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

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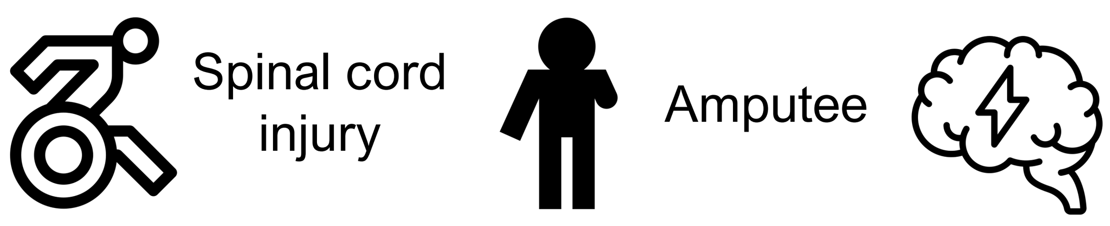
Introduction

Sedentary behavior is associated with adverse health outcomes.

- e.g., cardiovascular disease, obesity, all-cause mortality [1].
- Developing new technologies to encourage non-sedentary behavior is particularly important for individuals with disabilities -- twice as likely to be sedentary than the general population [2].



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.

Goal: Investigate the potential for biosignal interfaces to enable movement during technology use through the development and evaluation of a personalized gesture classifier.

Method

Participants

- Twenty-five participants with upper-body motor disabilities (spinal cord injury (N=13), muscular dystrophy (N=3), peripheral neuropathy (N=3), essential tremor (N=2), other motor disabilities (N=4)).

Sensors

- 16 EMG sensors (Delsys, Inc) on the participants' upper body.

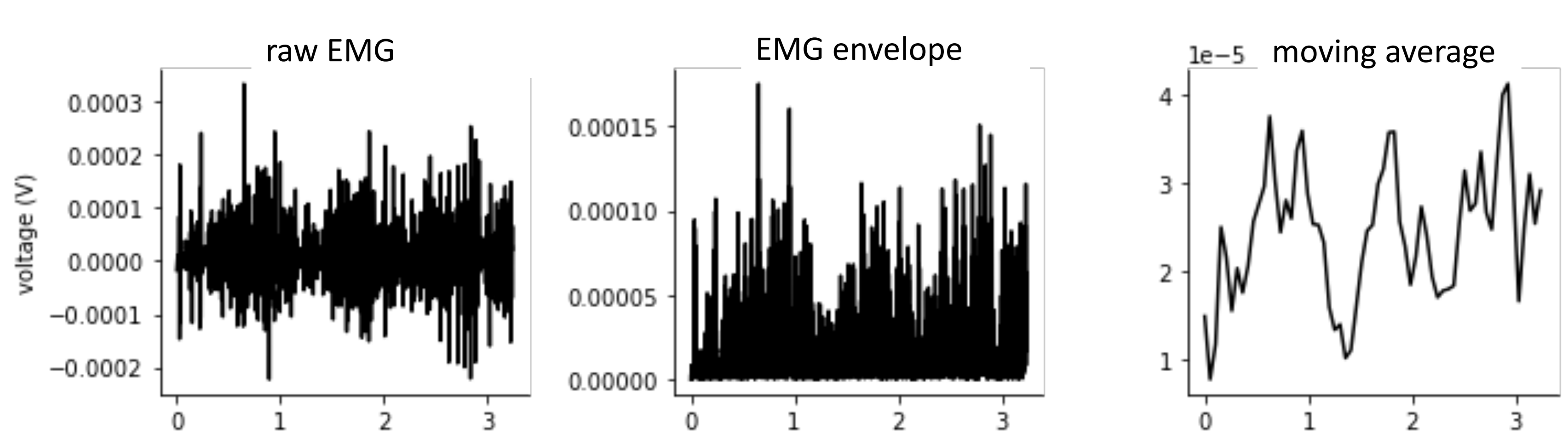
Protocol

Personalized Gesture Elicitation

Participants developed personalized gestures for 10 common device functions (e.g., rotate, zoom-in), and then perform their chosen gesture 10 times.

