An Extensible Platform for Measurement and Modification of Muscle Engagement During Upper-Limb Robot-Facilitated Rehabilitation

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***Abstract*—Populations with upper-limb neuromotor disabilities could greatly benefit from robot-mediated therapy, but the heterogeneity of these disorders, combined with unresolved questions around neuroplasticity mechanisms, hinders the standardized prescription of effective rehabilitation tasks and corresponding robot behaviors. Building on consensus that active neuromuscular engagement is vital for therapy, we introduce a novel, extensible rehabilitation robot platform to directly measure (and, ultimately, modify) user engagement at the muscle level. The system integrates surface electromyography to monitor muscle activation patterns during isometric tracking tasks in all 6 dimensions of hand exertion — beyond the planar constraints of most systems. Usability testing with 13 healthy and 2 post-stroke participants demonstrates the system's utility in analyzing motor behavior across varying poses, trajectories, and impairment levels. Preliminary results indicate that pose and task selection significantly impact activation patterns, highlighting the rehabilitative potential of systems that support motion along all axes and at multiple user poses and guiding our own planned augmentations of the platform (personalized controllers, additional sensing, etc.). To facilitate broader research into muscle activation–force relationships and address the scarcity of open-source upper-limb motor behavior data, we have released all collected data and analysis code as part of the OpenRobotRehab project on SimTK (`simtk.org/projects/openrobotrehab`) alongside this publication.**

***Index Terms*—rehabilitation robotics, human–robot interaction, biomechanics, surface electromyography (sEMG), user-centered design**

I. Introduction

Many patient populations, including individuals recovering from stroke or spinal cord injury, and those with cerebral palsy, multiple sclerosis, and other congenital or acquired neuromotor disorders, could benefit significantly from high-intensity motor therapy. In the context of a global shortage of therapists and caregivers [1], robot-mediated therapy is a promising method to rehabilitate such impairments [2]–[6]. However, the heterogeneity of individuals' motor behaviors and their evolution over time poses a significant challenge, and there remains no consensus on how rehabilitation robots should behave to optimize therapeutic outcomes — for example, when to provide assistance or resistance, and when to augment motion errors or correct them.

One rare point of consensus is that patients should be *actively engaged* in therapy, rather than passively moved by a device or therapist, which is key to inducing the neural plasticity that facilitates motor recovery [7]. While a number of rehabilitation robot control paradigms (detailed in section II below) have evolved to incentivize this engagement, they do not generally adapt to the muscle-level engagement actually observed in an individual user, and whether that engagement is healthy or pathological, nor do they leverage the full 6 dimensions (3 positional and 3 rotational) of possible effort at the hand. To address this gap, we propose a novel robotic rehabilitation system to directly measure and assess muscle-level engagement, and, ultimately, modify that engagement by prescribing personalized trajectories and robot behaviors across both positional and rotational axes. This paper presents the first steps toward the creation of this system. Specifically, our contributions include:

- development of a novel, extensible, proof-of-concept rehabilitation platform enabling muscle activation measurement (via surface electromyography, or sEMG), during isometric, force- and torque-based trajectory tracking tasks, robustly designed for future expansion (to include varied robot controllers and additional sensing modalities);
- a pilot, open-source data set, including all collected sensing and performance data, from 15 individuals (13 healthy and 2 post-stroke), at multiple poses, performing a variety of trajectory tracking tasks on this novel platform, enabling detailed examination of the relationship between applied 6D hand forces and torques and patterns of muscle engagement; and
- preliminary analyses of this force/torque–engagement relationship in this pilot cohort, as well as this cohort's subjective impressions of the system and protocol, motivating our planned augmentations of the system and highlighting the need for expanded research into the impacts of rehabilitation task selection on motor activation patterns.

The open-source data set noted above, as well as additional platform details and analysis code, has been made available as part of the OpenRobotRehab project on SimTK (`simtk.org/projects/openrobotrehab`).

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The study protocol employed in this work was approved by the University of Utah Institutional Review Board under Protocols IRB_00154923 and IRB_00098851 and written informed consent was obtained from each study participant.

II. Related Work & Context

Several control paradigms have evolved to motivate engagement during robot-mediated rehabilitation, including "assistance as needed" (AAN) [8], "intent-triggered" [8], and "dynamic difficulty adjustment" (DDA) [9] frameworks; however, these systems are all vulnerable to user laziness through their reliance on error signals and/or insufficiently comprehensive in their ability to adjust to individuals' diverse motor strategies and pathologies. Consequently, to date, no clinical trials of rehabilitation robots employing these paradigms have shown improvements in functional outcomes [10]–[13], for ambiguous reasons, illustrating the critical need for comprehensive, personalized models of individuals' neuromusculoskeletal engagement and how it changes under different robot control paradigms. Without such insights, we cannot systematically provide effective, engaging rehabilitation, nor can we quantify the efficacy of the control paradigms we already have.

