

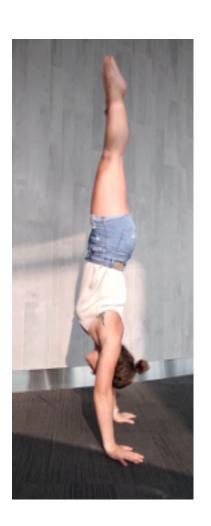
# Does motor variability influence learning in uncertain situations?

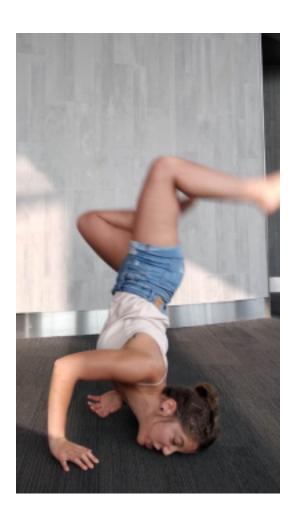
## Better Call Paul

Jana Masselink, Judith Rudolph, Serena Ricci, Marion Forano

# Phenomenon

My friend





Me...

# Phenomenon

Motor adaptation is a dynamic phenomenon



- What influences it?
  - individual abilities?
  - Different contexts?

# Research question

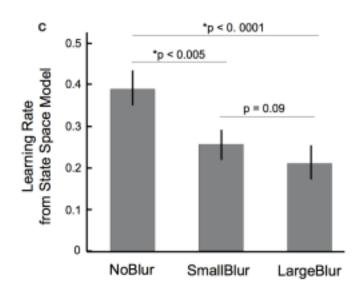
Investigating how individual differences in different contexts affect motor adaptation.



Is the effect of uncertainty perturbation on motor adaptation influenced by initial motor noise?

# Background

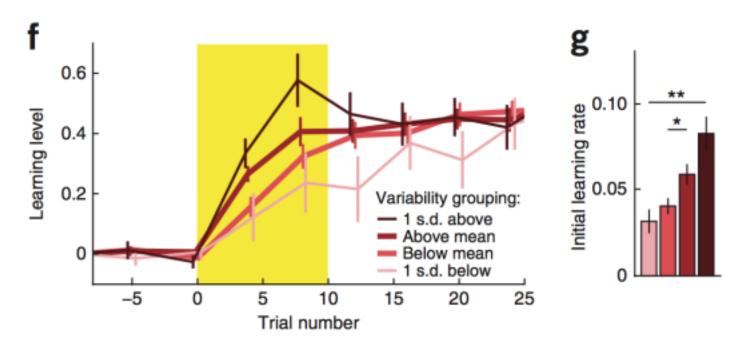
# 1. Perturbation uncertainty reduces motor adaptation



Wei & Körding, 2010; Körding & Wolpert, 2004

# Background

2. Initial movement variability (motor noise) improves motor adaptation

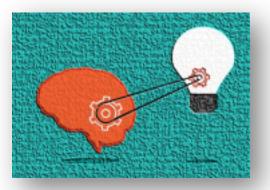


Wu, Miyamoto, Gonzalez Castro, Ölveczky & Smith, 2014

# Hypotheses

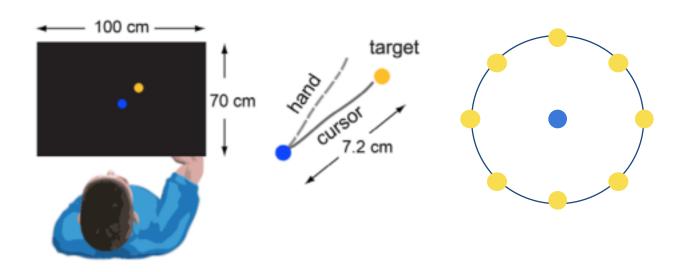
High initial motor noise leads to...

- 1. greater learning rate under high perturbation uncertainty
- 2. greater adaptation level under high perturbation uncertainty
- 3. smaller increase in motor noise during adaptation



## Task

Fernandes, Stevenson & Kording, 2012



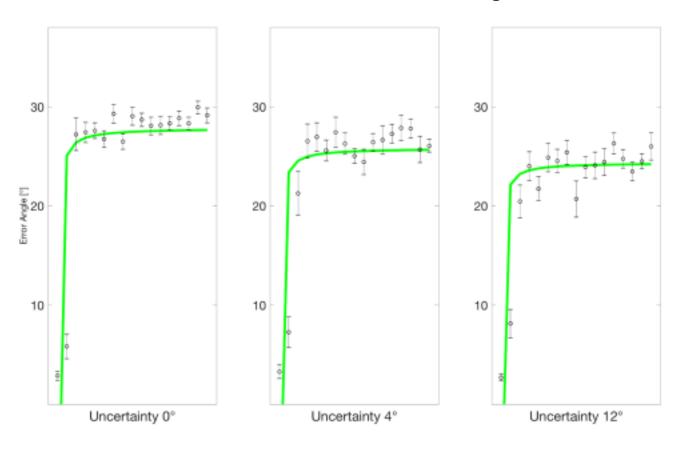
N = 16 Perturbation: +- 30° with 0, 4 or 12° uncertainty

Each uncertainty condition:

- 15 baseline movements
- 240 learning movements

# Task & Variables

## Fernandes, Stevenson & Kording, 2012



## Variables

## Input

- initial states
- prior
- true movement angular error

## **Latent variables**

- movement angle
- perturbation angle

## **Output**

- learning rate
- level of adaptation
- motor noise(initiated from baseline)

