Toward a Muscle-Synergy-Based Model of Post-Stroke Pathology in Robot-Assisted Rehabilitation

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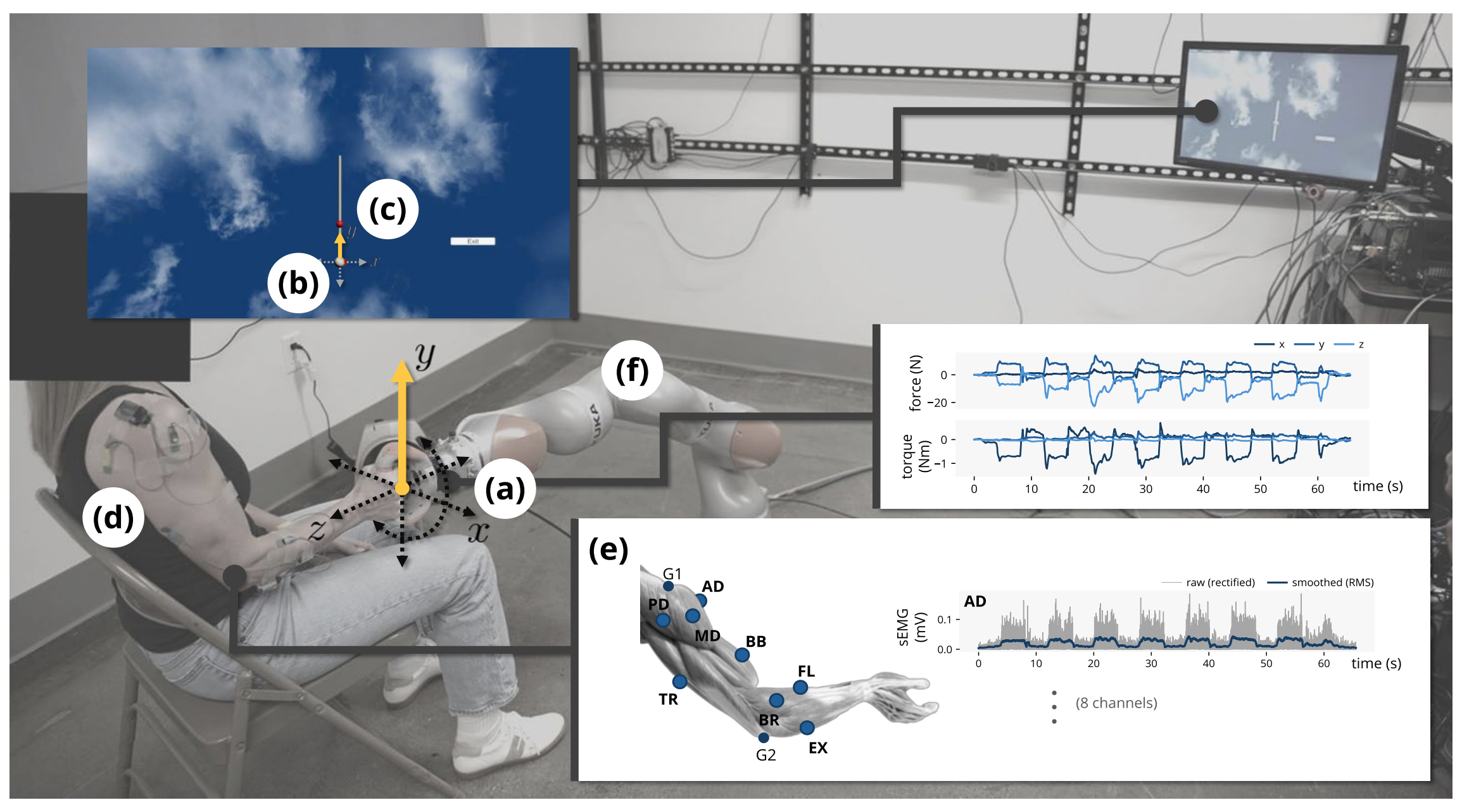
Motivation & Aims