Alongside these control schemes, muscle synergy analysis [14] has emerged as a promising approach to close this modeling gap by quantifying neuromotor behavior (and post-stroke impairment) and offering a window into how motor control is reorganized following neurological injury [15], [16]. Unlike traditional clinical assessments that primarily rely on kinematic performance or subjective scoring, synergy-based metrics capture the underlying coordination patterns of muscle activations, providing a more mechanistic understanding of motor deficits [17], [18]. However, while synergy-based assessments offer detailed neurophysiological insights, their direct integration into clinical rehabilitation — and particularly, into rehabilitation robotics — remains limited, and further validation and standardization is required to achieve widespread adoption of synergy-based paradigms in stroke rehabilitation protocols [17], [19].

To address this gap, we propose a novel sEMG-based rehabilitation paradigm that leverages these synergy analysis breakthroughs, including recent advancements demonstrating sEMG's potential in identifying muscle synergies to quantify post-stroke impairment [18]–[22]. Rather than employing the standard AAN-style assistance discussed above to enable users to complete specific tasks, we aim to prescribe tasks and robot behaviors to directly enhance user engagement and reduce pathological synergies at the neuromuscular level. Furthermore, because natural motion is not restricted to a single axis, we propose a system that can measure and rehabilitate motion along all 6 (positional and rotational) axes of hand action, a feature not prevalent in the planar rehabilitation systems that dominate the field of physical rehabilitation [23], [24] or in the anthropomorphic robots used for social rehabilitation [25].

The remainder of this paper presents the first steps toward such a system — one that enables this proposed engagement-centric control paradigm in all 6 dimensions — including hardware and software development of a (to begin, isometric) rehabilitation platform (section III); collection of pilot activation data from both healthy and impaired individuals completing a variety of multidimensional trajectory tracking tasks (section IV); preliminary analyses of those individuals' motor strategies and experiences using the platform (section V); and the resulting implications for future rehabilitation system design (section VI). While a full analysis of synergistic motor behavior is beyond the scope of this initial paper, we ultimately aim to perform such analyses on our collected data to inform future work on directly altering pathological synergies via robot intervention.

III. Rehabilitation Platform Design

In this section, we detail both hardware and software aspects of our proof-of-concept rehabilitation platform, as outlined in Figures 1 and 2, respectively. This section delineates both current capabilities and planned expansions (informed by the motor rehabilitation literature and our pilot data analysis in section V, as noted). Detailed system information, including firmware and software versions and configurations, can be found in the data release accompanying this paper.

A. Hardware

Our rehabilitation platform hardware consists of the following elements and associated capabilities:

1) Rehabilitation Robot: The core of our rehabilitation platform is an LBR iiwa 14 R820 7-degree-of-freedom cobot (KUKA AG, Augsburg, Germany), shown in Figure 1(f). The handle and force torque sensor (described below) through which the user interacts with the rehabilitation system are mounted to the cobot's end effector. This setup allows the robot to locate the interface at any point in space to accommodate different user poses and limb geometries. The robot currently serves as a static "jig" for isometric rehabilitation tasks, but will be augmented in future iterations of the system to move, and be moved, by the human user according to various robot control strategies (e.g., error correction or augmentation, resistance or assistance).

2) Force Torque Sensor & Handle: A SensONE 6-axis force torque sensor (Bota Systems AG, Zürich, Switzerland), shown in Figure 1(a), is used to measure the forces and torques applied to the end effector of the robot through a custom-built, ergonomic handle. In the future, additional handles will be designed to support varying user capabilities (e.g., under-wrist bracing for those unable to lift their arm, wrist attachments for those unable to grasp).

3) Surface EMG: Muscle activation data are collected from 8 key muscles of the arm — shown in Figure 1(e) — using two Trigno Quattro 4-channel sensor motes, controlled through a Trigno Base Station (Delsys, Inc., Natick, MA, USA), at 1000 Hz. Data are currently visualized and logged for motor pattern analysis via the software system described below; future iterations of the platform will use this data within the system control loop to adapt parameters of the game and robot behavior based on the user's muscle activations. We also aim to expand the platform to support additional sEMG channels and placements to enable even more comprehensive examination of muscle activation strategies in the arm and hand.

