A GAME-THEORETIC MODEL FOR CO-ADAPTIVE BMI

Maneeshika M. Madduri[1], Samuel A. Burden[1], Amy L. Orsborn[1,2, 3]
[1] Department of Electrical and Computer Engineering, University of Washington, Seattle WA 98105 USA
[2] Department of Bioengineering, University of Washington, Seattle WA 98105 USA
3 Washington National Primate Research Center, Seattle, WA 98105 USA

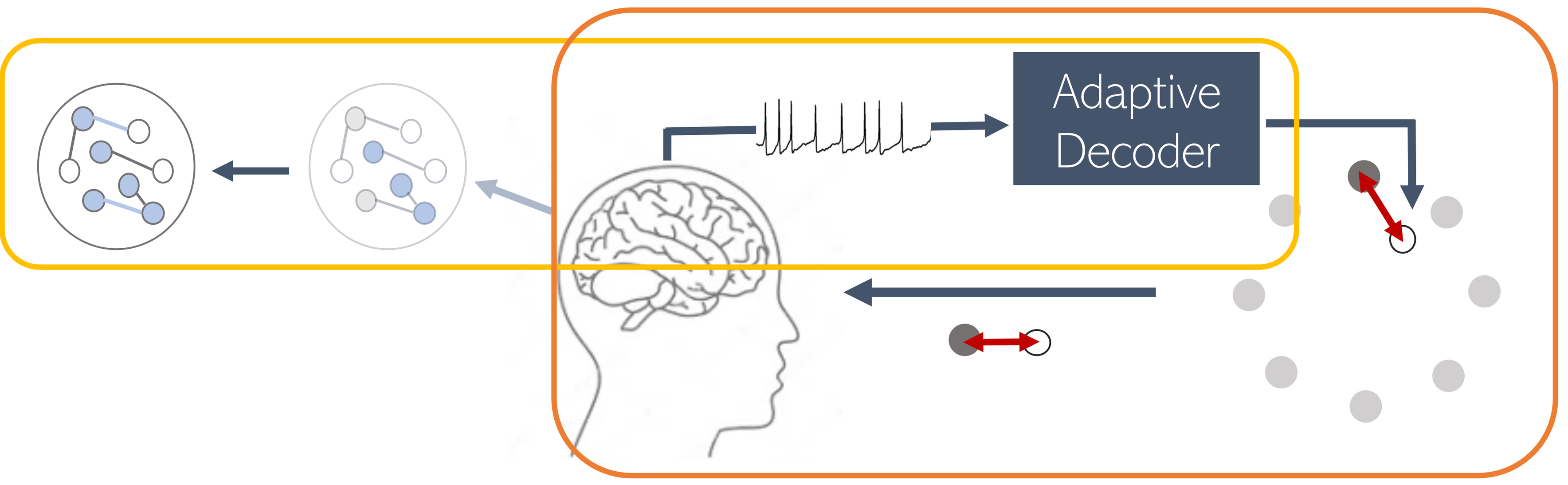
SUMMARY

Goal

- A theoretical framework **for simulating brain-machine co-adaption in brain-machine interfaces (BMIs)** to inform closed-loop decoder adaptation design[1,2]
- Can be extended to tasks with multiple dimensions and to different decoder models

