ASSESSING THE FEASIBILITY OF USING SONOMYOGRAPHY FOR UPPER LIMB PROSTHESIS CONTROL

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ABSTRACT

Sonomyography (SMG), or ultrasound-based sensing of muscle deformation, is an emerging modality for upper limb prosthesis control with potential to significantly improve functionality. SMG enables spatiotemporal characterization of both superficial and deep muscle activity, making it possible to distinguish the independent contributions of individual muscles during functional movements. Early offline studies have shown that SMG is capable of accurately classifying motor intent among able-bodied individuals, but it has not yet been shown whether individuals with upper limb absence can successfully use this modality for prosthesis control. This paper describes our ongoing work towards implementing SMG control for individuals with upper limb absence in offline and real-time settings. We provide strong evidence supporting the feasibility of using SMG to control upper limb prostheses.

INTRODUCTION

Although designs of electromechanical prosthetic hands have improved over time, surface electromyography (EMG) remains the most common modality for sensing and decoding user intent. Unfortunately, using EMG to control a prosthetic hand with multiple degrees of freedom can be challenging for individuals due to the poor amplitude resolution and low signal-to-noise ratio inherent in EMG signals [1]. Sonomyography (SMG) is an alternative approach that uses ultrasound imaging of muscle deformation to spatiotemporally resolve both surface and deep musculature in the residual limb. Using SMG, it is therefore possible to derive a rich set of prosthesis control signals that may better account for the independent contributions of individual muscles. For example, we previously used SMG to identify five individual digit movements in able-bodied individuals with 97% offline cross-validation accuracy [2] and fifteen complex hand grasps with 91% offline cross-validation accuracy [3]. More recently, we have extended this work to better understand whether SMG is a clinically viable control modality for individuals with upper limb absence. This paper will discuss our ongoing work in this area and highlight opportunities for future study.

DEVELOPING PROFICIENCY WITH SONOMYOGRAPHY

One factor that may affect the feasibility of using SMG for prosthesis control is the length of pre-prosthetic training time required for individual with upper limb absence to learn to use it. Prior to receiving a prosthesis, patients must develop an ability to produce control signals that are sufficiently consistent and separable for accurate grasp classification. The pre-prosthetic training process can be lengthy and difficult in the context of EMG control [4], which presents a barrier to adoption of a prosthesis. However, our testing with SMG suggests that patients can rapidly complete pre-prosthetic training.

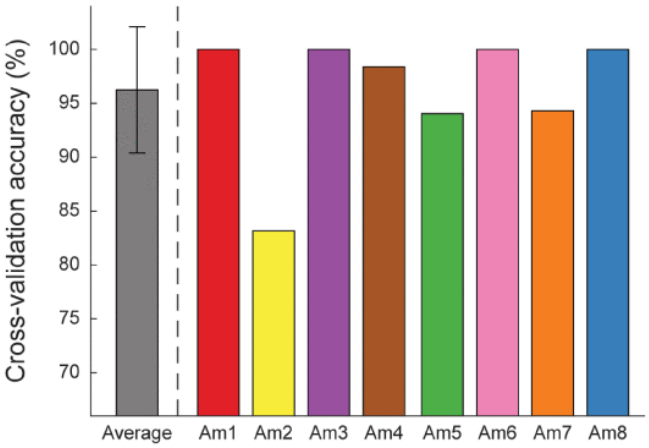

Figure 1: Average and individual classification accuracies during participants' first exposure to sonomyography.

In a sample of eight individuals with transradial limb absence, we characterized grasp classification performance during their initial and subsequent exposures to SMG in order to understand how proficiency develops over time. Participants were asked to repeatedly perform a set of 4-7 grasps while ultrasound images of their residual limb musculature were recorded using a commercial ultrasound transducer. Grasps were self-selected based on what each participant felt was intuitive to perform. The images were saved to a database and subjected to leave-one-out cross-validation with a modified 1-nearest-neighbor classifier [5]. This process was completed once while the participants were naïve to SMG control to establish baseline performance. To assess whether performance could improve with further instruction, it was then repeated three times while participants received verbal and visual biofeedback about their performance. Lastly, participants returned for a second session on a different day to assess between-day repeatability. Despite being naïve, the participants achieved high classification accuracy during their initial exposure to SMG (96.2 ± 5.9%; Figure 1). Moreover, the accuracy did not systematically change with the provision of biofeedback or between days. Our findings suggest that individuals who are naïve to SMG can quickly and consistently achieve reliable grasp classification [5].

