Dynamic Ensemble Bayesian Filter for Robust BCI Control of a Human with Tetraplegia

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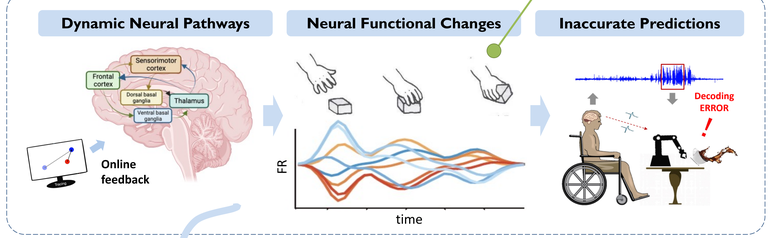
INTRODUCTION

Problem: The variability of neural signals has been a critical problem in robust online BCI control
- Influence of real-time feedback
- User's adaptation to the decoder

Neural function changes when control speed changes or error occurs [Shenoy *et al.*, 2017; Schwartz *et al.*, 2018].

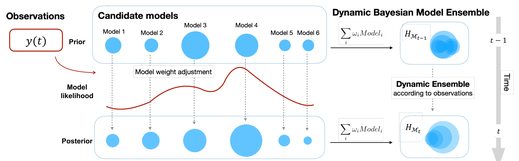


How to cope with neural functional changes to achieve robust online control?

DYNAMIC ENSEMBLE MODELING

The idea
- ✓ Using a pool of models to describe different neural functions
- ✓ Dynamically tuning the model weights to cope with neural changes

Adjusting model weights by likelihoods given the incoming observations.



- **State-space formulation.**

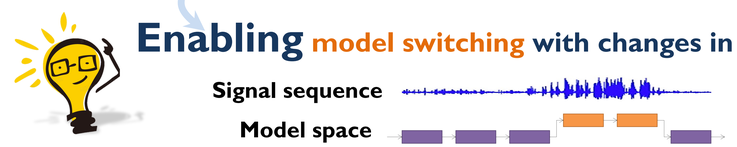
$$x_t = Ax_{t-1} + b + u_{t-1}$$
$$y_t = \mathcal{H}_{\mathcal{M}_t}(x_t) + v_{\mathcal{V}_t}$$

- **State estimation with recursive Bayesian filtering.**

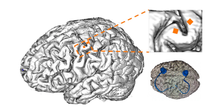
$$p(x_t|y_{0:t}) = \sum_{k=1}^{q} p(x_t|\mathcal{H}_{\mathcal{M}_t} = m_k, y_{0:t}) p(\mathcal{H}_{\mathcal{M}_t} = m_k|y_{0:t})$$

$$p(\mathcal{H}_{\mathcal{M}_t} = m_k|y_{0:t}) = \frac{p(\mathcal{H}_{\mathcal{M}_t} = m_k|y_{0:t-1}) p_k(y_t|y_{0:t-1})}{\sum_{j=1}^{q} p(\mathcal{H}_{\mathcal{M}_t} = m_j|y_{0:t-1}) p_j(y_t|y_{0:t-1})}$$

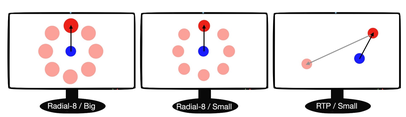
Enabling model switching with changes in signals.



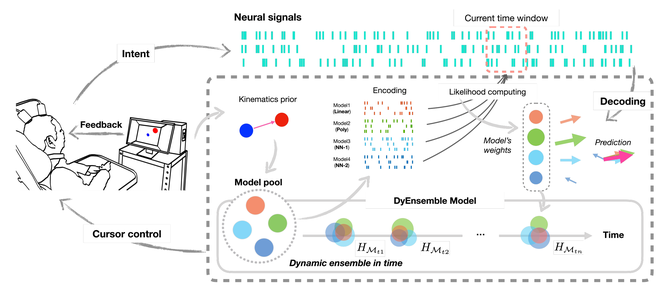
ONLINE BCI SYSTEMS



Two Utah arrays in the motor cortex



The 2-D cursor control paradigms

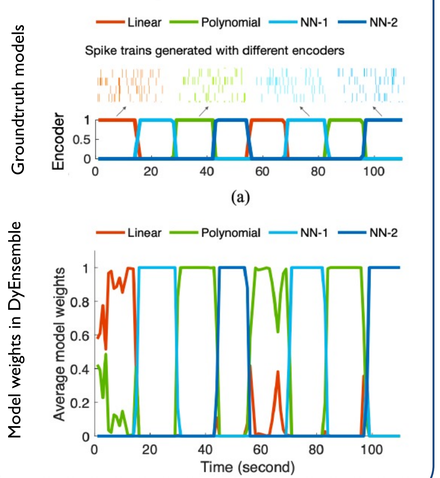


Online closed-loop BCI control using DyEnsemble

EXPERIMENTS AND RESULTS

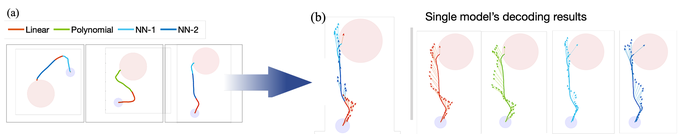
Simulations

DyEnsemble correctly assigns model weights in simulations



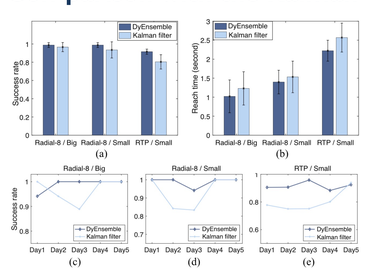
Online BCI control performance

Visualization of online model switches



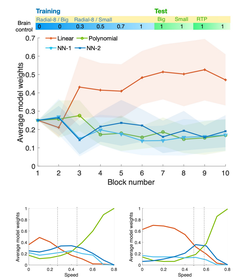
- DyEnsemble **switches** to the '**optimal**' model for each time slot to achieve more accurate online control.

Comparison with the Kalman filter



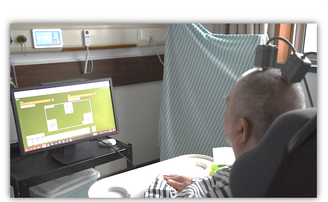
- DyEnsemble significantly **improves** the control accuracy (increases the success rate by 13.9% in the random target pursuit task) and robustness (performs more stably over different experiment days).

Analysis of the dynamic ensemble process



- Model ensemble changes during the closed-loop calibration, converging to a **linear dominant model** at full brain control stages.
- Linear models are favored at **low speeds** and polynomial models cover the **high speeds**.

- **Now Uncle Bobo can happily play his favorite mahjong with BCI !**



CONCLUSIONS

- ✓ **Dynamic** modeling is essential to robust online control in BCI systems.
- ✓ DyEnsemble can **adaptively** change model ensembles to cope with the variability in neural encoding.
- ✓ DyEnsemble provides a **flexible** adaptive neural decoding **framework**.

Please find details in our papers:

[1] Dynamic Ensemble Bayesian Filter for Robust Control of a Human Brain-machine Interface, *Arxiv* 2022 (***Trans. BME** minor*)
[2] Dynamic Ensemble Modeling Approach to Nonstationary Neural Decoding in Brain-Computer Interfaces, ***NeurIPS*** 2019

https://arxiv.org/abs/2204.11840
https://papers.nips.cc/paper/2019/file/3f7bcd0b3ea822683bba8fc530f151bd-Paper.pdf