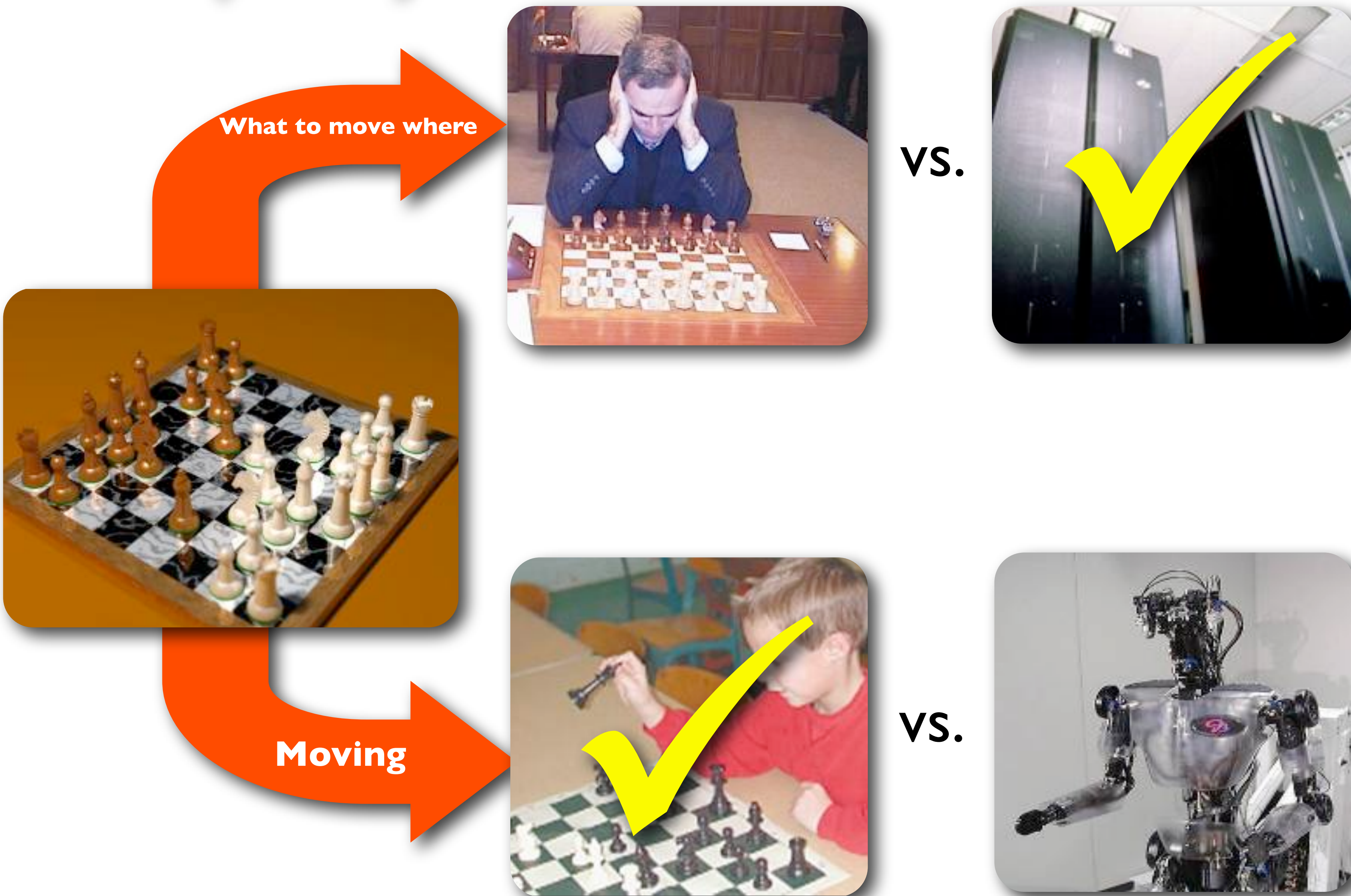
Probabilistic models of human sensorimotor control
Daniel Wolpert, University of Cambridge

Q. Why do we and other animals have brains?

A. To produce adaptable and complex movements

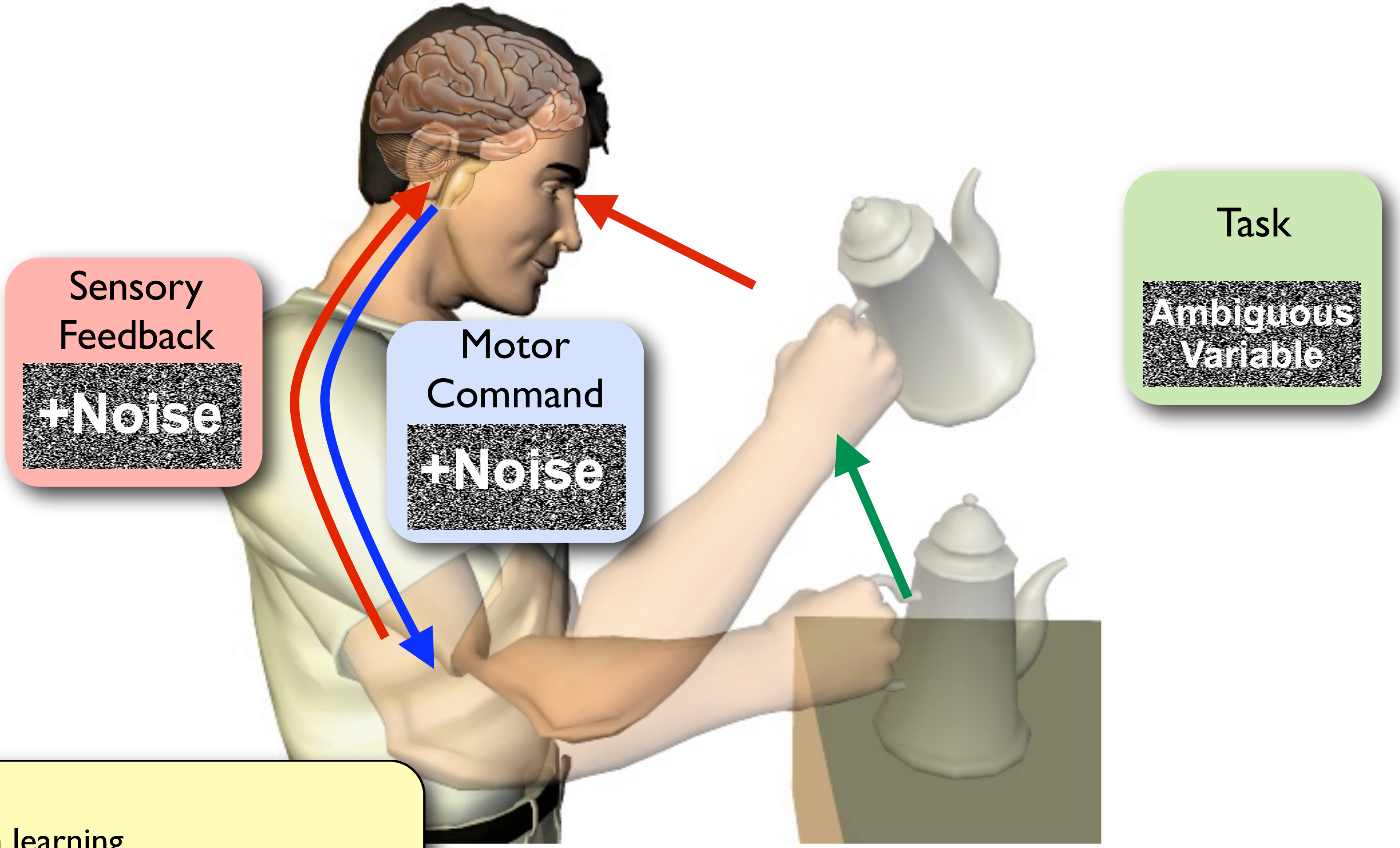
- movement is the only way we have of interacting with the world
  - communication: speech, gestures, writing are motor acts
  - sensory, memory and cognitive processes → future movements

Complexity of human movement control



Uncertainty in the control of movement

Noise: Unwanted disturbance corrupting a signals



Outline

- Bayesian learning
- Predicting consequences of actions
- Evaluating outcomes
- Optimal decisions
- Transitions from sensing to action

Bayesian Decision Theory

Rev. Thomas Bayes
1702-1761

"I now send you an essay which I have found among the papers of our deceased friend Mr Bayes, and which, in my opinion, has great merit...."

Essay towards solving a problem in the doctrine of chances (1764) Phil. Trans. Roy. Soc.