Data Processing

EMG envelope and moving average were computed.



Classification

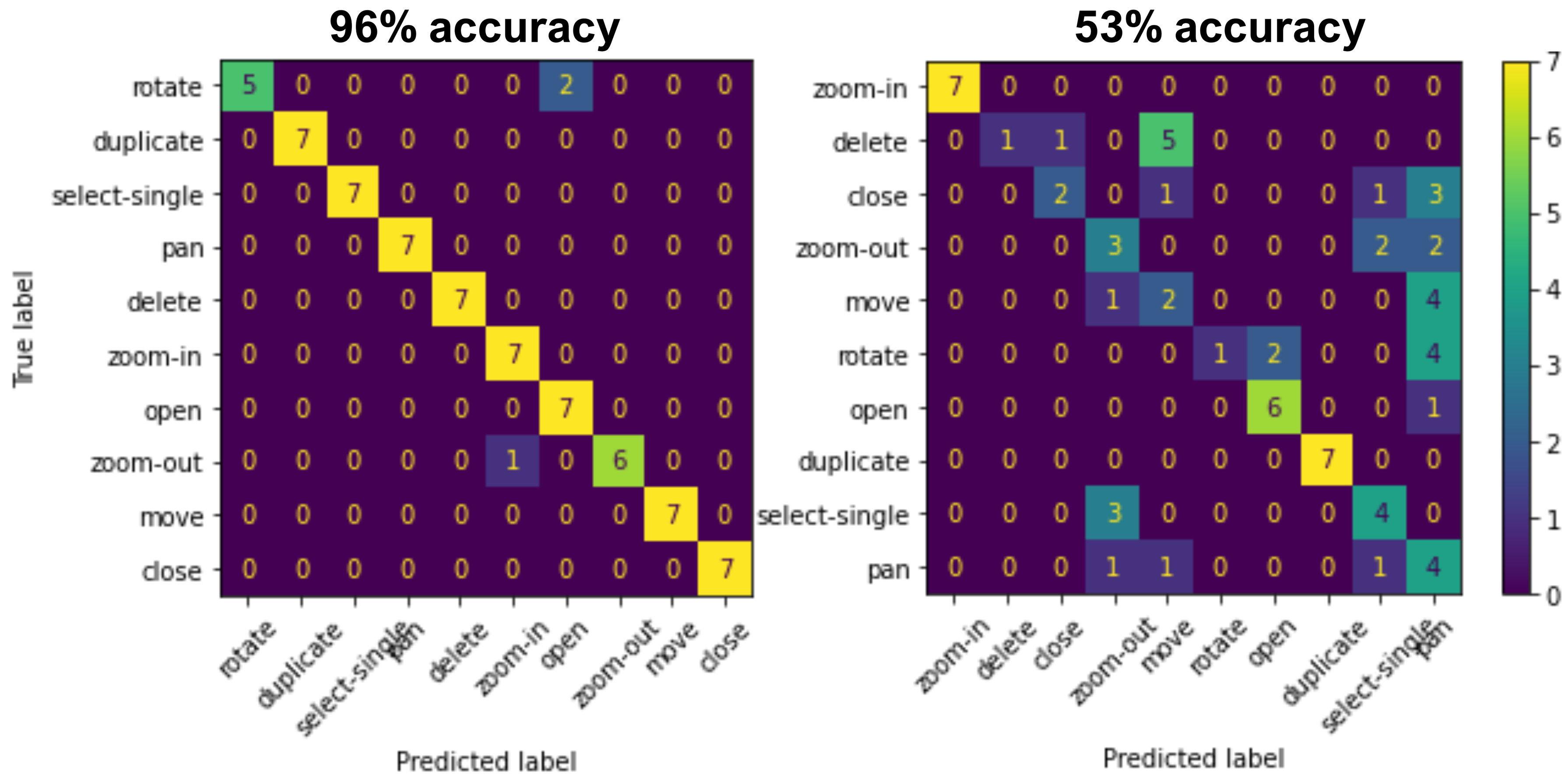
Nearest-neighbor algorithm with three training samples for each function to compute the gesture classification accuracy for each participant

Acknowledgement: Huge thanks to Dr. Jennifer Mankoff for her input on this project.

