



Modeling the relationship between reward and sensory feedback in sensorimotor adaptation

The cool, Kalm-an' collected

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Phenomenon

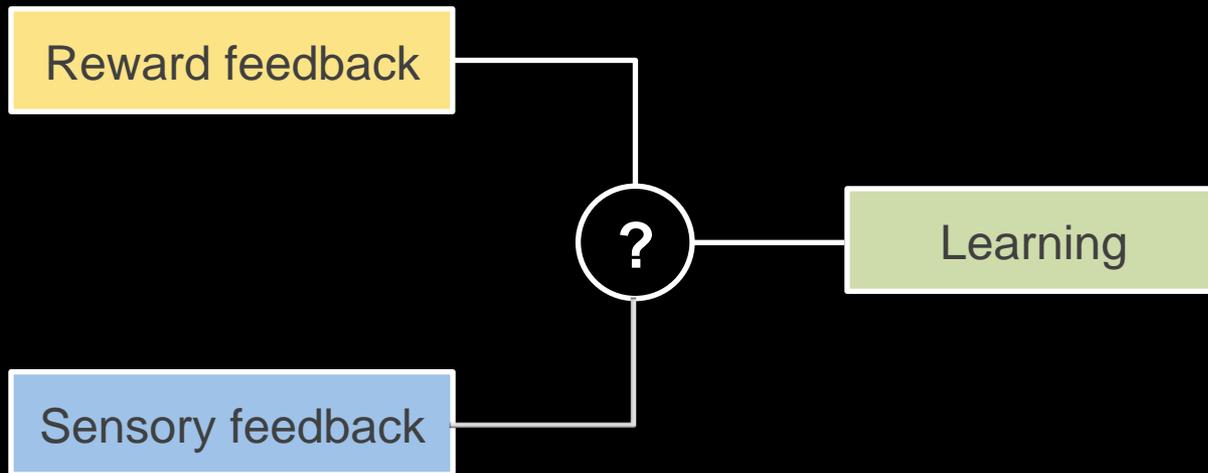


Phenomenon



Question

How are different sources of information combined during sensorimotor adaptation?



Background

- In adaptation tasks, **motor learning** has been shown to rely on **sensory feedback**.

(Krakauer et al., 2000; Ahmed & Wolpert, 2009; Izawa & Shadmehr, 2011; Nikooyan & Ahmed, 2012)

