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A biomimetic iBCI decoder for restoring hand function in people with spinal cord injury

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Introduction: Intracortical brain-computer interfaces (iBCIs) offer paralyzed individuals the ability to generate movement. While effective for guiding a computer cursor [1] or a robotic arm [2], [3], current systems lack the ability to control applied forces and adjust limb compliance—critical limitations for grasping and interacting with objects. To address this, we propose developing an iBCI that decodes intended muscle activity (EMG) from primary motor cortex (M1) recordings. This system would then control joint kinematics and impedance, as well as contact forces via a forward musculoskeletal model of the hand [4], more closely mimicking the natural function of M1 than do existing iBCI decoders. We hypothesize that this biomimetic iBCI will be easier to learn and outperform existing decoders for hand function tasks.

Material, Methods and Results: Data to train kinematic iBCIs is obtained as users observe and attempt to replicate a certain movement trajectory; the decoders are built by correlating the recorded neural activity with the observed kinematics. To create a muscle-based equivalent, we first needed to determine the muscle activity patterns that a paralyzed individual might use when observing and attempting to mimic hand actions. For this, we collected data from an able-bodied individual performing a series of multi-degree-of-freedom hand posture-matching movements. We recorded intrinsic hand muscle activity using high-density surface electrode grids (LISiN, Torino, Italy) placed on the dorsal and palmar side of the hand, along with intramuscular leads also targeting the dorsal interossei. We recorded extrinsic hand muscles using standard surface bipolar electrodes (Delsys Inc., Boston, USA) on the forearm. We were able to accurately classify hand postures using only data from the surface recordings. Intramuscular leads offered only minor improvements in accuracy. This suggests that high-density grids alone provide sufficient information about intrinsic muscle activity, potentially eliminating the need for intramuscular leads in the hand. We next used these EMG signals as decoding templates together with M1 data recorded from a spinal cord-injured participant, implanted with two microelectrode arrays (Blackrock Microsystems, Salt Lake City, UT) in the arm and hand representations of M1, who attempted the same posture-matching task. To ensure consistency between the able-bodied participant's actual movements and the paralyzed participant's attempted movements, we recreated the actual hand kinematics in virtual reality through an avatar hand, which the participant observed. They were prompted to attempt to replicate the motion using their own hand. Posture classification accuracy using the M1 signals was well above significance, but below that achieved in the able-bodied participant using EMG signals. We also used the M1 signals in combination with the EMG templates to compute EMG decoders. The predicted EMG activity from left-out M1 data had R^2 values (computed with respect to the separately recorded EMG templates) ranging from 0.2 to 0.4.

Conclusion: Our findings demonstrate that hand muscle activation can be effectively decoded from the M1 signals of a paralyzed participant attempting to imitate various hand postures. Although our experiments were limited to posture-matching movements, we intend to extend them to object manipulation and force generation. Our results represent a critical step towards using decoded EMGs to drive a musculoskeletal model of the hand for improved performance compared to standard kinematic decoders.

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