USING SONOMYOGRAPHY WITH PROXIMAL LIMB ABSENCE

Our initial offline investigations of SMG focused on able-bodied individuals and individuals with transradial limb absence. However, we also investigated whether SMG may be a suitable control modality for individuals with limb absence at more proximal levels. Absence of the forearm may create challenges for using SMG because the muscles associated with wrist, hand, and finger control are primarily located in the forearm. To explore this issue, we asked an individual with transhumeral amputation to perform 11 hand motions (including six grasps and flexion of each individual digit) interspersed by periods of rest. The participant achieved high classification accuracies during both

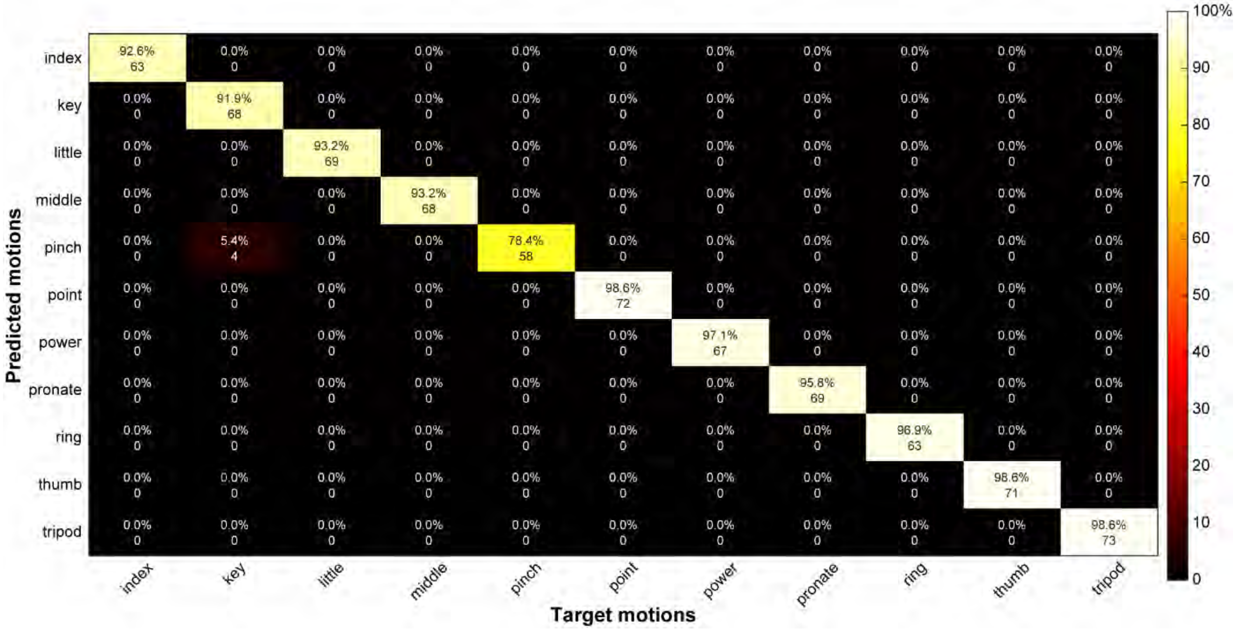

Figure 2: Confusion matrix for the motion end states achieved by an individual with transhumeral amputation. Integer values in each cell represent the total number of SMG image frames that were classified.

the motion end states (94.04%; Figure 2) and rest phases (98.34%) [6]. This promising result shows remarkable potential for using SMG to recognize individual finger movements and complex grasps in individuals with proximal limb absence. However, we acknowledge that our participant may have been uniquely able to achieve this outcome due to spontaneous muscle reinnervation, although his amputation surgery did not include targeted muscle reinnervation. More individuals must be assessed to understand how SMG can be best implemented in this population.

FUNCTIONAL TASK PERFORMANCE USING A SONOMYOGRAPHIC PROSTHESIS

Although we have shown that robust offline classification performance is possible with SMG, we also sought to understand the feasibility of using SMG to control a prosthesis in real-time functional settings. In contrast to the tightly-controlled settings in which offline classification performance is typically assessed, the use of a physical prosthesis involves many variabilities that can degrade classification performance. Notably, changes in the ultrasound imaging angle during arm movement could affect the acquired images, potentially causing misclassification. Thus, it must be confirmed whether classification is stable as users move their arm through their entire reachable workspace.

