# Towards an Optimal Model of Post-Stroke Sensorimotor Control

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**TAKEAWAY:** Our main findings are that post-stroke sensorimotor control can be modeled as an **optimal feedback controller** and adding a **delay and bias constants** improves the performance of this model. Furthermore, **model parameters** may be related to **clinical assessments**, but more participants are needed to draw clear conclusions.

## INTRODUCTION

- **Motor control** deficits are a common cause of **post-stroke disability**. Understanding post-stroke sensorimotor control could better inform rehabilitation.
- A model of post-stroke **upper-extremity** movement could provide insight into post-stroke sensorimotor control. Modeling post-stroke motor control requires a **patient-specific approach** that considers both limbs and accounts for **cognitive deficits**.
- We sought to (1) verify that an optimal control model is **feasible** for modeling post-stroke sensorimotor control on a tracking task and (2) understand how model parameters relate to post-stroke **motor and/or cognitive impairments**.

## METHODS

**Human Data:** The data for this study come from the **Rehabilitation Using Community-Based Affordable Robotic Exercise Systems (Rehab CARES)** clinicals trial (phase II), which aims to validate a robotic gym of 1-DOF rehabilitation robots for providing community-based post-stroke rehabilitation.

**Participants: 11 participants with hemiparesis resulting from stroke** (69 ± 5 years) were recruited. Inclusion criteria include 3 months post-stroke, completed CT or MRI scan, hemiplegia, with a Fugl-Meyer Upper Extremity (FM) score of between15 and 60. Exclusion criteria include severe spasticity, severe aphasia, and severe depression.

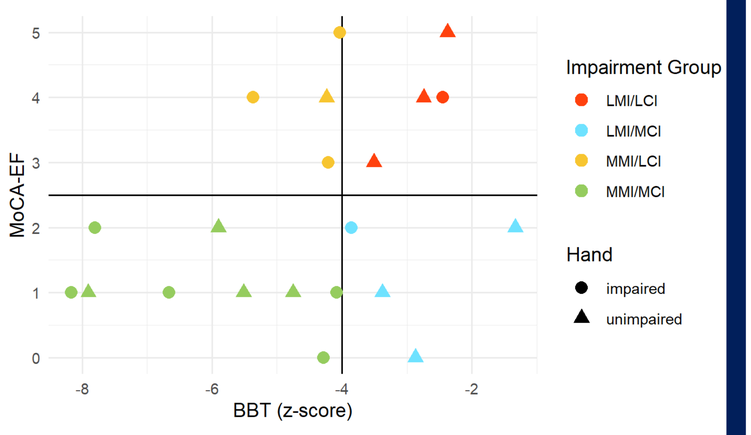
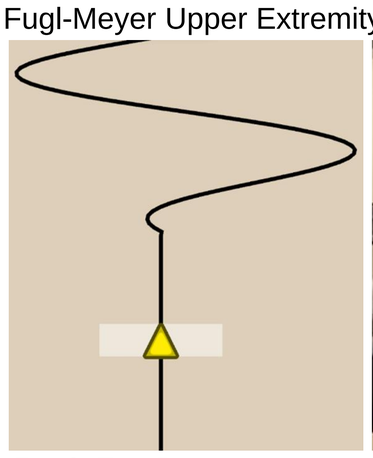
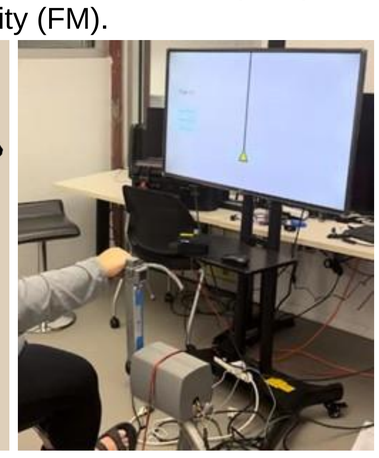



***Fig. 1:*** *Participants' impaired and less-impaired limbs sorted into impairment group by normalized BBT and MoCA-EF.*

**Clinical Assessment:** A battery of clinical assessments determined the level (low, L or moderate, M) of motor impairment (MI) and cognitive impairment (CI) (***Fig. 1***). Cognitive assessments include the Montreal Cognitive Assessment (MoCA), MoCA executive function sub-score (MoCA-EF), and Color Trails 1&2 (CT1, CT2). Motor assessments include the Blocks & Box test (BBT), Grooved Pegboard (GP), and Fugl-Meyer Upper Extremity (FM).





**Robotic Interface: THEABot**, developed by Recupero Robotics, LLC, is based on the Haptic TheraDrive robot. THEABot is a standalone1-DoF robot mounted on a movable base and is interfaced with a custom assessment and therapy gaming suite developed in collaboration with EnAble Games, LLC.