Result

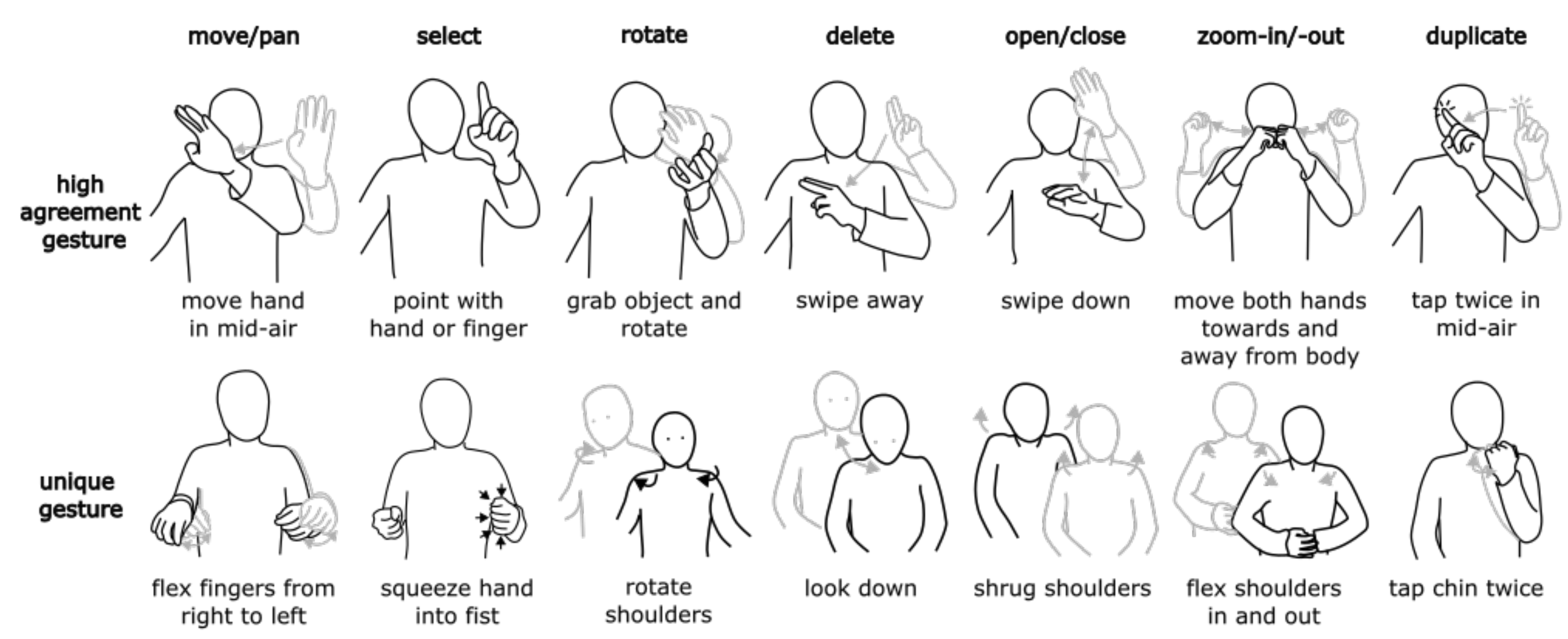
74% classification accuracy with three templates for 10 functions (10% chance accuracy).

- Participants who chose similar gestures to represent different functions (right) had lower classification accuracy than participants who chose different gestures to represent different functions (left).