Characterize how the **brain and decoder interact together** as both learn a BMI

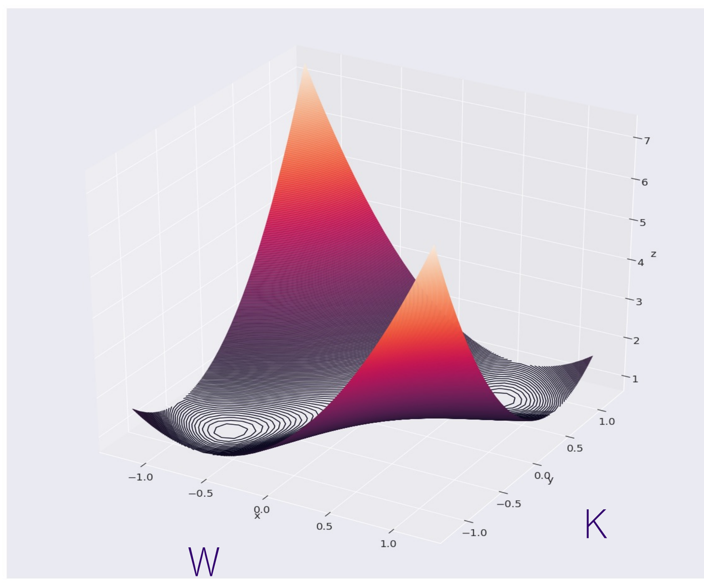
Explore conditions of the adaptive decoder that lead to **stable performance** of the user



Results

- **Model the brain and decoder as strategic agents** seeking to minimize their individual cost functions
- **Analyze the convergence of the brain-decoder co-adaptation** to stationary points
