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Adaptive Multiscale Brain Machine Interface Decoders

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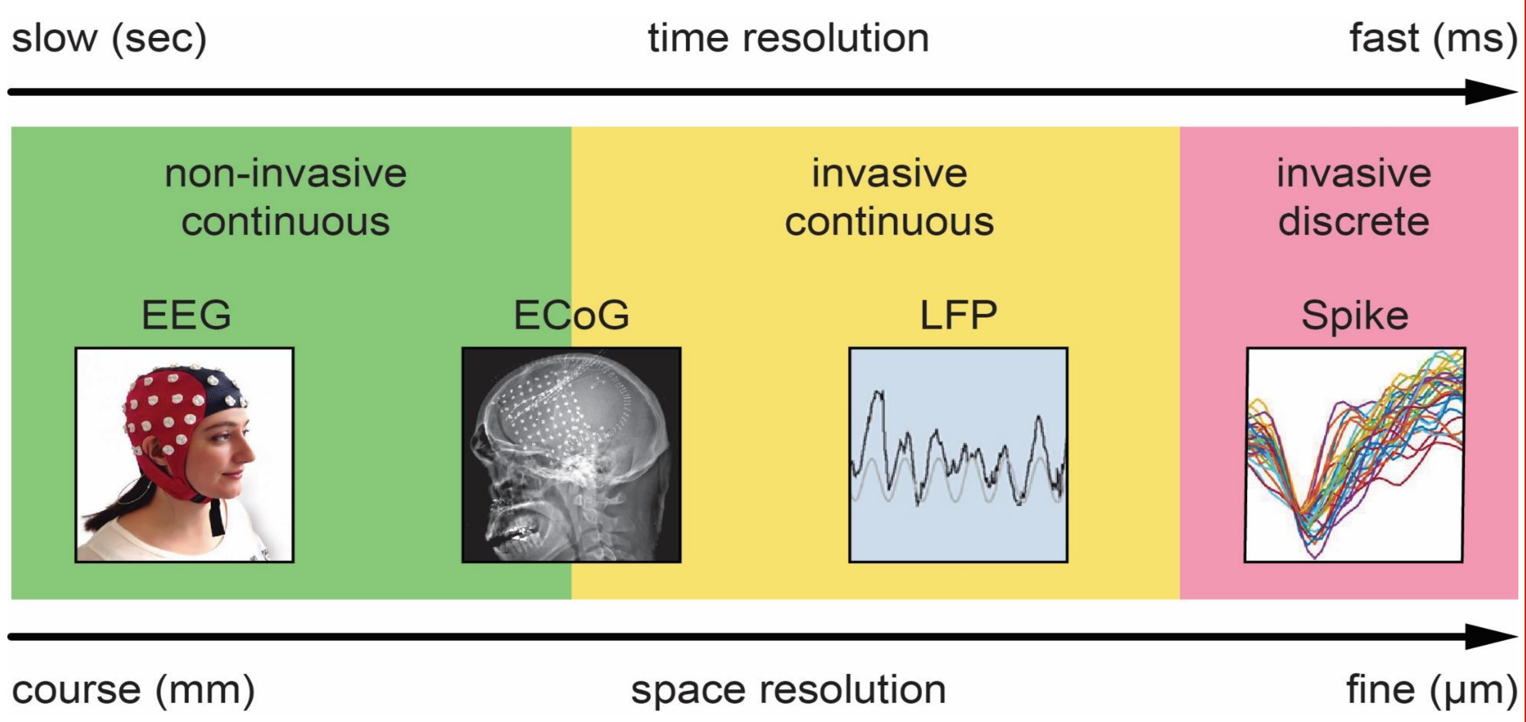
I. Introduction

- Multiscale neural activities can be recorded simultaneously, but they are different in many aspects. Also, the parameters of different stochastic models in the BMI need to be fitted in real time under the closed-loop scenario.
- The adaptive multiscale BMI can decode the kinematic state and tune parameters adaptively in real time.



