Modeling Neural Population Dynamics in a Point Process Filter for Neuroprosthetics Control

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Highlight

The goal of Brain-machine Interface (BMI) is to help the disabled restore their motor functions by controlling a neuroprosthesis to accomplish their movement intents. To achieve better BMI clinical applications, we study:

- A framework for **brain-control tasks evaluation** that simulates an online scenario
- Decomposed **internal** and **external** neural population dynamics in a point process filter
- Kinematics decoding from spike trains in **brain-control mode** of rat two-lever discrimination task

Introduction

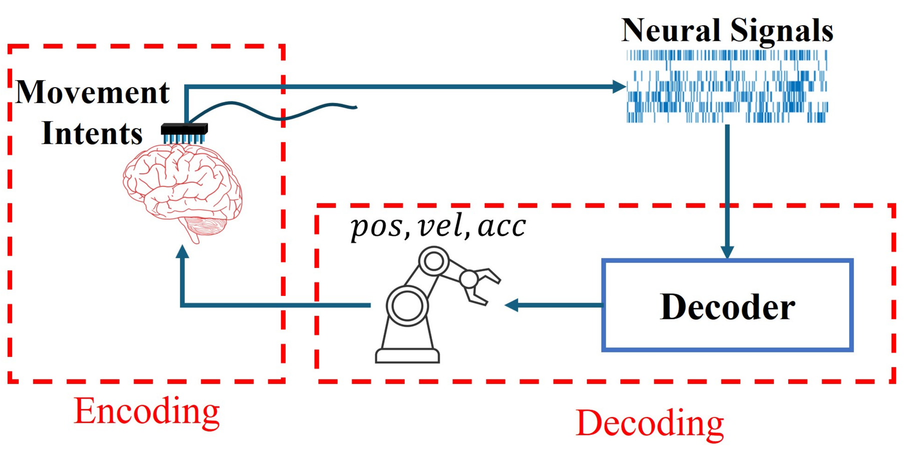

Figure 1. Brain-machine interface framework

- BMIs are systems that translate neural activities into digital control commands.
- Neural dynamics refers to the study of how neural activity evolves over time including
  - **internal** dynamics: e.g related to neural connectivity
  - **external** dynamics: e.g measured input (kinematics)
- Modeling neural dynamics contributes better neuroprosthetic control and understanding brain functions.

Experiment and Data Collection

The adopted BMI experimental paradigm in this paper involving rats was designed and conducted at The Hong Kong University of Science and Technology (HKUST). The procedures for handling animals in this study were reviewed and approved by the Animal Ethics Committee of HKUST.

- **Subject:** male SD rats
- **Task:** manual control and **brain control** for two-lever discrimination
- **Brain Region:** primary motor cortex (M1), media prefrontal cortex (mPFC)
- **Data:** binary-valued neuronal spike trains