- Bayesian statistics: making inferences based on uncertain information
- Decision theory: selecting optimal action based on inferences

Bayes rule

A = Disease **B = Positive blood test**

$$P(\underbrace{A,B}_{\text{A and B}}) = P(\underbrace{A|B}_{\text{A given B}})P(B) = \underline{P(B|A)P(A)}$$

Neuroscience

A= State of the world **B=Sensory Input**

$$\overbrace{P(\text{state}|\text{sensory input})}^{\text{Belief in state AFTER sensory input}} = \frac{\overbrace{P(\text{sensory input}|\text{state})}^{\text{Evidence}}\overbrace{P(\text{state})}^{\text{Belief in state BEFORE sensory input}}}{P(\text{sensory input})}$$

Posterior **Likelihood** **Prior**

Bayesian Learning

Real world tasks have variability, e.g. estimating ball's bounce location

Sensory feedback (Likelihood)

Vision

+

Task statistics (Prior)

Not all locations are equally likely

=

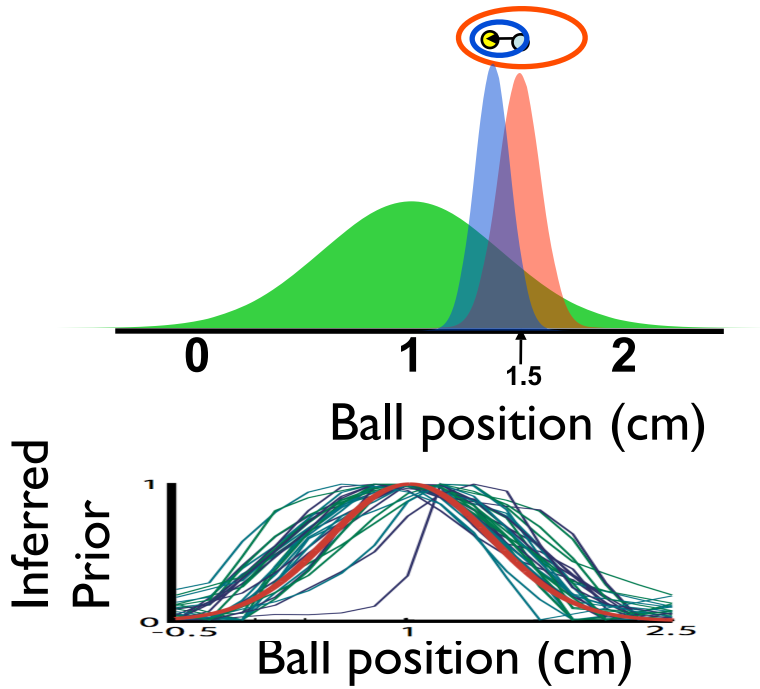
Optimal estimate (Posterior)

$$\underbrace{P(\text{state}|\text{sensory input})}_{\text{Posterior}} \propto \underbrace{P(\text{sensory input}|\text{state})}_{\text{Likelihood}} \underbrace{P(\text{state})}_{\text{Prior}}$$

Does skill learning use Bayes rule?

The brain would need to represent
- the statistics of the task (prior)
- the noise in its own sensors (likelihood)

$$\underbrace{P(\text{state}|\text{sensory input})}_{\text{Posterior}} \propto \underbrace{P(\text{sensory input}|\text{state})}_{\text{Likelihood}} \underbrace{P(\text{state})}_{\text{Prior}}$$



(Körding & Wolpert, Nature, 2004)

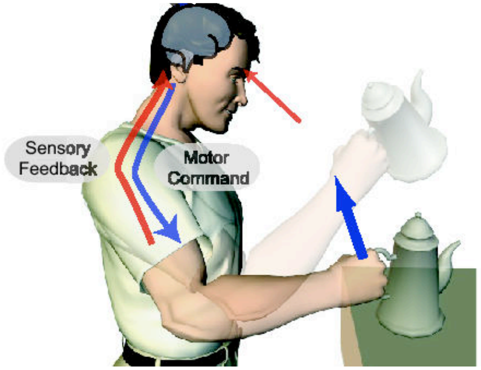
- Sensorimotor systems
  - Represents the distribution of tasks
  - Estimates its own sensory uncertainty
  - Combines these two sources in a Bayesian way

II. Predicting the consequences of action

$$\underbrace{P(\text{state}|\text{sensory input})}_{\text{Posterior}} \propto \underbrace{P(\text{sensory input}|\text{state})}_{\text{Likelihood}} \underbrace{P(\text{state})}_{\text{Prior}}$$

Fundamental for

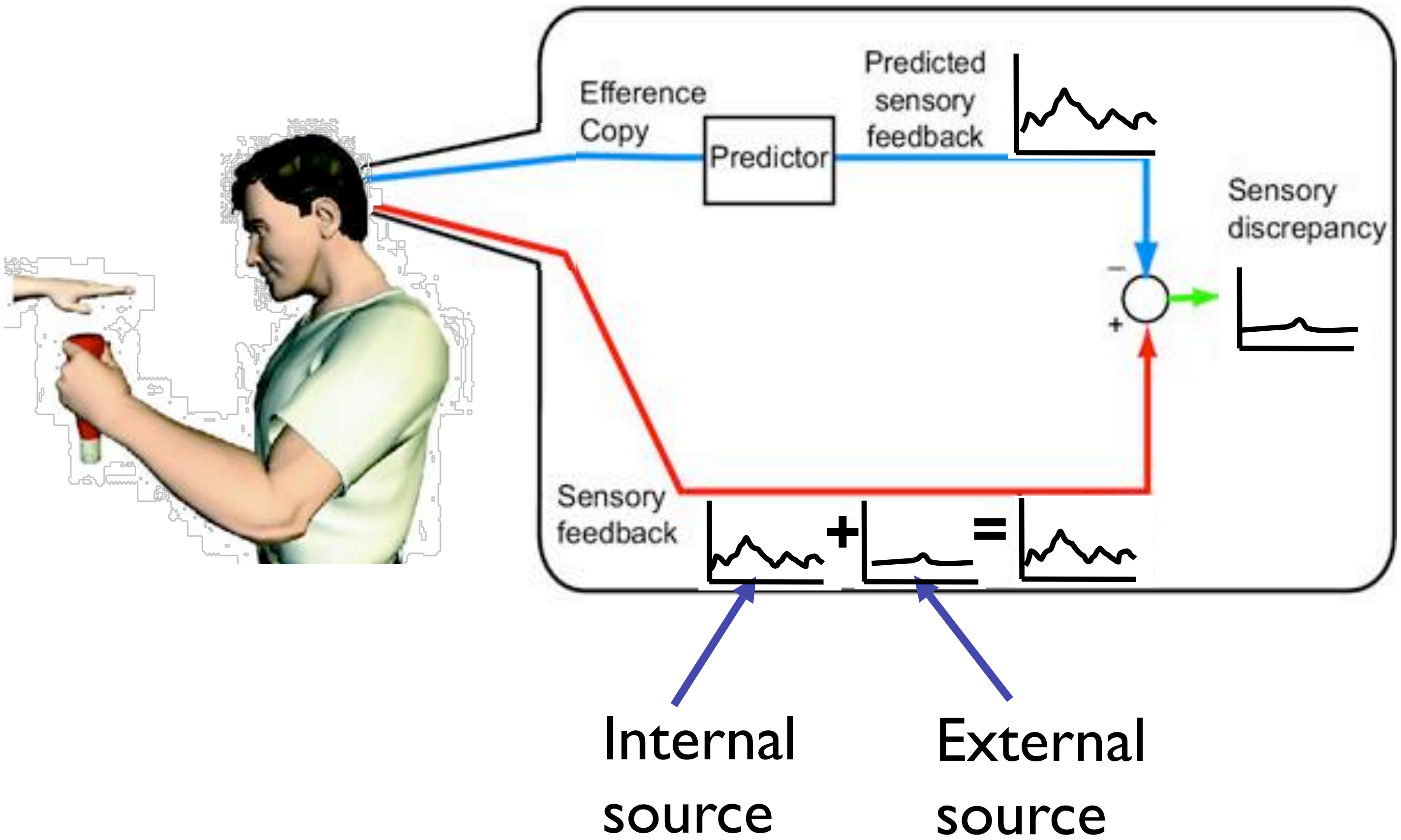
1. Control with delays
2. Mental simulation
3. Likelihood estimation
   Wolpert & Kawato, Neural Networks 1998
   Haruno, Wolpert, Kawato, Neural Computation 2001
4. Sensory filtering