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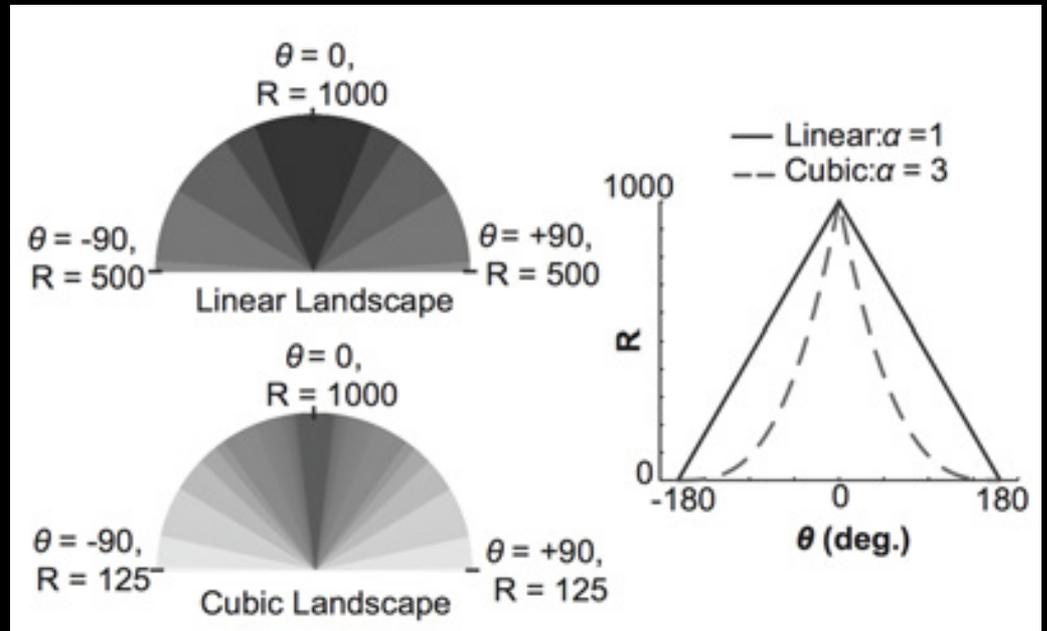
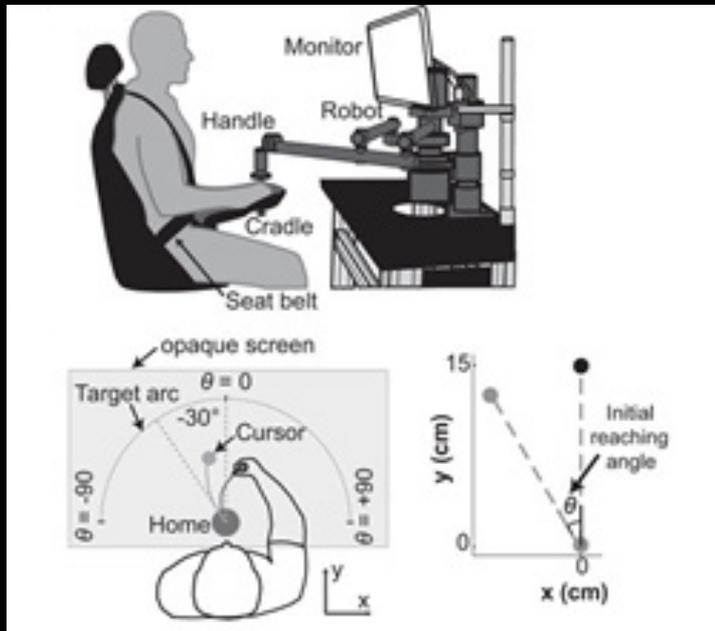
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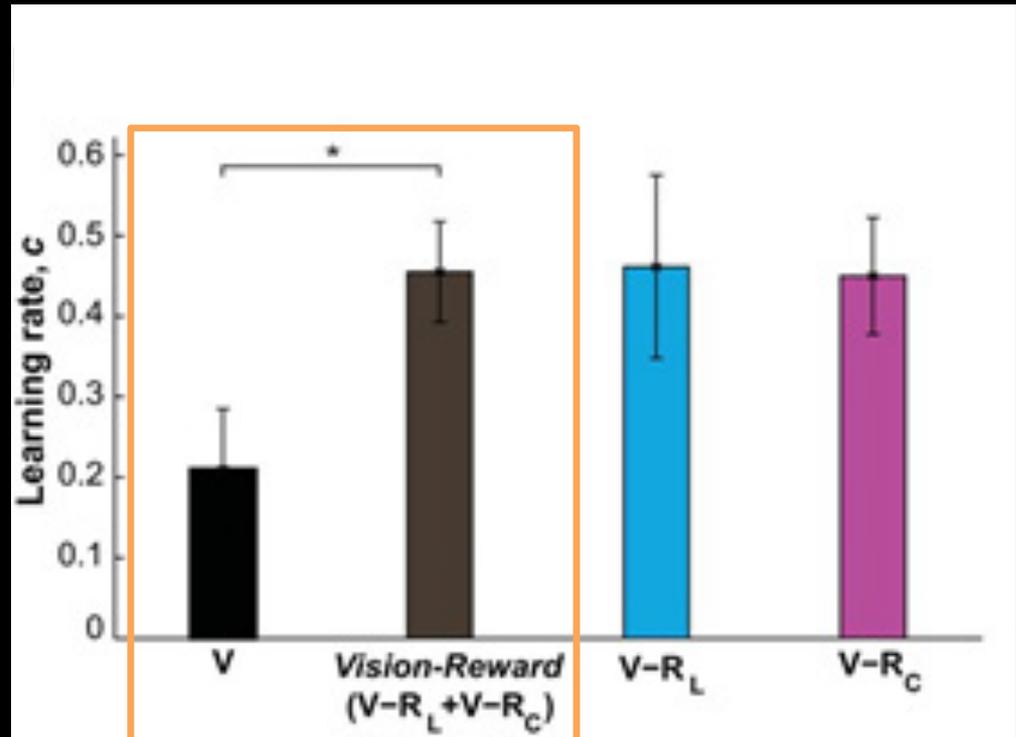
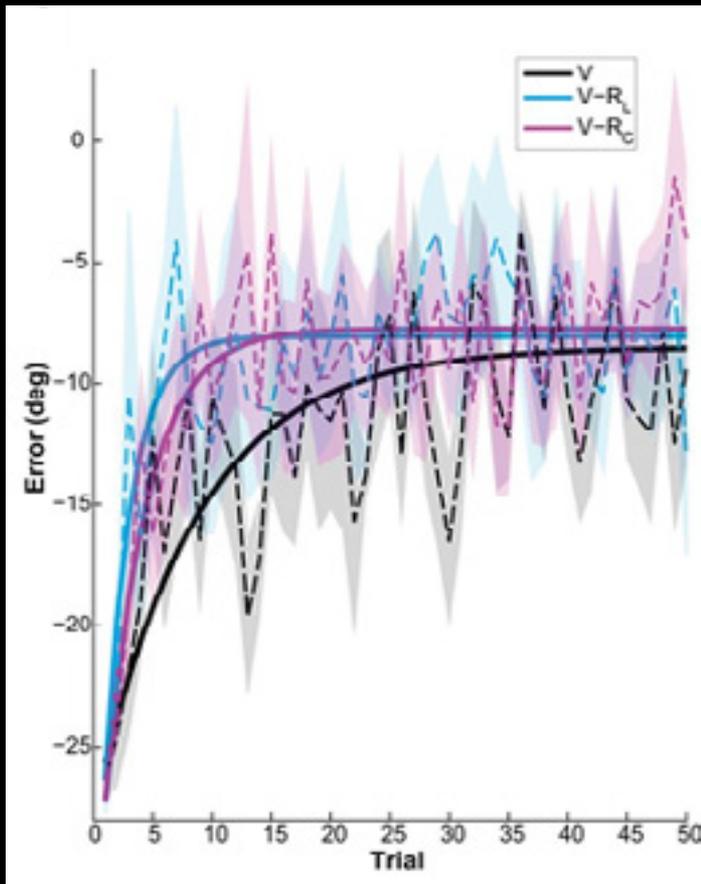
- In adaptation tasks, **motor learning** has been shown to rely on **sensory feedback**.
- Recent studies argued that **reward feedback** may also drive adaptation.
- When combined, sensory and reward feedback may **accelerate** motor learning, reducing end-point reaching variability.