- **Robot-assisted rehabilitation** is a promising tool for upper-limb motor recovery, but its efficacy is limited by **insufficient insight into users' diverse patterns of neuromuscular engagement**, inhibiting our ability to assess and improve motor capabilities.
- To enable such insights, we have developed a **rehabilitation robot platform** to **collect detailed neuromuscular engagement data** (i.e., muscle activations, as measured via surface electromyography, or sEMG) during performance of 6D isometric trajectory tracking exercises [1].
- With the goal of **quantifying the differences between healthy and pathological motor strategies**, we perform **synergy-based analyses of users' motor behavior** during completion of a variety of trajectory tracking tasks on this platform, toward building **robust, generalizable models of neuromuscular engagement** that can ultimately guide robot interventions for effective rehabilitation.



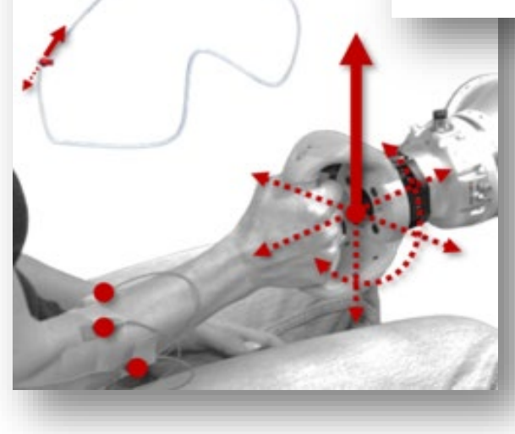
Surface EMG electrode placements: anterior deltoid (AD), middle deltoid (MD), posterior deltoid (PD), and biceps brachii (BB), grounded at the acromion (G1); triceps brachii (long head, TR), brachioradialis (BR), wrist flexors (FL), and wrist extensors (EX), grounded at the olecranon (G2).