Sensory prediction

Our sensors report afferent information combining

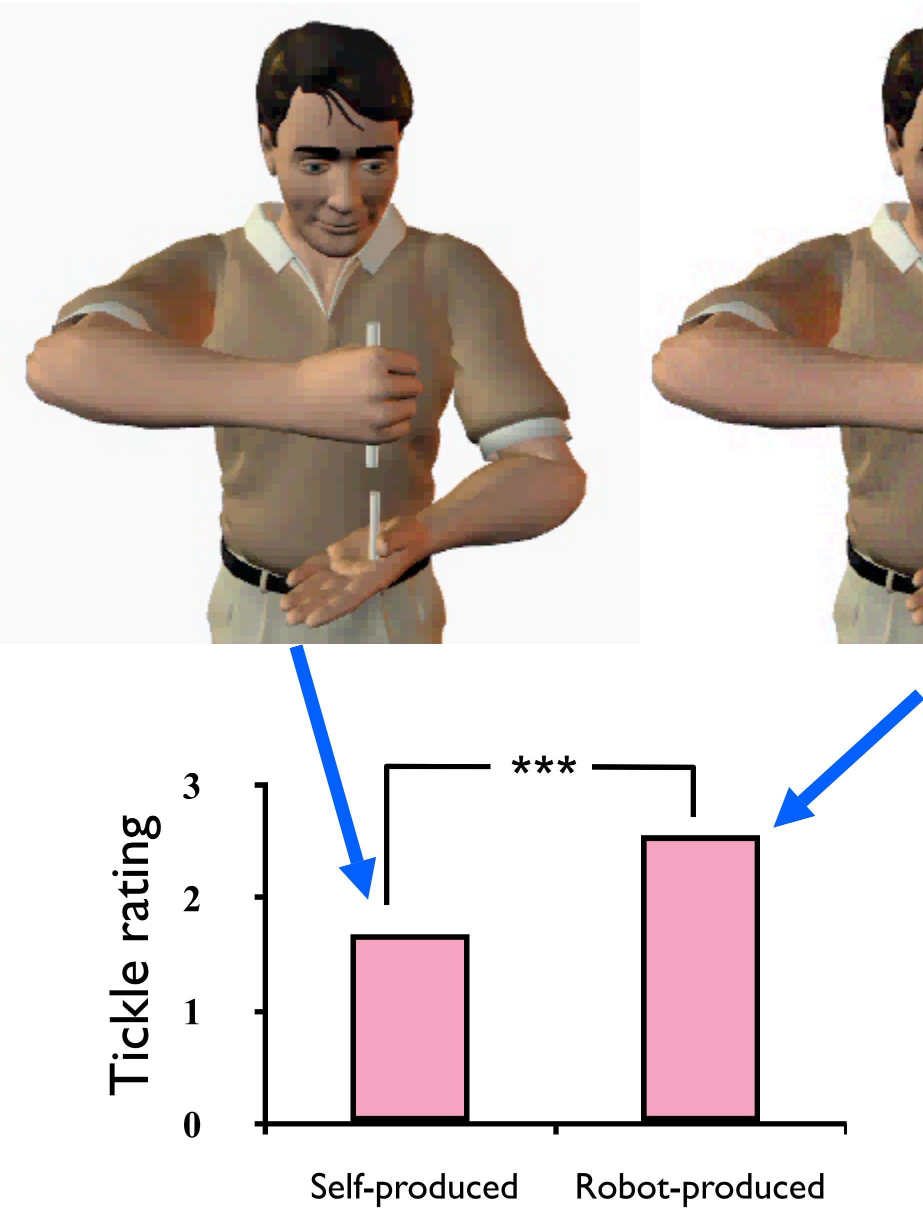
- Ex-afferent information: changes in outside world
- Re-afferent information: changes we cause



Tickling

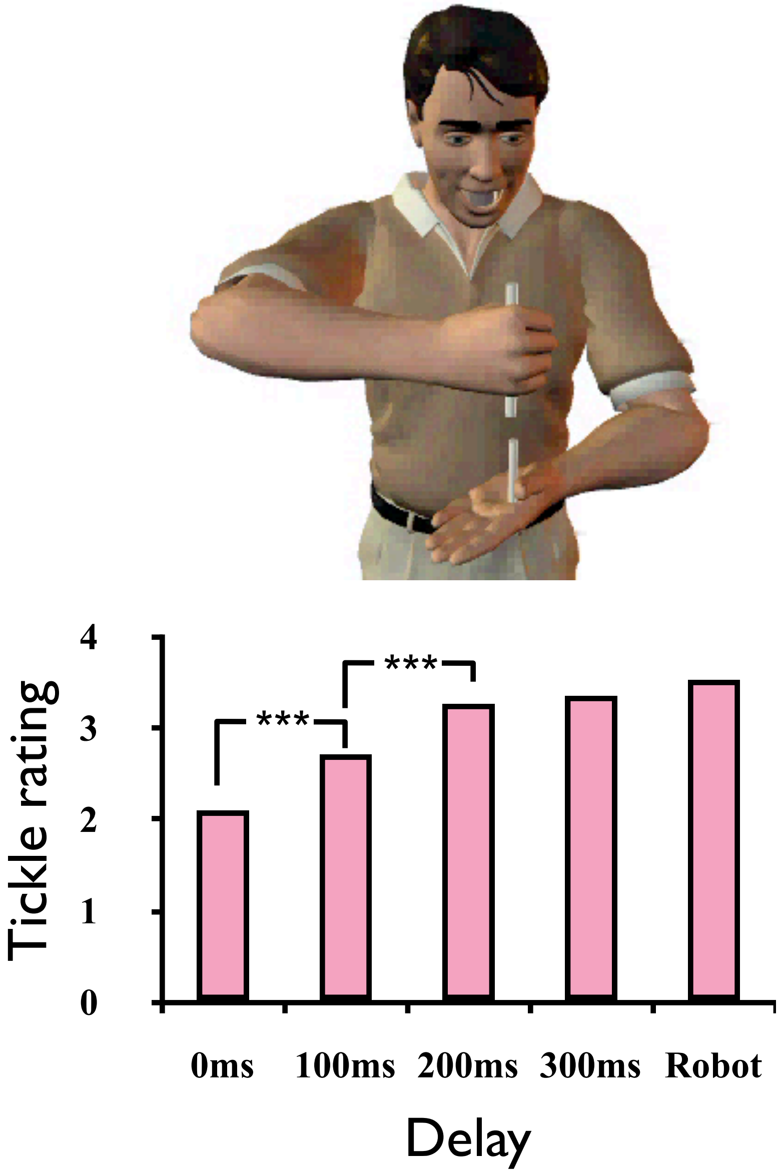
Self-administered tactile stimuli rated as less ticklish than external tactile stimuli.

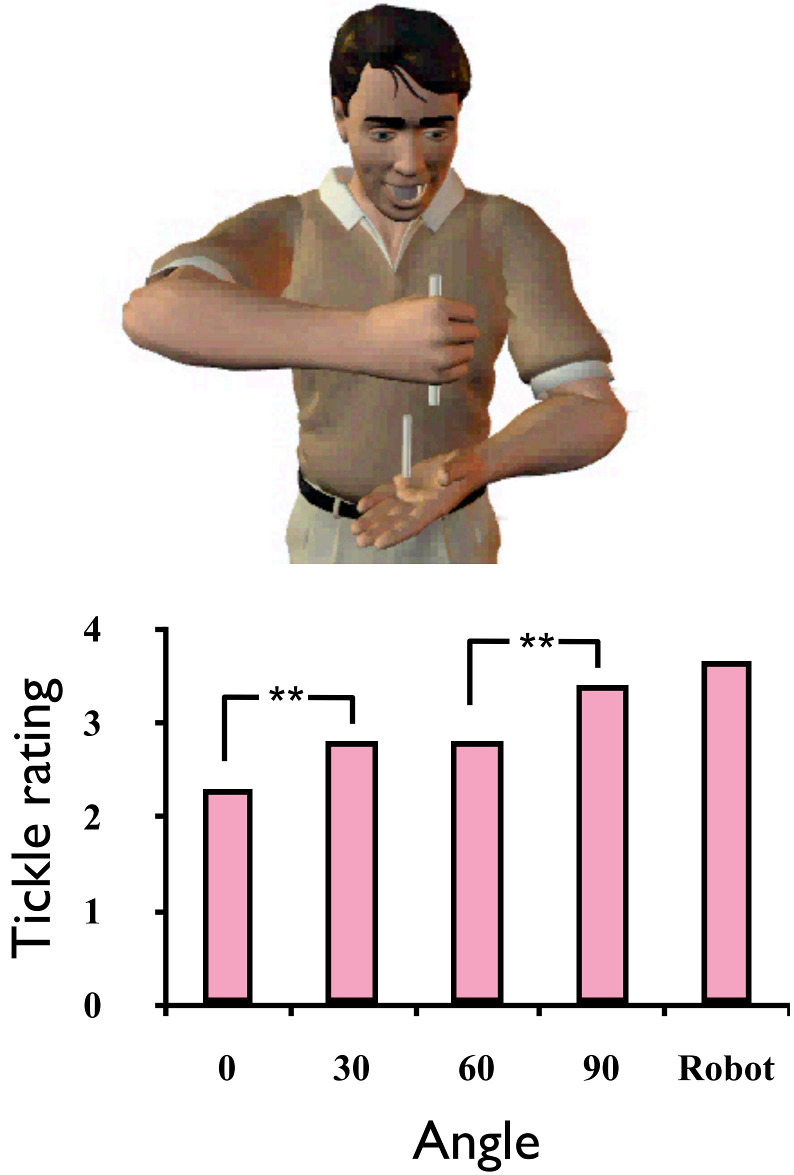
Does prediction underlie tactile cancellation in tickle?



Gain control or precise spatio-temporal prediction?