References:

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M. Shanechi et al., Nature Communications, 2016;
A. Orsborn et al., IEEE Trans. Neural Syst. Rehabil. Eng., 2012;
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II. Multiscale BMI Decoder

- The dynamic system and the observation models

Kinematic state $x_t = A x_{t-1} + B u_t + w_t$

Continuous signal $y_t = C x_t + v_t$

$$p(N_t^{1:C}|x_t) = \prod_{c=1}^{C} (\lambda(t|x_t;\phi_c)\Delta)^{N_t^c} \exp(-\lambda(t|x_t;\phi_c)\Delta)$$

Discrete signal — Firing rate — Time bin

- Conditionally independent assumption

$$p(y_t, N_t^{1:C}|x_t) = p(y_t|x_t)\,p(N_t^{1:C}|x_t)$$

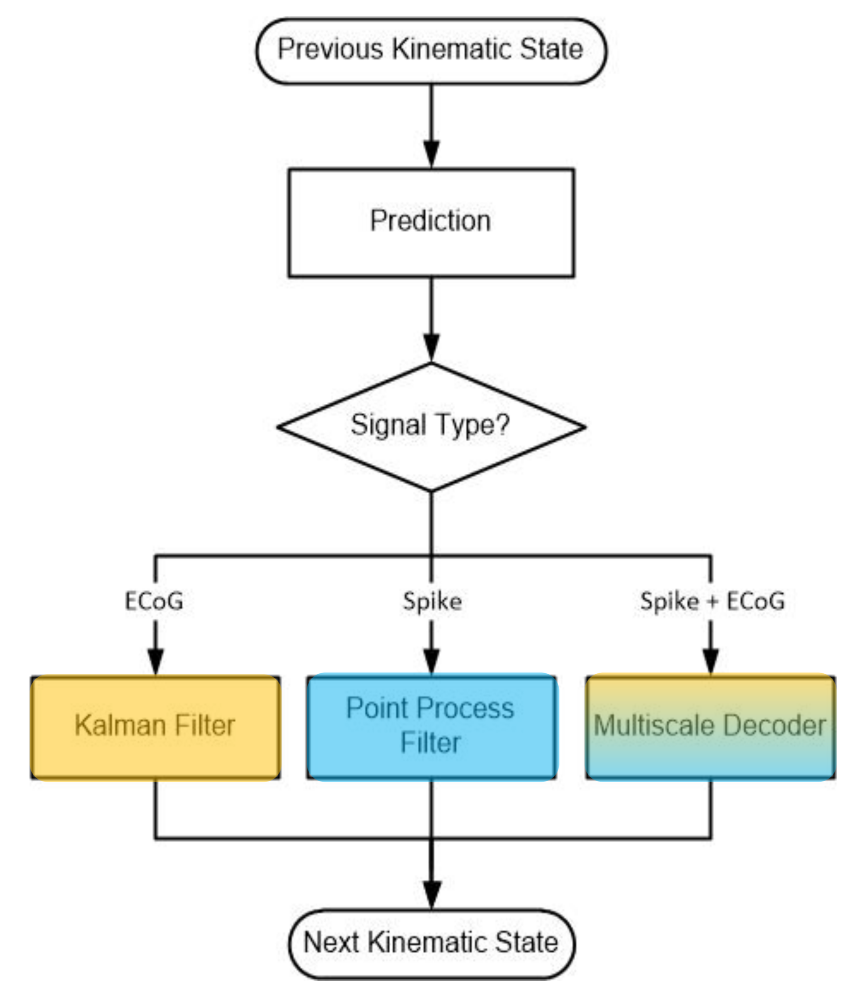
- The prediction

$$x_{t|t-1} = A x_{t-1|t-1}$$
$$Q_{t|t-1} = A Q_{t-1|t-1} A^T + W$$

- The update

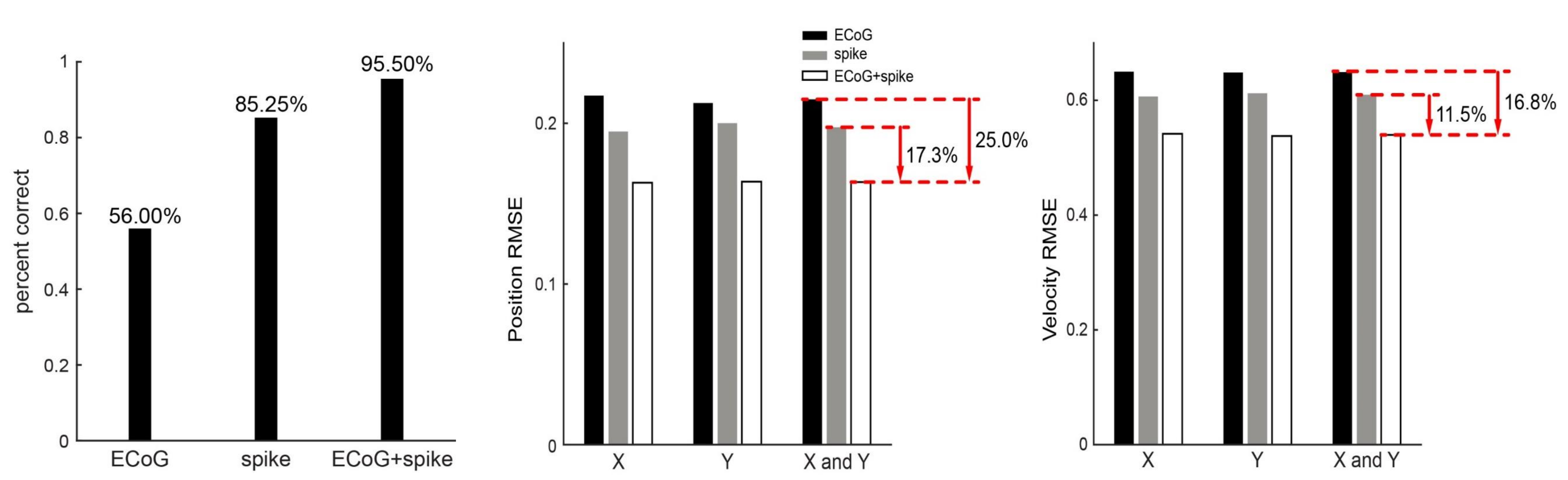
$$Q_{t|t}^{-1} = Q_{t|t-1}^{-1} + C^T V_t^{-1} C + \left[\sum_{c=1}^{C} \tilde{\alpha}_c \tilde{\alpha}_c^T \lambda_c(t|x_t)\Delta\right]_{x_{t|t-1}}$$