(Krakauer et al., 2000; Ahmed & Wolpert, 2009; Izawa & Shadmehr, 2011; Nikooyan & Ahmed, 2012)

Nikooyan & Ahmed (2012)



Reward accelerates learning



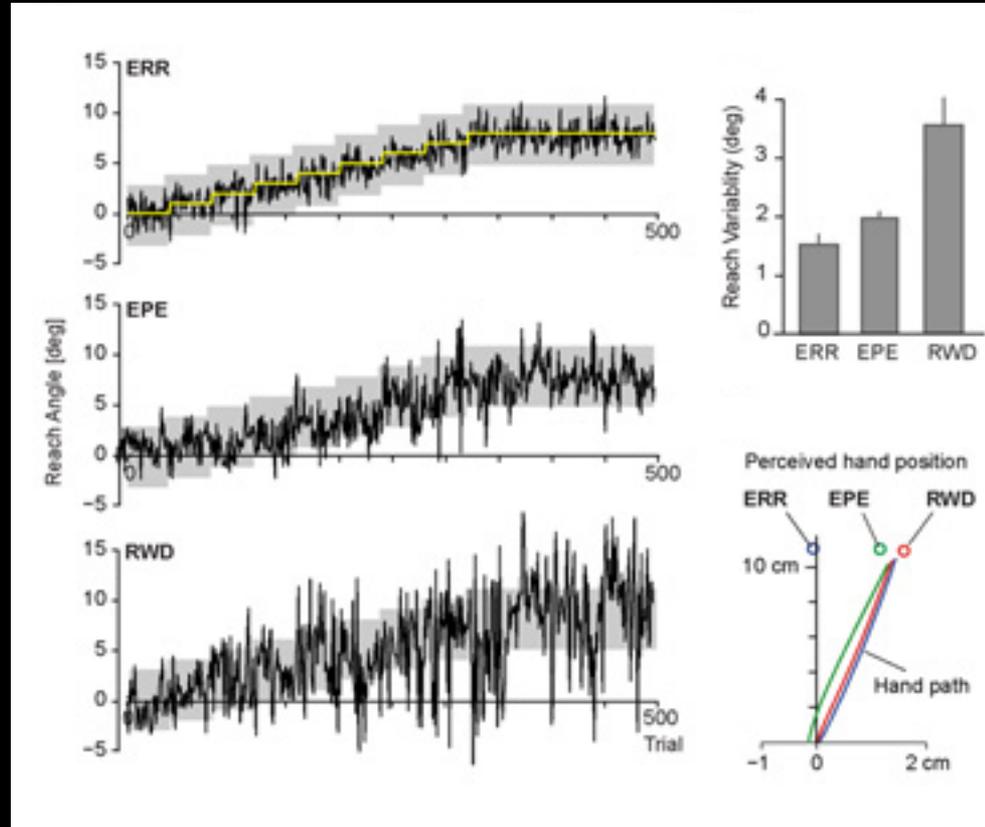
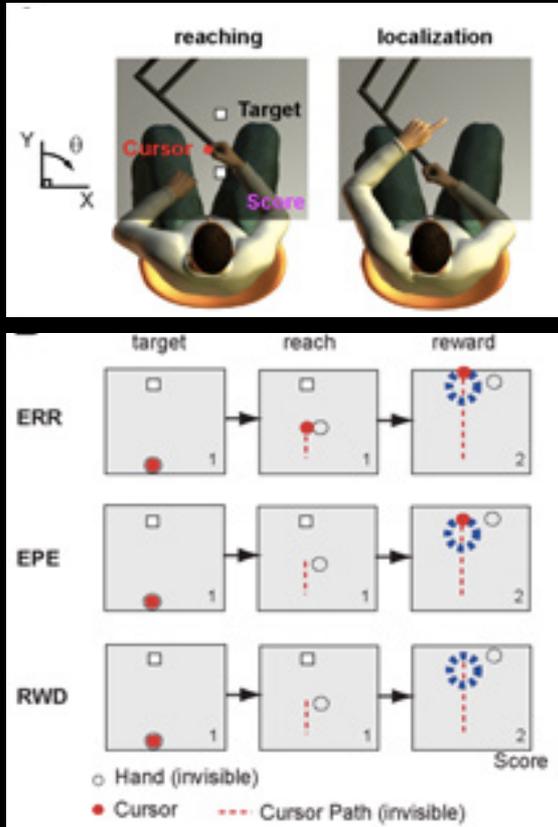
Hypotheses

Accelerated learning (**L**) during sensorimotor adaptation results from the combination of reward (**R**) and sensory (**S**) feedback:

$$H1: L = f(a*S + b*R)$$

$$H2: L = f(a*S + b*R + c*S*R)$$

Izawa & Shadmehr (2011)



ERR: online visual feedback and reward group
EPE: end-point only visual group
RWD: reward only group

Parameters and variables

INPUT

X_0 state (position at time 0)

P perturbation

HIDDEN VARIABLES

U motor command

\hat{e}_r expected reward

\hat{e}_s expected sensory
feedback

OUTPUT

\hat{X} state (position at time t)

e_r reward prediction error

e_s sensory prediction error

PARAMETERS:

σ_y --> noise observation

σ_u --> noise motor command

σ_h --> noise hand position

σ_p --> noise expected perturbation

α_v --> learning rate sensory feedback

α_r --> learning rate reward feedback

γ --> discount rate reward feedback

Selected toolkit

1. STATE SPACE MODEL

- Incorporate reward and sensory prediction errors in the trial-to-trial change in the motor commands