Spatio-temporal prediction

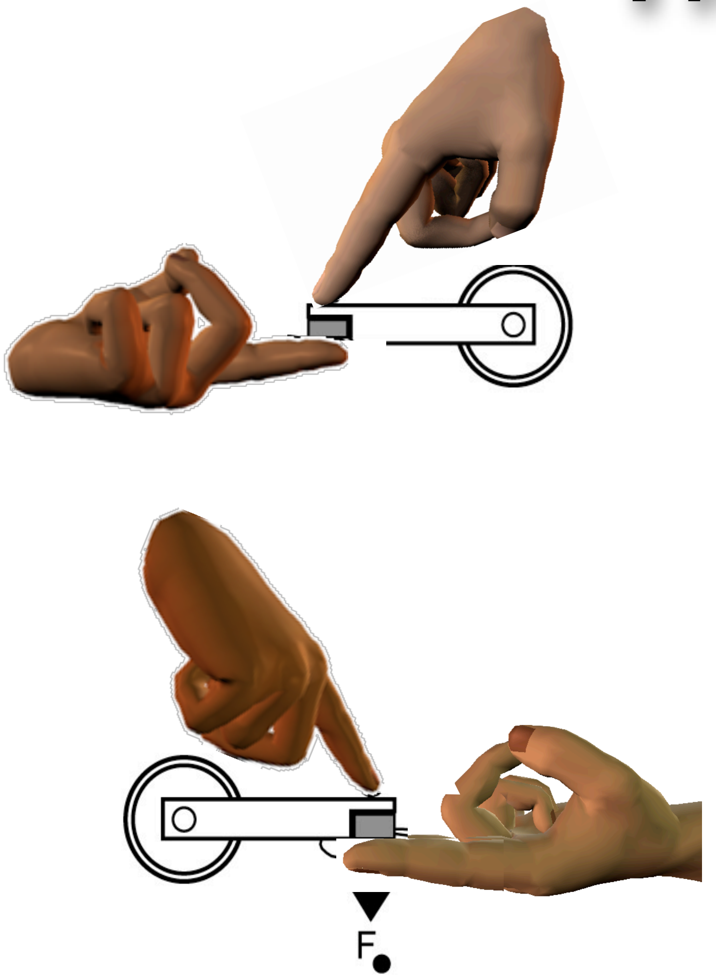


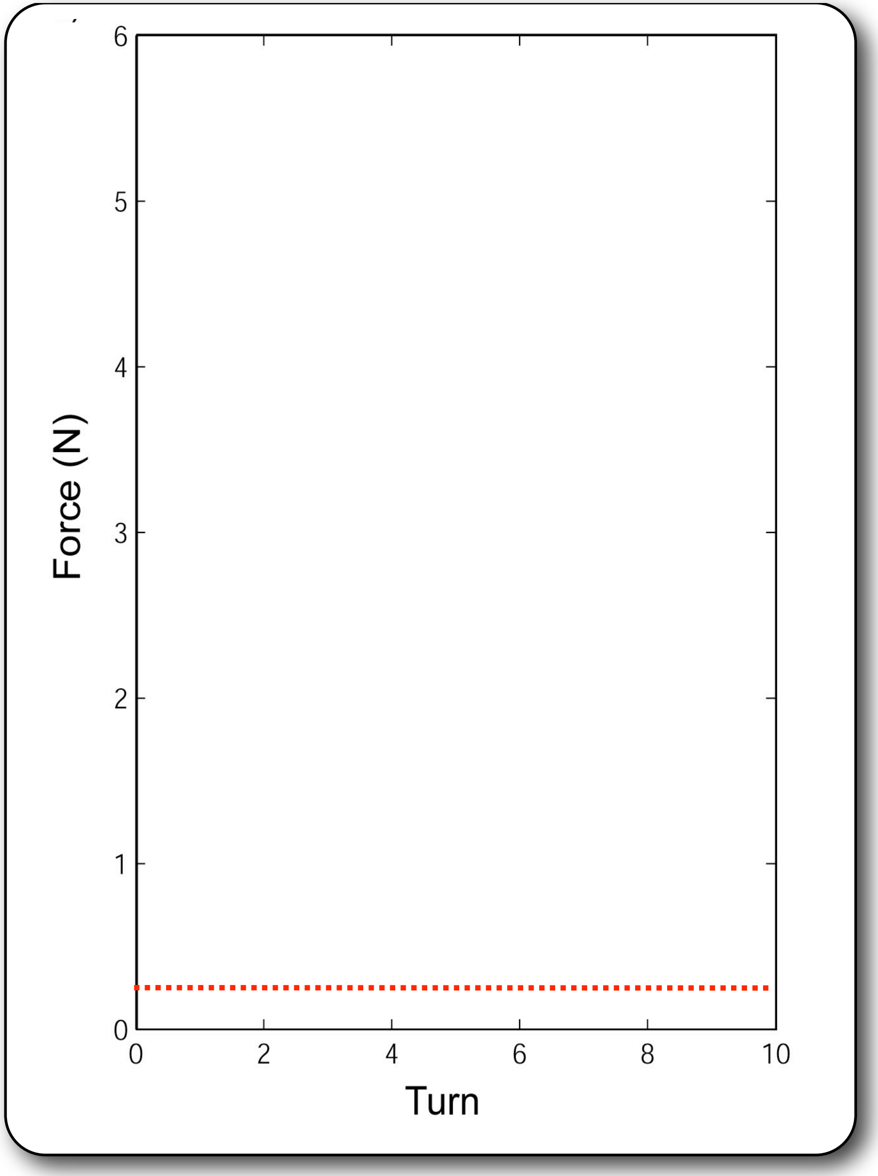


(Blakemore, Frith & Wolpert. J. Cog. Neurosci. 1999)

The escalation of force

Tit-for-tat

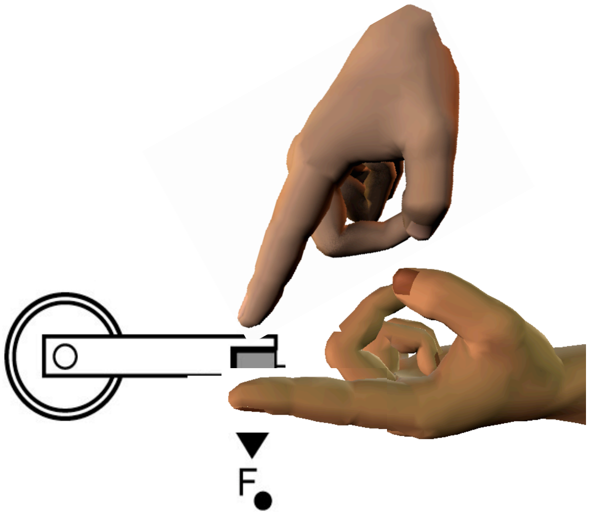


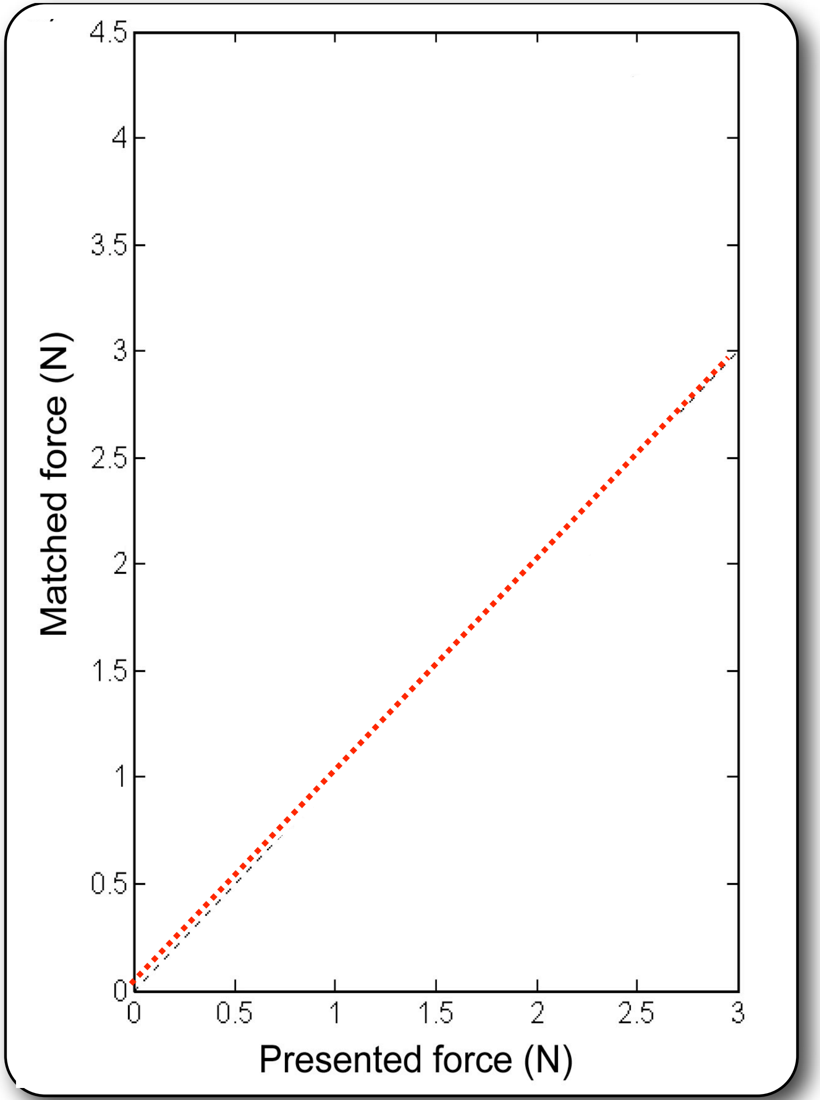


Force escalates under rules designed to achieve parity: Increase by ~40% per turn

(Shergill, Bays, Frith & Wolpert, Science, 2003)