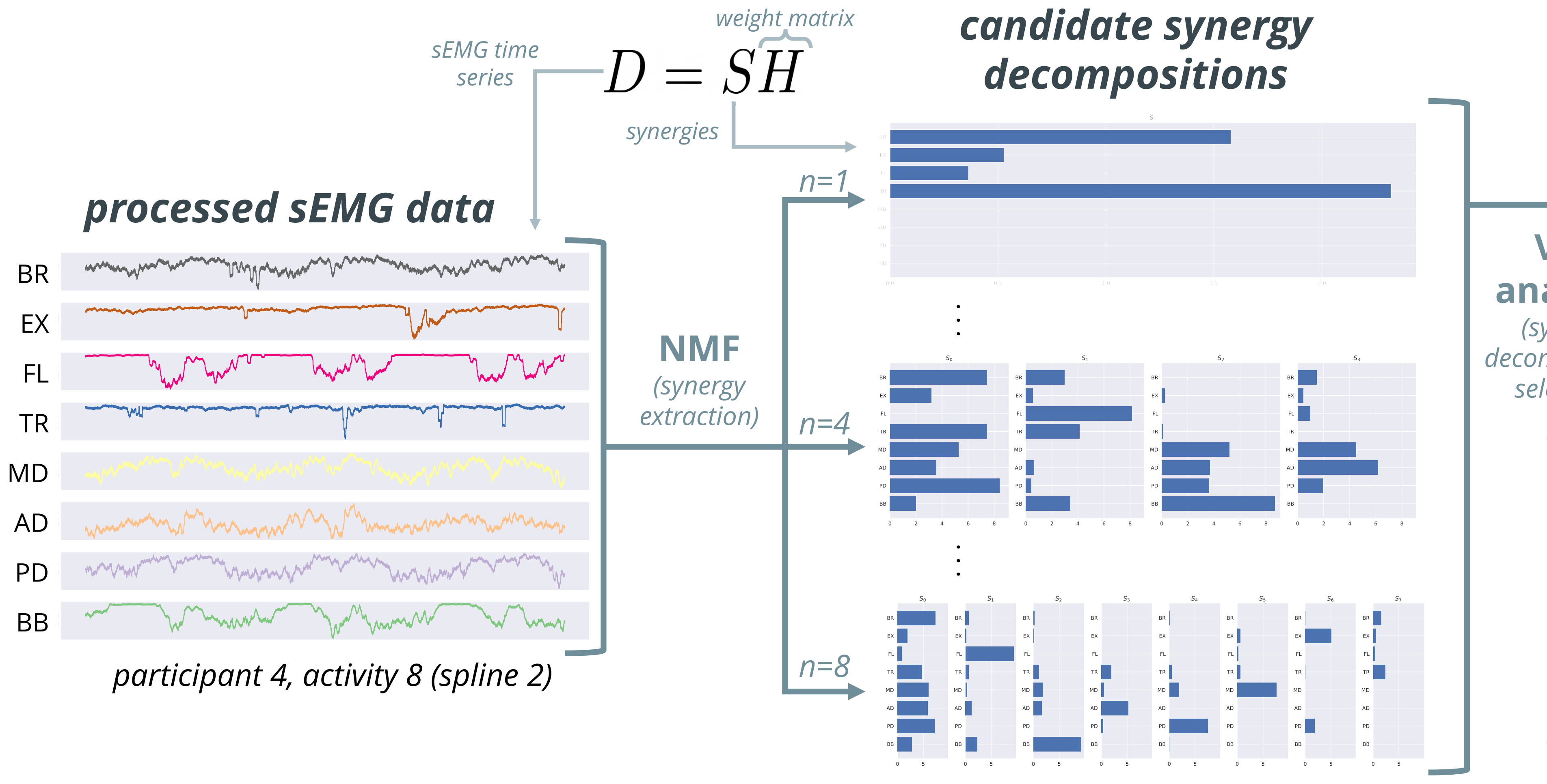
Motor rehabilitation platform [1] from which muscle activation data were collected for engagement analysis. Users exert forces and torques on load cell (a) through the attached handle, which are then mapped to x–y coordinates of on-screen avatar (b) to allow users to follow red target ball (c) through different trajectories, while surface electromyography (sEMG) electrodes (d) placed on key muscles of the arm (e) record muscle activations. The system currently supports isometric rehabilitation tasks at arbitrary poses — robot (f) remains static — but will be expanded in the future to support a variety of robot controllers.

