Personalized Gesture Classification for Encouraging Non-Sedentary Behavior During Technology Use in People with Motor Disabilities

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***Abstract*— We developed a personalized electromyography gesture classifier to encourage non-sedentary behavior during technology use. Sedentary behavior is associated with negative health outcomes, and individuals with disabilities are twice as likely to be sedentary compared to the general population. Our classifier had 74% accuracy for 10 gesture classes across 25 participants with upper-body motor disabilities.**

***Clinical Relevance*— Our work highlights the potential for personalized gestures to encourage non-sedentary behavior during technology use for people with motor disabilities.**

I. Introduction

Biosignal interfaces (e.g., electromyography (EMG), accelerometers) enable people with motor disabilities to interact with their technologies accessibly while also encouraging movement and non-sedentary behavior [1]. Sedentary behavior is associated with adverse health outcomes, including cardiovascular disease, obesity, and all-cause mortality [2]. Developing new technologies to encourage non-sedentary behavior is particularly important for individuals with disabilities as they are twice as likely to be sedentary than the general population [3]. We investigate the potential for biosignal interfaces to enable movement during technology use through the development and evaluation of a personalized gesture classifier. The gesture classifier works well with only a few training examples and across a wide range of motor disabilities and upper-body gestures.

II. Methods

Twenty-five participants with upper-body motor disabilities (spinal cord injury (13), muscular dystrophy (3), peripheral neuropathy (3), essential tremor (2), other motor disabilities (4)) participated in the study. EMG sensors (Delsys, Inc.) were placed on 16 locations on the participants' upper body. Participants were asked to elicit personalized gestures for 10 common device functions (e.g., *rotate, zoom-in*), and then perform their chosen gesture 10 times. Prior to gesture classification, the EMG envelope (40 Hz high-pass 4^{th} order Butterworth filter, rectification, 40 Hz low-pass 4^{th} order Butterworth filter) and moving average (100 ms window with 50% overlap) were computed. We then applied a nearest-neighbor algorithm with three training samples for each function to compute the gesture classification accuracy for each participant.

*Research supported by Meta, UW CREATE, and a NIDILRR ARRT Training Grant 90ARCP0005-01- 00.

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III. Results

On average, our gesture classifier had a 74% classification accuracy with just three templates for 10 device functions (with 10% chance accuracy). As the participants had very different motor disabilities, with some having very limited movement (e.g., muscular dystrophy) and others having full range of motion (e.g., essential tremor), the types of gestures that participants came up with varied widely.

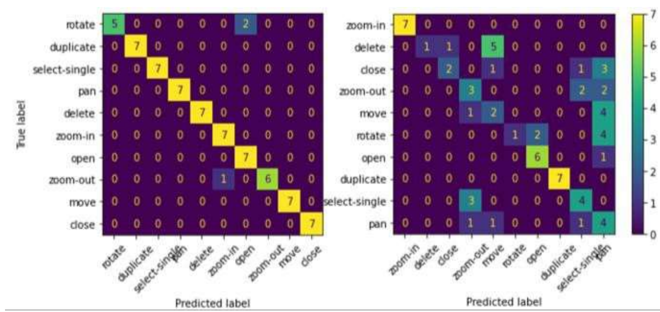

Figure 1. Gesture classification accuracy confusion matrix for two participants (left: 96%, right: 53%). The classifier did not perform as well when participants chose similar gestures for different device interactions.

IV. Discussion & Conclusion

Compared to other datasets where participants were asked to perform gestures chosen by researchers [4], our work is unique in that the gestures were generated by our participants. Personalizing the gestures to each individual's unique abilities [5] ensures that the movements are accessible while still encouraging movement. Our work is the first step towards integrating personalized biosignal algorithms to encourage non-sedentary behavior during technology use. As one participant said, "*all movement is rehabilitative*."

Acknowledgments

Thanks to Jennifer Mankoff for her help on this project.

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