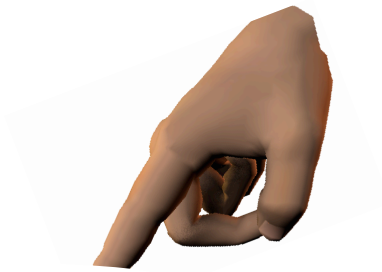
Perception of force

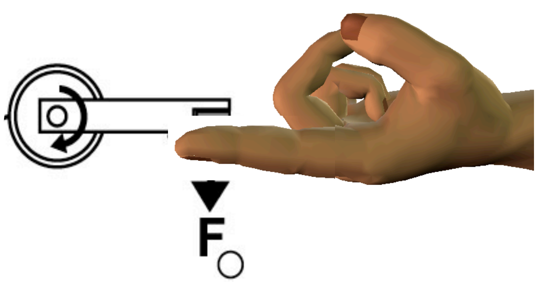


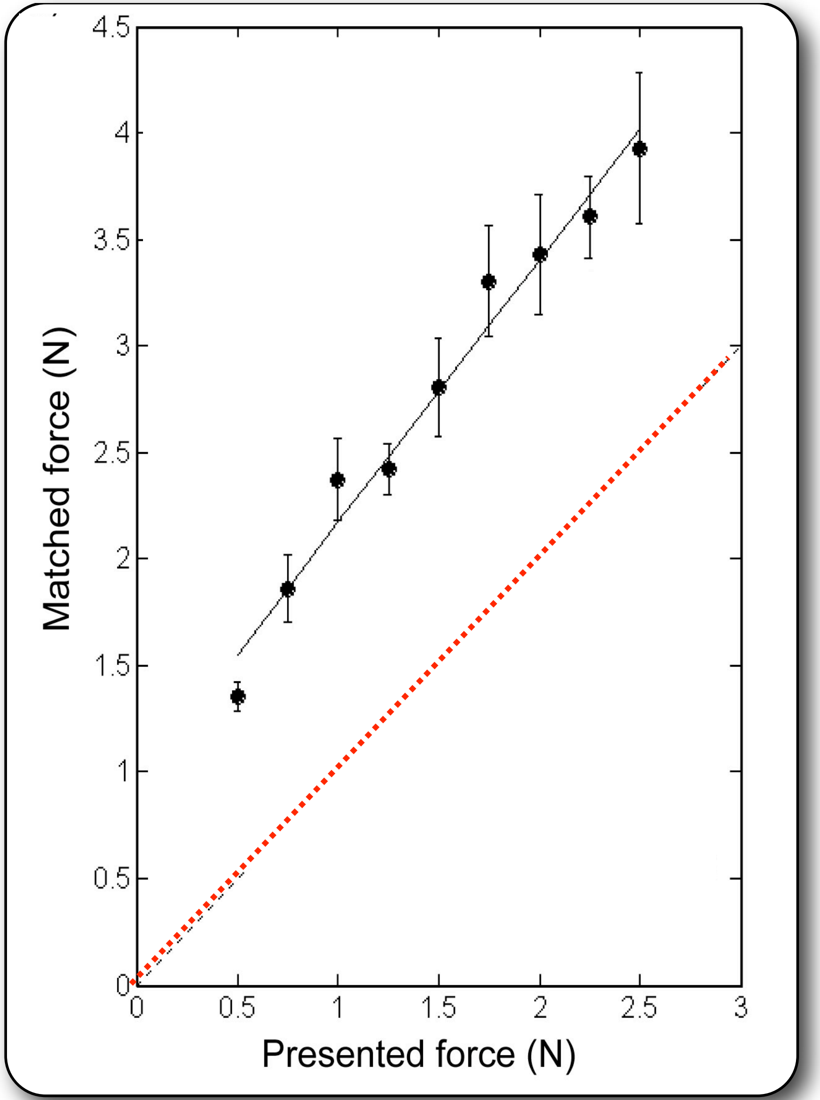


70% overestimate in force

Perception of force

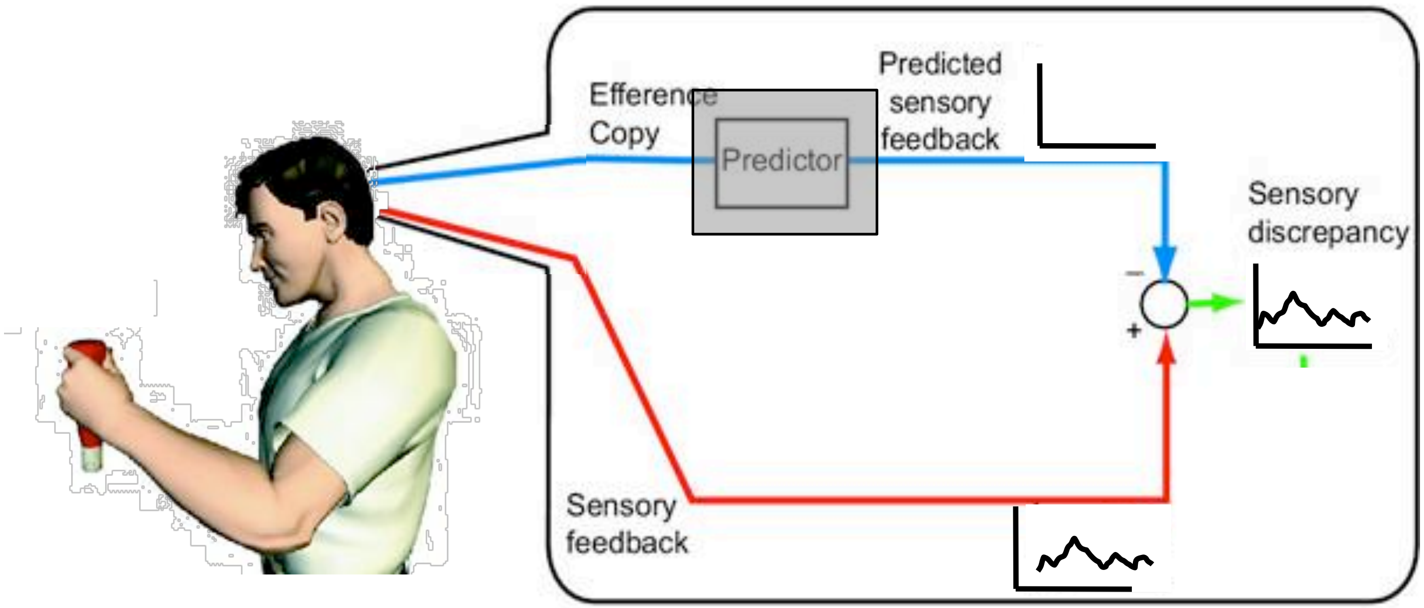






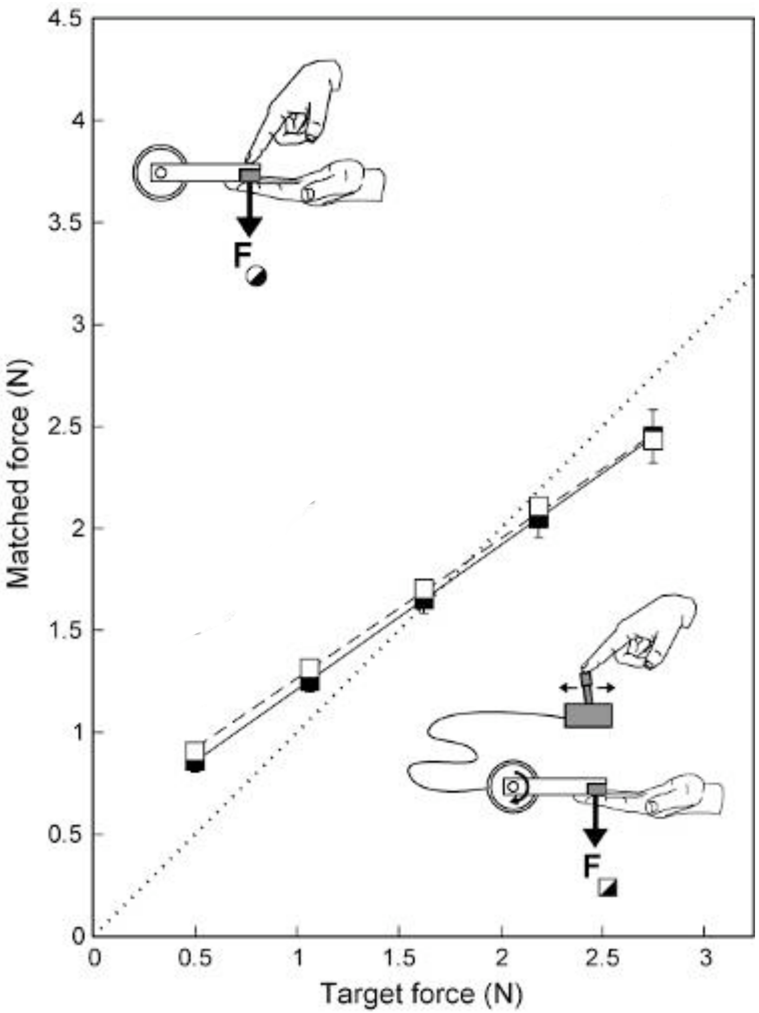
Labelling movements & delusions of control

Failure to make correct sensory predictions (Frith 1987 Psychol. Med.)



