Transformer-Based Trajectory Prescription for sEMG-Optimizing Robot-Mediated Rehabilitation

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We present a transformer- and flow-matching-based model that **prescribes personalized arm exercises that activate a user's muscles in desired ways**, toward more effective neuromotor rehabilitation.

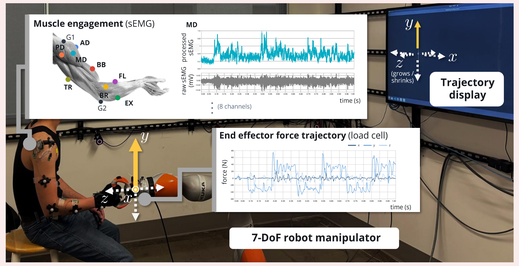
1 WHY

Effective therapy requires healthy muscle engagement, but existing robots just optimize kinematics.

- **Robot-mediated therapy** could close the access gap for the **2.4 billion people who could benefit from rehabilitation** [1].
- **Existing robot systems** rely on error correction to desired kinematic motions ("assistance-as-needed") but **have not shown meaningful improvements beyond standard of care** [2].
- Neuroscience points to what is missing: **recovery depends on reinforcing healthy patterns of muscle activation**, not only on guiding motion [3, 4]. Those patterns differ for every patient, but current systems neither measure nor target them.

2 WHAT

We construct a model that maps target muscle engagement to the prescribed end-effector trajectory that will induce it.



SYSTEM REQUIREMENTS

- **R1** **Predict end effector force trajectory** required to induce target muscle activations, as measured by surface electromyography (sEMG).
- **R2** **Model uncertainty** to enable flagging out-of-distribution targets to reduce likelihood of unsafe prescriptions.
- **R3** **Calibrate quickly** to new users.

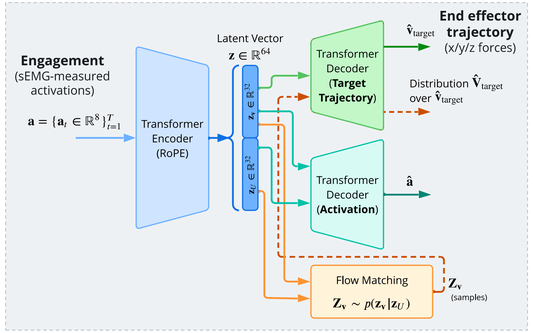
SPONSORS

This work was supported by the Dept. of Mechanical Engineering at the University of Utah.

3 HOW R1 R2

We encode a latent representation of the engagement–trajectory relationship and user-specific behavior, augmented with flow matching to model uncertainty.

ARCHITECTURE

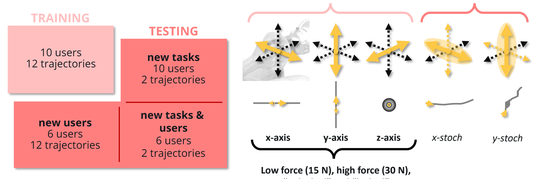


A **RoPE transformer encoder** [5] maps 8-channel sEMG to $\mathbf{z} = [\mathbf{z}_t, \mathbf{z}_U]$, giving trajectory and user behavior a latent each. **Flow matching** [6] samples $\mathbf{z}_v$ given $\mathbf{z}_U$, so the model outputs a distribution over prescriptions, pulled toward the training data. The activation decoder is used in training only.

TRAINING LOSS

$$\mathcal{L} = \lambda_1 \left\| \mathbf{v}_{\text{target}} - \hat{\mathbf{v}}_{\text{target}} \right\|_2^2 + \lambda_2 \|\mathbf{a} - \hat{\mathbf{a}}\|_2^2 + \lambda_3 \|\mathbf{z}_v - \mathbf{Z}_v\|_2^2$$

DATA AND SPLITS



10 s windows, 1 s stride:
6,480 training and 4,562 test windows.

User Demographics: 5 F, 11 M, age 28.4 ± 7.0

ACKNOWLEDGEMENTS

Thanks to Ajay Anand and Jono Jenkens for their assistance on the system that enabled data collection, which is adapted from the OpenRobotRehab 1.0 platform [7].

4 PREDICTION PERFORMANCE R1 R2

Our model predicts trajectories corresponding to measured engagement better than baselines and ablations.

METRICS

$$\text{MSE}_{\text{TD}} = \frac{1}{n_{\text{trials}} n_{\text{windows}}} \sum_{i=1}^{n_{\text{trials}}} \sum_{j=1}^{n_{\text{windows}}} \left\| \mathbf{v}_{\text{target}} - \hat{\mathbf{v}}_{\text{target}} \right\|_{2,ij}^2 \qquad \text{MSE}_{\text{FM}} = \frac{1}{n_{\text{trials}} n_{\text{windows}}} \sum_{i=1}^{n_{\text{trials}}} \sum_{j=1}^{n_{\text{windows}}} \left\| \mathbf{v}_{\text{target}} - \mathbb{E}[\hat{\mathbf{V}}_{\text{target}}] \right\|_{2,ij}^2$$

Our **full model** predicts trajectories for new tasks, users, and new user–task combinations with **<8% error**.