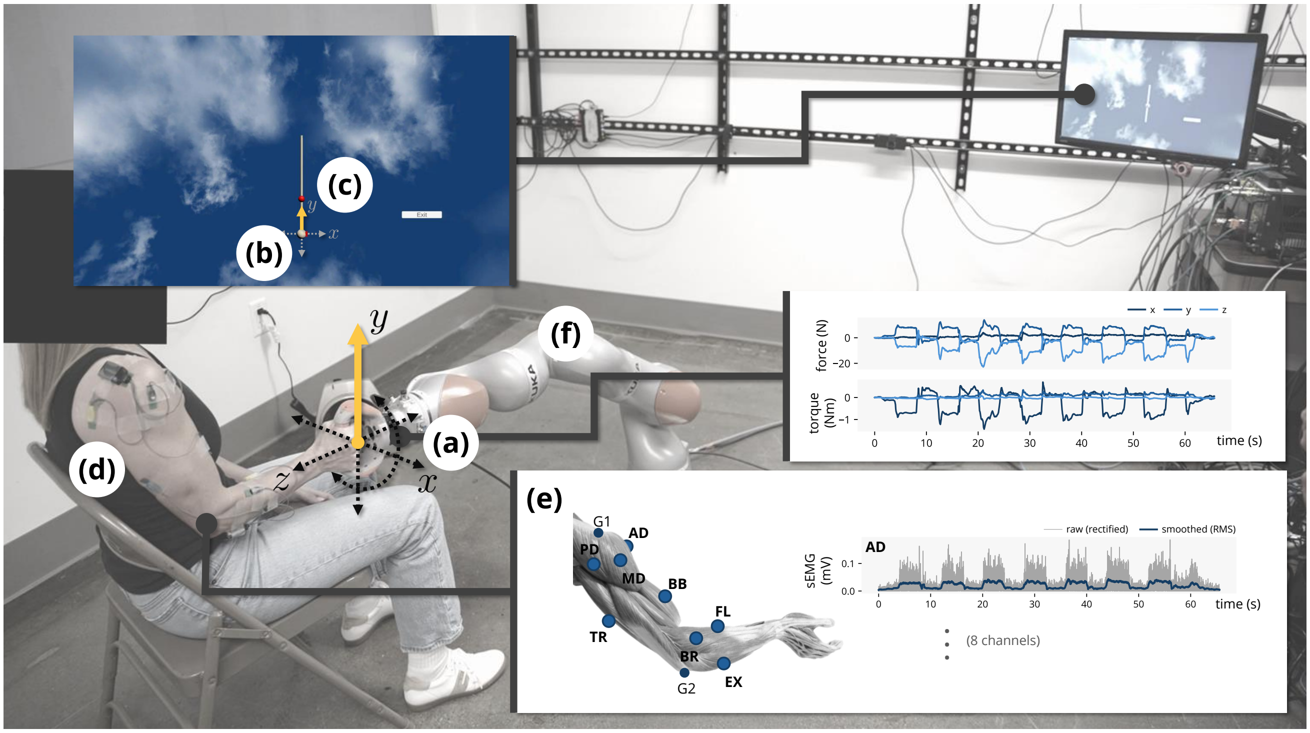

Fig. 1. Motor rehabilitation platform enabling measurement of muscle engagement during trajectory tracking tasks. Users exert forces and torques on load cell (a) through the attached handle, which are then mapped to x–y coordinates of on-screen avatar (b) to allow users to follow red target ball (c) 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. 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).

B. Software

The hardware elements above, when networked together, enable the user to play a force-based trajectory tracking rehabilitation game while muscle activations are recorded for analysis. Details of this software and the platform's associated network architecture, as well as our plans for future expansion, are described below.

1) Rehabilitation Game: The platform's rehabilitation game, consisting of varied trajectory tracking tasks, is developed in Unity (Unity Software Inc., San Francisco, CA, USA). To play, users exert forces and torques on the above-described handle. These values are then linearly mapped to the (x, y) position of a small ball avatar (Figure 1(b)). Users are instructed to follow the position of a red target ball (Figure 1(c)) as it traverses a displayed trajectory. The specific mapping between 6-axis force/torque values and on-screen avatar positions, as well as the number of repetitions before the game ends, varies by trajectory and is documented in Table I, enabling examination of motor behavior under a wide variety of isometric exertions. Current trajectories and mappings are designed to span the space of forces and torques required during activities of daily living (ADLs), while the goal remains displayable on a 2D screen; future iterations of the system will use a virtual and/or augmented reality headset to display 3D trajectories, enabling even more complexity in game tasks (and, thus, motor behaviors).

2) Network Architecture: The rehabilitation game and hardware sensors are integrated across two desktop computers through a ROS2 network (Open Source Robotics Foundation, Inc., San Jose, CA, USA), as detailed in Figure 2. To enable integration with this network, sEMG data are routed through the Trigno Control Utility (TCU) (Delsys, Inc., Natick, MA, USA) to Motive 3.1 software and then through the associated NatNet SDK (NaturalPoint, Inc. DBA OptiTrack, Corvallis, OR, USA). To facilitate this data transfer, a Delsys Trigger Module is subordinated to an OptiTrack OptiHub controller, allowing recording start/stop signals to be passed down the system from the Motive software to the Trigno Quattro modules. All sensor data and game state information, as well as freeform typed investigator notes, are aggregated into a single time-synced recording ("rosbag") and stored locally, such that all sensor data streams can be accessed for analysis and full trial playback as desired.