- Simulate the brain-decoder interactions using stochastic gradient descent to confirm mathematical analysis
- Construct a computational basis for less mathematically-tractable BMI formulations.

Potential Function Landscape



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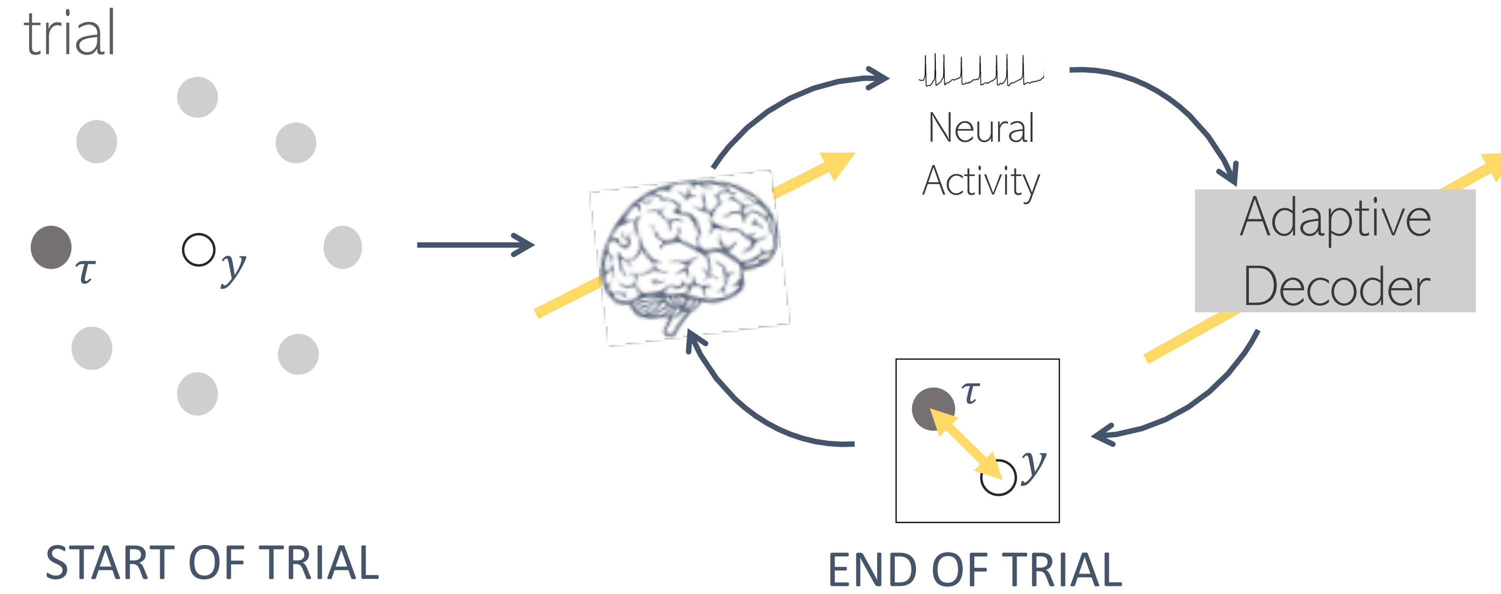
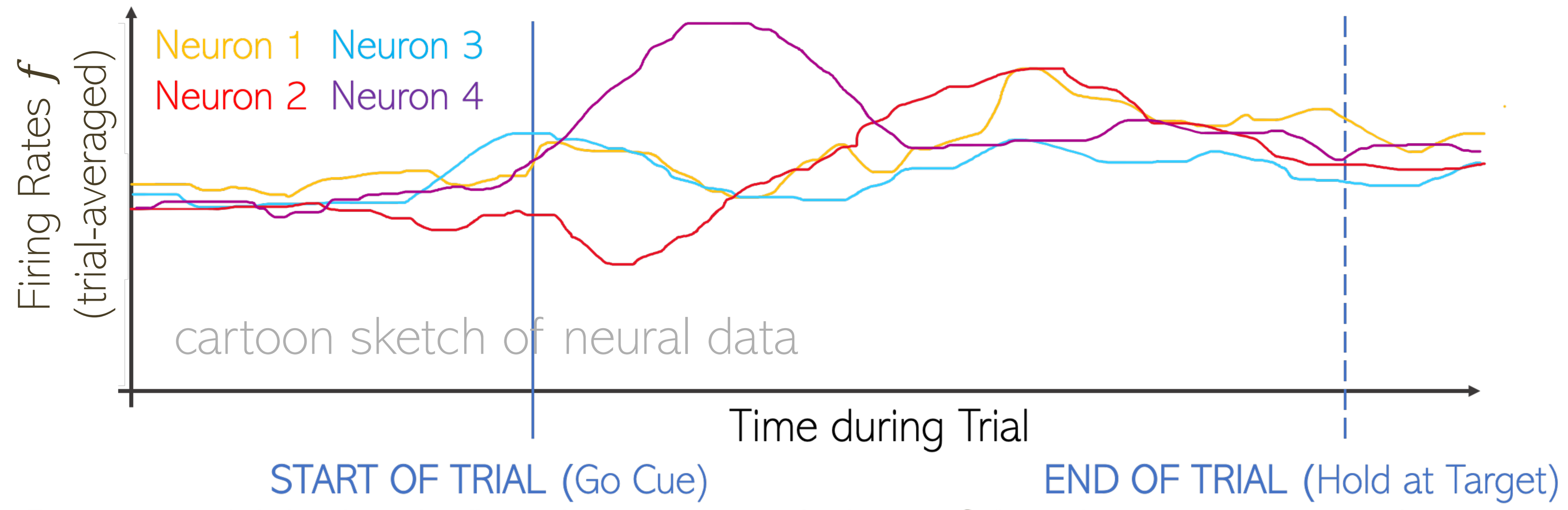
CO-ADAPTIVE BMI MODEL FORMULATION