= not me

Prediction deficits in patients with schizophrenia



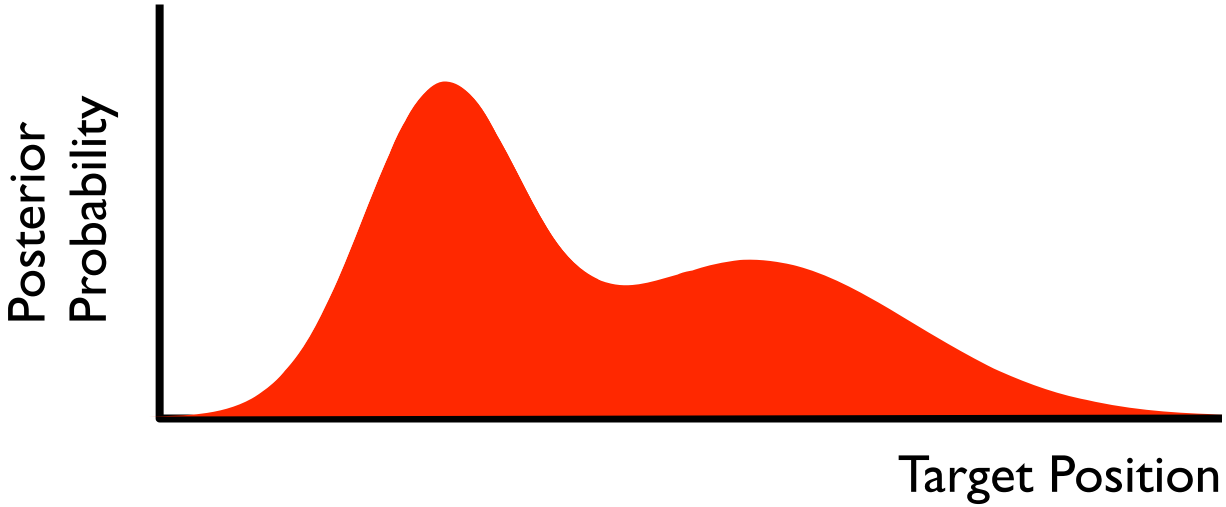
Patients ■ ●
Controls □ ○

- The brain predicts sensory consequences
- Sensory cancellation in force production
- Defects may be related to delusions of control in schizophrenia

(Shergill, Samson, Bays, Frith & Wolpert, Am J. Psychiatry, 2006)

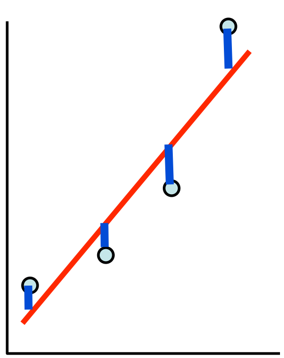
III. Loss Functions in movement

$$\underbrace{P(\text{state}|\text{sensory input})}_{\text{Posterior}} \propto \underbrace{P(\text{sensory input}|\text{state})}_{\text{Likelihood}}\ \underbrace{P(\text{state})}_{\text{Prior}}$$



What is the performance criteria: loss?

Statistics

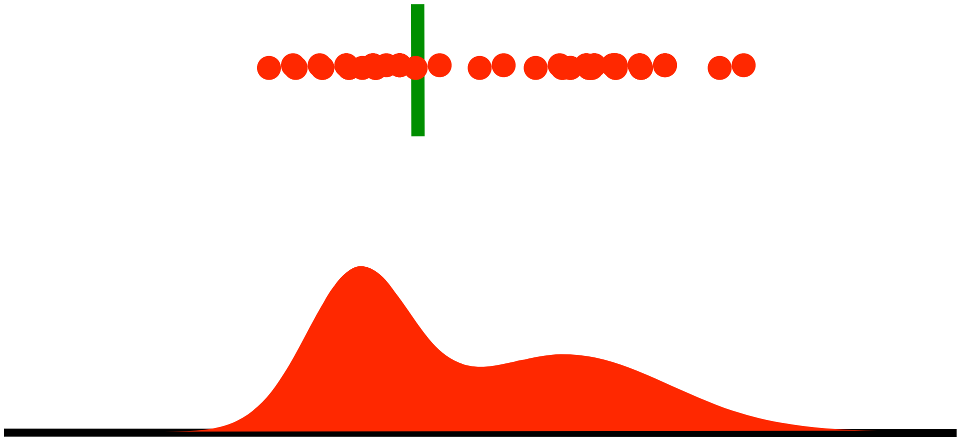


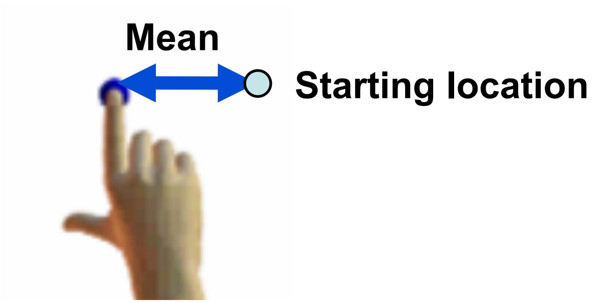
Minimizing squared error for mathematical simplicity

Neuroscience

What measure of error does the brain care about?

Virtual pea shooter





(Körding & Wolpert, PNAS, 2004)