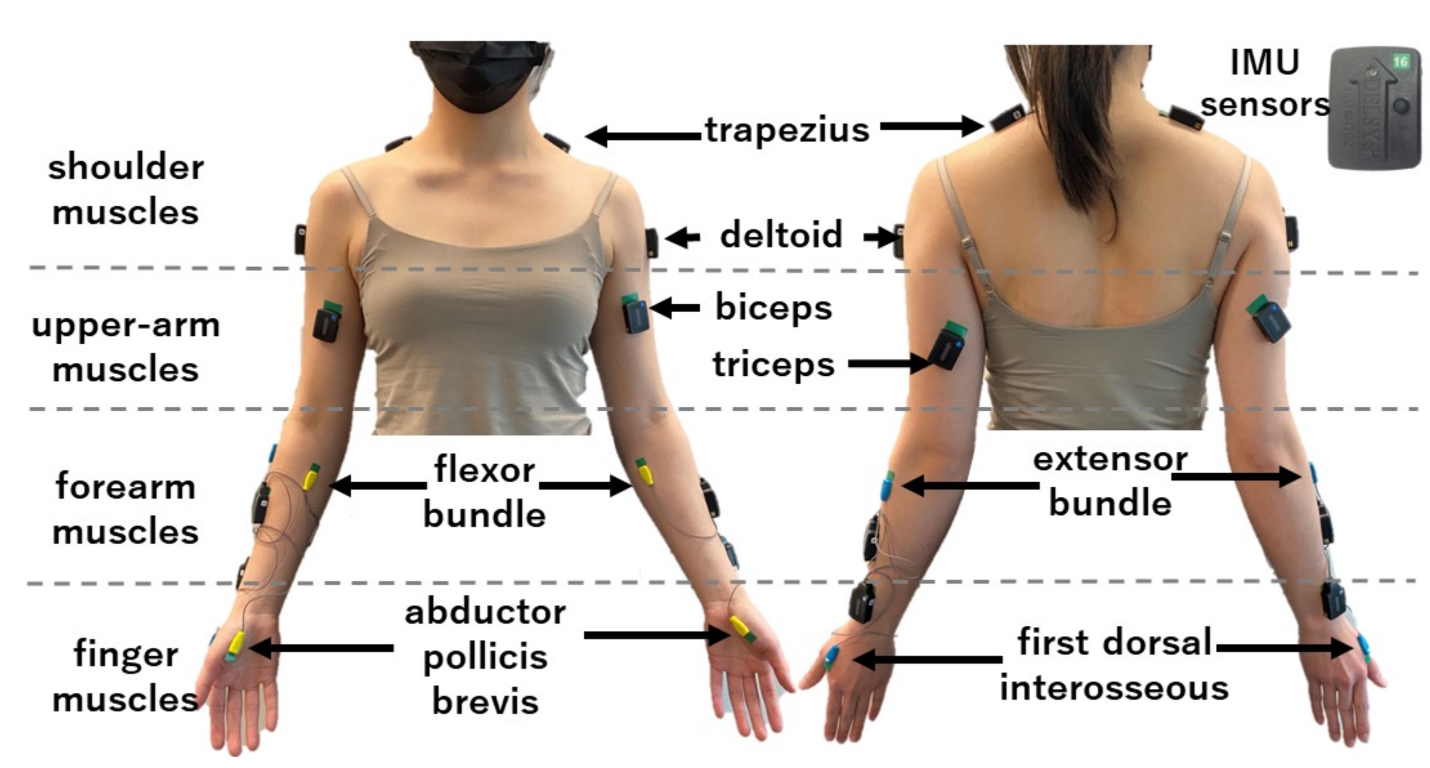


Varying motor abilities affected the types of gestures that participants came up with.

- Some had very limited movement (e.g., muscular dystrophy) and others had full range of motion (e.g., essential tremor).
- Individuals with greater movement limitations chose more unique gestures.



Sensors were placed across the participants' upper-body to maximize their abilities.



Discussion & Conclusion

- Our biosignal dataset is unique in that the gestures were generated by our participants and personalized to their abilities [3].
- Personalizing the gestures to each individual's unique abilities [4] 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.

"All movement is rehabilitative"