the electrode-skin impedance were controlled factors in the study, the increasing repeatability trend can be best explained by physiological adaptations of the subjects through learning to perform consistent muscle contractions. In addition and complementary to user adaptation, it is important that the pattern recognition control system (i.e., the algorithm) adapt to EMG signal non-stationarities, such as electrode location shift, muscle fatigue, and varying limb orientations during training. Furthermore, Vidovic et al. found that classification accuracy increased from 75% to above 92% when utilizing an adaptive calibration method as compared with a static training paradigm, a promising result for clinical implementation [9].

Some users choose to calibrate their prosthesis control multiple times each day, and calibration routine improvements are some of the most requested enhancements of the commercial pattern recognition control system. Currently available pattern recognition control systems discard collected EMG data by default when a new calibration is performed. The goals of the adaptive calibration approach are to improve prosthesis control (by utilizing a larger set of EMG data for training the pattern recognition control system) and to reduce the amount of time spent recalibrating the system. This can be accomplished by making use of the historical EMG data to improve the generalizability of the controller to EMG signal variability and adapting the controller with the most recently collected set of calibration data. In this contribution, a machine learning supervised adaptation calibration paradigm for improving prosthesis control and potentially reducing the need for recalibration is presented.

METHODS

Seven intact-limb subjects (four males and three females) and four subjects with transradial limb difference (three males and one female) completed the following IRB-approved experiment. An elastic cuff with eight, equidistantly-spaced, bipolar electrode pairs was donned on the upper forearm approximately two cm distal to the elbow with a ground electrode placed collinear with the olecranon. A software interface guided the collection of the following muscle contraction data: wrist supination and pronation, hand open, key grip, chuck grip, fine pinch grip, and point grip. These movements are commercially available and routinely used in powered prostheses (i.e., wrist rotators and multi-articulating hands). Subjects were verbally instructed to perform medium strength, constant-force muscle contractions but were provided with no biofeedback. Subjects completed seven data collection sessions each consisting of eight repetitions of all collected muscle contractions. This data collection procedure is common in the field of myoelectric pattern recognition control [1, 10-11].

Five paradigms for the training and testing of the pattern recognition classifier were examined: training on the first session and testing on each subsequent session ("Static", i.e., across-session testing with a static decoder), training on session N and testing on session N+1 ("Across", i.e., across-session testing), training with adaptation that remembers all data ("Pooled", i.e., training with data from all sessions prior to the testing session), training and testing with adaptation with a fixed memory ("Adapt.", i.e., across-session testing with adaptation), and training and testing with data from a single session ("Within", i.e., within-session testing). Classification error rates were used to assess offline classifier-training paradigm performance. A 2-way ANOVA with classification error rate as the response variable and training paradigm as a fixed factor was completed. Additionally, the impact of increasing the number of available functional hand grasps (i.e., one, two, three, or four hand grasp patterns) on classifier error rate was also examined. Finally, qualitative user feedback from beta-testing of the calibration scheme was analysed to assess clinical implementation.

RESULTS & DISCUSSION

Both subject groups (i.e., intact-limb subjects and subjects with transradial limb difference) show the same classifier-training paradigm performance trends. The results highlight that the adaptive calibration scheme resulted in classification error rates lower than the "Static" classifier-training paradigm, which performed the poorest of all five conditions (Figure 1). When compared with static decoding, the classification error rate of the supervised adaptation paradigm was significantly lower ($p < 0.05$). Presumably, the "Static" condition performed poorly because it could not adapt to EMG signals changes across the eight testing sessions, which mirrors how the existing commercial controller might behave if used on subsequent days without retraining. The "Within" condition, which mirrors how the existing commercial controller might behave if retrained before each period of use, performed best for both subject groups. The within-session testing condition was expected to have the highest classifier performance because the EMG forearm cuff was not doffed between the classifier training and testing, meaning the electrode locations and electrode-skin impedance values were effectively equivalent across the training and testing data sets. The results of the other conditions were not statistically different. Trends toward improvements in classification error rates were noted from the across-session condition to the across-session with pooled training data condition and further from "Pooled" to the across-session with adaptation condition. It is likely that more subjects are required to achieve appropriate statistical power to detect differences between the "Across", "Pooled", and "Adapt." conditions. The preliminary data support the hypothesis that the use of supervised adaptation would decrease the need for frequent recalibration of the pattern recognition control system. Further exploration to ensure clinical viability is necessary. It is expected that the performance of the adaptation classifier-training paradigm would approach and potentially surpass that of the within-session case with a greater number of data collection sessions added to the pattern recognition control system. Qualitatively, subjects found that prosthesis control improved and that controller recalibration was not needed as often with adaptive calibration.

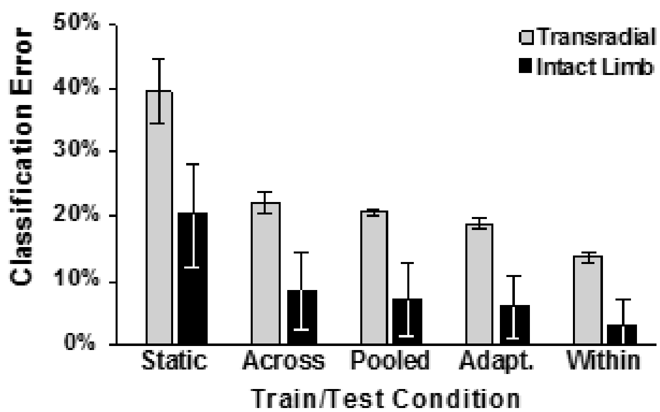

Figure 1: Results showing the classification error rates with standard error (error bars) for all five training paradigms arranged by subject group.

CONCLUSION

While many users express appreciation for the on-the-go recalibration (i.e., prosthesis-guided calibration) feature of commercial pattern recognition control, the rigidity of the calibration routine has at times proven to be burdensome. An adaptive approach may provide a means not only to reduce the frequency of recalibration, but also to improve functional prosthesis control. By adding new data to the classifier rather than completely clearing the classifier, we should develop a system that generalizes to more movements and use conditions. Further investigation into the robustness of adaptive calibration across many different muscle contraction patterns and clinical settings is being explored.

SIGNIFICANCE

Pattern recognition control of upper-limb prostheses is growing in clinical acceptance. The implementation of supervised controller adaptation into the commercial pattern recognition system is expected to improve real-time, home-use performance and decrease the need for recalibration, a development with far-reaching clinic impact. Improvements to calibration, especially those resulting in greater prosthesis control, improve the viability of pattern recognition control in comparison with conventional amplitude-based control approaches.

DISCLOSURE

Dr. Levi Hargrove has a financial interest in Coapt, LLC.

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