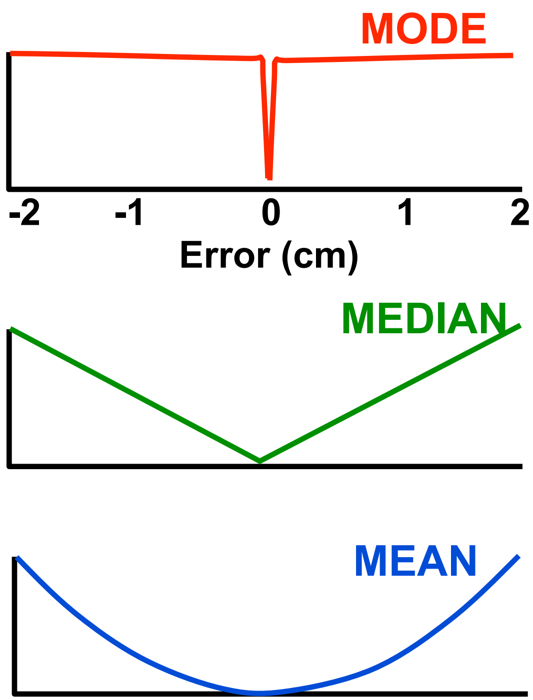
Probed distributions and optimal means

Possible Loss functions

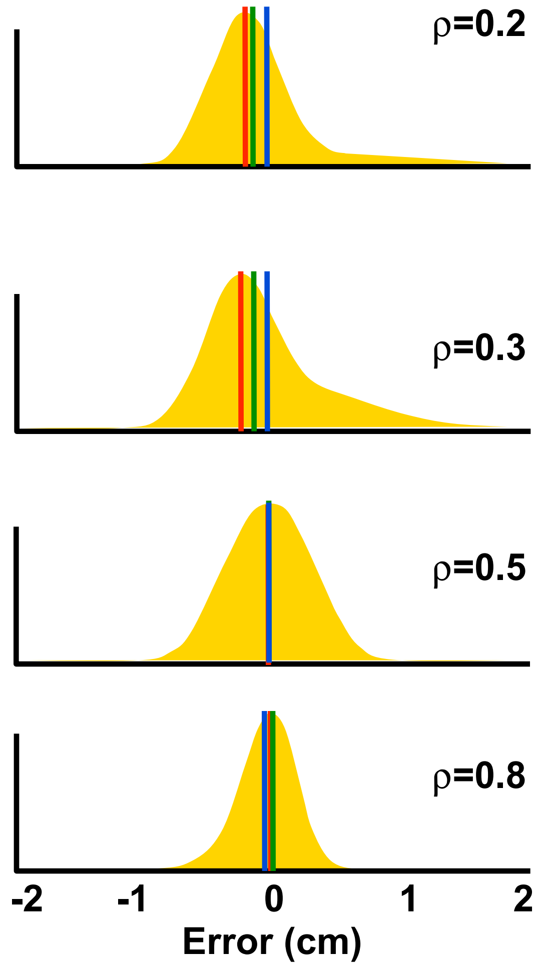
Maximize Hits

$$\text{Loss} = |error|$$

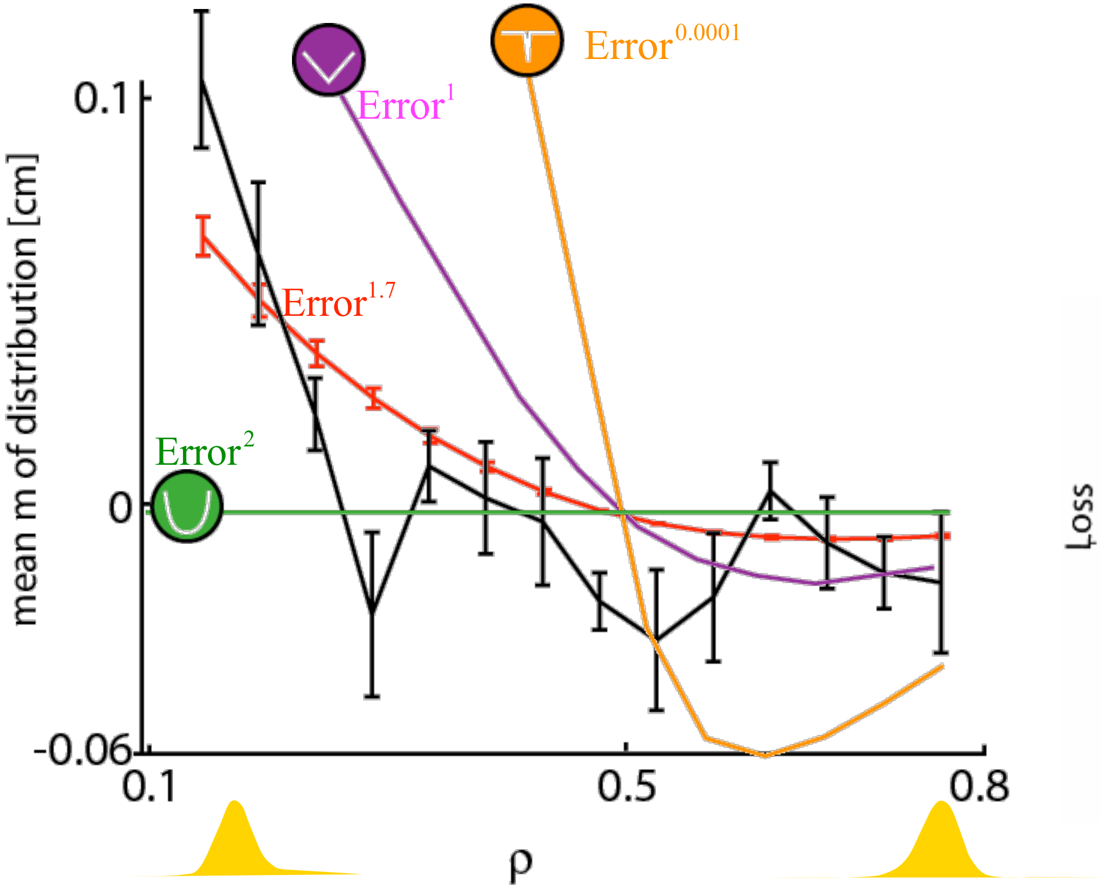
$$\text{Loss} = (error)^2$$

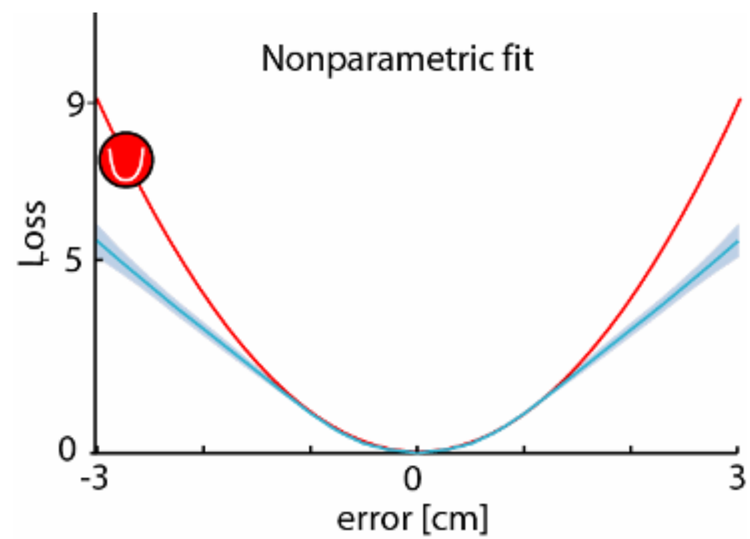


Distributions

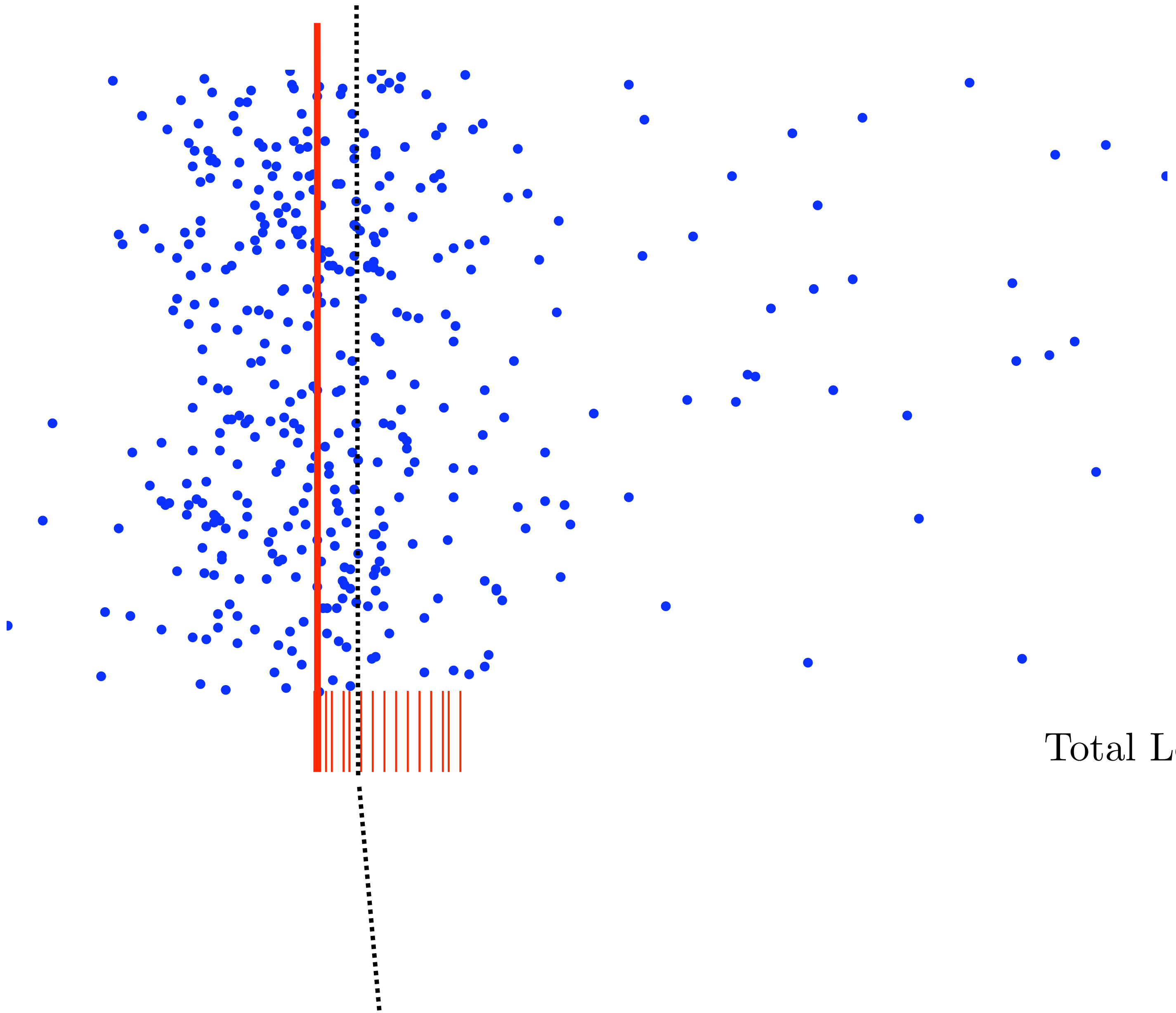


Loss function is robust to outliers





- Loss function for pointing
    - Mean squared error with robustness to outliers

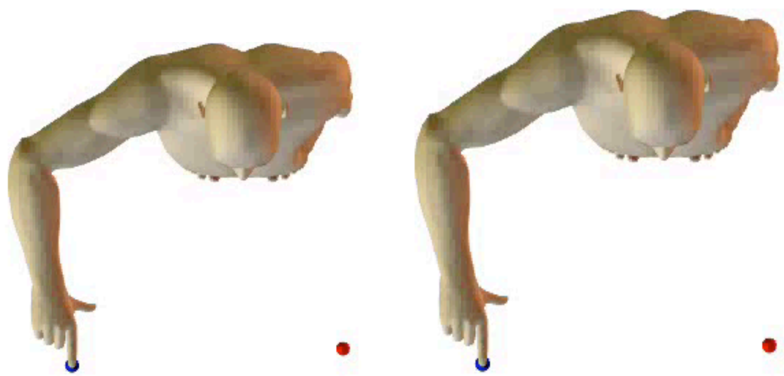


$$\text{Total Loss} = \sum_{dots} error^{\alpha}$$

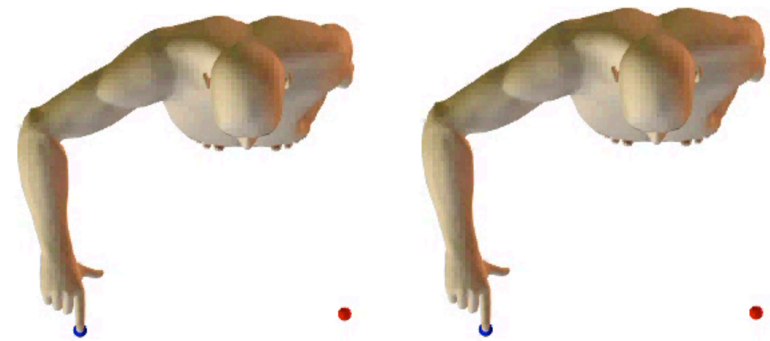
IV. Optimal Decisions

- Tasks are usually specified at a symbolic level
- Movements are specified at a detailed level: 600 muscle activations

