Unifying the sensory and motor components of sensorimotor adaptation

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Introduction

- Adaptation to shifted visual feedback consists of **sensory** and **motor** components [4]
  - **Sensory adaptation:** compensation for miscalibrations of vision and proprioception
  - **Motor adaptation:** compensation for errors in movement execution
- Does the motor system solve these problems independently, or in a unified manner?

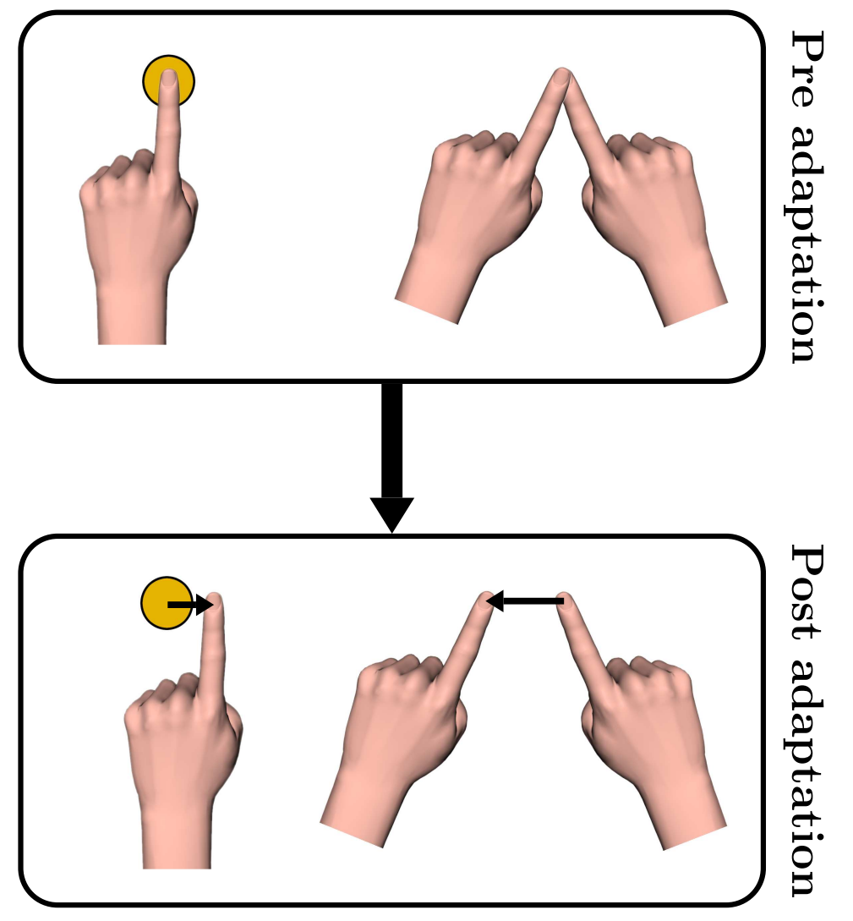
Sensory adaptation

- Shifts in vision and proprioception induced by persistent discrepancy between modalities
  - e.g. while wearing prism goggles
- Compensation for miscalibrations of vision and proprioception

$$v = y + r^v + \epsilon^v \qquad (r^v = \text{ visual shift})$$
$$p = y + r^p + \epsilon^p \quad (r^p = \text{Proprioceptive shift})$$

- Can be measured through sensory alignment tests
  - Use left hand as unadapted probe
- Affects movements **planning**

Sensory alignment tests:



Previous models of sensory adaptation

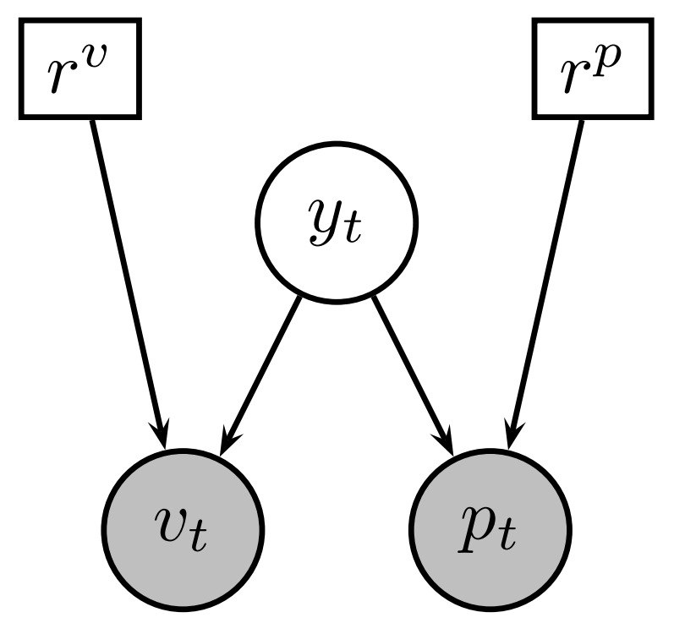
- Sensory miscalibrations r^v, r^p estimated via EM-based procedure [2]
- E-step:
  - Max. likelihood estimation of hand position

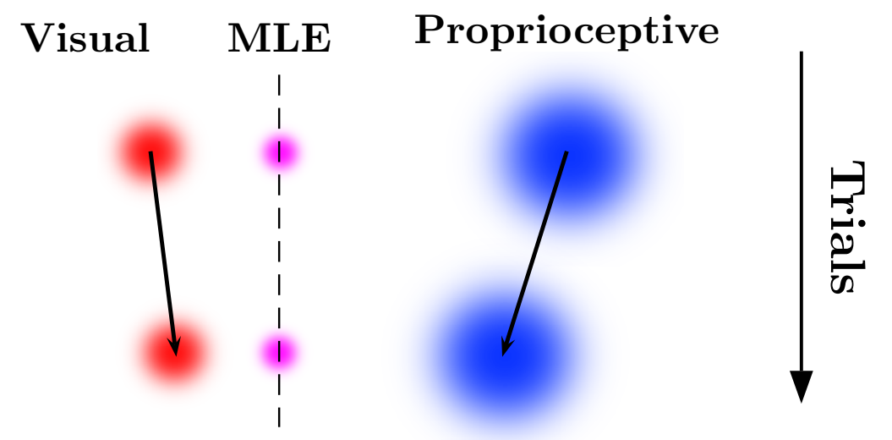
$$\hat{y}_t^{MLE} = \frac{\sigma_p^2}{\sigma_v^2+\sigma_p^2}(v_t - \hat{r}_t^v) + \frac{\sigma_v^2}{\sigma_v^2+\sigma_p^2}(p_t - \hat{r}_t^p)$$

- M-step:
  - Adapt both senses towards max. likelihood estimate of hand position

$$\hat{r}_{t+1}^v = \hat{r}_t^v + \gamma\sigma_p^2[(v_t - \hat{r}_t^v) - (p_t - \hat{r}_t^p)]$$
$$\hat{r}_{t+1}^p = \hat{r}_t^p + \gamma\sigma_v^2[(p_t - \hat{r}_t^p) - (v_t - \hat{r}_t^v)]$$

Sensory adaptation model:





Motor adaptation

- Compensation for errors in movement **execution**
  e.g. caused by a change in arm dynamics r^y
- Sensory adaptation only accounts for 50% of adaptation to shifted visual feedback
- Remaining adaptation is **motor**