Note that sensor data from, and control interfaces to, the rehabilitation robot have not yet been implemented; the current platform allows the end effector of the robot to be positioned at arbitrary locations using its associated pendant controller, but no robot data is collected or used in the current software system. In the future, we will leverage the robot's native ROS2 interfaces to both control robot behavior and log its associated kinematic and dynamic data.

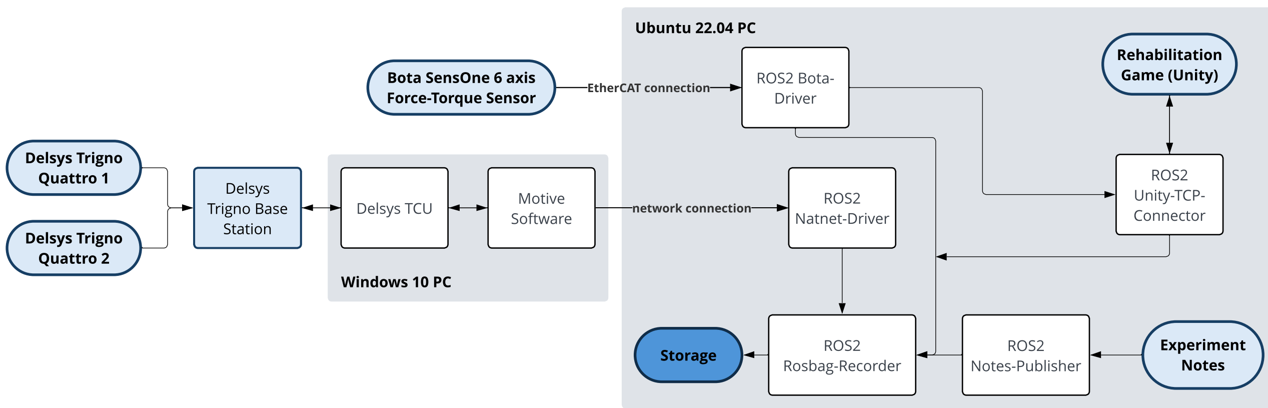

Fig. 2. Software architecture of motor rehabilitation platform. Delsys Trigno sEMG sensor motes, Bota SensOne force torque sensor, Unity rehabilitation game, and typed investigator input are networked via Delsys Trigno Control Utility (TCU), OptiTrack Motive software, and ROS2 network to enable time-synced streaming and storage of muscle activation, force/torque, and game state data, as well as typed investigator notes.

TABLE I
TRAJECTORY TRACKING TASKS & MAPPINGS

Goal Trajectory	Input	Output (Game)	Repetitions
x-axis	x-axis force	x coordinate	7
y-axis	y-axis force	y coordinate	7
z-axis	z-axis force	y coordinate	7
torque	z-axis torque	x coordinate	5
circle (CW[1])	(x, y)-axis force	(x, y) coordinate	3
circle (CCW[2])	(x, y)-axis force	(x, y) coordinate	3
spline 1 (CCW[2])	(x, y)-axis force	(x, y) coordinate	3
spline 2 (CW[1])	(x, y)-axis force	(x, y) coordinate	3

Screenshots of each trajectory are included with data release.
[1]clockwise [2]counter-clockwise

IV. Pilot Data Set Collection

To illustrate the capabilities of the above rehabilitation platform, assess users' subjective impressions of the system, and provide initial data with which to study variations in human motor strategies, data were collected from a pilot cohort of healthy and post-stroke participants as they performed various isometric trajectory tracking tasks in multiple poses.

Preliminary findings on observed muscle activation patterns and how they vary across individuals and rehabilitation tasks, as well as subjective participant feedback, follow in section V. In addition, to help alleviate the dearth of open-source data sets of this type, the complete data set, including raw and processed force torque and sEMG values, game performance data, and complete subject demographic information, has been released with this paper for further exploration by our own and other research groups.

A. Participant Demographics

Data were collected from 13 healthy individuals and 2 stroke survivors, for a total of 15 participants.[1] The 13 healthy individuals included 7 male individuals and 6 female, 9 right-handed individuals and 4 left-handed, of ages 29.5 ± 14.0 (mean $\pm$ standard deviation, min 20, max 70). Of the two stroke survivor participants, both in the chronic phase of pediatric stroke, the first was female, age 24, right-side hemiparetic, and reports being right-handed prior to her stroke. The second was male, age 34, left-side hemiparetic, and does not report handedness prior to neurological injury. Both stroke survivors exhibited mild spasticity (2 and 1, respectively, at the hand on the Modified Ashworth Scale [26]) and mild decreases in muscle strength (4/4 and 4+/4+, respectively, for flexion and extension of the wrist on the Manual Muscle Testing scale [27]).[2]

B. Study Procedures

The following section, alongside Figure 3, details the procedures used in pilot data set collection from the above participants.