Methods & Results

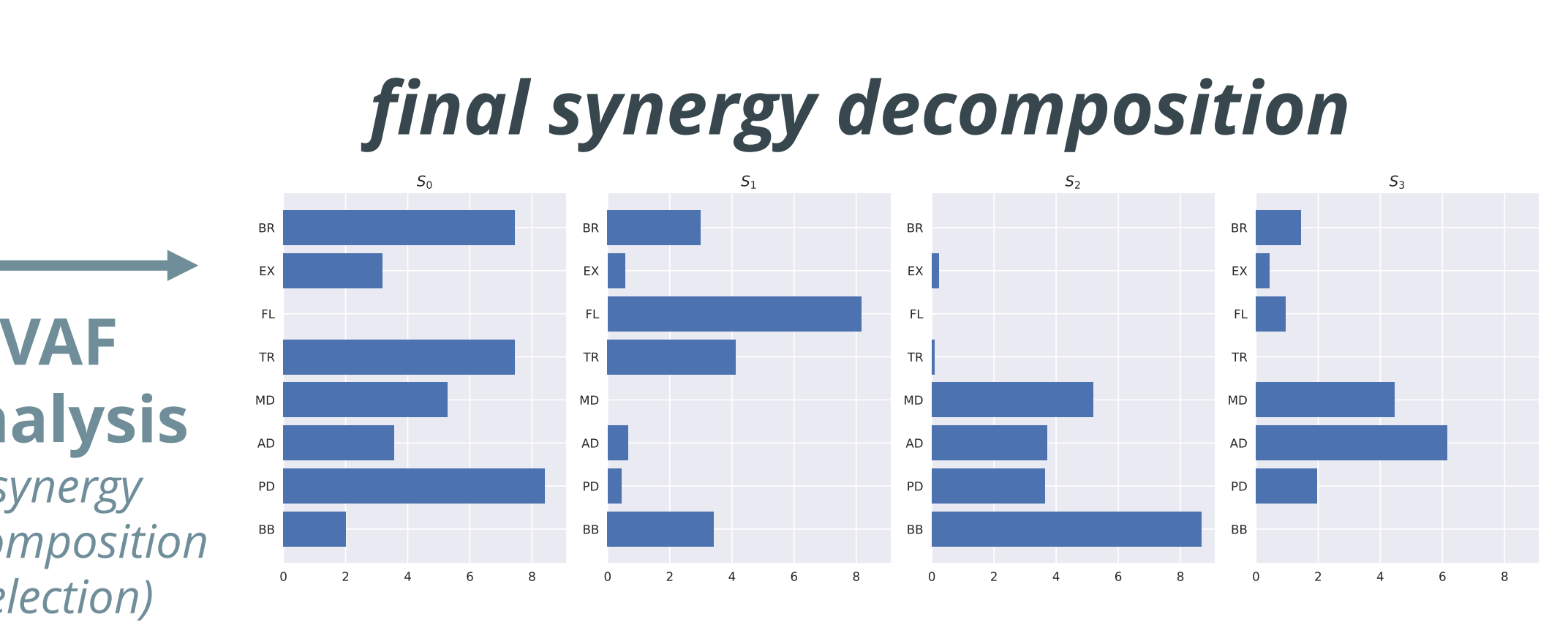
Synergy Extraction

Surface EMG data were analyzed from the **OpenRobotRehab 1.0** data set [1], which comprises time-series muscle activation, end effector force, and game performance data from **13 healthy** and **2 post-stroke participants** as they performed **various isometric trajectory tracking tasks** in multiple poses.





participant 4, activity 8 (spline 2)



For each participant and tracking task, synergies were extracted from sEMG data using **Non-Negative Matrix Factorization** (NMF) [2] with different assumed numbers of synergies (n=1–8).

The final synergy decomposition was selected via the following literature-established [3] procedure:

1. For each participant and activity, **variance accounted for (VAF)** [4] was computed for each candidate decomposition (1–8 synergies).
2. The final decomposition was selected as the lowest dimensionality at which the average VAF across participants was > 0.90, each participant's VAF was > 0.85, and the increase in VAF if the next-highest number of synergies had been selected was < 0.03.

This procedure provided an optimal low-dimensional representation of motor behavior, and **consistently selected decompositions of n=3–5 synergies**, in agreement with patterns reported in established literature [5].