Previous models of motor adaptation

- Estimate r^y by gradient descent on squared error (State-space model [1])

$$\hat{r}_{t+1}^u = \hat{r}_t^u + \beta(u_t + \hat{r}_t^u - \hat{y}_t)$$

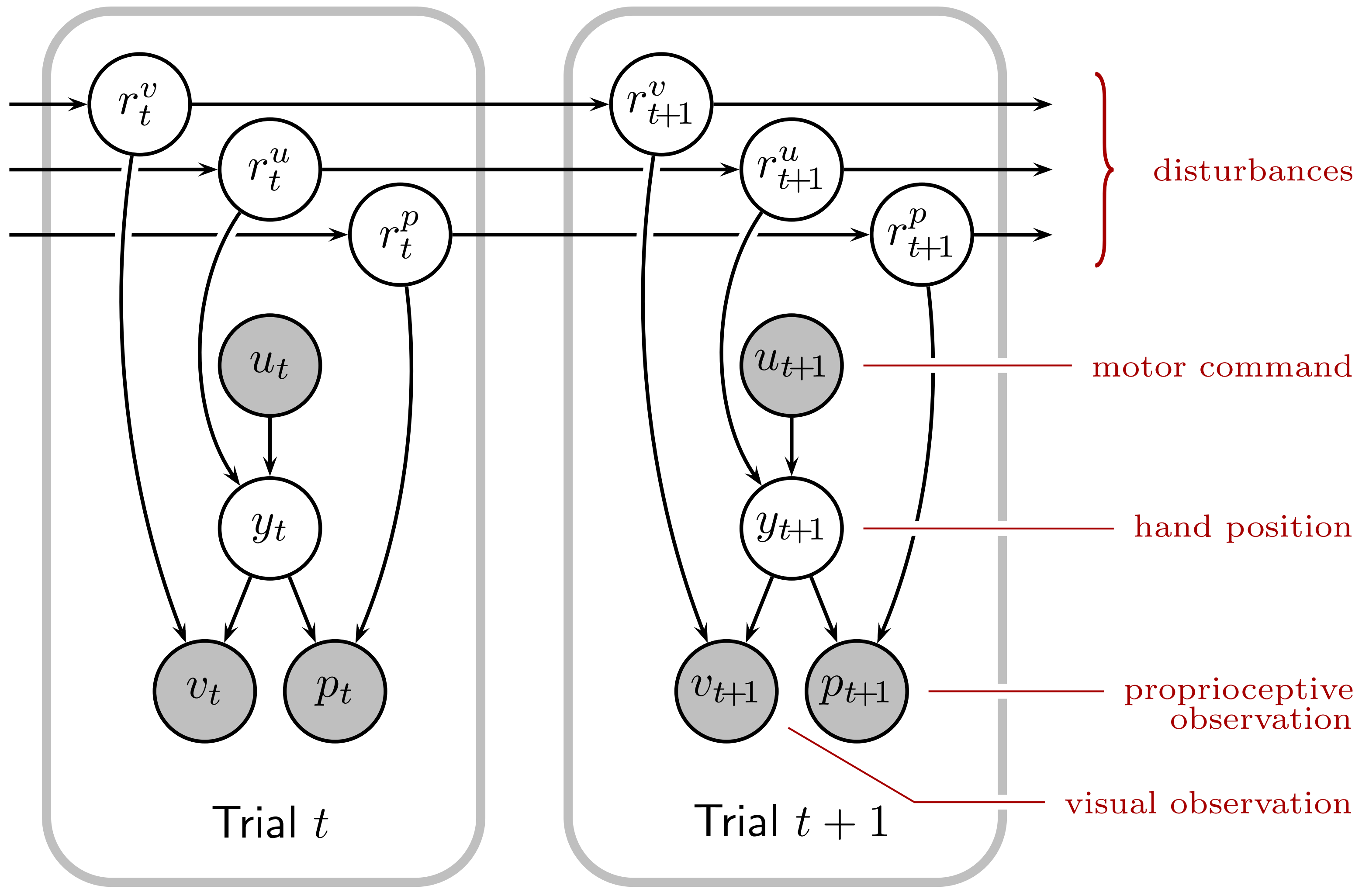
- Can use MLE of hand position, $\hat{y}_t^{MLE}$ when dealing with multiple modalities