1) Consent & Subjective Data Collection: After providing written informed consent on arrival, each participant completed an intake survey to obtain their baseline affect using the Self-Assessment Manikin (SAM) [28]. The SAM was also completed at the experiment midpoint and after all core experiments were completed, alongside Likert-scale [29] and free-response assessments of comfort, fatigue, motivation, and platform usefulness. Notes on participant feedback when conversing during experiments were also recorded by investigators for inclusion in subjective analysis.

2) Participant Sensorization: After completing the intake survey, participants were instrumented with 8 sEMG electrodes on key muscles of the arm, as described in section III and shown in Figure 1(d)–(e). For all healthy participants, the right arm was sensorized and subsequently used to play the rehabilitation games, allowing us to compare cohorts of dominant-hand users and lightly "impaired" non-dominant

[1]Two additional healthy participants also completed the study (male, left-handed, age 33 and male, right-handed, age 23), but their data was erroneously not recorded due to network issues, so their demographics are not included in the aggregate statistics above, nor is their partial sensor and performance data included in subsequent analyses or data release. As they performed the same experimental tasks, however, their feedback is included in the subjective platform impressions discussed in section V-F.

[2]For additional demographic data, broken down by subject, see the full open-source data release.

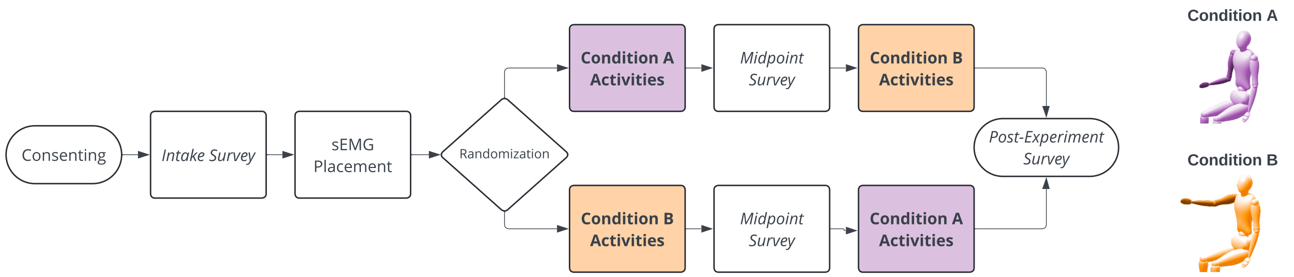

Fig. 3. Experimental flow during collection of pilot data set. Participants were consented and surveyed, then completed trajectory tracking tasks at two ADL-inspired poses (Conditions A and B) in randomized order before providing final survey feedback.

users. For post-stroke participants, the paretic arm was sensorized and tested, as it is the primary target for rehabilitation.[3]

Participants' skin was first cleaned and lightly abraded with alcohol wipes to remove dead skin, then electrodes adhered using Trigno adhesives (Delsys, Inc., Natick, MA, USA) and reinforced using transparent "transpore" surgical tape. Electrodes were precisely positioned using the protocol described in our supplemental data release, then manually adjusted by the investigator by real-time inspection of the signal traces to pick up data from the desired muscles with minimal noise.

3) Core Experimental Activities: Once instrumented with sEMG sensors, participants were seated comfortably upright, feet planted (as able), in a stationary, armless chair at the rehabilitation platform described in section III. The robot end effector was then moved to allow the participant to grasp the handle at one of two poses, illustrated in Figure 3: Condition A (right upper arm comfortably adducted (vertical), right elbow flexed $\sim 90°$ with forearm parallel to the floor) or Condition B (shoulder flexed forward slightly above horizontal and slightly externally rotated, elbow almost fully extended). These two poses were selected to span a workspace useful during activities of daily living, and their order was randomized per-participant, as shown in Figure 3, to avoid the confounding effects of fatigue when analyzing muscle activations across conditions.

Once posed, participants completed the 8 trajectory tracking tasks detailed in Table I. For each task, participants were first allowed to practice following the displayed trajectory as many times as desired, then verbally confirm that they were ready to begin the real trial, at which point data was collected for the listed number of trajectory repetitions. Participants were required to rest for at least 2 min between the first 3, the subsequent 3, and the final 2 tasks to avoid excessive fatigue, and were encouraged to request additional breaks as needed.