***Fig. 2:*** *TheaBot robot and trajectory tracking task*

**Trajectory Tracking Task:** The trajectory tracking task is designed to assess motor performance by asking the player to follow a pseudo-sinusoidal wave for 15s. Participants complete 15 trials of this task with the same trajectory. Only the middle five trials are used to fit the models described in the next section.

**Modeling Approach:** For this initial implementation, we simplify the system dynamics to a point mass in discrete time.

$$x_{k+1} = Ax_k + Bu_k \qquad A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \qquad B = \begin{bmatrix} 0 \\ \Delta t \end{bmatrix}$$

***Table I:*** *Feedback control models*

| Model | Description | Tuned Parameters |
|---|---|---|
| M1 | standard model | $K_p, K_v$ |
| M2 | bias model | $K_p, K_v, \zeta$ |
| M3 | delay model | $K_p, K_v, \gamma$ |
| M4 | bias and delay model | $K_p, K_v, \zeta, \gamma$ |

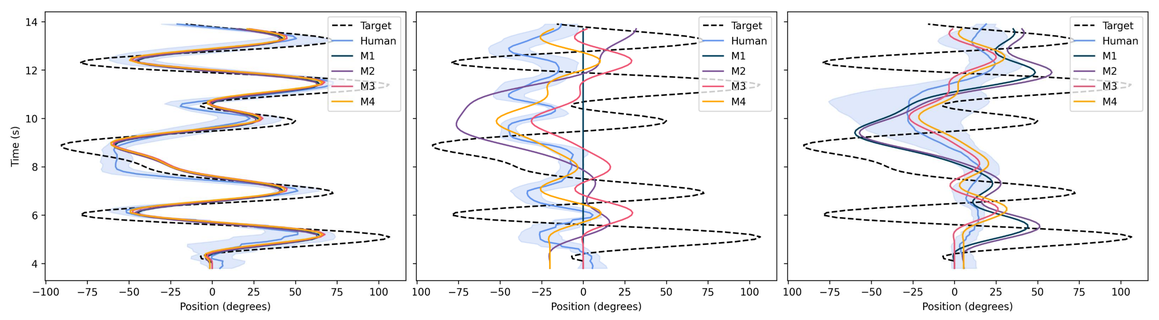
**Feeback Control Model:** The model is based on a feedback controller with a gains on error in position (Kp) and velocity (Kv) [1]. We adjust the target trajectory with constants: a delay term (γ) and a bias term (ζ). We create 4 models to determine the impact of these constants (***Table I***).

$$u_k = -Kx_k = [K_p \quad K_v] \begin{bmatrix} \theta_{t,k+\gamma} - \theta_{h,k} + \zeta \\ \dot{\theta}_{t,k+\gamma} - \dot{\theta}_{h,k} \end{bmatrix}$$

**Inverse Optimal Control:** We define the inverse optimal control problem as an inverse linear quadratic regulator (LQR). We solve the inverse LQR problem according to the linear matrix inequality and gradient descent method [2].

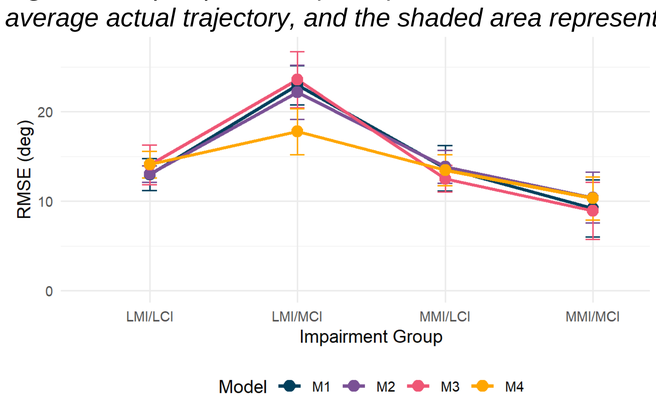
$$J = \sum_{k=0}^{\infty} x_k^T Q x_k + u_k^T R u_k$$

## RESULTS




*(011, impaired arm, LMI/LCI)* *(003, less-impaired arm, LMI/MCI)* *(002, less-impaired arm, MMI/MCI)*

***Fig. 3:*** *Exemplar plots of 3 participants' actual and modeled trajectories. The blue line represents the average actual trajectory, and the shaded area represents the standard deviation across all 5 trials.*




**Model Performance:** Model performance depends on **participant impairment** (***Fig. 3***). M4 performs (non-significantly) better for the LMI/MCI group (***Fig. 4***). M4 is used in the linear regressions.

**Linear Regression:** The more impaired limb outperforms the less-impaired limb in the linear regression analysis (***Fig. 5-6***).