As a first step to understanding this issue, we asked an individual with bilateral limb absence at the wrist disarticulation level to perform a series of functional tasks using a prosthesis controlled by SMG. To collect data for training a linear discriminant analysis classifier, the participant moved her arms throughout her reachable workspace in a pre-defined pattern while maintaining a set of muscle contractions. Each contraction was mapped to a specific grasp within the prosthetic hand. Tripod grasp was initiated by wrist flexion, index finger point was initiated by wrist extension, and rest was initiated by a relaxed muscle state.

The participant then performed three functional tasks that involved grasping and moving one-inch wooden blocks. These tests were repeated every 30 minutes across three hours of continuous prosthesis wear without retraining the classifier. Box and Blocks Test (BBT) performance was measured by the number of blocks transferred over a barrier in one minute. Targeted Box and Blocks Test (tBBT) performance was measured by the time required to move 16 blocks over a barrier into predetermined positions. Rainbow Test performance was measured by the time required to move blocks located at various heights from a white board to a box at waist height. During each break between tests, the participant turned off the prosthesis and performed pre-defined tasks that were staggered to require increased arm movement over time. In addition to the test outcomes measures, we quantified the number of transient classification bouts to characterize the efficiency of grasp selection. A transient bout was defined as an instance when the classifier predicted a grasp for less than five consecutive frames. Fewer transient bouts indicate increased efficiency.

The participant successfully completed all tasks throughout the three-hour testing period [7]. The outcome measures remained generally stable over time (Figure 3), although we did observe a slight improvement in test scores during BBT with the left arm ($p = 0.038$) and during tBBT with the right arm ($p = 0.011$). There was only one negative effect of socket wear time on performance, as evidenced by a small increase in the number of transient bouts during the Rainbow test with the left arm ($p = 0.027$). Our results show that training a classifier to predict hand grasps while moving the arm throughout the reachable workspace is a practical strategy for reducing misclassification related to changing arm position. Additionally, this study supports the feasibility of using SMG to control upper limb prostheses in real-world applications.

CONTINUING WORK

As part of our continuing work towards demonstrating the utility of SMG control, we are working to develop wearable low-power ultrasound systems that can be integrated into a prosthetic socket. The functional tests reported in this paper were conducted with the participant tethered to a tablet-based commercial ultrasound system that could not easily be transported. We expect to see improved real-world performance when using a system optimized for SMG control that allows the user to move freely. We also anticipate that an optimized system would enable users to wear an SMG sensor for prolonged periods of time, permitting additional study on the stability of grasp classification during daily activities.

We envision a future with SMG as a viable option for upper limb prosthesis control, and we encourage research that examines the capacity of SMG to increase functional outcomes and satisfaction among prosthesis users. Future work will focus on systematically evaluating the functional benefits of SMG control, such as whether using SMG contributes to higher scores on standard clinical tests, improved quality of movement, greater patient-reported satisfaction, and reduced cognitive load. Although myoelectric control strategies continue to demonstrate remarkable clinical utility, we anticipate situations in which SMG control would be considerably advantageous. There is also opportunity to examine hybrid approaches using both SMG and EMG to enable more intuitive control for users with upper limb loss.

