Functional Muscle Synergies: Interpretable Characterizations of Abnormal Neuromuscular Behavior from Trial Repetitions

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Introduction: Robot-facilitated rehabilitation has the potential to standardize therapy assistance and improve clinical outcomes by enabling prescription of precise, user-specific tasks and interventions. Understanding whether therapy is effective requires characterizing whether performed motions are healthy and intervening accordingly, but standard synergy-based modeling methods are limited in two ways: first, they may fail to distinguish healthy and unhealthy behaviors for users with less severe impairments [1], and second, their analysis does not admit clear prescriptions for how behavior should be modified to reach a healthier state.

In previous work [1], we identified Hidden Markov Models (HMMs) as a modeling technique capable of addressing the first limitation. Specifically, we showed that the Viterbi path of an HMM trained on time series muscle activations measured via surface electromyography (sEMG) as users performed repeated isometric exertions (e.g., alternating left and right pushes) on the OpenRobotRehab platform [2] (Figure 1) exposed different temporal behavior between healthy and post-stroke participants, even when synergy-based decompositions did not obviously map to these cohorts. However, because we trained these initial HMMs on the full sEMG time series, each HMM transition matrix described system behavior at the level of individual samples (i.e., the next sEMG value), rather than the next behavioral state transition (e.g., from left to right), limiting model interpretability. To enable more interpretable models, and to address the second limitation above, we present a novel use of functional principal component analysis (FPCA) [3] to characterize the temporal behavior underlying our HMM-based modeling results, enabling insights on motor behavior to inform future rehabilitation robot control schemes.

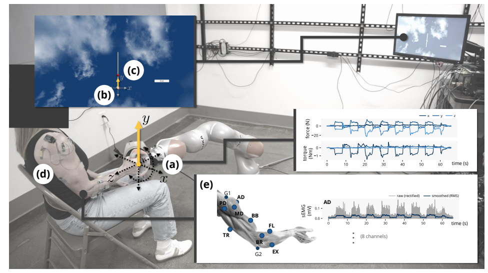

Figure 1: Motor rehabilitation platform enabling measurement of muscle engagement during trajectory tracking tasks. Users exert forces and torques on load cell (a) through the attached handle, which are then mapped to x–y coordinates of on-screen tracker (b) to allow users to follow red target (c) through different trajectories, while surface electromyography (sEMG) electrodes (d) placed on key muscles of the arm (e) record muscle activations. Surface EMG electrode placements: anterior deltoid (AD), middle deltoid (MD), posterior deltoid (PD), biceps brachii (BB), triceps brachii (long head, TR), brachioradialis (BR), wrist flexors (FL), and wrist extensors (EX).

Methods: We apply the following modeling method to 8-channel sEMG time series data collected from 13 healthy and 2 post-stroke participants performing 4 distinct repeated isometric tasks (left/right, up/down, in/out, roll left/right, alternating $7\times$) in 2 pose conditions, a subset of the OpenRobotRehab 1.0 data set [2]. First, we find the multivariate FPCA decomposition of the sEMG time series data for each trial and retain the first 4 resulting principal components, which reliably account for $>95\%$ of the variance, reducing the dimensionality of each trial's sEMG time series from $\approx 8 \times 60,000$ samples to 2×7 vectors in $\mathbb{R}^4$ that represent the trial as a coordinate space of sEMG over repeated motions. We then initialize an HMM with two hidden states (one state per alternating direction) and fit the model to the FPCA decomposition of the sEMG time series. This procedure results in the following model components: (1) functional principal components that model the modes of significant variation across each force direction, which we can then further compress for display using UMAP [4]; (2) an HMM transition matrix (Markov chain) that models the dynamics of switching between force directions; and (3) an HMM emission matrix consisting of Gaussian distributions that parametrize the region of decomposition space corresponding to different force directions.

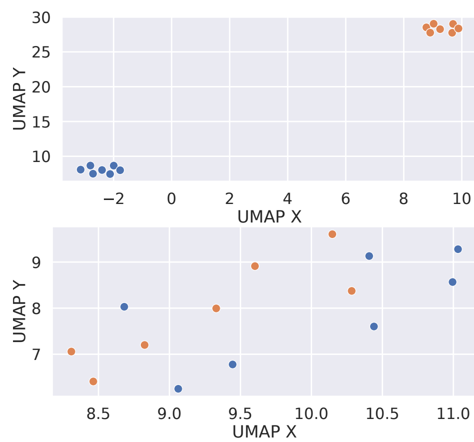

Figure 2: Comparison of exemplar UMAP-projected FPCA decompositions of sEMG data collected from healthy (*top*, participant 2) and post-stroke (*bottom*, participant 22) participants [2] performing 7 alternating left (*orange*)–right (*blue*) (x-axis) motions.

Results & Discussion: Exemplar decompositions for one healthy (*top*) and one post-stroke (*bottom*) participant performing one task are shown in Figure 2. In the sEMG decomposition space, distances correspond to changes in sEMG behavior. For healthy participants, we found that each force direction prescribed during a task generally had a distinct cluster in the sEMG decomposition space. For post-stroke individuals (and, occasionally, for healthy individuals exhibiting atypical behaviors), this distance was significantly reduced, and often clusters weren't separated. This overlap indicates that their sEMG was constrained to a reduced space — an important finding, as their trajectory tracking task performance remained similar to the healthy cohort and did not reflect this underlying neuromotor pathology.

Analysis of the HMM dynamics similarly revealed that while healthy participants' stationary (ergodic) state distribution generally converged to the expected 50/50 split across force directions, post-stroke participants' did not, indicating that they were more likely to get "stuck" in a single sEMG behavior state, despite their performant completion of the force trajectory tasks.

Significance: We demonstrate that our FPCA/HMM modeling method is capable of detecting and measuring temporal and behavioral sEMG patterns that differ between healthy and post-stroke (or otherwise atypical) populations in a data set for which standard synergy methods failed to do so [1]. Since FPCA is invertible, we can measure how pathological an individual's sEMG is, find paths through the decomposition space, and develop robot controllers that are capable of perturbing participants such that their pathological behavior is mitigated. The generative nature of HMMs allow us to simulate sEMG data under different transition dynamics, including whether different interventions result in healthier behavior (i.e., patterns more similar to the healthy cohort) in the sEMG decomposition space.

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References: [1] A. Anand et al. (2026), *Under review (IEEE)*. [2] A. Anand et al. (2025), *ICORR*. [3] H.L. Shang (2014), *AStA*. [4] J. Healy and L. McInnes (2024), *Nature Reviews Methods Primers*.