After completing all tasks in their first assigned condition, participants completed the midpoint survey, investigators re-posed the robot to the second condition, and all tasks were repeated at this new pose using the same protocol. Participants then completed the post-experiment survey, were de-sensorized, and exited the study.

C. Data Post-Processing & Release

At study completion, data were cleaned and post-processed for release and further analysis. Trial data was first clipped to include the precise data between start and end timestamps of each rehabilitation task. Next, each channel of sEMG data (pre-rectified by the software pipeline) was smoothed with a 400-sample RMS filter. To remove artifacts caused by (reasonably rare) bumped wires and non-isometric motions, the mean value of each channel, for each subject across all activities and conditions, was calculated, and any data points more than 4 standard deviations greater than this mean were saturated at this value. Each sEMG signal was then normalized to the maximum value of this outlier-reduced signal (in practice, this saturating value), again calculated per-subject across all activities and conditions.[4]

These processed data (alongside raw rectified sEMG signals) have been released for open-source analysis with this paper and are used in our preliminary analyses below.

V. Preliminary Analyses of Task-Dependent Muscle Engagement

Ultimately, we aim to augment the rehabilitation platform described in section III to prescribe poses, trajectories, and robot behaviors to induce desired patterns of muscle engagement in individual device users. In this section, we leverage the data set above to gain preliminary insights on how altering poses and trajectories generates changes in motor behavior, and how these changes vary across impairment levels. We also briefly discuss participants' subjective impressions of our system and suggested enhancements. These analyses not only inform our plans for future system development, but suggest promising directions for further study of upper-limb motor behavior by the wider rehabilitation community.

The analyses below constitute only a small fraction of those enabled by the collected data set. We outline our own plans for its future exploration in section V-E, and encourage other

[3]Note that the second stroke survivor was the only participant for which we measured data from the left arm. This participant completed the same (non-mirrored) rehabilitation tasks, which means that some trajectory tracking tasks are not precisely equivalent in terms of required motor strategy. For our preliminary analyses in section V, we primarily treated this discrepancy as a source of noise, except where noted as impacting overall findings.

[4]Note that we normalized to this maximum value because in the context of multi-joint motions, the more standard maximum voluntary contraction (MVC) value becomes poorly defined, as well as potentially hazardous to test in certain impaired populations.

teams to perform their own to support their own rehabilitation system development.

A. Muscle Activation Metric: Area Under the Curve

For our initial analyses comparing muscle activations across poses, trajectory tracking tasks, and impairment levels, we used the area under the curve (AUC) of each processed sEMG signal trace, normalized by trace length, as an aggregate measure of a given muscle's level of activation over the length of the trial. In the future, we aim to employ richer analysis methods to describe the time-dependent and synergistic aspects of the observed data, as discussed in section V-E below.

B. Pose-Dependent Engagement

To explore the relationship between kinematic pose and muscle activation pattern, we examined the AUC-quantified level of activation for each muscle, aggregated across all participants, for each experimental condition (i.e., pose), for each of the trajectory tracking tasks. In general, we found that for the same trajectory, Condition B (arm lifted) elicited an increase in activation of the shoulder muscles (PD, AD, and MD), but had inconsistent impact on arm and wrist muscles, as is expected from the active arm gravity compensation required by that pose. Figure 4 shows illustrative data from the y-axis task, in which this relationship is demonstrated. This trajectory-independent finding suggests that in future rehabilitation systems, the body pose during each activity can be employed as a variable to directly modulate muscle activations toward rehabilitatively desirable patterns.

C. Trajectory-Dependent Engagement

We explored the relationship between task trajectory and muscle activation in an analogous manner, again aggregating AUC-quantified activations for each muscle across all participants and observing relative levels of activation during each activity. Given the wide variety of muscle exertions required to generate each trajectory's varied, time-dependent forces and torques, a plethora of different patterns can be observed; for this first exploratory study, we present a single exemplar result, shown in Figure 5, that illustrates the manner in which different types of trajectories reliably induce changes in specific muscle activations. Even this simple result, which only scratches the surface of the rich patterning observed, supports the idea that prescribed motions can be strategically designed to target specific muscle groups, further enabling the development of more individualized robotic rehabilitation therapies.

D. Engagement Across Impairment Levels

Both healthy and (mildly impaired) post-stroke participants were sufficiently able to complete all trajectory tracking tasks[5] to generate associated muscle activations, confirming the feasibility of system usage by those with motor impairment. Using

[5]Qualitatively, our post-stroke and healthy participants performed comparably well; a full quantitative analysis of tracking performance (described in section V-E as future work) is beyond the scope of this paper.