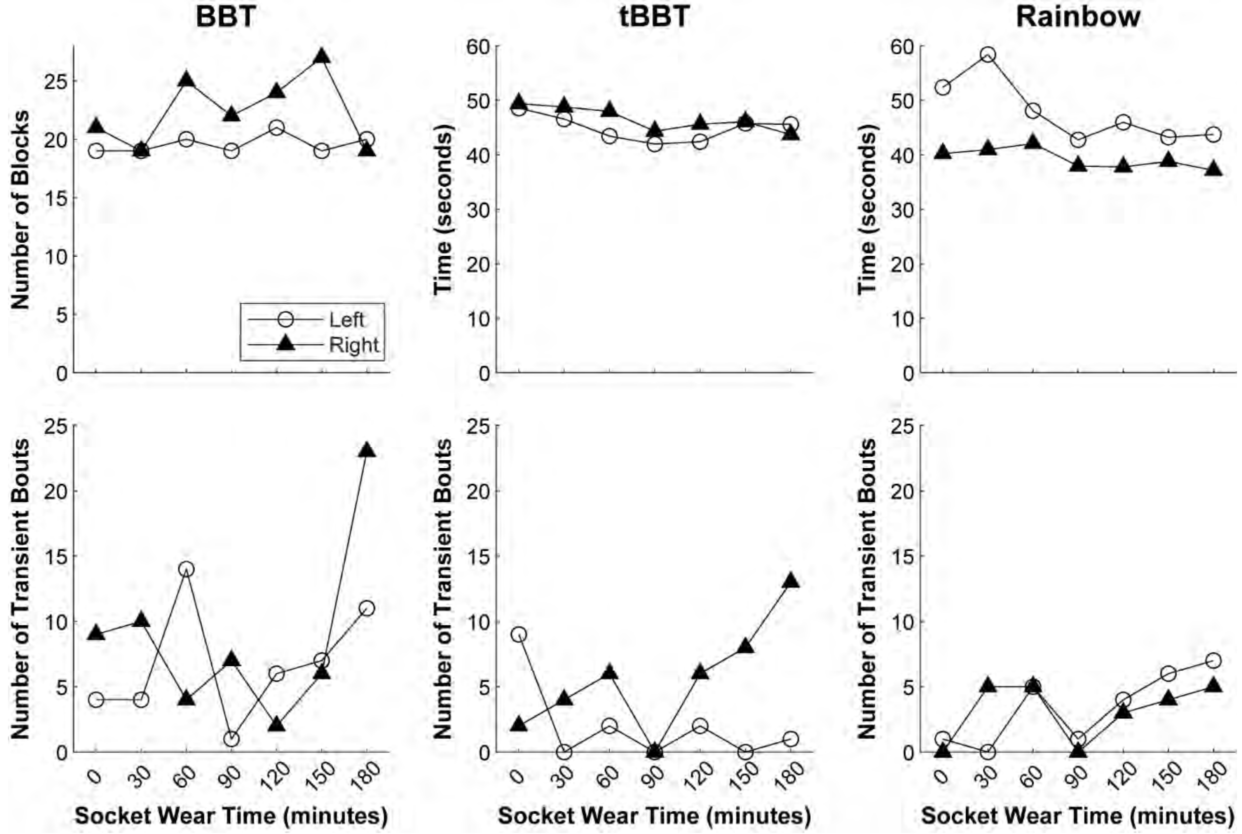

Figure 3: Functional outcome measures achieved during testing (BBT = Box and Blocks Test; tBBT = Targeted Box and Blocks Test)

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REFERENCES

[1] E. Clancy, E. L. Morin, and R. Merletti, “Sampling, noise-reduction and amplitude estimation issues in surface electromyography,” *J. Electromyogr. Kinesiol.*, vol. 12, pp. 1–16, 2002.

[2] S. Sikdar *et al.*, “Novel method for predicting dexterous individual finger movements by imaging muscle activity using a wearable ultrasonic system,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, pp. 69–76, 2014.

[3] N. Akhlaghi *et al.*, “Real-time classification of hand motions using ultrasound imaging of forearm muscles,” *IEEE Trans. Biomed. Eng.*, vol. 63, pp. 1687–1698, 2016.

[4] A. W. Franzke *et al.*, “Users’ and therapists’ perceptions of myoelectric multi-function upper limb prostheses with conventional and pattern recognition control,” *PLOS ONE*, vol. 14,, p. e0220899, 2019.

[5] S. Engdahl *et al.*, “Classification performance and feature space characteristics in individuals with upper limb loss using sonomyography,” *IEEE J. Transl. Eng. Health Med.*, vol. 10, pp. 1–11, 2022.

[6] S. Engdahl, A. Dhawan, G. Lévay, A. Bashatah, R. Kaliki, and S. Sikdar, “Motion prediction using electromyography and sonomyography for an individual with transhumeral limb loss,” *medRxiv*, 2020.

[7] S. Engdahl, S. Acuña, E. King, A. Bashatah, and S. Sikdar, “First-in-human demonstration of functional task performance using a sonomyographic prosthesis,” *submitted to Front. Bioeng. Biotechnol.*, 2022.