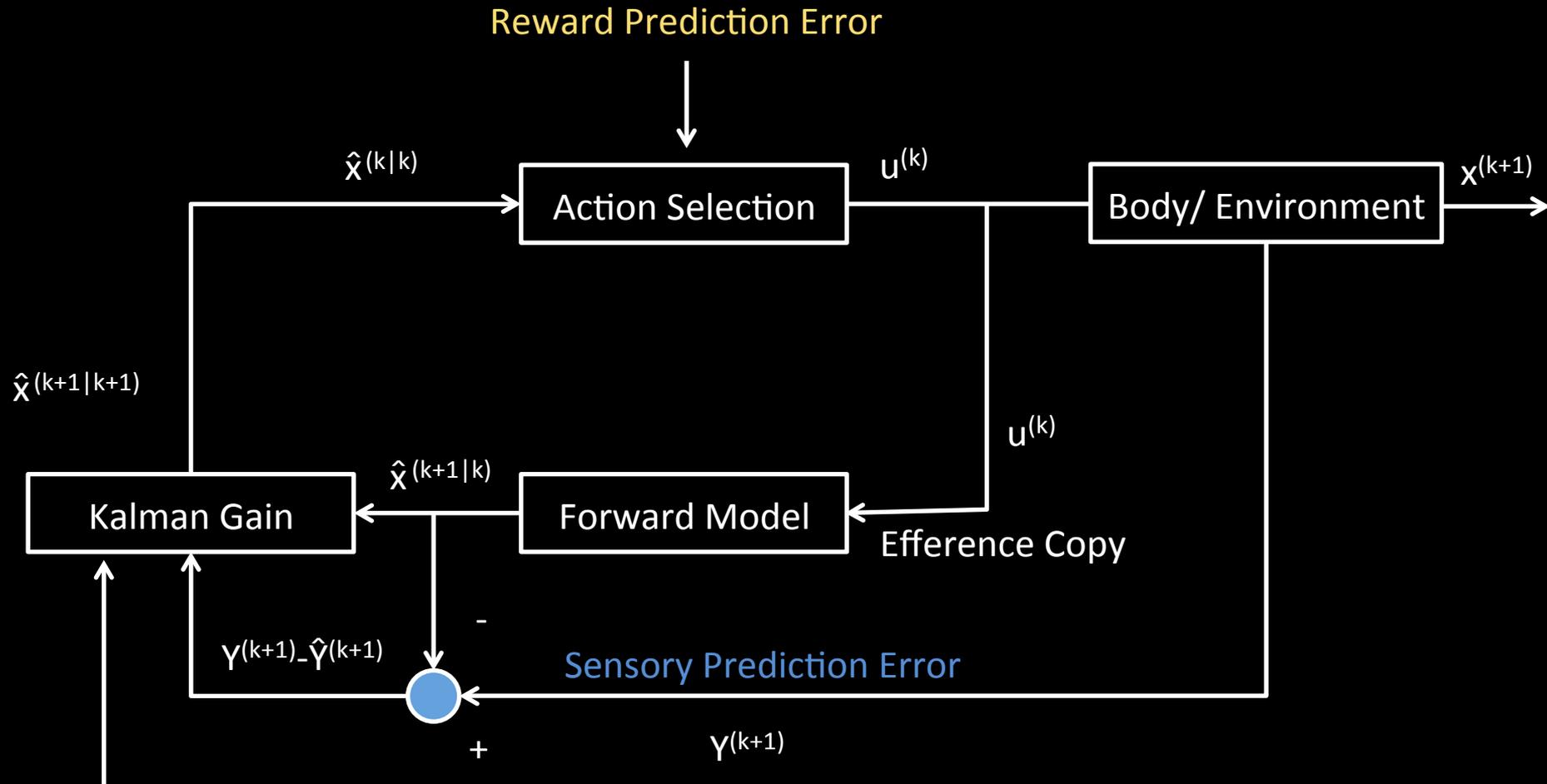
2. KALMAN FILTER

- Correct the prediction to minimize the sensory prediction error

3. TEMPORAL DIFFERENCE ERROR LEARNING

- Incorporate reinforcement learning into our model of reward-based learning

Model schematic

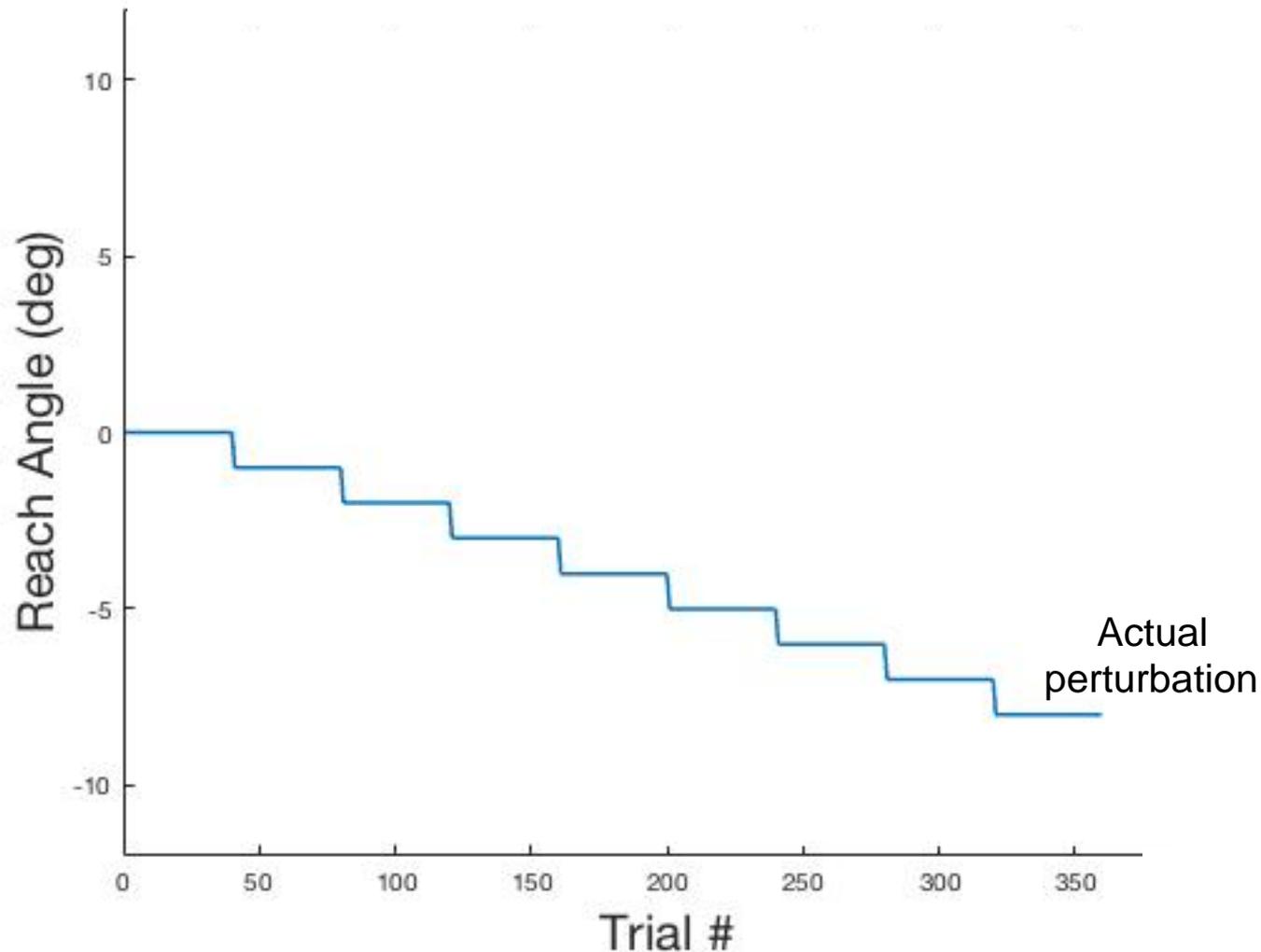


Reward Prediction Error

(Adapted from: Izawa & Shadmehr, 2011)