***Fig. 4:*** *Median and standard error of model RMSE*

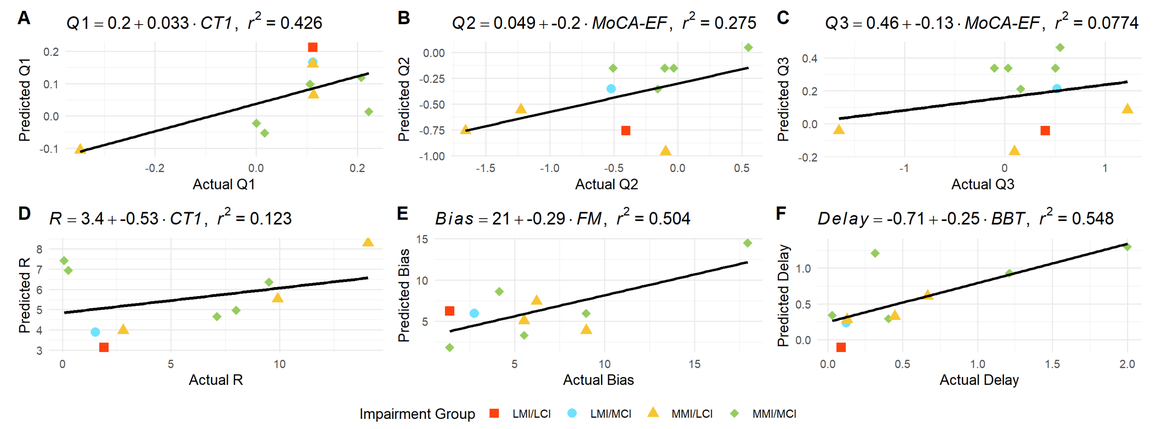



***Fig. 5:*** *Linear regression results for the impaired limb model parameters*

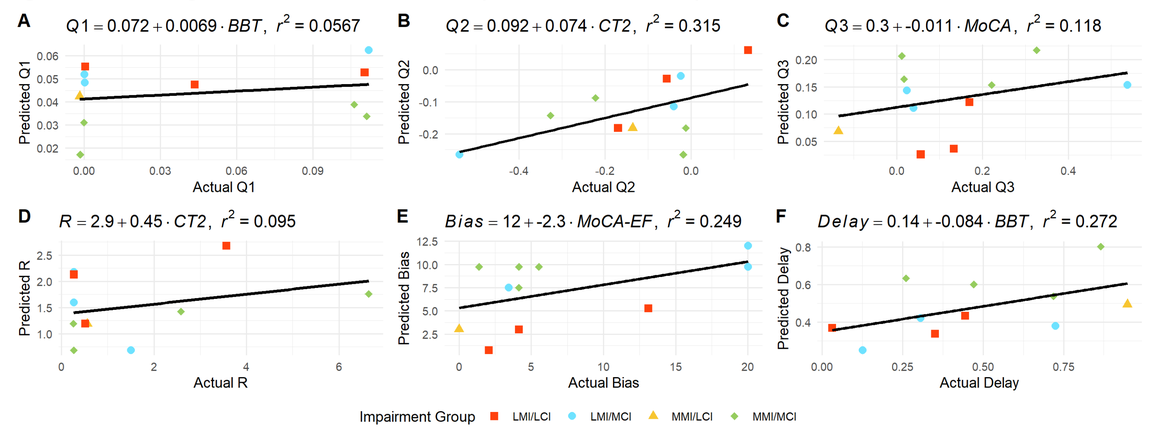



***Fig. 6:*** *Linear regression results for the less-impaired limb model parameters*

## DISCUSSION

- **Adding delay and bias may account for differences in tracking behavior due to motor and cognitive impairments.** All models perform similarly, but M4 shows a modest improvement for the LMI/MCI group (***Fig. 4***). This difference may be explained by not all participants exhibiting delay or bias (***Fig. 3***).
- **Inverse optimal control is feasible for modeling post-stroke tracking.** The inverse model produces feedback control gains that are almost identical to the least squares fit feedback controller.
- **Model parameters are related to impairments, particularly cognitive**. Bias is associated with a motor metric (FM) in the impaired limb but a cognitive metric (MoCA-EF) in the less-impaired limb. Except for the less-impaired Q1 model, all cost function parameters are most correlated with cognitive metrics (***Fig. 5-6***).
- **This is a preliminary investigation of the model.** Future work should include a larger population, more in-depth system identification, and a kinematic analysis.

**References:**
[1] Takagi, M. Hirashima, D. Nozaki, and E. Burdet, "Individuals physically interacting in a group rapidly coordinate their movement by estimating the collective goal," Elife, vol. 8, 2019.
[2] M. C. Priess, R. Conway, J. Choi, J. M. Popovich, and C. Radcliffe, "Solutions to the inverse LQR problem with application to biological systems analysis," IEEE Transactions on Control Systems Technology, vol. 23, no. 2, pp. 770–777, 2015.

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