Previous models can be combined to form a model of both sensory and motor adaptation (MLE model)

- Implicit assumption that sensory and motor adaptation are *independent*
- i.e. They are driven by distinct error signals and can occur independently of one another

A Unified Model

Consider full generative model of sensory feedback:



- Three potential sources of error:
  - Dynamics disturbance
  - Visual miscalibration
  - Proprioceptive miscalibration

$$y_t = u_t + r_t^y + \epsilon_t^y \qquad \epsilon_t^y \sim N(0, \sigma_y^2)$$
$$v_t = y_t + r_t^v + \epsilon_t^v \qquad \epsilon_t^v \sim N(0, \sigma_v^2)$$
$$p_t = y_t + r_t^v + \epsilon_t^p \qquad \epsilon_t^p \sim N(0, \sigma_p^2)$$

- More compactly: $\begin{pmatrix} v_t - u_t \\ p_t - u_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} r_t^v + \epsilon_t^v \\ r_t^p + \epsilon_t^p \\ r_t^u + \epsilon_t^u \end{pmatrix}$ or $\mathbf{z}_t = H(\mathbf{r}_t + \boldsymbol{\epsilon}_t)$

- Assumed disturbance dynamics:

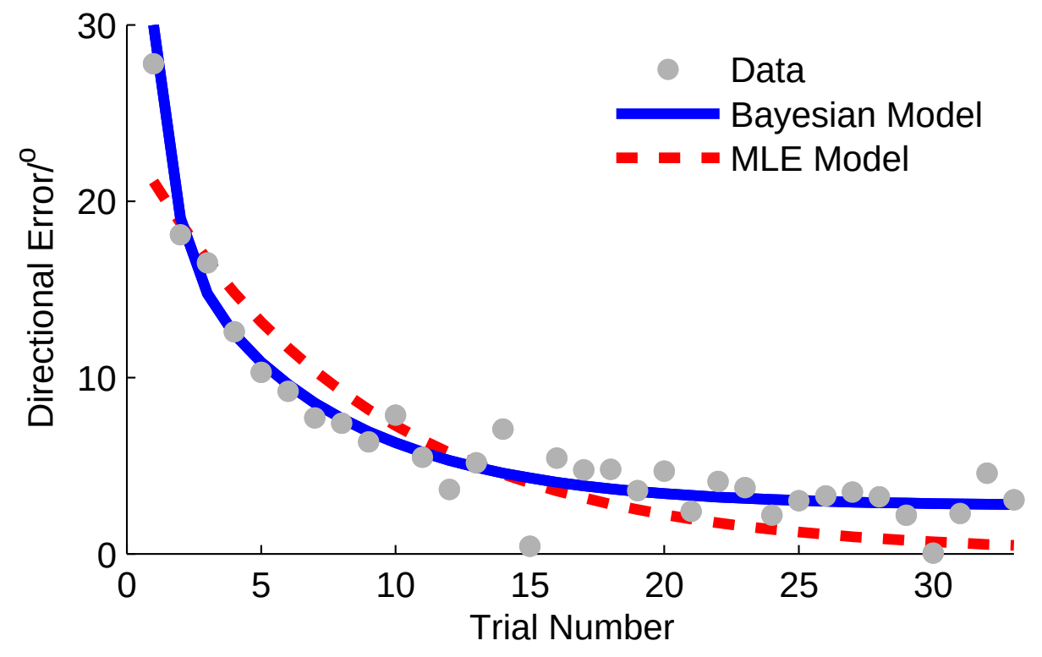
$$\mathbf{r}_{t+1} = A\mathbf{r}_t + \boldsymbol{\eta}_t \qquad \boldsymbol{\eta}_t \sim N(\mathbf{0}, Q) \qquad (1)$$

