Partitioning Feedforward from Feedback Components of Bayesian Sensorimotor Learning

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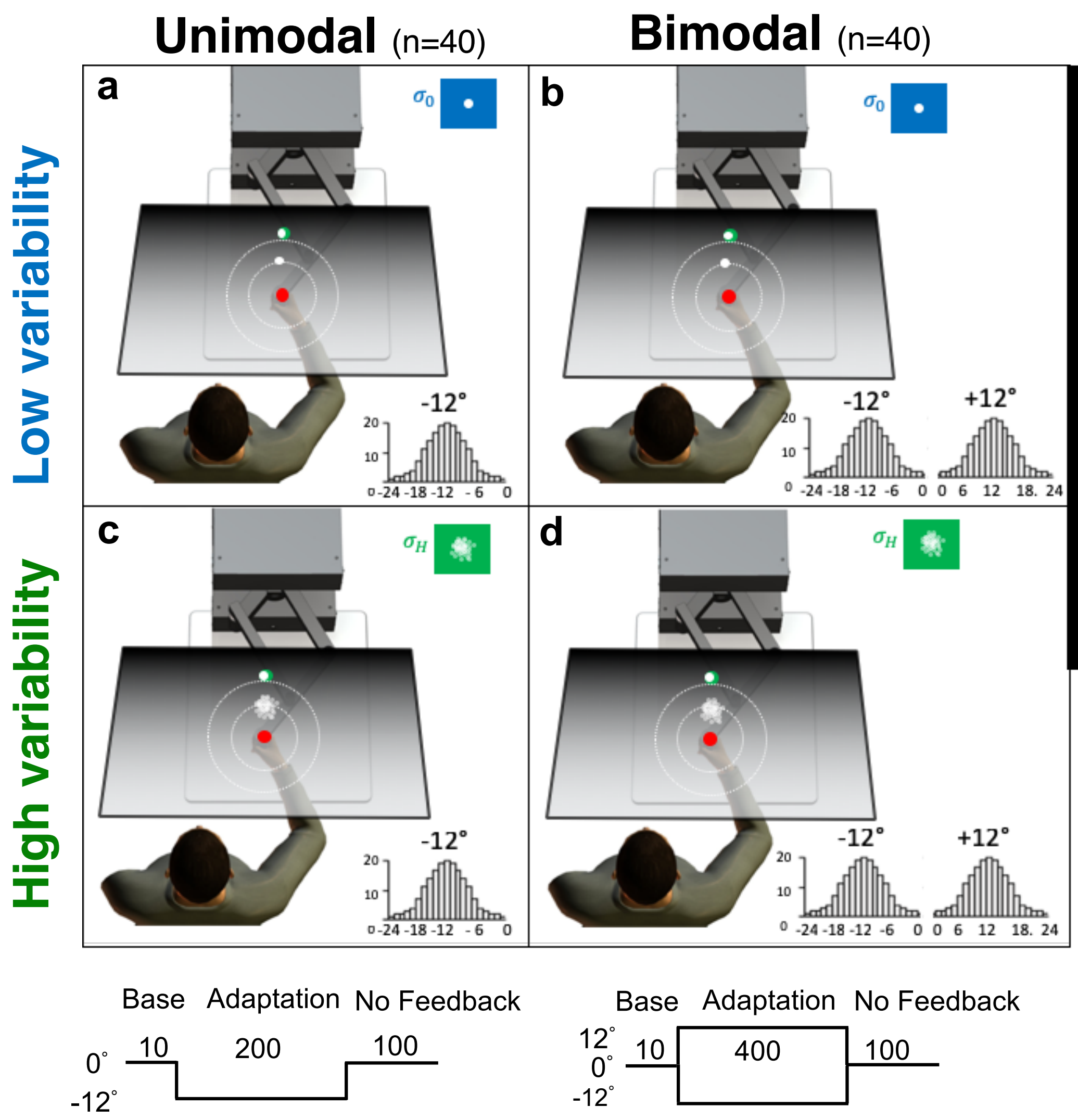
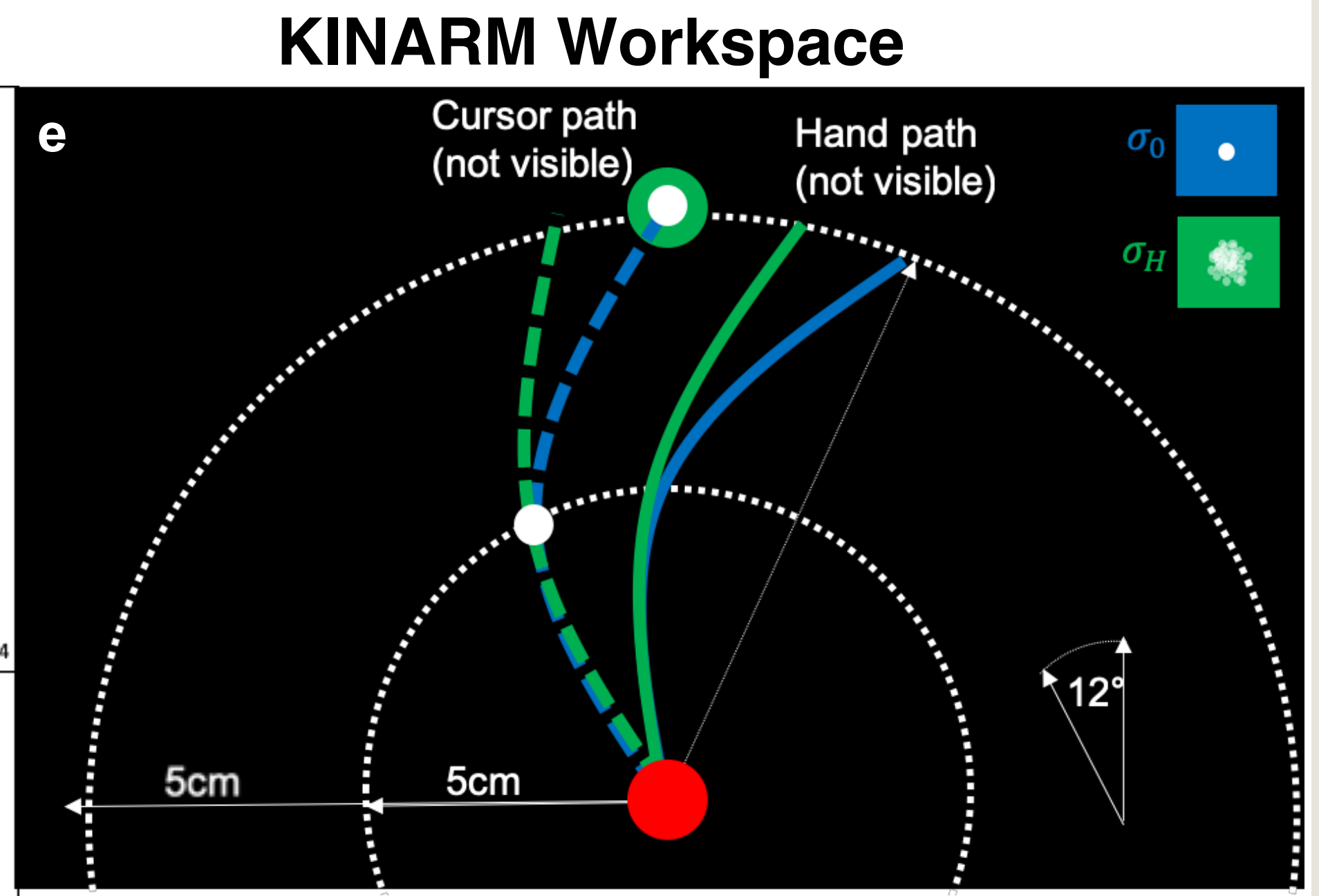
Overview and aims