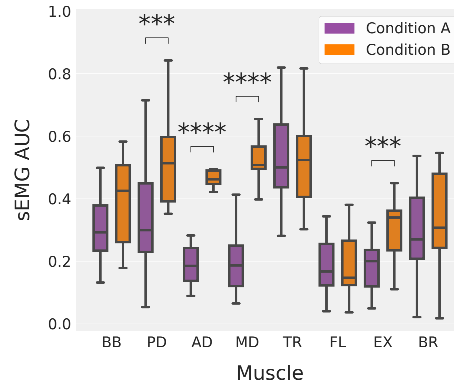

Fig. 4. Cumulative activations of each of the 8 arm muscles (calculated as area under the sEMG curve (AUC), as detailed in section V-A), aggregated across all participants, during the y-axis trajectory tracking task across both tested pose conditions (shown in Figure 3). Adjusting from Condition A (arm low) to Condition B (arm high) caused a largely consistent increase in activation of the muscles required to lift the arm (PD, AD, and MD), across this and all other trajectories, suggesting that pose can be used to selectively modulate muscle activations for rehabilitative purposes. In the activity shown, PD, AD, and MD all showed statistically significant differences across conditions (as calculated via Wilcoxon signed-rank statistical test, reported as $*p < 0.05$, $**p < 0.01$, $***p < 0.001$, $****p < 0.0001$). An addition statistical difference was observed in EX, but was not observed consistently across other unreported trajectories. Statistical annotations displayed via [30].

the same AUC-quantified activation from previous analyses, post-stroke and healthy participants (including left-handed participants using their right hand) exhibited similar motor strategies, as illustrated during the y-axis activity[6] in Figure 6. The one exception is that one stroke survivor exhibited almost no activation of the brachioradialis (BR), which may be the result of nonuse by the participant or of sensor malfunction.[7] Despite this similarity, however, investigators qualitatively observed characteristic compensatory motions in both post-stroke participants (as well as in our age-70 left-handed participant), including various rotations of the torso and lifting and flexing of the shoulder and elbow. This discrepancy suggests the need for more sophisticated sensing (including motion capture and/or inertial measurement sensing to capture joint angles and torso pose) and analyses (discussed below in section V-E) to describe these pathologies, at least in the mildly impaired individuals tested, as well as additional data collection from post-stroke individuals to enable non-anecdotal findings.

E. Future Isometric Analyses

The data collected during this study, though limited to isometric exertions, constitute a novel archive with which to study patterns of motor behavior across individuals as they engage with the end effector of rehabilitation robots. The

[6]Note that while this task is right/left symmetric and thus the data presented are directly comparable for both stroke survivors, this is not true for other task plots included with data release; analyses of these supplementary plots must account for this discrepancy.

[7]Erratic behavior of this electrode was observed by investigators during the trial in our otherwise-reliable sEMG system, and it is unclear whether this was the result of true motor behavior or sensor failure, a question we will explore during expanded future data collection.

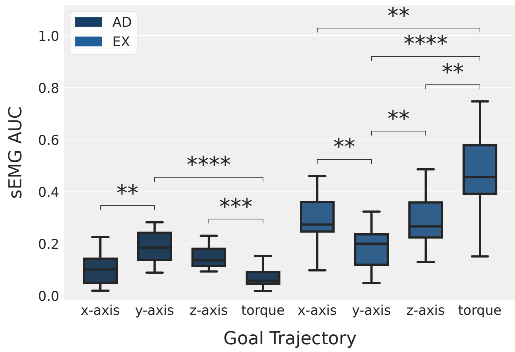

Fig. 5. Cumulative activations of the AD and EX arm muscles, aggregated across all participants, during the 4 single-axis trajectory tracking tasks in pose Condition A. The choice of trajectory — x-axis, y-axis, z-axis, or (z-axis) torque — substantially influenced the activation of both the shoulder flexor (AD) and the wrist extensor (EX). Specifically, movements typically associated with the AD, such as forward and upward motions at the shoulder (y- and z-axis tasks), demonstrated significantly increased activation patterns when compared with x-axis force and z-axis torque (as calculated via Kruskal-Wallis statistical test, reported as $*p < 0.05$, $**p < 0.01$, $***p < 0.001$, $****p < 0.0001$). Similarly, tasks requiring twisting movements at the wrist (here, the torque task) showed significantly increased EX activation compared with the non-twisting x-, y-, and z-axis tasks. Significant differences were also observed, to a lesser degree, among EX activations in the non-twisting tasks. These observed patterns provide evidence that force- and torque-requiring trajectories can be combined to independently modulate desired muscle activations. Statistical annotations displayed via [30].

