A Hierarchical Machine Learning Approach for Real-Time BMI Control of an Upper-Body Exoskeleton

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Abstract

In recent decades, two distinct technological advances have been made to understand and improve rehabilitation after a stroke: human-robot interaction and brain-machine interfaces (BMI). Integrating their individual efforts is a largely unexplored yet opportune area that could have profound clinical implications. However, a significant challenge is whether motor intentions from the user can be accurately and reliably detected using non-invasive BMIs in the presence of instrumental noise and passive movements induced by the rehabilitation exoskeleton. As an alternative to current attempts aiming for continuous control, this study instead proposes a novel real-time streaming hierarchical machine-learning approach that detects the onset and offset of motor imagery to control passive arm movements induced by an upper-body exoskeleton. The presented method allows for a more natural sense of functional control and could provide a useful tool for future neurorehabilitation applications.

1 Demonstration Description

This demonstration shows a subject operating a brain-machine interface (BMI) [Wolpaw *et al.*, 2020] based on motor imagery (MI), i.e., imagining the kinesthetics of a movement without actually executing it [Pfurtscheller and Neuper, 2001]. The BMI analyzes the subject's electroencephalogram (EEG) signals to identify when they initiate and terminate a MI reaching task. If the BMI detects the MI onset, then the robot initiates a predefined reaching task toward an object (targets indicated by the color balls across the subject). While reaching, if the BMI detects the end of MI, the robot terminates its movement. The subject receives proprioceptive feedback via neuromuscular electrical stimulation that indicates the accumulated evidence of the BMI for two classes: MI onset and MI offset. When the evidence crosses a predefined threshold, the respective command gets delivered to the robot. Such proprioceptive feedback promotes the subject's learning of better BMI control [Biasiucci *et al.*, 2018; Corbet *et al.*, 2018]. The video depicts two scenarios: *i)* the subject performs the reaching MI task inside the exoskeleton, and their arm is passively moved by the robot; *ii)* the subject operates the BMI but sitting next to the robot to show that the robot reaching movement is initiated by the subject-driven BMI and not overtly controlled by any subject movement. The exhibition illustrates how our BMI-controlled upper-body exoskeleton could assist stroke patients affected by arm paralysis by performing functional reaching movements and, furthermore, could elicit strong rehabilitation effects [Briggs *et al.*, 2013; Biasiucci *et al.*, 2018]. This project is a collaborative initiative between the Clinical Neuroprosthetics and Brain Interaction Lab (Department of Electrical and Computer Engineering and Department of Neurology) and the Rehabilitation and Neuromuscular Robotics Lab (Department of Mechanical Engineering) at The University of Texas at Austin.

2 Methods

2.1 BMI Architecture

The BMI has two decoders; the first detects the transition from rest to MI onset, while the second detects the transition from MI maintenance to MI offset. Both decoders utilize a Riemannian geometry-based, minimum distance to the mean classifier [Barachant *et al.*, 2010], which is robust to non-stationary MI-related EEG patterns. The two decoders work in a cascading manner: a positive output of the first one initiates the robot's reaching movement and activates the second decoder, whose positive output stops the robot. The decoders were trained on covariance matrices extracted from 0.5-second, overlapping data segments from each class over four runs of 20 trials each. We employed an adaptive online re-centering method [Kumar *et al.*, 2019] to match the distribution of the incoming real-time data to the previously recorded training data to allow for more robust and stable performance over multiple sessions.

2.2 Upper-Limb Exoskeleton

Harmony is a bi-manual rehabilitation robot with seven active degrees of freedom (DOF) per side, including five DOF for the shoulder complex [Kim and Deshpande, 2017]. Harmony was specifically designed for the rehabilitation of neurological patients and can provide safe position and force control, as well as accurate measurements of the upper-limb kinematics [de Oliveira *et al.*, 2019]. In this study, Harmony performed three types of active, goal-directed reaching tasks emphasizing shoulder and elbow movements in a randomized order.

References

[Barachant *et al.*, 2010] A. Barachant, S. Bonnet, M. Congedo, and C. Jutten. Riemannian geometry applied to BCI classification. In *9th International Conference LVA/ICA*, pages 629–636, 2010.

[Biasiucci *et al.*, 2018] Andrea Biasiucci, Robert Leeb, Iñaki Iturrate, Serafeim Perdikis, Abdul Al-Khodairy, Tiffany Corbet, et al. Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke. *Nature Communications*, 9(1):2421, 2018.

[Briggs *et al.*, 2013] Farran Briggs, George R Mangun, and W Martin Usrey. Attention enhances synaptic efficacy and the signal-to-noise ratio in neural circuits. *Nature*, 499(7459):476–480, 2013.

[Corbet *et al.*, 2018] Tiffany Corbet, Iñaki Iturrate, Michael Pereira, Serafeim Perdikis, and José del R Millán. Sensory threshold neuromuscular electrical stimulation fosters motor imagery performance. *NeuroImage*, 176:268–276, 2018.

[de Oliveira *et al.*, 2019] Ana C de Oliveira, Chad G Rose, Kevin Warburton, Evan M Ogden, Bob Whitford, Robert K Lee, and Ashish D Deshpande. Exploring the capabilities of Harmony for upper-limb stroke therapy. In *IEEE 16th International Conference on Rehabilitation Robotics*, pages 637–643, 2019.

[Kim and Deshpande, 2017] Bongsu Kim and Ashish D Deshpande. An upper-body rehabilitation exoskeleton Harmony with an anatomical shoulder mechanism: Design, modeling, control, and performance evaluation. *The International Journal of Robotics Research*, 36(4):414–435, 2017.

[Kumar *et al.*, 2019] Satyam Kumar, Florian Yger, and Fabien Lotte. Towards adaptive classification using Riemannian geometry approaches in brain-computer interfaces. In *7th International Winter Conference on Brain-Computer Interface*, pages 1–6, 2019.

[Pfurtscheller and Neuper, 2001] Gert Pfurtscheller and Christa Neuper. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89(7):1123–1134, 2001.

[Wolpaw *et al.*, 2020] Jonathan R Wolpaw, José del R Millán, and Nick F Ramsey. Brain-computer interfaces: Definitions and principles. In José del R Millán and Nick F Ramsey, editors, *Handbook of Clinical Neurology*, volume 168, pages 15–23. Elsevier, 2020.