Modeling a center-out cursor BMI task[3-5]

- Target position (τ) presented to user (W) at start of trial (t)
- User neural activity--firing rates (f)--input to adaptive decoder
- Adaptive decoder (K) outputs a cursor position (y)
- BMI task error $(\varepsilon = \|\tau - y\|_2^2)$ adapts brain and decoder for next trial

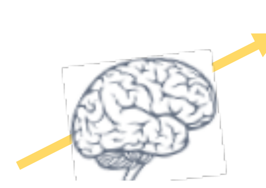


Connection to Experimental Design (*in progress*)



Proposed Method: Combine neural data f for the position-velocity adaptive decoder (Smoothbatch[1]) by vectorizing f over multiple timepoints in the trial from the start of trial to the end of trial

Brain and Decoder Transformations



BRAIN
$$f = W\tau + b$$

DECODER
$$y = Kf + a$$

Adaptive Decoder

BRAIN UPDATE
$$W_{t+1} = W_t - \gamma_W g(C_B)$$

DECODER UPDATE
$$K_{t+1} = K_t - \gamma_K g(C_D)$$

BRAIN COST
$$C_B(W,K) = error(\tau, y) + \lambda_W \|W\|_2^2$$

DECODER COST
$$C_D(W,K) = error(\tau, y) + \lambda_K \|K\|_2^2$$

$$\frac{\partial C_B}{\partial W} = \frac{\partial P}{\partial W}$$

Can track the changes of both agents with one *Potential Function*

$$\frac{\partial C_D}{\partial K} = \frac{\partial P}{\partial K}$$

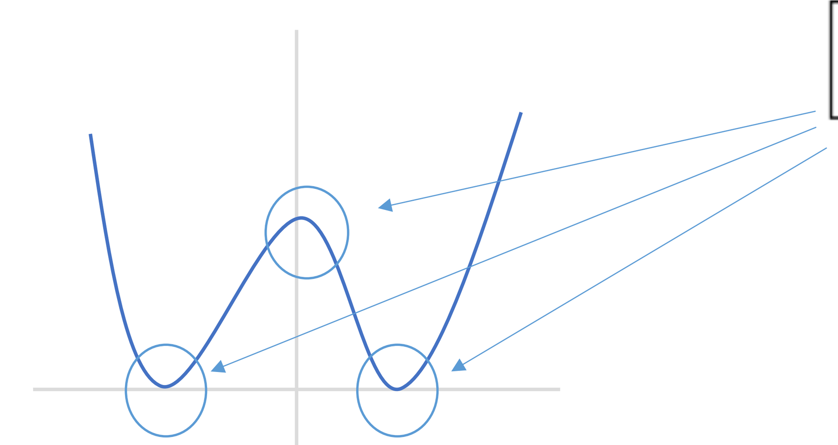
POTENTIAL FUNCTION
$$P(W,K) = error(\tau, y) + \lambda_W \|W\|_2^2 + \lambda_K \|K\|_2^2$$

STATIONARY POINT ANALYSIS

$$P(W,K) = error(\tau, y) + \lambda_W \|W\|_2^2 + \lambda_K \|K\|_2^2$$

$$\begin{bmatrix} \mathbf{W}_S \\ \mathbf{K}_S \end{bmatrix} = \begin{bmatrix} \sqrt{-\frac{\lambda}{\tau^2}+1} \\ \sqrt{-\frac{\lambda}{\tau^2}+1} \end{bmatrix}, \begin{bmatrix} -\sqrt{-\frac{\lambda}{\tau^2}+1} \\ -\sqrt{-\frac{\lambda}{\tau^2}+1} \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\lambda_W = \lambda_K = \lambda$$