Movement planning and execution are accomplished through optimal integration of sensory information and internal predictive signals[1,2,3]. This integration may occur in a Bayes-optimal manner during visuomotor feedback control[4,5]. However, it remains unclear whether feedforward updating in visuomotor adaptation follows similar Bayesian principles[6]. We replicate Körding and Wolpert's (2004) findings that humans can integrate sensory information in Bayes-optimal fashion during feedback control, and extend these findings by asking whether feedforward adaptation also follows Bayesian principles, and what the time course for Bayesian integration is in both feedforward and feedback control.

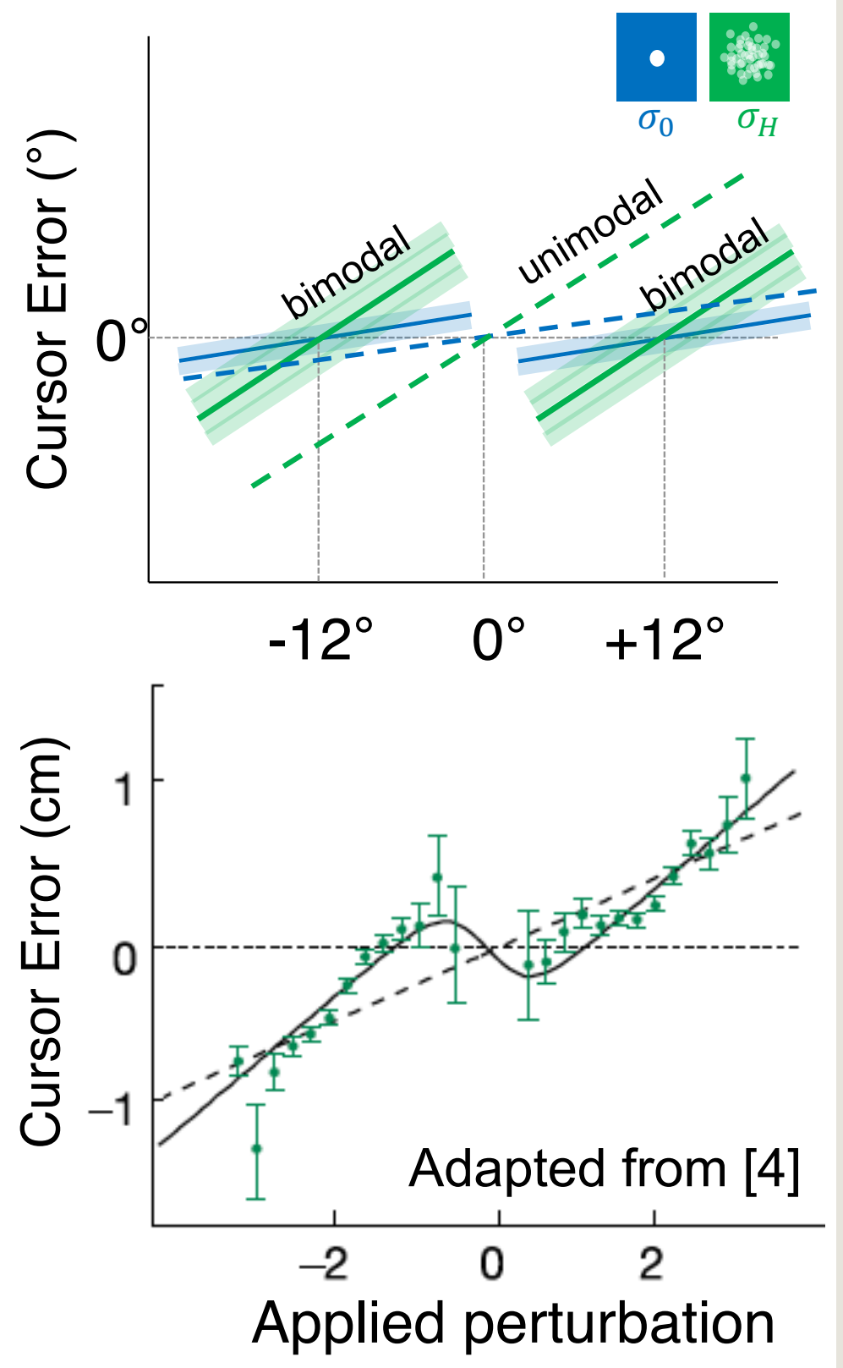
Methods





Experimental paradigm. (a-d) Pattern of midpoint feedback (colored inset), endpoint visual feedback, and distribution of applied rotation for each group. **(e)** KINARM workspace with example hand and cursor paths shown for different visual uncertainty conditions when a 12° CCW rotation is applied. Dashed white curves indicate spatial thresholds for triggering feedback.

Predictions



Adapted from [4]

- Adaptation will be faster and occur to a greater extent in the low variability group compared to the high variability group.
- Cursor and endpoint error (EE) will reflect Bayesian integration of the current sensory feedback (likelihood) and the learned prior throughout adaptation.
- Initial movement error (IME) (shortest path to target - movement vector 150ms after movement onset) will reflect the learned prior (uninfluenced by current sensory feedback), which follows a simple Bayesian update rule:

$$\mu_{prior}^{(i)} = \frac{\sigma_{prior}^2}{\sigma_{sensed}^2 + \sigma_{prior}^2}[x_{sensed}] + \frac{\sigma_{sensed}^2}{\sigma_{sensed}^2 + \sigma_{prior}^2}\left[\mu_{prior}^{(i-1)}\right]$$

- Accordingly, the unimodal group will learn a prior of -12.0 ± 4.0° and the bimodal group will learn an average of the CW and CCW prior distributions (0°).