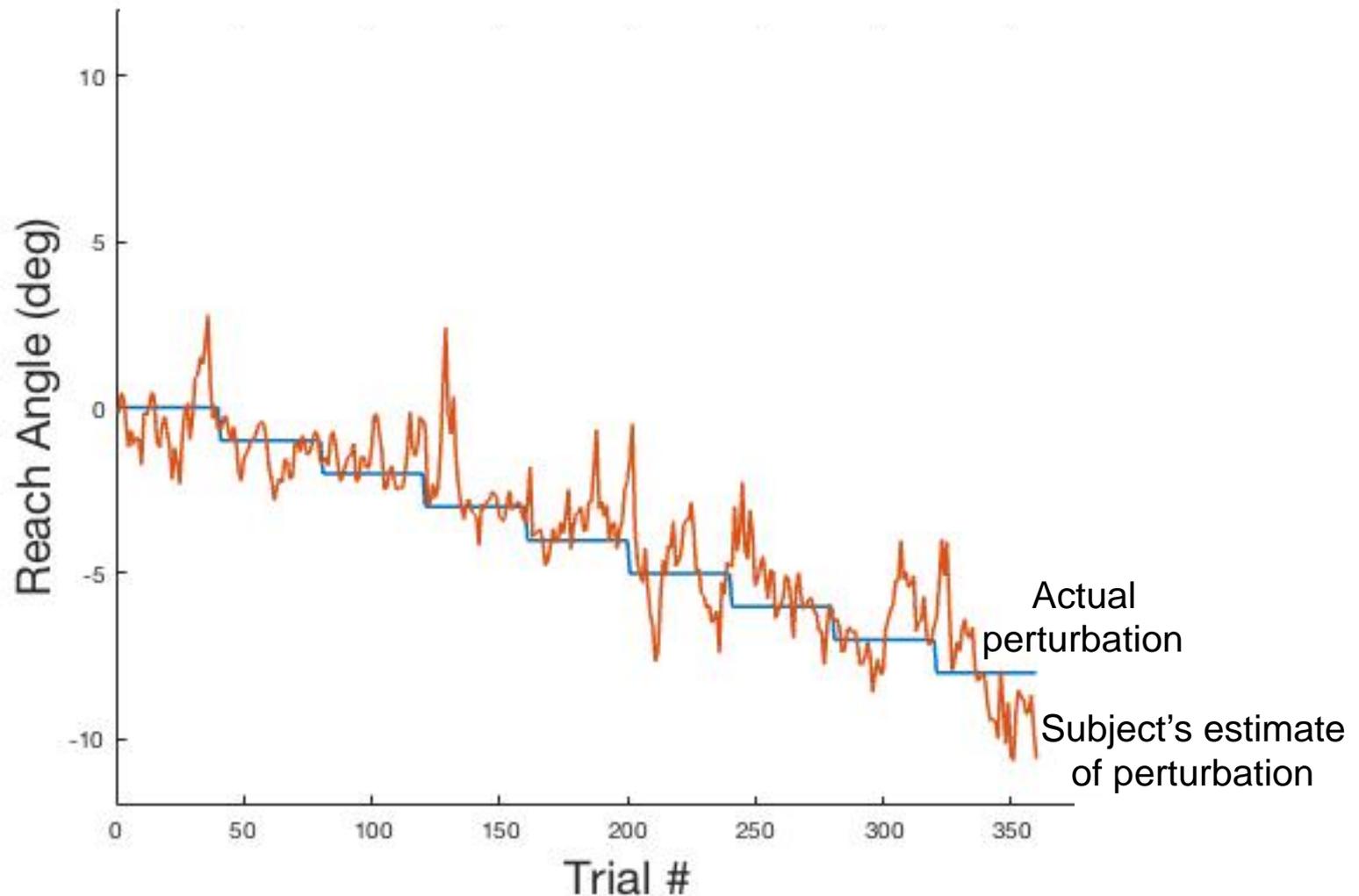
Izawa & Shadmehr simulations

Izawa and Shadmehr (2011) Simulation



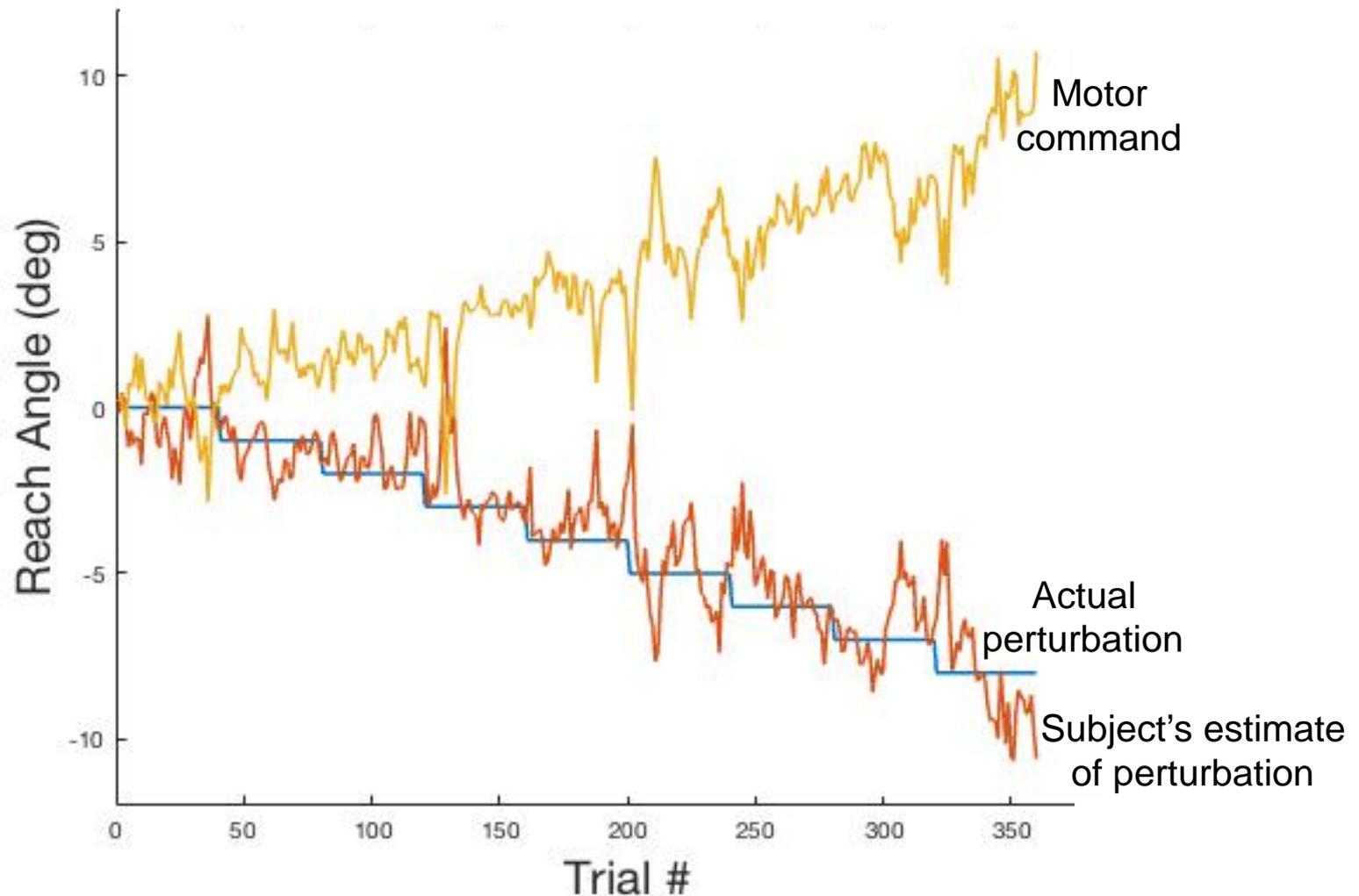