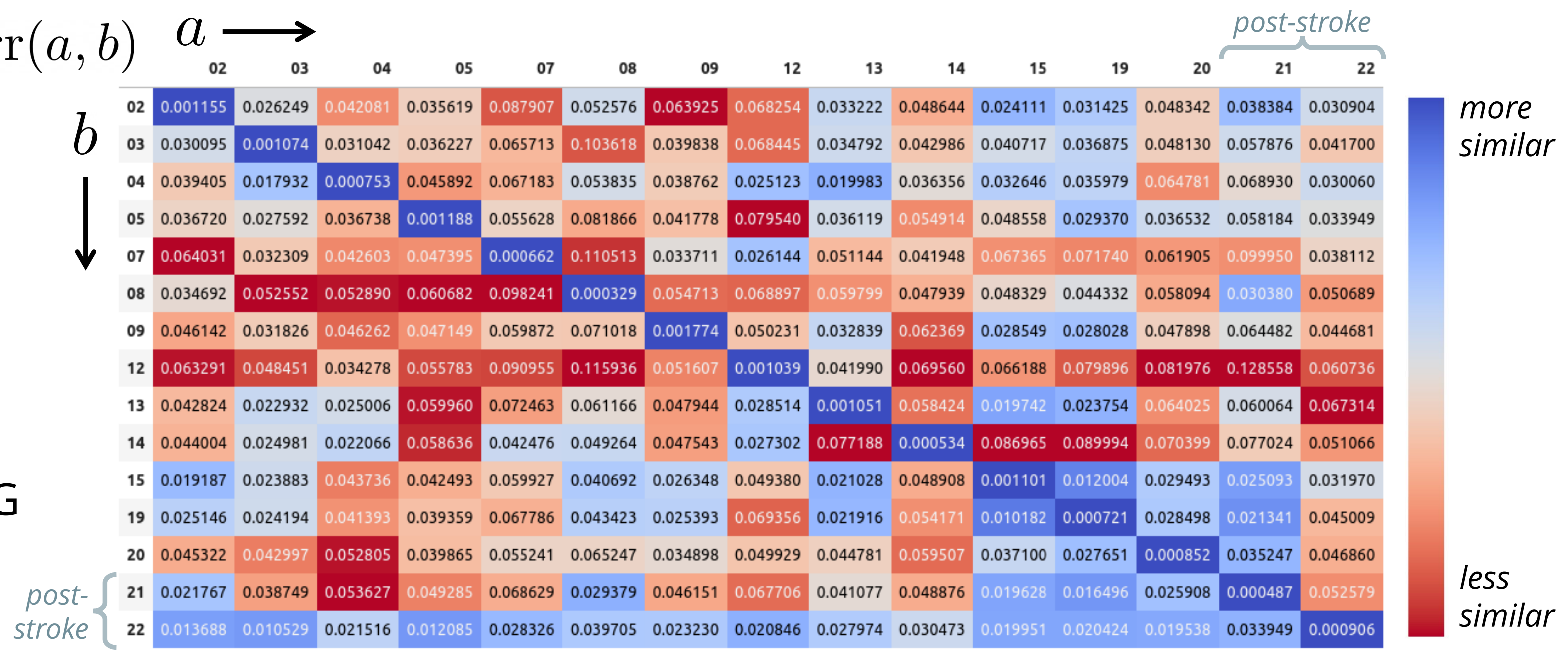
Comparison Across Participants

To **compare motor behaviors across healthy and post-stroke participants**, we defined modified mean squared error (MSE) measure

$$\mathrm{err}(a,b) = \frac{1}{n_{\text{samples}} \cdot n_{\text{muscles}}} \|S_b H_a - D_a\|_F^2$$

which describes the error when participant a's sEMG data is constructed using participant b's synergy matrix for a given activity.