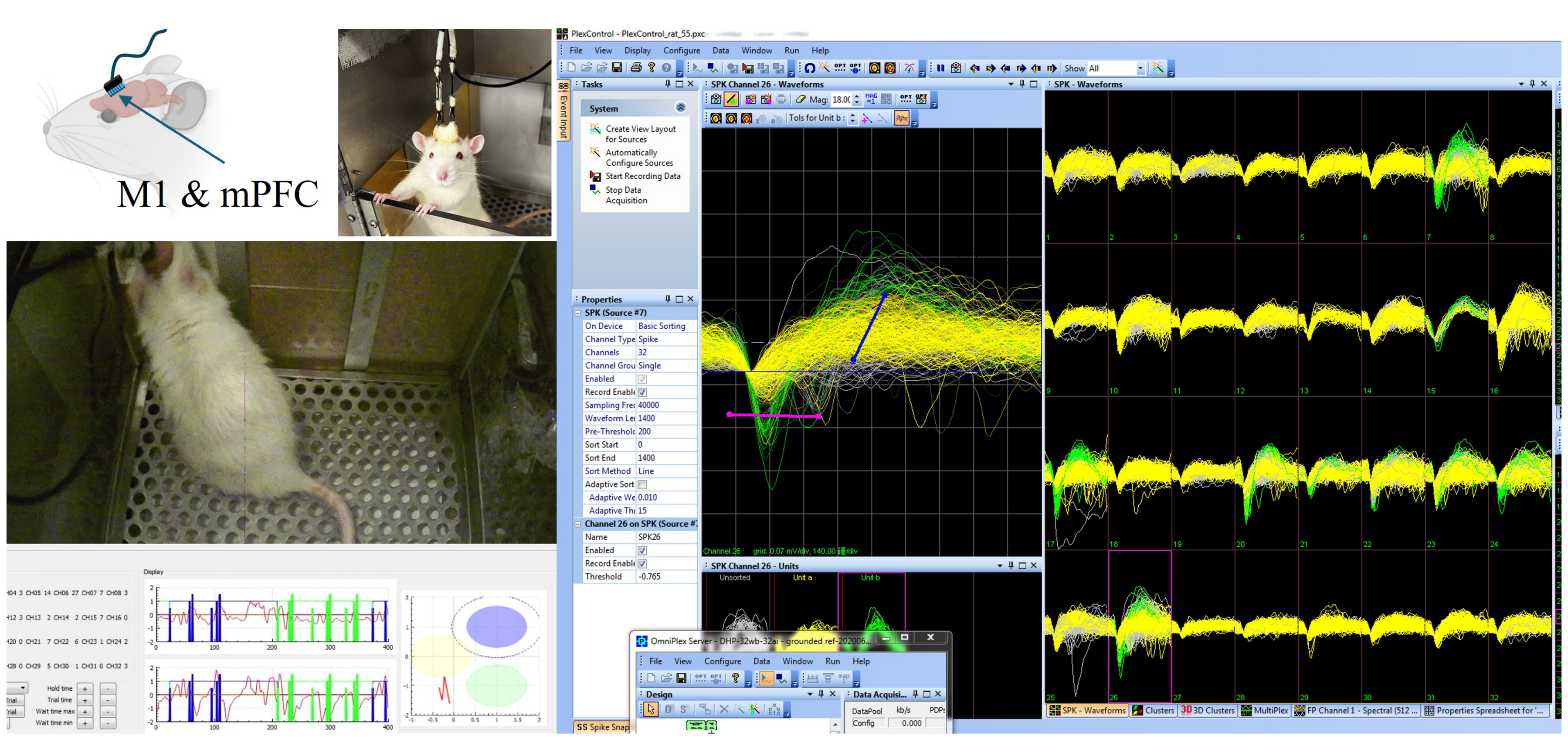

Figure 2. Surgery, behavior training and data collection.