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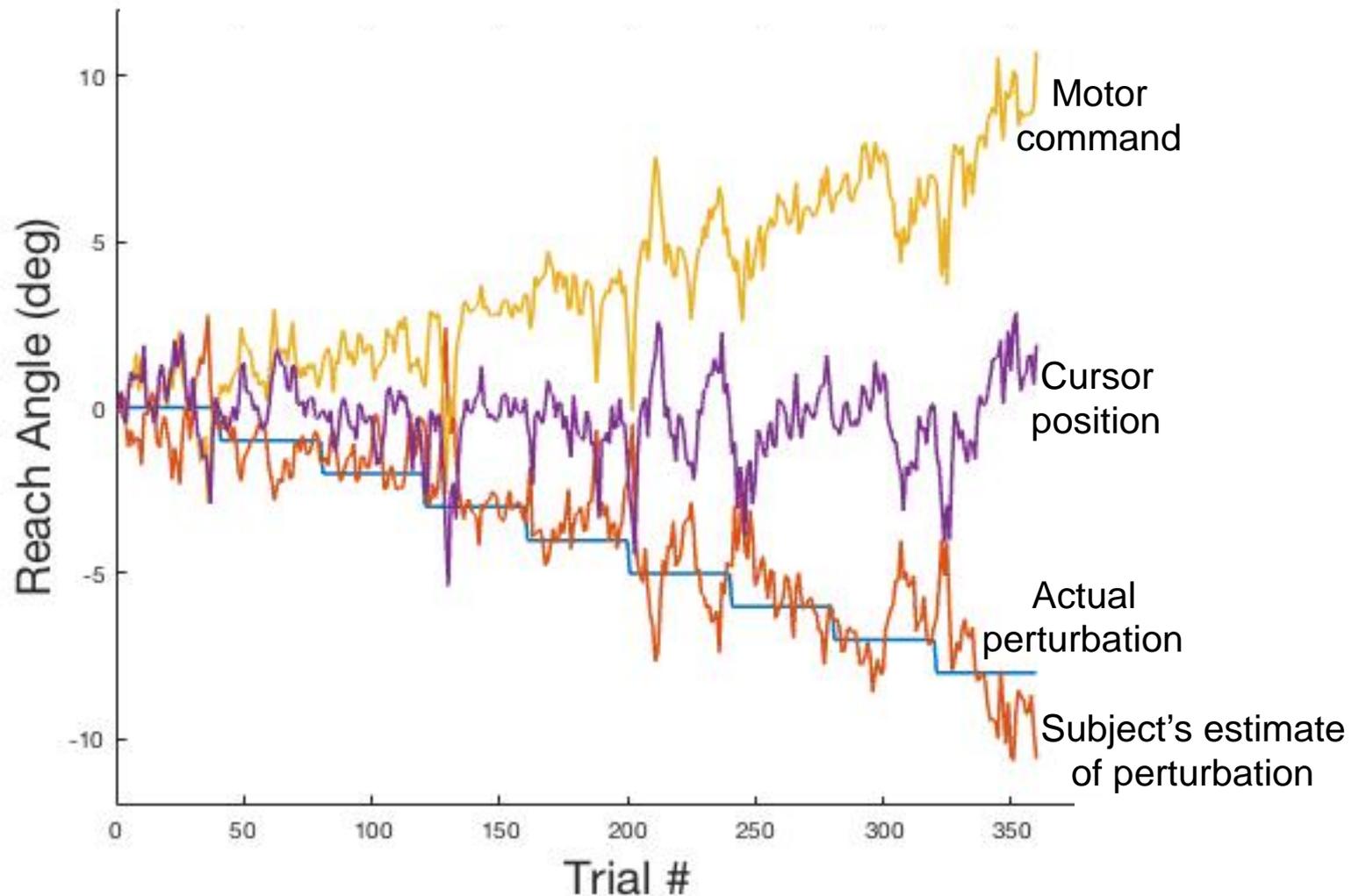
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