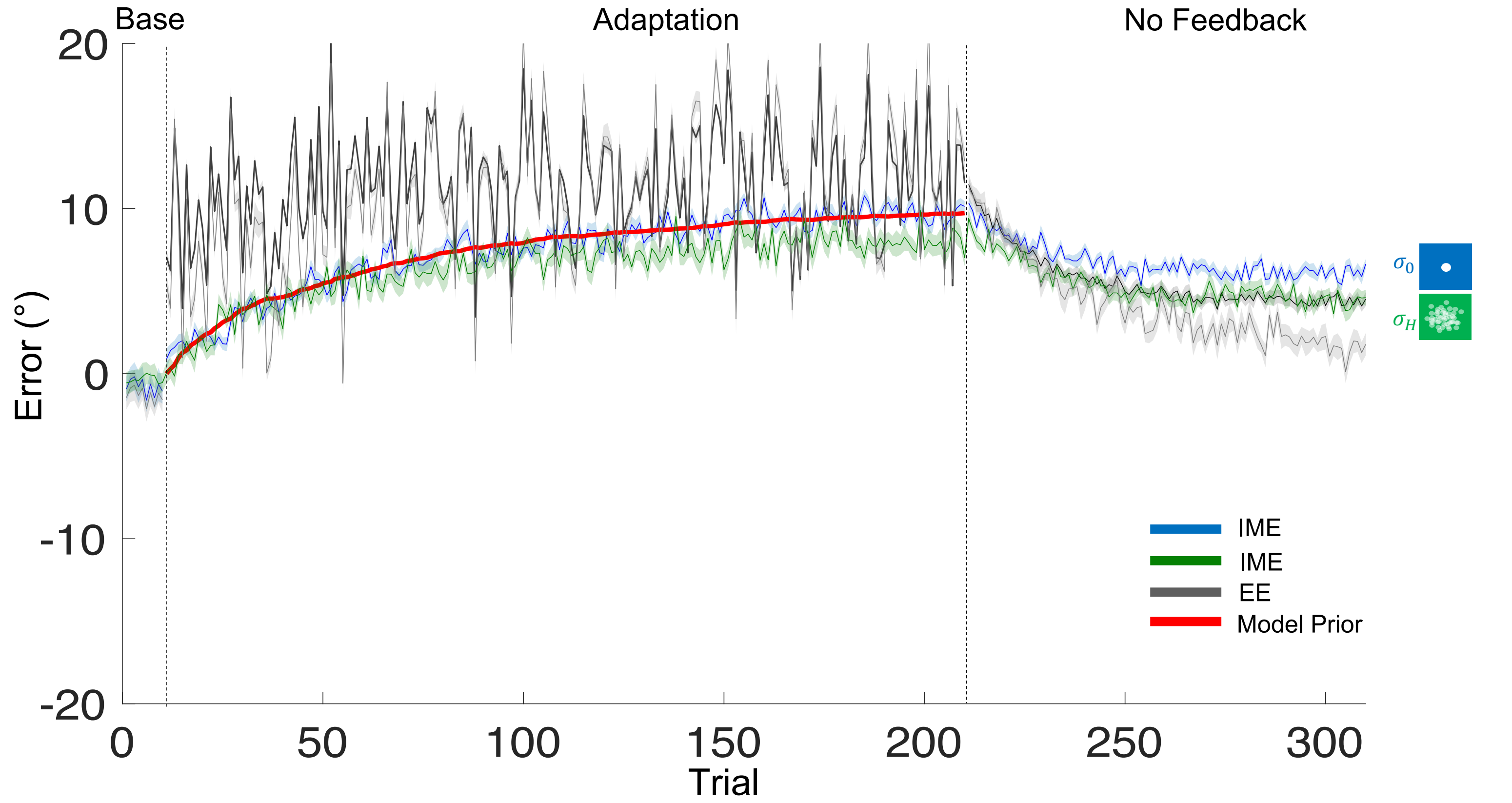
References

[1] Flanagan, J. R., & Wing, A. M. (1993). *Experimental Brain Research*, *95*(1), 131-143. **[2]** Wolpert, D. M., & Kawato, M. (1998). *Neural networks*, *11*(7-8), 1317-1329. **[3]** Sabes, P. N. (2000). *Current opinion in neurobiology*, *10*(6), 740-746. **[4]** Körding, K. P., & Wolpert, D. M. (2004). *Nature*, 427(6971), 244-247. **[5]** Hewitson, C. L., Sowman, P. F., & Kaplan, D. M. (2018). *eNeuro*, 5(4) **[6]** Cheng S, Sabes PN (2006) *Neural Computation*, (18)