$$x_{t|t} = x_{t|t-1} + Q_{t|t} \times \left[C^T V_t^{-1}[y_t - C x_t]\right]_{x_{t|t-1}} + Q_{t|t} \times \left[\sum_{c=1}^{C} \tilde{\alpha}_c [N_t^c - \lambda_c(t|x_t)\Delta]\right]_{x_{t|t-1}}$$

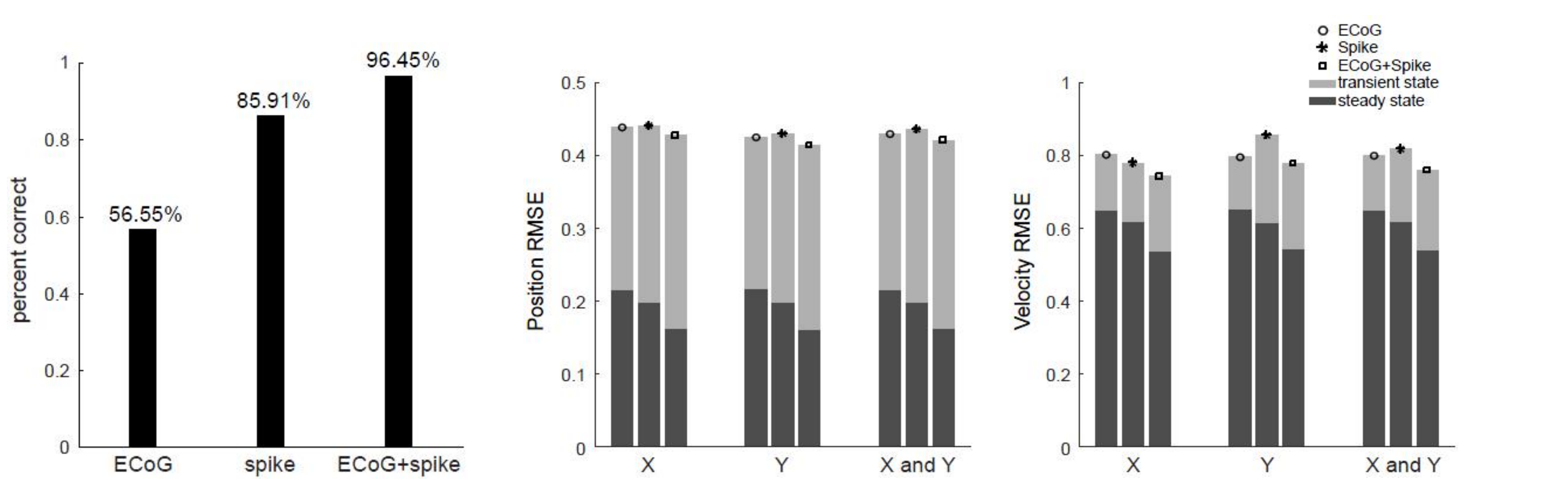


IV. Results

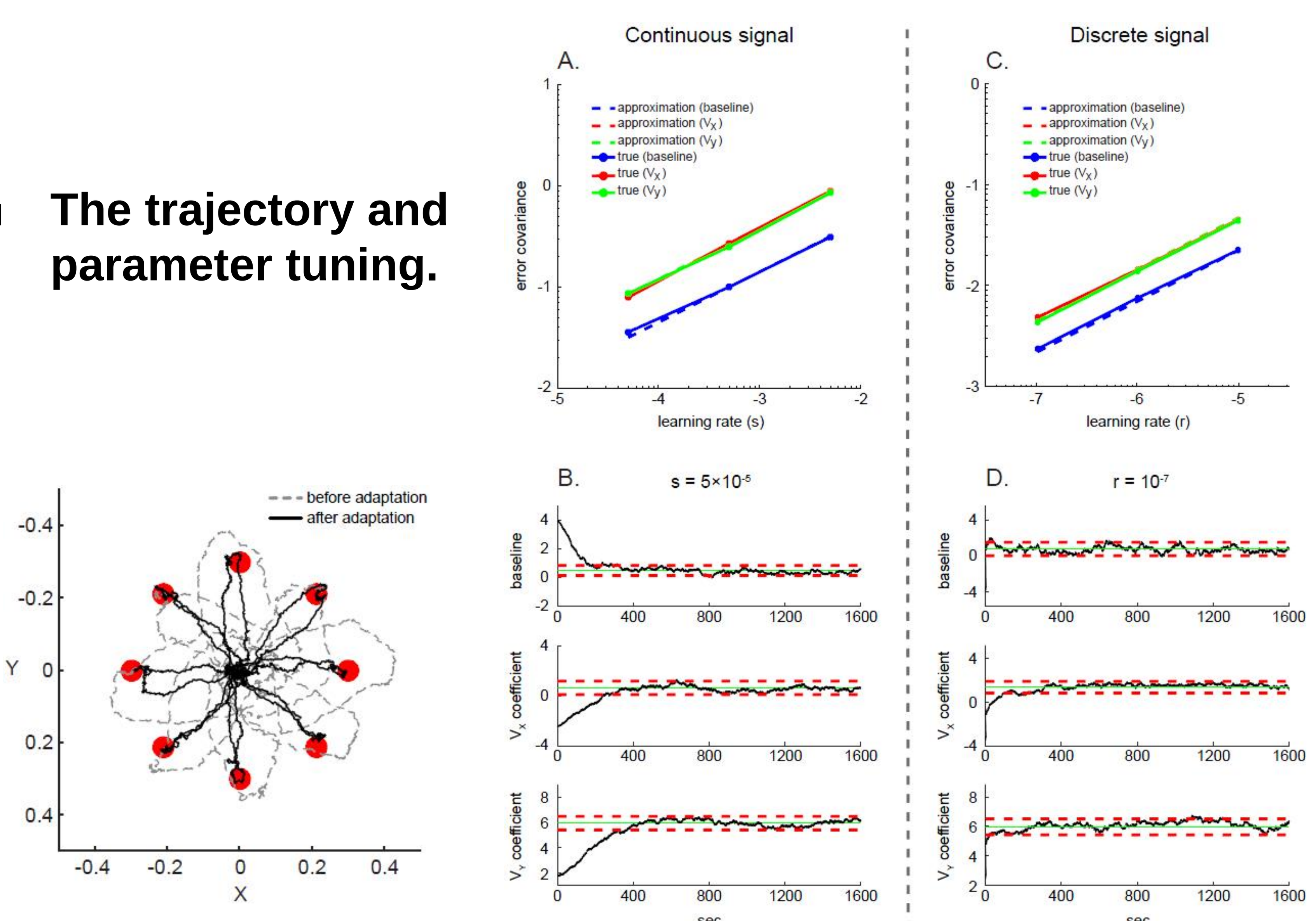
- **The RMSE and percent correct with known parameters.**