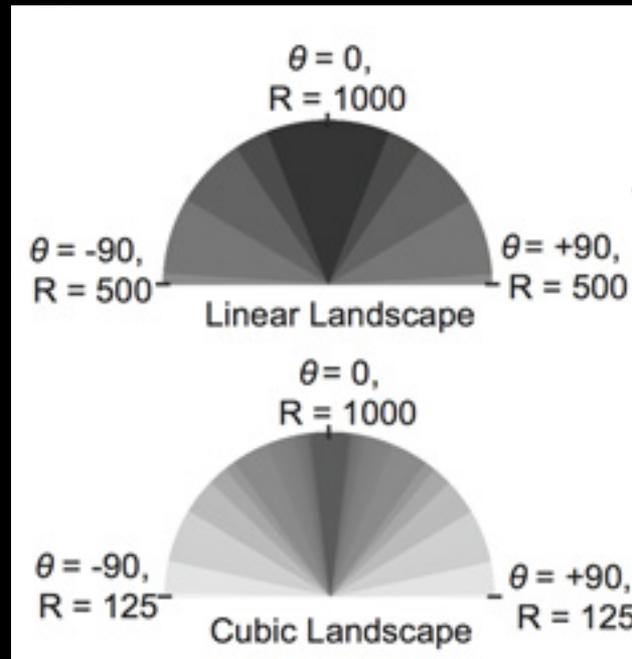
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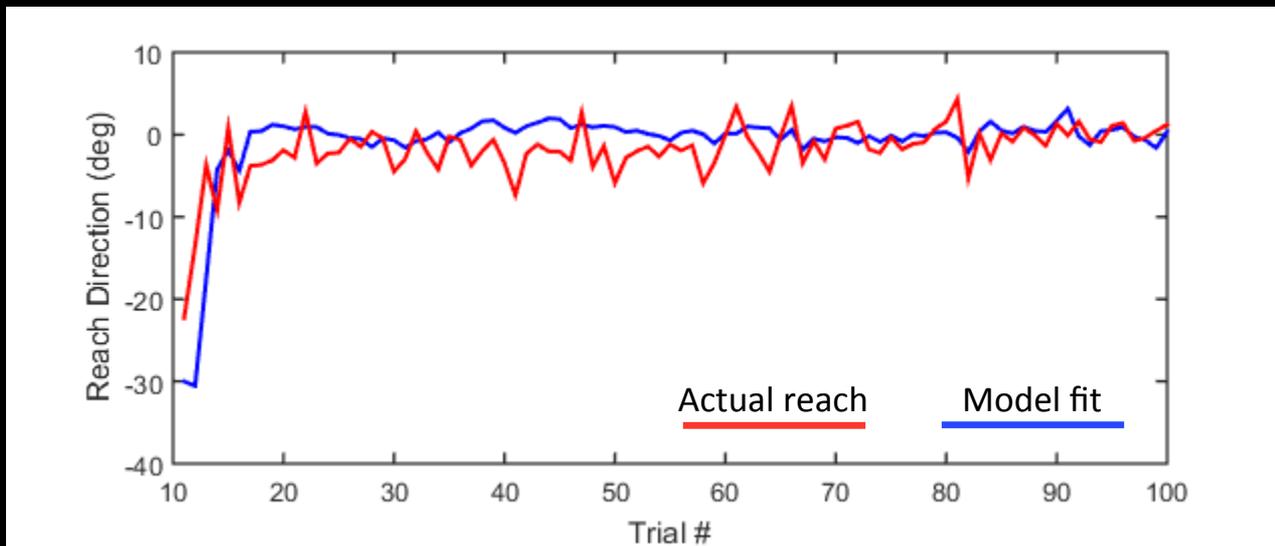
Changes to the original model