Results

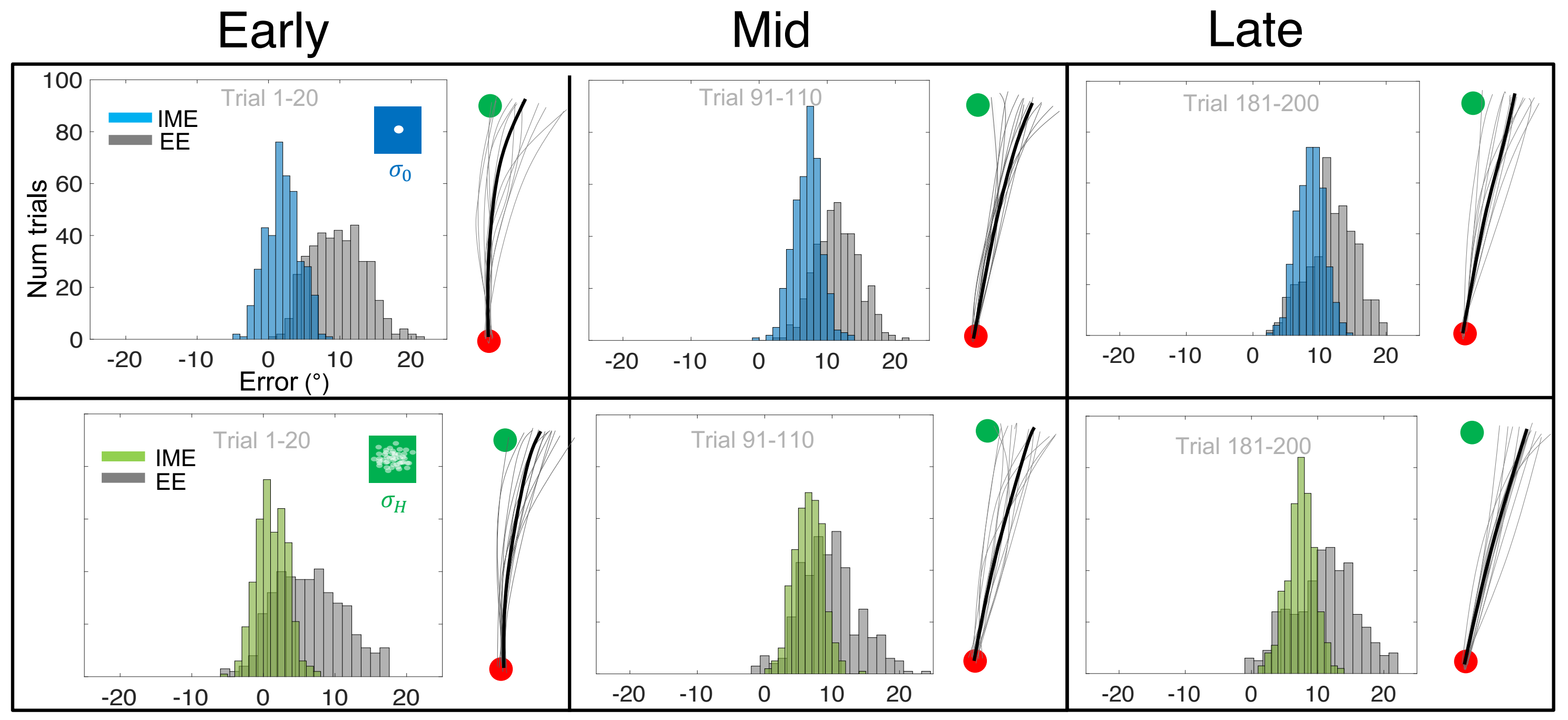
Unimodal

Rate and extent of adaptation is proportional to variability of sensory likelihood.