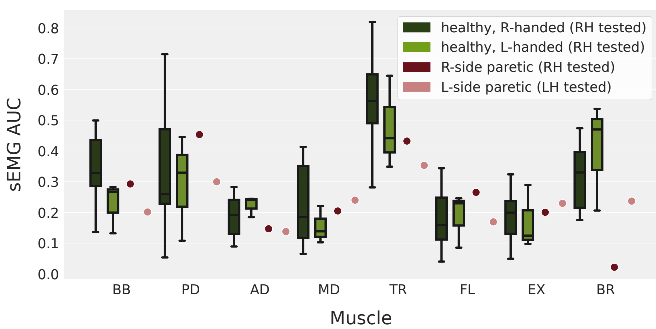

Fig. 6. Cumulative activations of each of the 8 arm muscles, during the y-axis trajectory tracking task in pose Condition A, for aggregated healthy right-handed and left handed participants (all completing the tasks with the right arm) and for individual post-stroke participants (completing the tasks with their paretic arm). Both healthy and post-stroke participants effectively completed the tasks, confirming the feasibility of system usage in the target population. Aside from consistent nonuse of the brachioradialis (BR) by one stroke survivor (which may also be the result of technical malfunction), post-stroke participants exhibited similar motor behavior to that of healthy individuals as evaluated by this metric, despite qualitative observation of compensatory motions, suggesting the need for more sophisticated temporal analyses and/or additional sensing to describe these pathological movements.

preliminary analyses above examine only a single aspect of this patterning, leveraging the same aggregate AUC measure of muscle activation to begin elucidating which muscles are activated under what circumstances, and neglect many aspects of these signals (including time- and co-dependence) that are key to fully understanding both healthy and pathological motion. In the future, we aim to employ tools like statistical parametric mapping [31] and synergy analysis [18] to assess and describe the observed motor behavior in its full temporal richness.

In addition, the analyses above compare muscle activation levels regardless of task performance: while participants largely followed each assigned trajectory, they varied in both how much they deviated from the assigned path and the extent to which they exerted forces and torques in "null" dimensions that did not impact cursor movement for a given task.[8] Future analyses will probe these relationships more deeply by explicitly relating activations to observed forces (through both data-driven methods and physiology-based modeling systems [32]) and examining the relationship between displayed and executed trajectories.

F. *Subjective Impressions of the Platform*

Both quantitative and qualitative analysis of subject feedback showed a largely positive impression of the system, which participants described as "fun" to use and largely "responsive" to their desired motions. Several participants provided concrete feedback on system improvements, which we will implement in the next version of the platform and should be considered in the development of future rehabilitation systems generally (including the need for a more comfortable and supportive chair, and for a larger screen to capture a wider field of view, reducing visual distractions and enhancing focus). Participants also emphasized the importance of maintaining cognitive engagement through interactive and engaging activities. One participant noted that their engagement in the activity contributed to lower levels of habitual pain, underscoring the potential therapeutic benefits of enhanced engagement beyond the motor neuroplasticity we explicitly target with this system.

Unsurprisingly, due to the additional gravity compensation required, participants found pose Condition B significantly more fatiguing, as measured by Likert scale feedback at the midpoint survey after all tasks at a single experimental condition had been completed.[9] This statistical finding was further supported by subjective remarks, with multiple participants reporting that Condition B was more challenging. Notably, one participant remarked that while Condition B was more difficult compared with Condition A, its difficulty was comparable to that of a traditional rehabilitation therapy session, indicating that the protocol overall was not prohibitively fatiguing for those with only mild impairment. To allow those with more severe motor impairment to use the platform in the future, we aim to incorporate gravity compensation systems through wrist-supporting end effectors and supportive robot controllers.

[8] An example of the latter can be seen in the force torque traces in Figure 1: accomplishing the displayed y-axis task required force only in the y direction (upward and downward), but this participant also exerted substantial force along the z axis (in and out) that was disregarded by the game but is definitionally reflected in the observed muscle activation.

[9] Of the 17 participants who completed the study, 8 were randomized to perform tasks at pose Condition A first, while 9 performed Condition B first. A Wilcoxon rank-sum statistical test indicated that Condition B was statistically more fatiguing than Condition A ($p = 0.05$). No significant differences were found across the intake, mid-point, and post-experiment surveys on the valence, arousal, and dominance scales of the Self-Assessment Manikin (SAM) or the Likert scale used to assess participant comfort.

VI. Conclusions & Future Work

The neurorehabilitation field is still contending with many foundational questions around neuroplasticity, rehabilitation task prescription, and device control. There is thus a great need for improved tools to explore large cohorts of patients in standardized, replicable, extensible, and clinically interpretable ways, and to do so during natural, multidimensional motion. This paper presents our first step toward such a tool: a modular, robust framework to enable wide ranging, controller-agnostic study of these questions and precise quantification of motor behavior across all isometric dimensions of the end effector workspace. We look forward to expanding this system's capabilities in all the ways detailed throughout this paper in order to address these questions — and, ultimately, provide more effective neuromotor therapy — and invite the wider rehabilitation and neuromechanics communities to leverage our data to do the same.

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