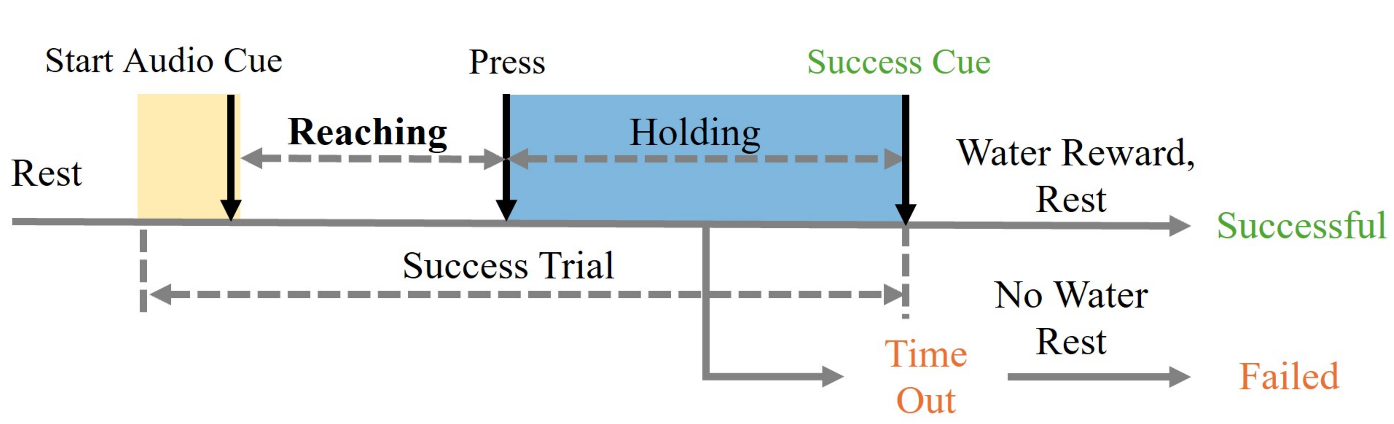

Figure 3. Schedule for animal behavior training

Method

Framework

- Assume:
  - Rats have good response and discrimination to the start cues
  - They have correct movement intents despite of failed online trials
- Decoding and achieve success before the success or ending of the online trial (successful and failed trials)

Generalized linear model with preferential subspace (GLMPS)

- Latent states x_k in training data are obtained based on PSID [1].
- Point process filter based on GLM [2] for $[z_k, x_k]^T$.

$$\begin{cases} [z_{k+1}, x_{k+1}]^T = A[z_k, x_k]^T + w_k, \\ y_k \sim Poisson(\lambda_k), \\ \lambda_k = f(z_k, x_k) \end{cases} \tag{1}$$

Results

Better **success rate**: We compare four methods in **high-lever** trials of **brain-control** tasks, namely

- Kalman filter (KF): 62.3%, smoothed firing probabilites of M1 [3]
- PSID: 36.2%, preferential subspace identification [1]
- GLMPS: 70.8%, GLM-based point process filter with preferential subspace