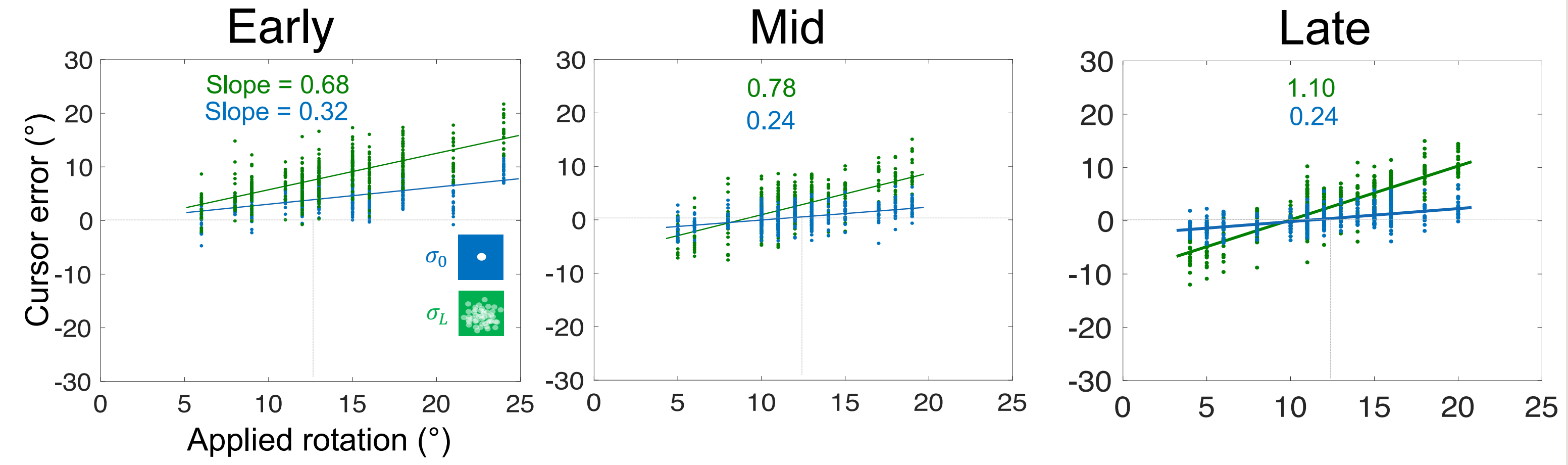


Initial movement error indicates
μ_{prior} = -9.6 ± 3.5° (81% adaptation) for σ_0
μ_{prior} = -8.2 ± 3.7° (70% adaptation) for σ_H

Bayes update model
μ_{prior} = -9.2 ± 4.0 °
(generalized from baseline)



- IME indicates a trend toward the prior from mid-adaptation onwards (σ_0 and σ_L).