$\mathrm{err}(a,b)$



	02	03	04	05	07	08	09	12	13	14	15	19	20	21	22
02	0.001155	0.026249	0.042081	0.035619	0.087907	0.052576	0.063925	0.068254	0.033222	0.048644	0.024111	0.031425	0.048342	0.038384	0.030904
03	0.030095	0.001074	0.031042	0.036227	0.065713	0.103618	0.039838	0.068445	0.034792	0.042986	0.040717	0.036875	0.048130	0.057876	0.041700
04	0.039405	0.017932	0.000753	0.045892	0.067183	0.053835	0.038762	0.025123	0.019983	0.036356	0.032646	0.035979	0.064781	0.068930	0.030060
05	0.036720	0.027592	0.036738	0.001188	0.055628	0.081866	0.041778	0.079540	0.036119	0.054914	0.048558	0.029370	0.036532	0.058184	0.033949
07	0.064031	0.032309	0.042603	0.047395	0.000662	0.110513	0.033711	0.026144	0.051144	0.041948	0.067365	0.071740	0.061905	0.099950	0.038112
08	0.034692	0.052552	0.052890	0.060682	0.098241	0.000329	0.054713	0.068897	0.059799	0.047939	0.048329	0.044332	0.058094	0.030380	0.050689
09	0.046142	0.031826	0.046262	0.047149	0.059872	0.071018	0.001774	0.050231	0.032839	0.062369	0.028549	0.028028	0.047898	0.064482	0.044681
12	0.063291	0.048451	0.034278	0.055783	0.090955	0.115936	0.051607	0.001039	0.041990	0.069560	0.066188	0.079896	0.081976	0.128558	0.060736
13	0.042824	0.022932	0.025006	0.059960	0.072463	0.061166	0.047944	0.028514	0.001051	0.058424	0.019742	0.023754	0.064025	0.060064	0.067314
14	0.044004	0.024981	0.022066	0.058636	0.042476	0.049264	0.047543	0.027302	0.077188	0.000534	0.086965	0.089994	0.070399	0.077024	0.051066
15	0.019187	0.023883	0.043736	0.042493	0.059927	0.040692	0.026348	0.049380	0.021028	0.048908	0.001101	0.012004	0.029493	0.025093	0.031970
19	0.025146	0.024194	0.041393	0.039359	0.067786	0.043423	0.025393	0.069356	0.021916	0.054171	0.010182	0.000721	0.028498	0.021341	0.045009
20	0.045322	0.042997	0.052805	0.039865	0.055241	0.065247	0.034898	0.049929	0.044781	0.059507	0.037100	0.027651	0.000852	0.035247	0.046860
21	0.021767	0.038749	0.053627	0.049285	0.068629	0.029379	0.046151	0.067706	0.041077	0.048876	0.019628	0.016496	0.025908	0.000487	0.052579
22	0.013688	0.010529	0.021516	0.012085	0.028326	0.039705	0.023230	0.020846	0.027974	0.030473	0.019951	0.020424	0.019538	0.033949	0.000906

exemplar reconstruction error, activity 8 (spline 2)

No consistent differences in reconstruction error were observed across healthy and impaired participants, and no participant groups exhibiting similar motor strategies were obvious.

We also analyzed the cosine similarity between different participants' synergies and similarly observed **no reliable differences between impaired and unimpaired participants**.

Limitations & Future Work

Our preliminary analyses indicate that Individuals, whether **impaired** or **unimpaired**, may **not** be easily **categorized into distinct groups based on their synergy decomposition alone**. To determine whether patterns can be observed with more granular analysis, we are planning the following study extensions:

- **fine-grained partitioning of movements within a task** prior to synergy decomposition;
- investigation of **NMF consistency across hyperparameters**, and of additional decomposition methods;
- implementation of **improved processing pipelines** for streamlined model iteration;
- development of **improved metrics for synergy comparison**;
- collection of **additional, non-isometric data sets**; and
- incorporation of **neuromechanical modeling techniques** [6] to directly relate synergistic activations to hand forces, rather than the specified (possibly poorly completed) trajectory tracking task.

We ultimately aim to leverage these models of motor behavior to **inform the design of robotic controllers that impel users away from pathological motor behaviors** and promote the adoption of healthy motor strategies.

Ongoing Extensions & Context

This work was undertaken as part of the Utah HRELab's **OpenRobotRehab** project. Check out other related projects here at RehabWeek!

- ***An Extensible Platform for Measurement and Modification of Muscle Engagement During Upper-Limb Robot-Facilitated Rehabilitation*** (ICORR paper 277)
- ***Enhancing 6-DoF Rehabilitation Task Guidance with Augmented Reality*** (late-breaking abstract)

Acknowledgments / Sponsors / References

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