Fast Response: reach or finish the desired target in less time

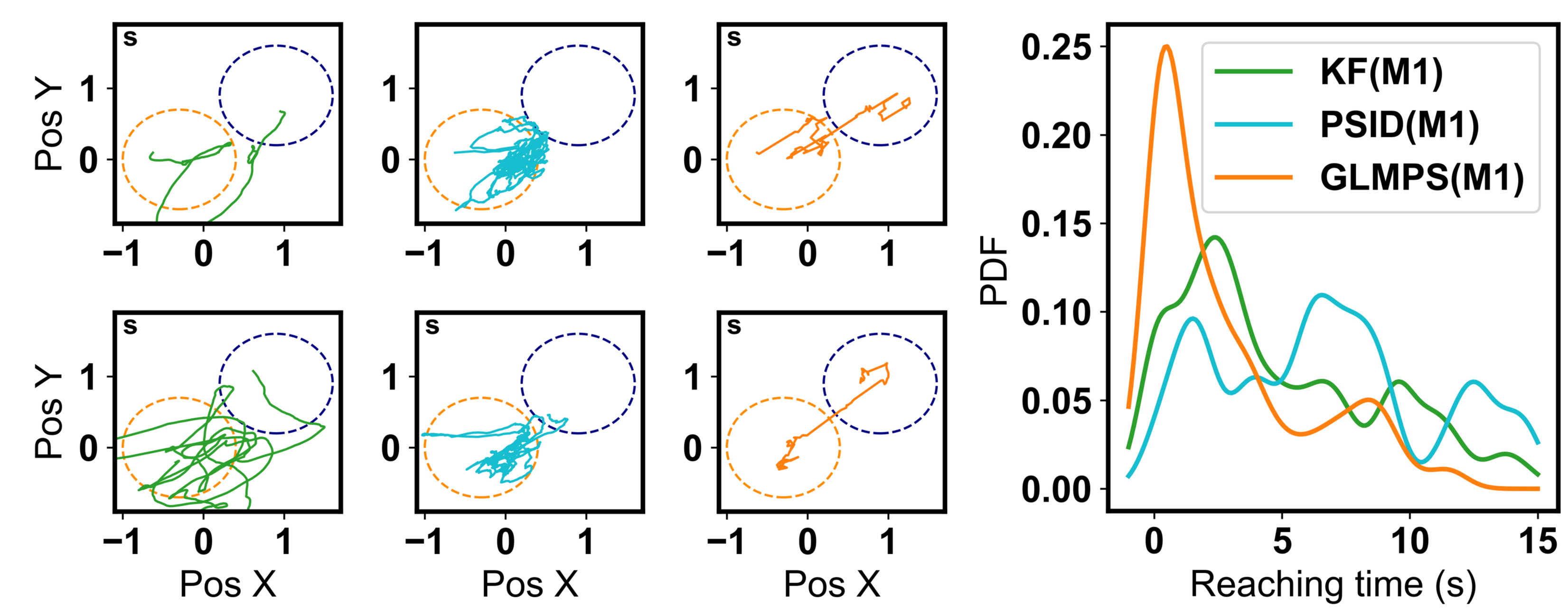

Figure 4. Decoded trajectories on a 2D plane and reaching time distribution

Consistent Direction: keep consistent movement toward the target

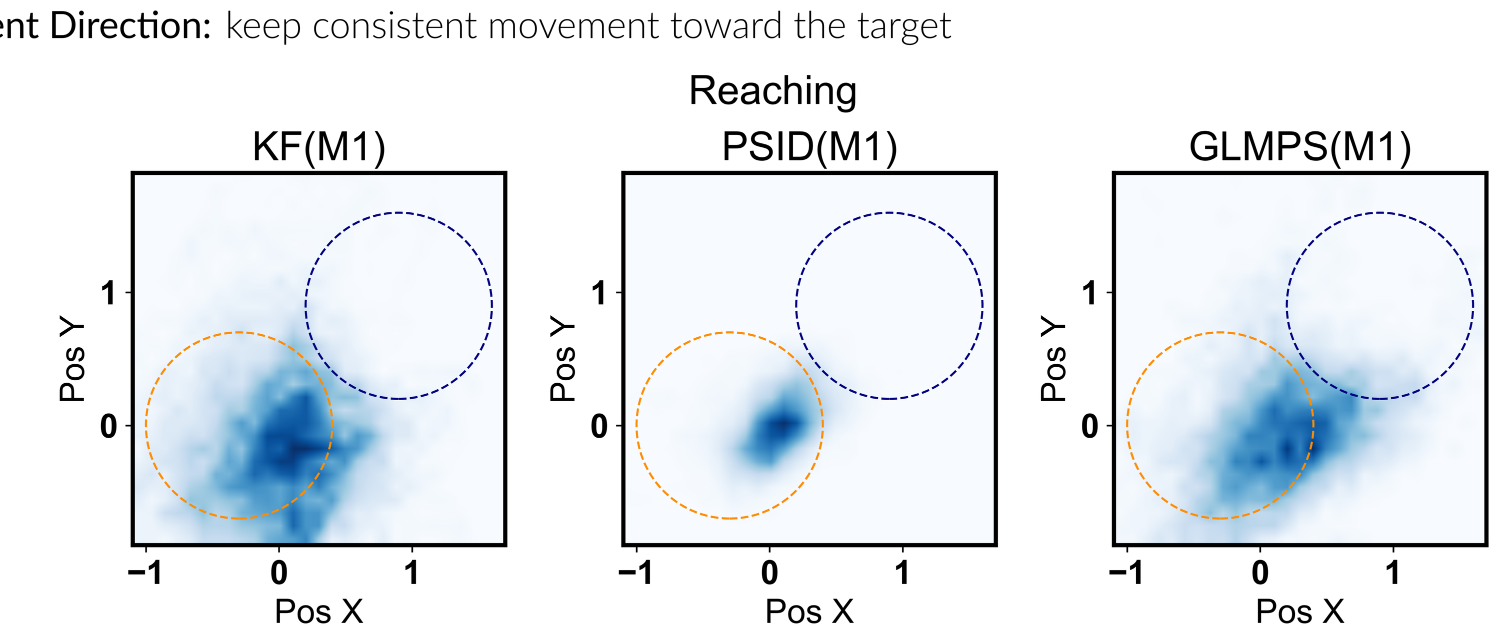

Figure 5. Trajectory distribution during reaching

Neural Dynamics for Kinematics: contribute to discriminating behavioral stages

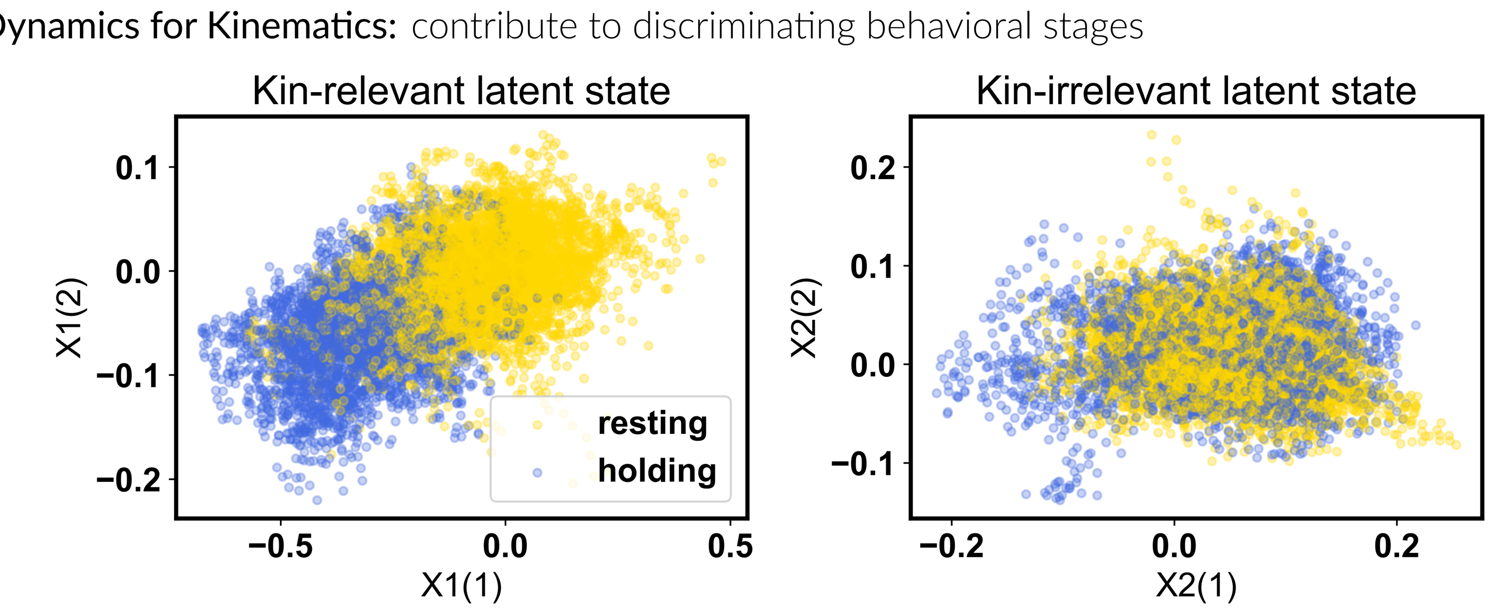

Figure 6. Scatters of extracted latent states during different behavioral stages

Conclusion and Future Work

We design an evaluation framework and a method to model external and internal neural dynamics in a point process filter for BMI. In future, we will analyze how neurons alter the engagement [4] in these factors during different behavioral phases. This will contribute to application in clinical scenarios.

Lab & Personal Information

I am on job market for **junior faculty** as well as **postdoc** position. Please feel free to reach out to me if you have any questions about our work.

Our Lab

Personal Homepage (Li, Mingdong)

References

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