## Selected toolkit

## **Adaptive Kalman Filter**

- ➤ Bayesian model for combining predicted and actual sensory feedback
- Considers environmental uncertainty
- K adjusted by the actual error statistic contained in the model x' and in the measurement y

## **Model schematic**

## Input

#### **Initial Prior**

$$A = \begin{bmatrix} 0.998 & \alpha \\ 0 & 0.95 \end{bmatrix}$$

$$R_1 = 1$$

$$Q = \begin{bmatrix} \sigma_m & 0 \\ 0 & \sigma_n \end{bmatrix} = \begin{bmatrix} 0.24 & 0 \\ 0 & 4.96 \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

$$B = \left[e^1 \cdots e^m\right] \sum_{t=1}^m \frac{1}{e^t}$$

### **Initial State**

$$x_1 = \begin{bmatrix} \theta_m \\ \theta_p \end{bmatrix}$$

$$V_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

#### Observation

 $y_k$ 

## State prediction

$$\hat{x}_k = A. \ x_{k-1}$$

$$\hat{V}_k = A. V_{k-1}.A' + Q$$

$$\hat{R}_k = \hat{R}_{k-1} + B.((e_{k-m:k-1})^2 - \hat{R}_{k-1})$$

## Adaptive Kalman Filter

## State Update

$$K = \hat{V}_{k}.H'.S^{-1}$$

$$e_{k} = (y_{k-n+1:k}-H.\hat{x}_{k}).n^{-1}$$

$$x'_{k} = \hat{x}_{k} + K_{k}.e_{k}$$

$$V_{k}' = (I - K_{k}.H). \hat{V}_{k}$$

 $S_k = H.\hat{V}_k.H' + \hat{R}_k$ 

## Output

$$\begin{pmatrix} x \\ V \\ \alpha \end{pmatrix}$$

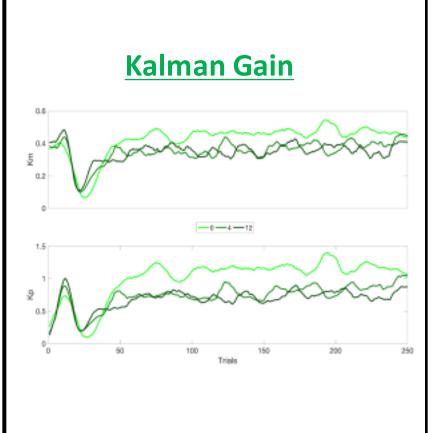
# Simulations / results

Uncertainty 12\*

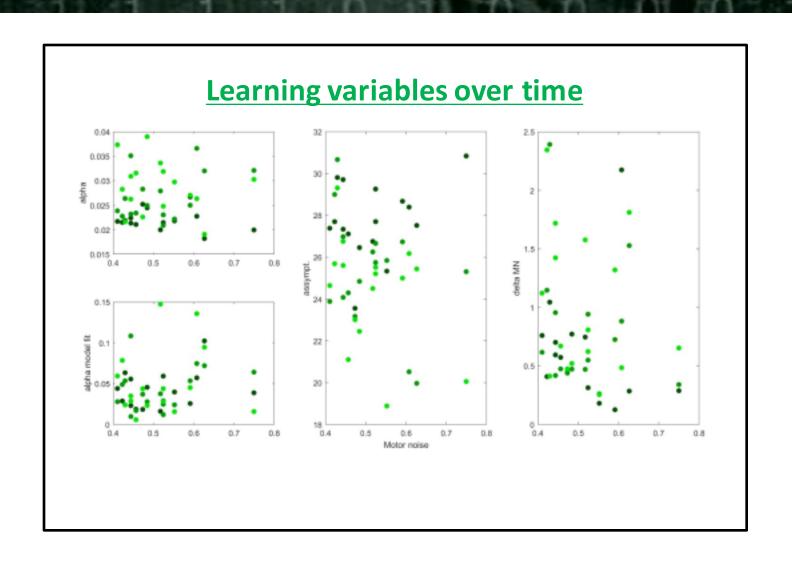
# State movement angle 30 10 10 10

Uncertainty 4°

Uncertainty 0°



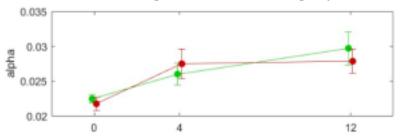
# Simulations / results

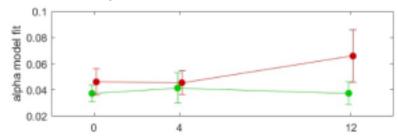


## Simulations / results

High initial motor noise =>

1.. Greater learning rate under high perturbation uncertainty

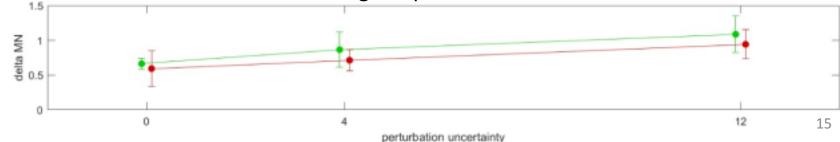




2. Bigger adaptation level under high perturbation uncertainty



3. Smaller increase in motor noise during adaptation



## Critical model evaluation

- The model does not account for differences in motor planning noise and motor execution noise
  - -> motor planning noise might aid adaptation under environmental uncertainty while execution noise reflects lower adaptation ability (van Beers, 2009)
- Insufficient data
  - -> more baseline trials needed
  - -> no movements to other target directions in between
- Specific criteria to define high and low motor noise

## Summary

- What have you learned?
  - implementation of Kalman filter
  - choice of parameters has a great impact on model outcomes
  - importance of structuring a modelling project
  - benefit from working (and chilling) in a group



# Conclusion