Bayesian model: Adaptation = Inference of disturbances

- Linear/Gaussian → Kalman filter
- 2 observation modalities, 3 unknown disturbances
  - Adaptation depends strongly on assumed disturbance dynamics (1)

Fits to visuomotor adaptation data

- Adaptation to a 30^o rotation of visual feedback (data from [3])



- Compare model fits via Akaike information criterion (lower = better)

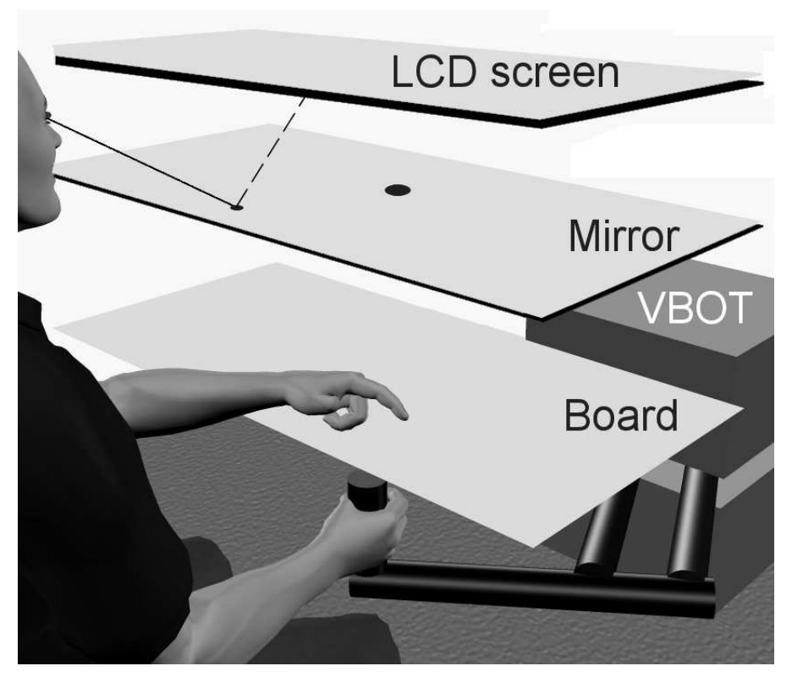
MLE-based model: $AIC = 159.6$
Bayesian model: $AIC = 126.0$

- Bayesian model provides a better fit
- However, a stronger test is possible to distinguish decisively between these models:

Sensory and motor adaptation are no longer independent in the Bayesian model

- **Prediction:** Force field adaptation will also lead to sensory adaptation, *even though there is no discrepancy between senses*
- Not predicted by MLE model

