Preliminary Evaluation of the MoBL-ARMS Dynamic Upper Limb Model For Estimating Muscle Activation During End Effector Robot-Mediated Rehabilitation

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Introduction: A majority of stroke survivors require physical therapy to restore their upper limb function and strength, leading to high demand for accessible and effective treatments [1]. Robot-mediated rehabilitation is a promising technology to address this need, but existing systems emphasize moving the user (e.g., assistance as needed systems [2]) rather than activating desired muscles or compelling them into healthy movement patterns [3].

Designing robotic rehabilitation strategies that quantifiably improve muscle engagement for stroke survivors and other patients with upper-limb impairments requires modeling their upper-limb neuromuscular activity and how it differs from that of healthy participants. However, when users grasp a robot, their neuromotor behavior changes, and standard sensors that directly measure these changes, such as surface electromyography (sEMG) [4], are limited to superficial muscles. Neuromusculoskeletal simulators like OpenSim [5] provide estimates of all muscle forces, but it is unclear if they can reliably capture this interactive behavior. In this work, we evaluate the extent to which the current most comprehensive OpenSim upper-limb neuromuscular model, MoBL-ARMS [6,7], reflects empirical sEMG-observed muscle activations when interacting with a KUKA-based end-effector robot rehabilitation platform [8] shown in Figure 1.

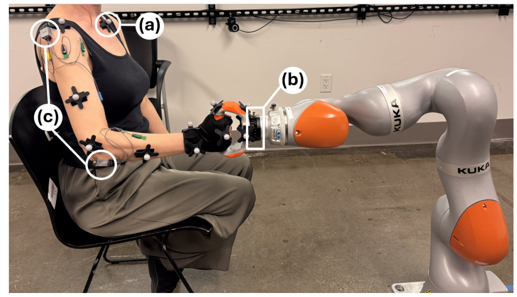

Figure 1: Robot rehabilitation platform used in evaluating MoBL-ARMS prediction quality. Motion capture markers (a) and force/torque sensor (b) provide inputs to the MoBL-ARMS model, and predicted muscle activation values are compared with signals measured from sEMG sensors (c).

Methods: To predict muscle activation using the MoBL-ARMS model, we must first solve for joint kinematics and joint dynamics, then for muscle forces and activations. To solve for joint kinematics, the positions of the 10 motion capture markers on the right arm and torso (shown in Figure 1) were recorded using an OptiTrack motion capture system, then processed in Motive software to fill gaps and label markers based on a customized skeleton. The MoBL-ARMS model was scaled to the user's geometry using these marker positions at a static pose recorded before experimental data collection. Inverse kinematics was then solved using the scaled model on OpenSim 4.5. The results of inverse kinematics, as well as forces and torques recorded by a Bota 6-DoF load cell attached to the robot's handle, were then used to solve inverse dynamics. To estimate muscle activations, we used static optimization with inverse dynamics as the input, and tuned maximum isometric muscle forces as needed to enable convergence. To compare with these OpenSim-simulated activations, two Delsys Quattro sensors were used to record sEMG data from 8 muscles in the participant's right arm (anterior, posterior, and middle deltoids; biceps, triceps, wrist flexors, wrist extensors, and brachioradialis).

To eliminate confounding factors and maintain interpretability for our initial evaluations, we collected preliminary data from a single participant (female, age 46) performing a controlled isometric elbow flexion task. The participant was asked to keep an upright pose, facing the robot, while holding a handle attached to the robot horizontally, keeping their elbow at 90 degrees of flexion and pushing upward, with 0%, 50%, and 100% of their effort in sequence while the robot remained static.

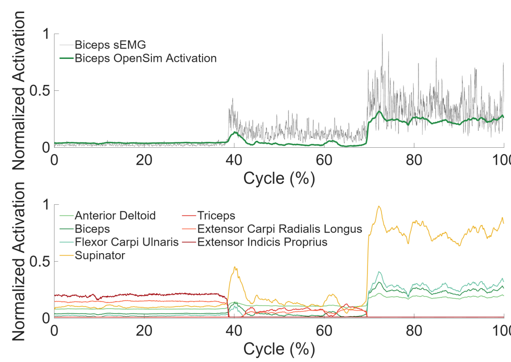

Figure 2: *Top*: OpenSim-solved muscle activation of the long head of the biceps and filtered and rectified sEMG of the same muscle during isometric elbow flexion at 0%, 50%, and 100% effort. *Bottom*: A subset of OpenSim-predicted activations illustrating a mix of realistic predictions (*green*), realistic patterns at unrealistic magnitude (*yellow*), and implausible activation patterns (*red*).

Results & Discussion: The OpenSim muscle activation model converged after the participant-scaled MoBL-ARMS maximum isometric force values were doubled for all 50 muscles. An illustrative subset of model performance results is shown in Figure 2.

Figure 2 (*top*) shows example model-predicted and (normalized) sEMG-measured muscle activations for the biceps, which are qualitatively similar, illustrating reasonable model performance that is physiologically plausible. Predictions for other sEMG-measured muscles were also generally reasonable, except as noted in Figure 2 (*bottom*), which shows a subset of the 50 predicted muscles that illustrate a range of model behavior. Some muscles, like the anterior deltoid, biceps, and flexor carpi ulnaris, behaved as expected. Other muscles, such as the triceps, extensor carpi radialis longus, and extensor indicis propius, showed less physiologically plausible activation patterns, activating and then deactivating across the different exertion stages, perhaps reflecting different local optima found by the static optimization calculation. Supinator activation was also predicted to be abnormally high, perhaps due to the optimization exploiting some non-physiological aspect of model geometry. Collectively, these results illustrate that the MoBL-ARMS model is promising for simulating neuromotor behavior when interacting with a robot, but even under highly controlled conditions, some predictions appear erroneous, and further investigation is needed into the underlying sources of modeling error before expanding model use to more dynamic motions.

Significance: Neuromusculoskeletal models can provide valuable insights into neuromotor behavior despite many underlying assumptions, but they have rarely been validated when interacting with rehabilitation robots. This study presents the first steps toward using such models to gain insight into deep muscle activation during robot interactions, paving the way for our own design of rehabilitation robot control strategies and for similar model evaluations of other parts of the body.

References: [1] Kim et al. (2022), *Brain and NeuroRehabilitation*. [2] Blank et al. (2014), *Current Physical Medicine and Rehabilitation Reports*. [3] Gassert et al. (2018), *JNER*. [4] Jarque-Bou et al. (2018), *Sensors*. [5] Seth et al. (2018), *PLOS Comp. Bio.*. [6] Saul et al. (2015), *Comp. Meth. Biomech. Biomed. Engin.*. [7] McFarland et al. (2019), *J. Biomech. Eng.* [8] Anand et al. (2019), *ICORR*.