The LSTM is competitive on new tasks (0.068 vs. 0.067) and on new tasks & users (0.063 vs 0.062), but weaker on new users and the training set.

Flow matching lowers error by ≈1–2%.

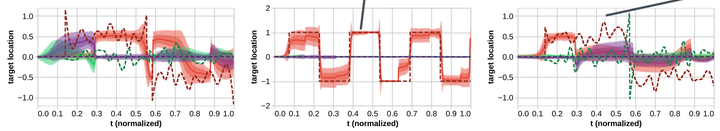
TRAJECTORY PREDICTION PERFORMANCE OF BASELINES, ABLATIONS, AND FULL MODEL

T = trajectory decoder, A = activation decoder, F = flow matching. Bold = lowest mean per column.

Model	T	A	F	Train	New tasks	New users	New tasks & users
MSE_{TD} · deterministic decoder							
Naive MLP	•			0.106 ±0.273	0.097 ±0.233	0.238 ±0.462	0.106 ±0.204
LSTM	•			0.155 ±0.308	0.068 ±0.143	0.191 ±0.354	0.063 ±0.128
Minimal	•			0.016 ±0.109	0.108 ±0.211	0.099 ±0.256	0.115 ±0.213
+ Act. Dec.	•	•		**0.005** ±0.074	0.117 ±0.267	0.088 ±0.252	0.110 ±0.228
+ Flow Mat.	•		•	0.069 ±0.216	0.115 ±0.239	0.095 ±0.255	0.106 ±0.185
Full	•	•	•	0.009 ±0.110	0.084 ±0.227	0.086 ±0.252	0.082 ±0.211
MSE_{FM} · mean of 25 flow-matching samples							
+ Flow Mat.	•		•	0.076 ±0.213	0.114 ±0.241	0.098 ±0.246	0.106 ±0.196
Full	•	•	•	0.010 ±0.094	**0.067** ±0.190	**0.077** ±0.211	**0.062** ±0.174

EXEMPLAR PREDICTION PERFORMANCE

Error is lowest when targets lie inside the training distribution.



known user (P09), **new task** (T14) | **new user** (P11), **known task** (T07) | **new user** (P16), **new task** (T14)

Outside the training distribution, flow matching predicts with higher error and less confidence, a proxy for the safety of the trajectory's execution. This is not a safety guarantee.

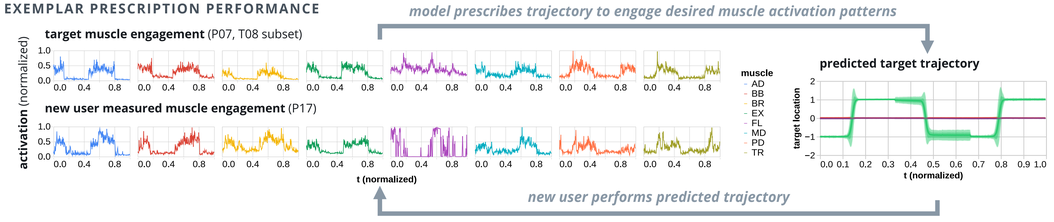
OPEN DATA AND CODE

hrelab.mech.utah.edu/publication/2026-corl-parra

5 PRESCRIPTION PERFORMANCE R1

Participants completing prescribed trajectories demonstrate desired muscle engagement.

EXEMPLAR PRESCRIPTION PERFORMANCE

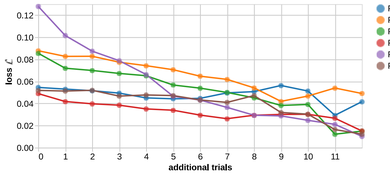


Five participants (P08 and P13 from original cohort, P17–P19 new) achieved consistent **≈15% activation error** (measured via RMSE) on this exemplar trajectory.

6 PERSONALIZATION R3

Performance improves with minutes' fine tuning to an individual user.

LOSS $\mathcal{L}$ VS ADDITIONAL TRIALS



CALIBRATION TIME

$\mathbf{T_{cal} \approx n_{trials} \times \{60, 20\}\ s + 35\ s}$

60 s or 20 s tasks; each re-training run takes about 35 s.

Re-training on 1–12 of a new user's trials **lowers loss for all 6 test users ≈2–12%**, with the plot demonstrating the calibration time/accuracy trade-off.

LIMITATIONS AND FUTURE WORK

Next. Post-stroke cohorts, dynamic end-effector tasks, a pathology-specific residual model, and added safety layers (joint and speed limits, control barrier functions).

Limits. Healthy participants and isometric tasks only. Flow-matching uncertainty was examined qualitatively. Hyperparameters were chosen largely by intuition.

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