- Switched from binary reward to a reward gradient
- Implemented an abrupt perturbation



Nikooyan & Ahmed Fits

Representative subject



Model predictions qualitatively matched majority of subjects

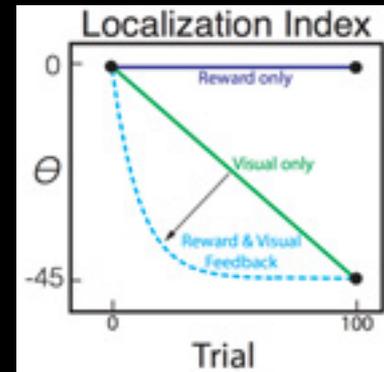
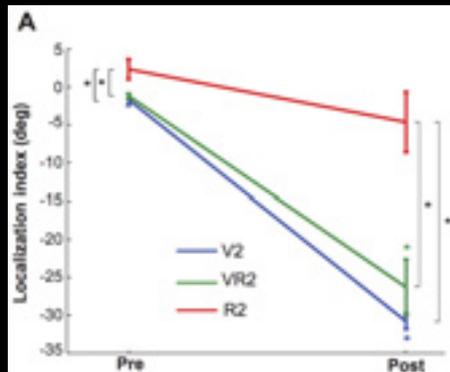
Model testing re. hypotheses

Model fits to raw data from (Nikooyan and Ahmed) did not show significant weight changes on the reward term.

- Our current model shows near zero reward weighting when visual feedback is of high quality.
- May not be sensitive to the reward weighting.
- Insufficient time/data to assess multiplicative model

Critical model evaluation

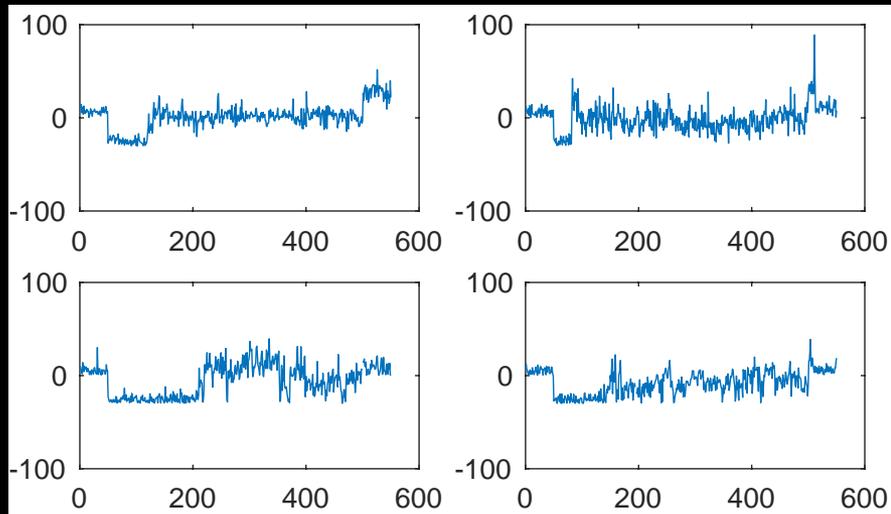
- Original prediction was that reward and sensory feedback are either linearly combined or non-linearly combined.
 - Our analysis did not answer this question.
- However, this would entail different localization index curves, which could be assessed with a new experiment.



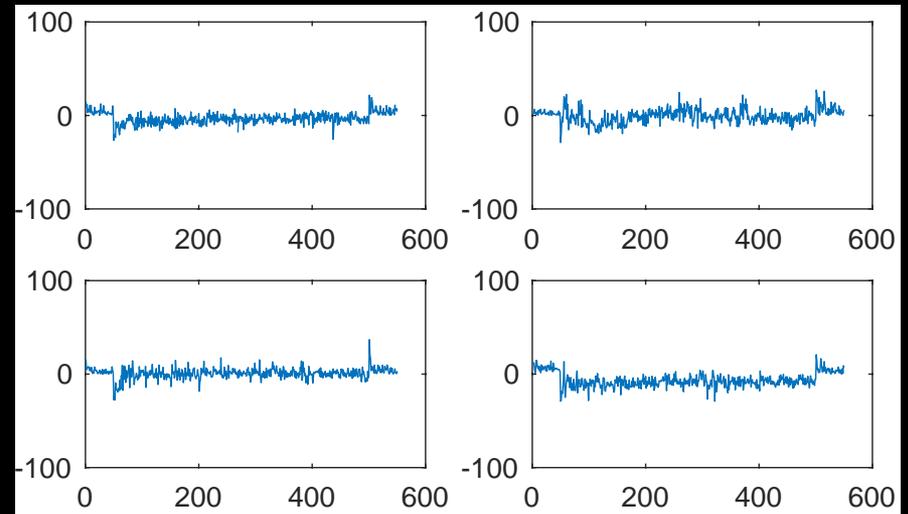
Nikooyan and
Ahmed (2012)

Aha?!

Reward without Visual Feedback



Reward with Visual Feedback



Summary & conclusions

- What have you learned?
 - Izawa and Shadmehr model may be generalizable to more complex adaptation tasks.
 - The degree to which an individual relies on sensory or reward feedback may not be a constant.
 - Free parameters that are determined a priori can have a significant effects on model fit
 - Papers should include the value of these parameters or the accompanying code.

What have you learned?

- Don't take published models for granted.
- The NIH should invest greater resources in theoretically driven research.

What have you learned?



**KEEP
KALM-AN'
CARRY
ON**

Acknowledgements

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