- **The RMSE and percent correct with unknown parameters.**

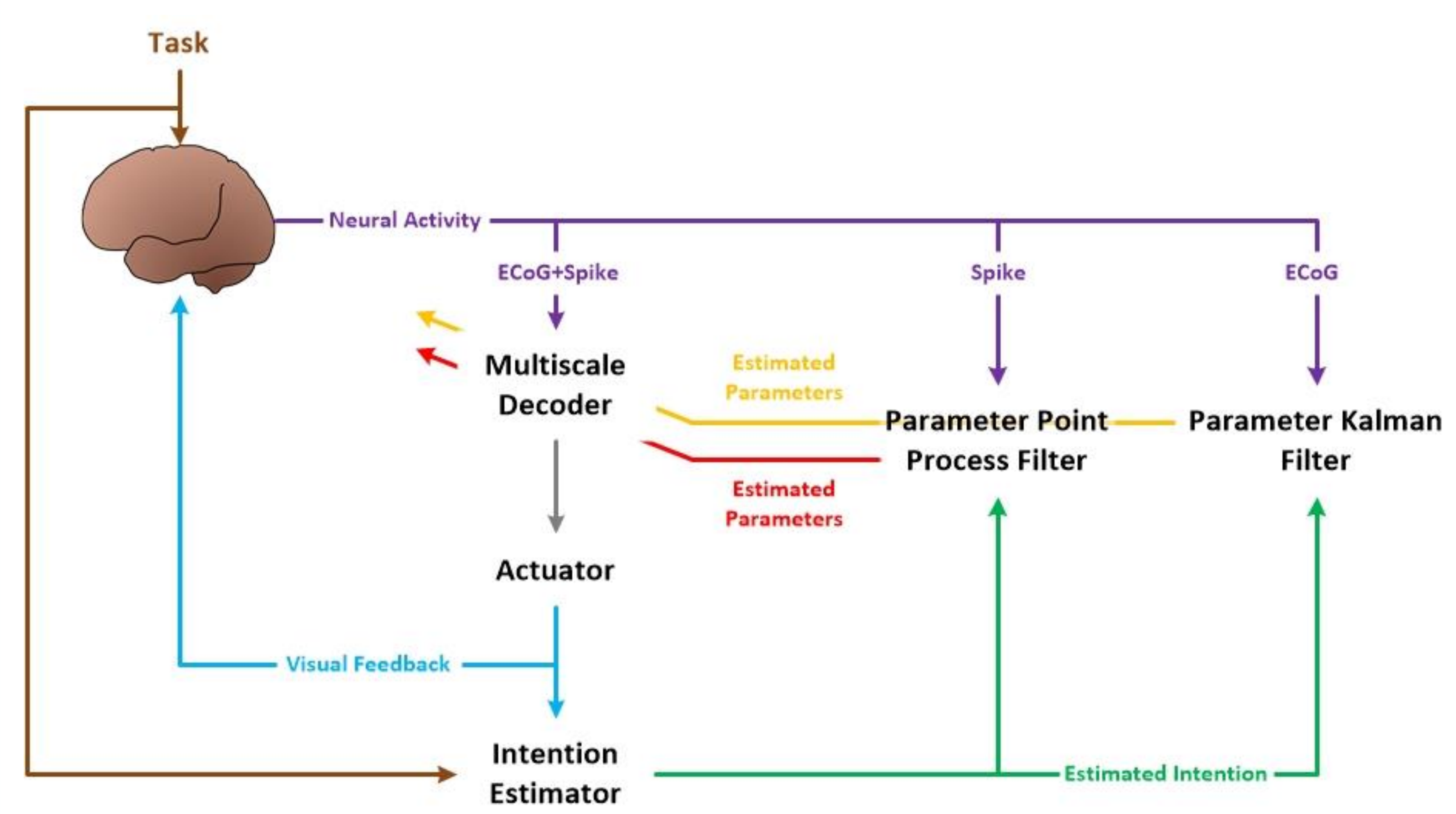


- **The trajectory and parameter tuning.**



III. BMI with Adaptation

- The adaptive multiscale BMI framework



- The adaptive filters

$$\phi_{t|t-1} = \phi_{t-1|t-1}$$
$$Q_{t|t-1} = Q_{t-1|t-1} + Q \quad \text{The learning rate}$$
$$Q_{t|t}^{-1} = Q_{t|t-1}^{-1} + \hat{v}_t \hat{v}_t' \lambda(t|\phi_{t|t-1})\Delta$$
$$\phi_{t|t} = \phi_{t|t-1} + Q_{t|t}\hat{v}_t(N_t - \lambda(t|\phi_{t|t-1})\Delta)$$
$$\psi_{t|t-1} = \psi_{t-1|t-1}$$
$$S_{t|t-1} = S_{t-1|t-1} + S \quad \text{The learning rate}$$
$$S_{t|t}^{-1} = S_{t|t-1}^{-1} + \hat{v}_t \hat{v}_t' Z^{-1}$$
$$\psi_{t|t} = \psi_{t|t-1} + S_{t|t}\hat{v}_t Z^{-1}(y_t - \hat{v}_t'\psi_{t|t-1})$$

Learning rates can be calibrated by our previous work.

V. Conclusion

- We confirm in simulations that the multiscale BMI can enhance the decoding performance.
- The adaptive filters can track the parameters of the neural encoding models in real time. Also, the steady state error covariance can be estimated precisely.
- The next step is applying the adaptive multiscale BMI in experiments.

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