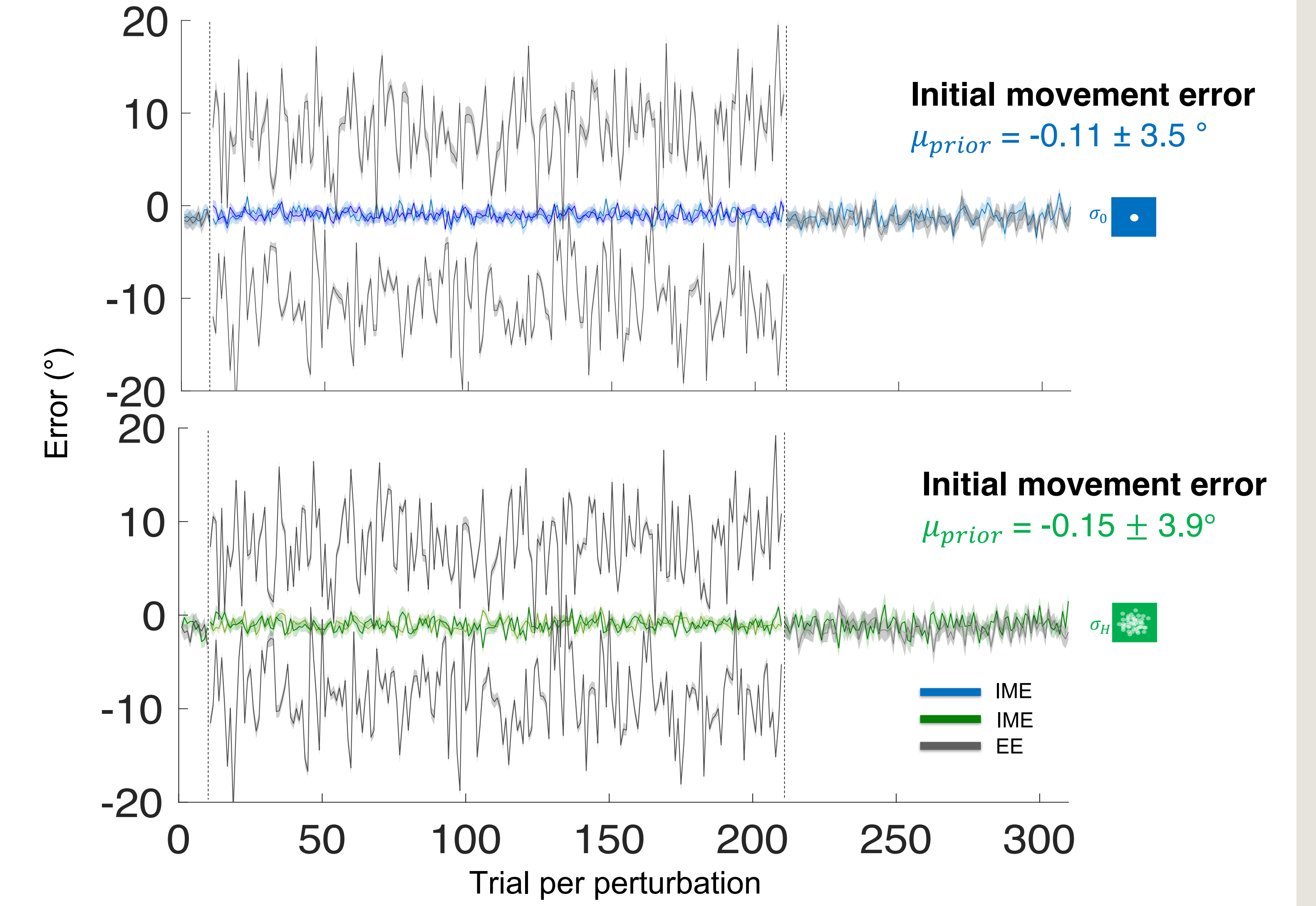


Bayesian integration (representative subject)

- Cursor error increases as function of noisy visual uncertainty throughout adaptation, indicating Bayesian integration of likelihood.
- Abscissa intersects the mean of the prior from mid/late adaptation.

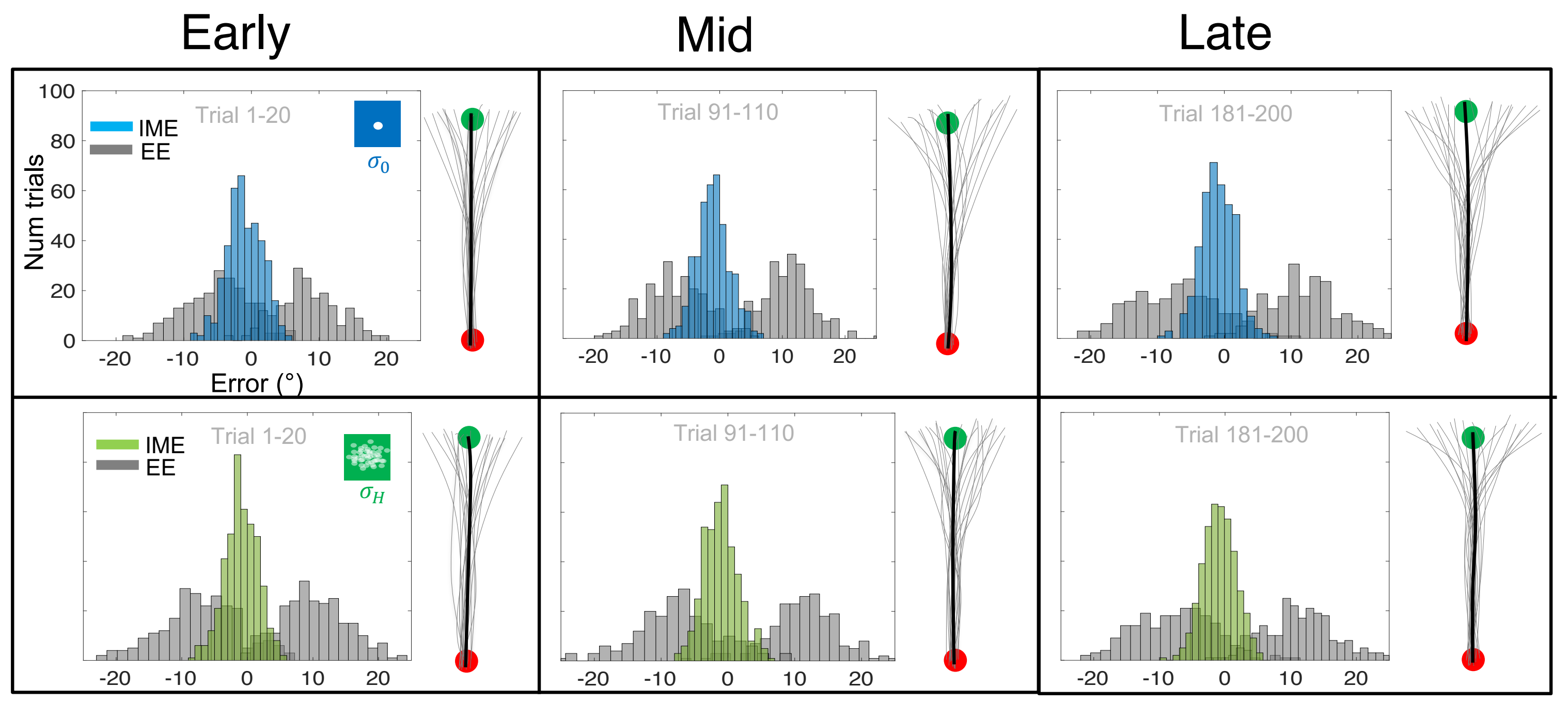
Results (cont.)