Stable Fixed Points

$$\lambda > 0, \frac{\lambda}{\tau^2} < 1$$

Linearization around the fixed points

- Non-linear dynamics can be approximated as linear closed to fixed points

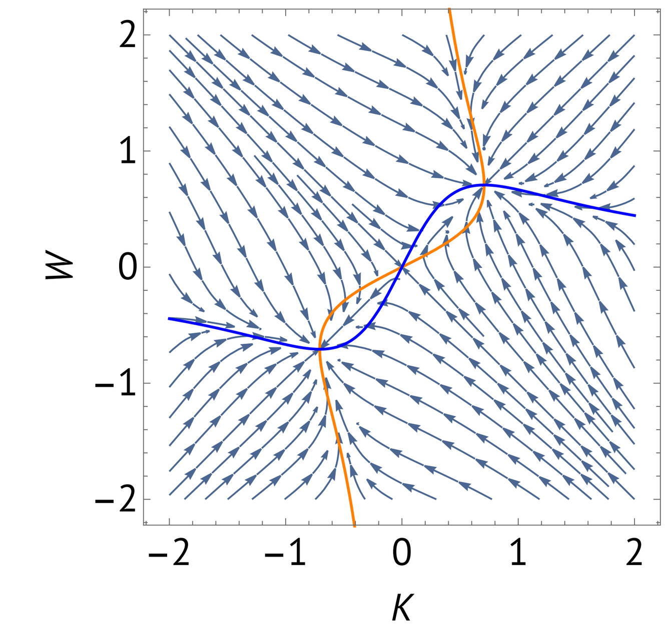
Task Error at Fixed Points

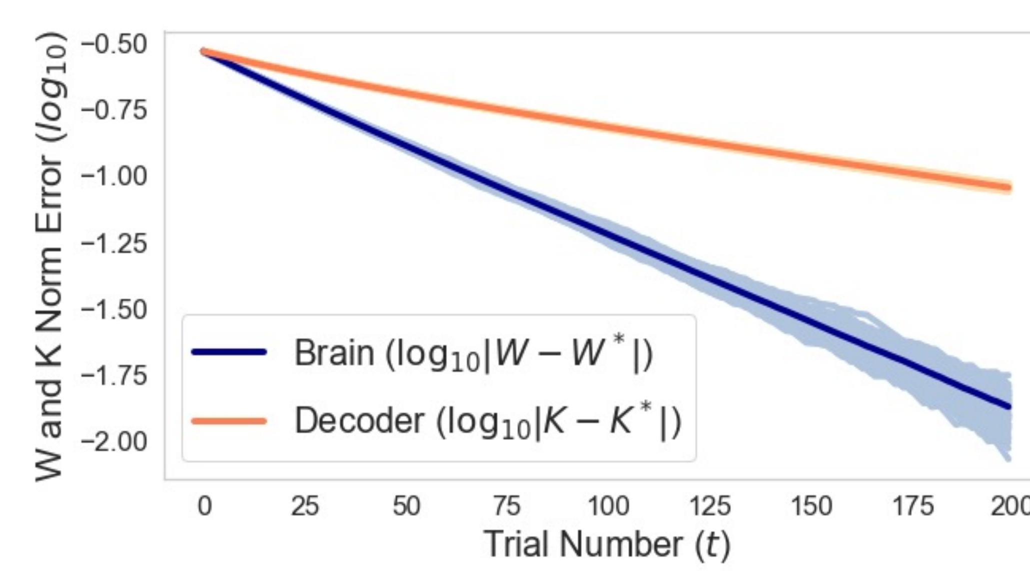
$$error_S(\tau, y) = \left\| \tau - \left(1 - \frac{\lambda}{\tau^2}\right)\tau \right\|_2^2$$

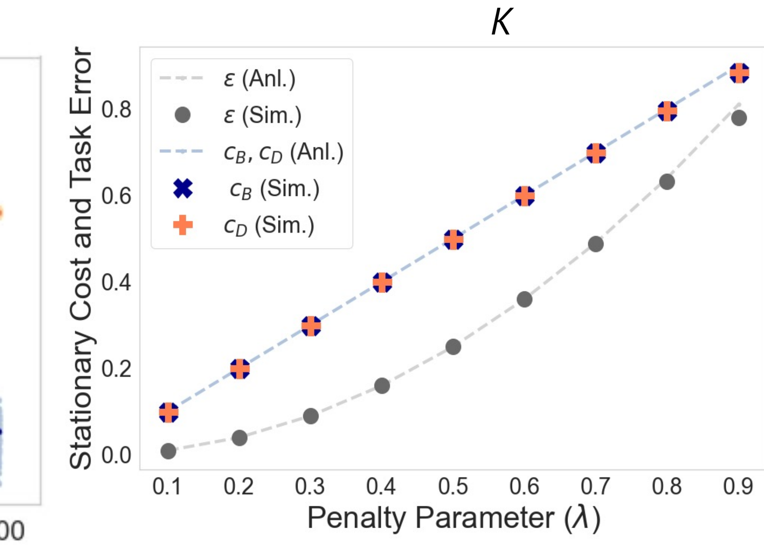
$$error\,(\tau, y) = \|\tau - y\|_2^2$$
$$error\,(\tau, y) = \|\tau - K(W\tau)\|_2^2$$

STOCHATIC GRADIENT DESCENT SIMULATIONS

- Using stochastic gradient descent algorithm[6] to simulate the brain-decoder dynamics
- Focused on the stationary points and the task error







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