Experiment



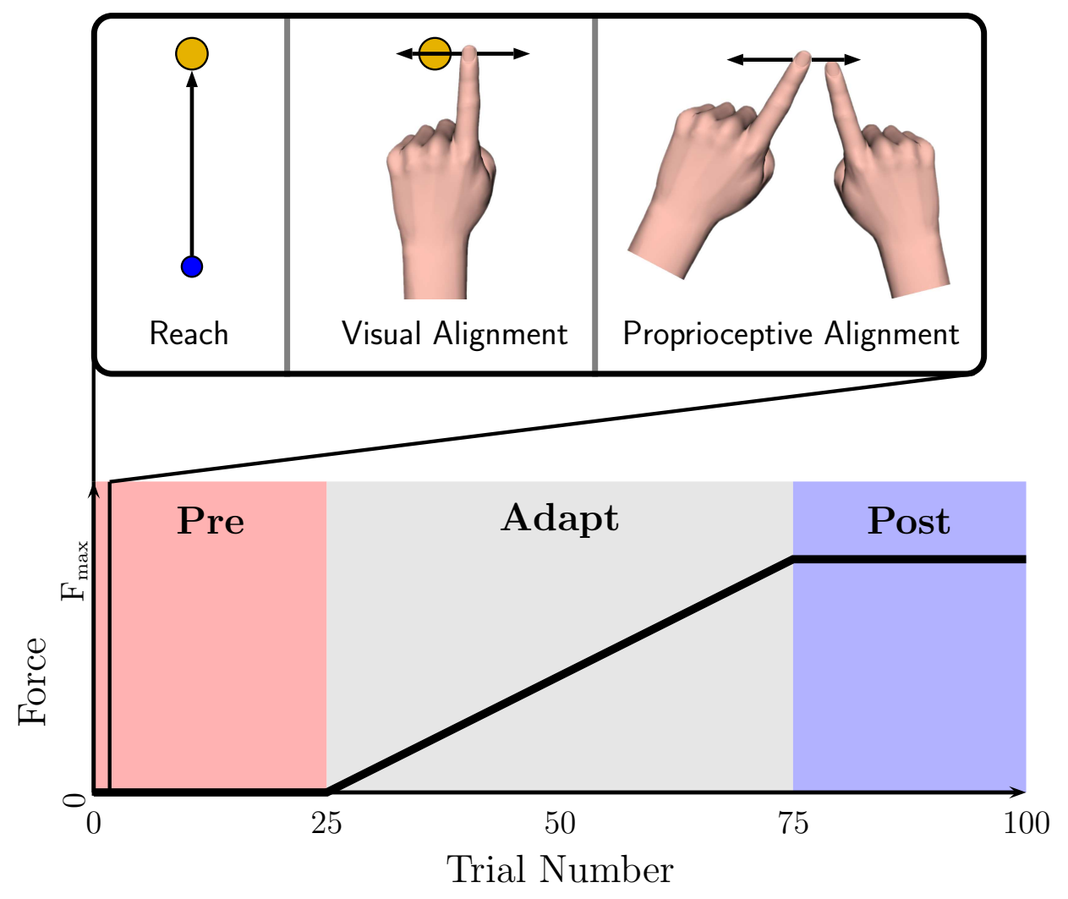
Test whether force field adaptation also leads to sensory adaptation

Experimental setup

- 11 right-handed subjects
- Mirror/projection setup provided veridical feedback of right hand position
- 3 phases to each trial:
  - Reaching movements to a visual target (with visual feedback)
  - Visual alignment test
  - Proprioceptive alignemnt test
- 25 pre-adaptation baseline trials
- Velocity-dependent force field gradually introduced over next 50 reach trials