Bimodal

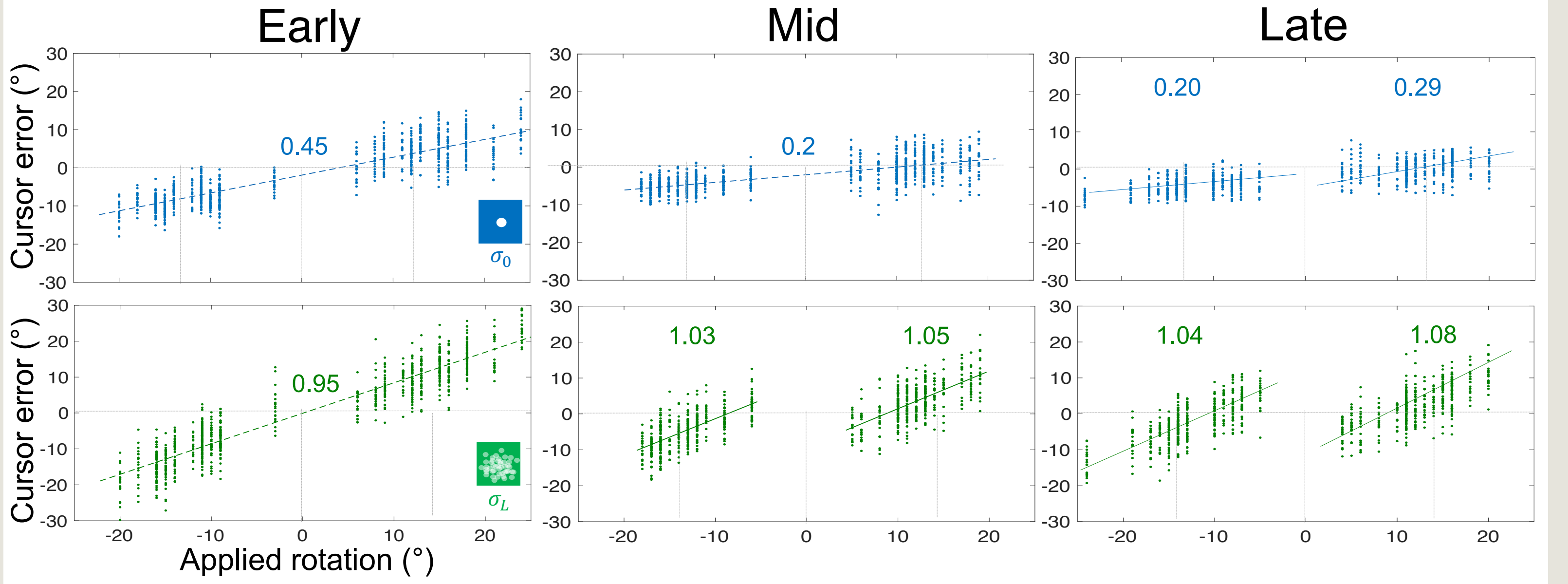


Initial movement error
μ_{prior} = -0.11 ± 3.5 °

Initial movement error
μ_{prior} = -0.15 ± 3.9°



- IME indicates a prior of 0° that remains stationary throughout adaptation (σ_0 and σ_L).



- Unimodal prior during early adaptation. Bimodal prior emerges mid-adaptation onwards.

Conclusions

- The rate and extent of visuomotor adaptation is proportional to the variability of the sensory likelihood.
- Initial movement error, which reflects feedforward rather than feedback influences, provides an accurate estimate of the evolving visuomotor prior.
- A unimodal prior is learned when either a unimodal or bimodal distribution of visuomotor rotations is imposed, as predicted by a Bayesian update model.
- Bayesian integration in sensorimotor learning[4] involves both *feedforward* and *feedback* components.