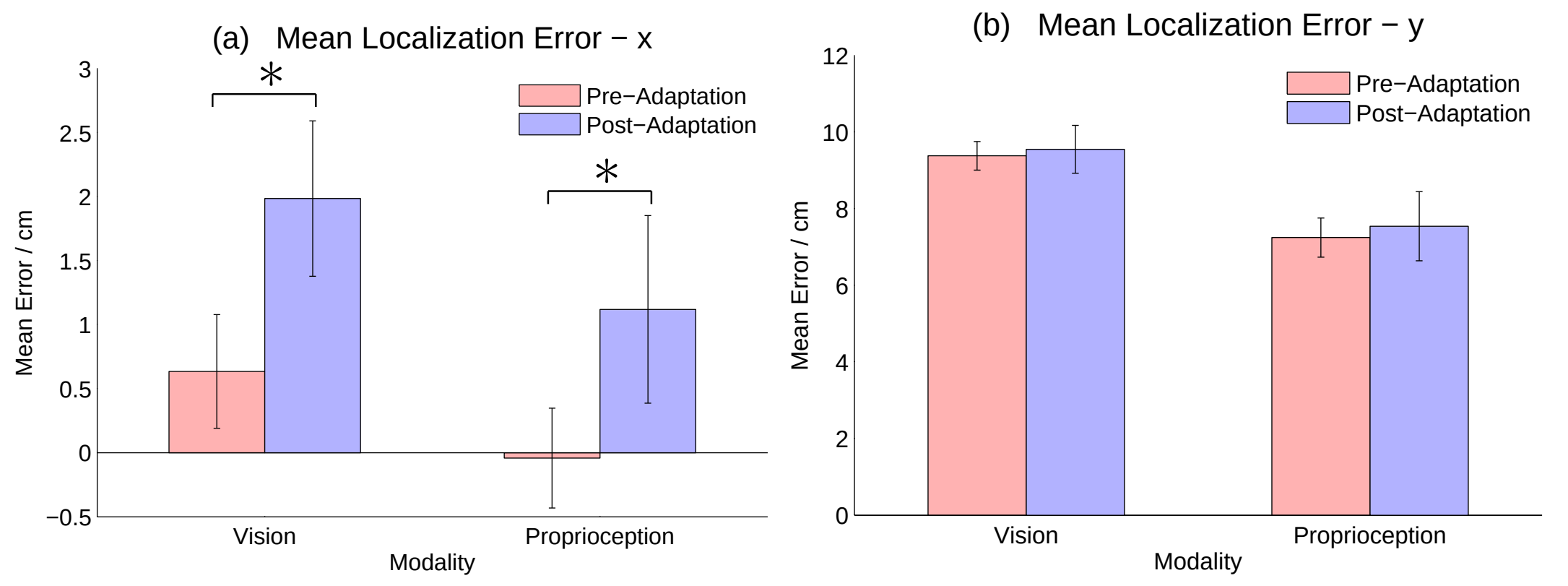
$$F_x = \alpha\dot{y} \qquad (2)$$

- 25 post-adaptation trials with maximum force field strength



Results

- Comparison of average alignment test errors pre- vs post-adaptation
- Results represent average across subjects. Error bars = SEM

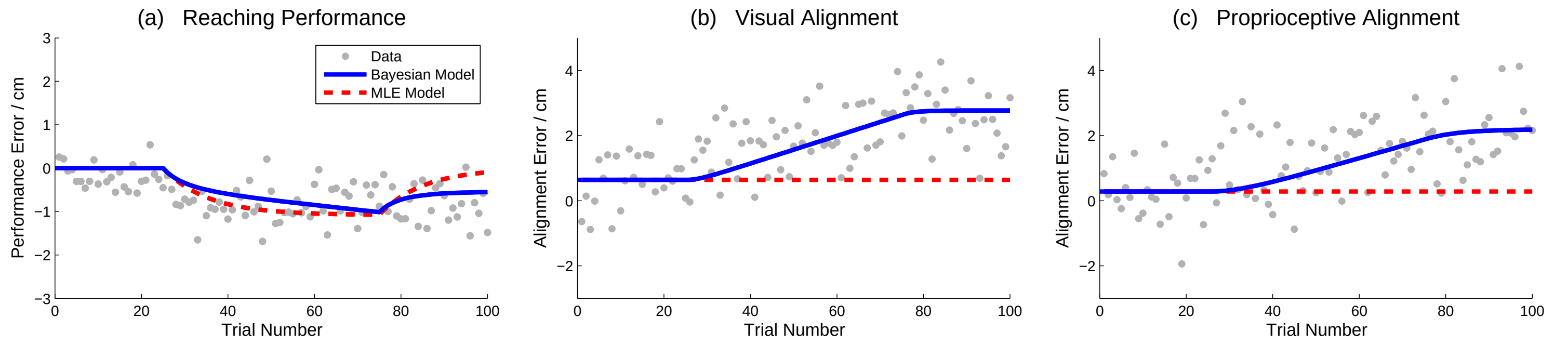


$* \ p < .05$
(1-tailed t-test)

Shifts only found in direction of perturbation

Model fits to data

- Parameters estimated by minimizing squared prediction over both reaching and alignment test performance



Conclusions

- Sensory and motor adaptation are *not* independent
  - Cannot induce one without the other
- Strongly supports the Bayesian adaptation model
- The brain solves adaptation problems in a statistically principled and unified manner

References

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