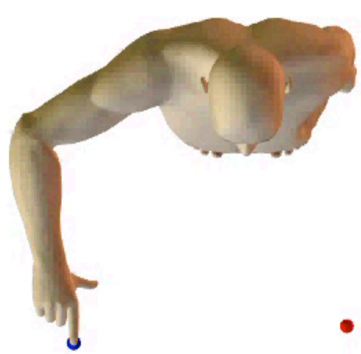
Duration



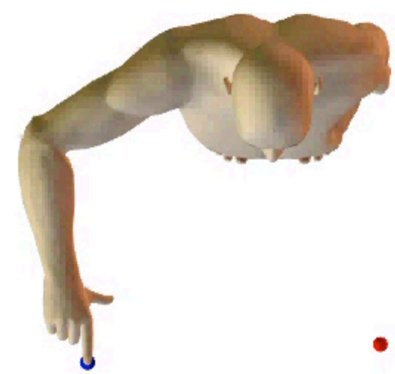
Hand trajectory



Arm configuration



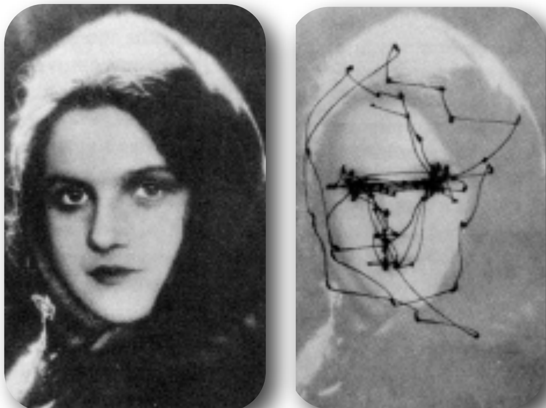
Muscles

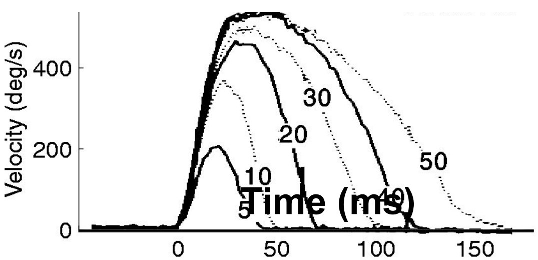


Movement evolution/learning results in stereotypy

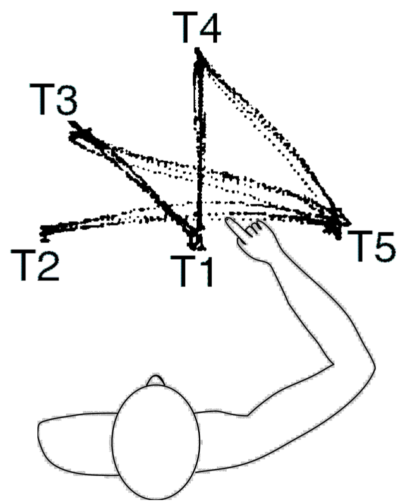
Movement evolution/learning results in stereotypy

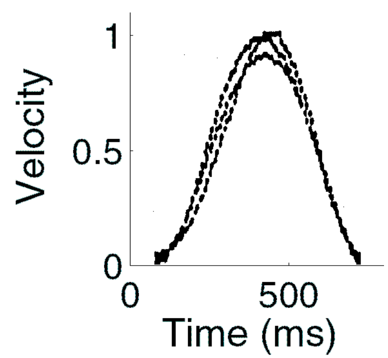
Eye-saccades

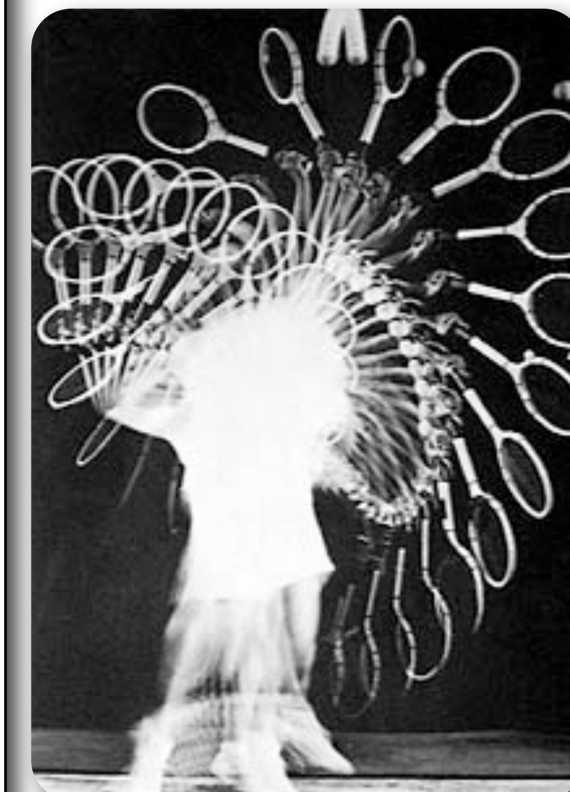




Arm- movements





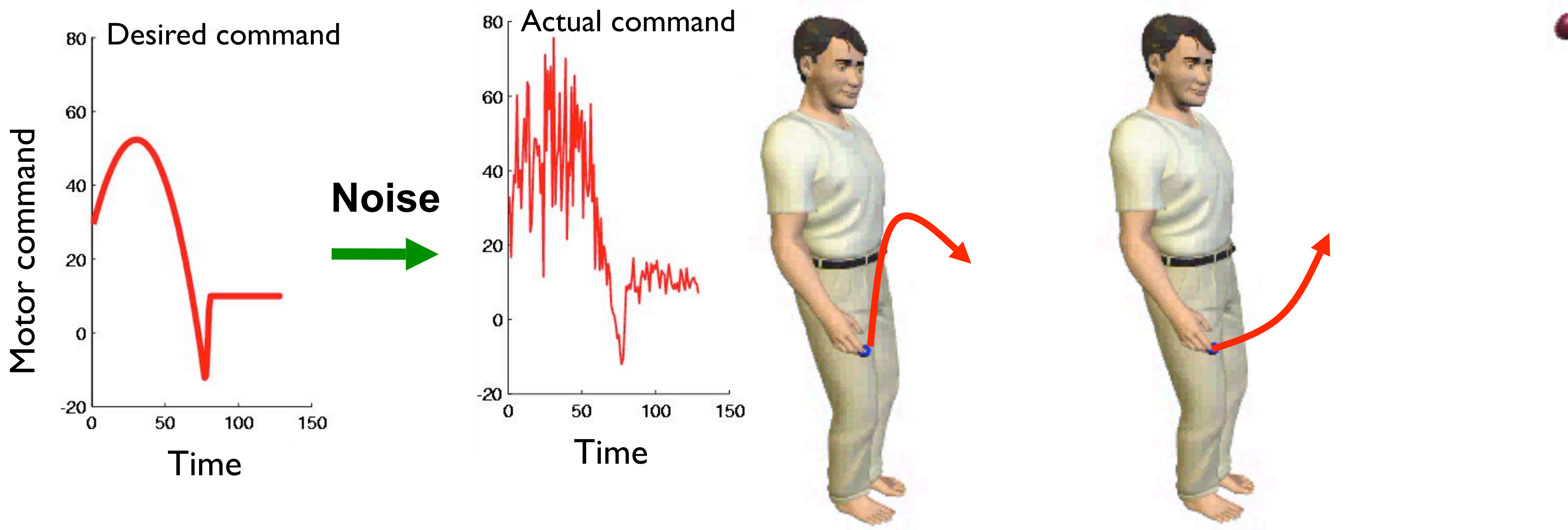


The Assumption of Optimality

Movements have evolved to maximize fitness

- improve through evolution/learning
- every possible movement which can achieve a task has a cost
- we select movement with the lowest cost

Signal-dependent noise and optimal control



motor commands → probability distribution (statistics) of movement.

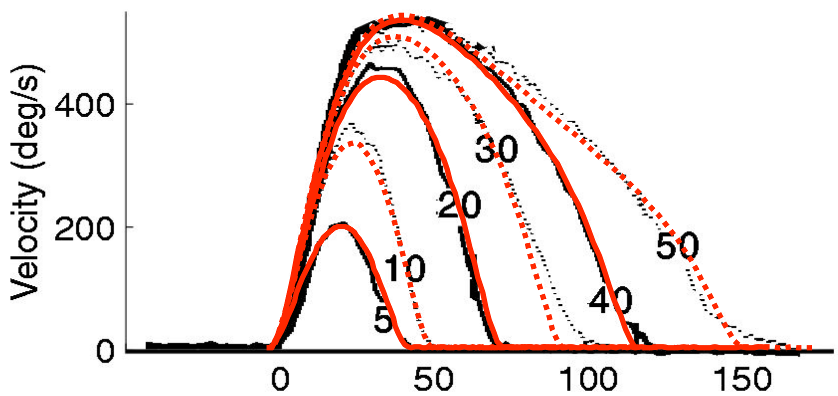
Optimal motor commands ← desired distribution (statistics) of movement.

(Harris & Wolpert, 98, Hamilton & Wolpert JNP 2002, Van Beers, Haggard & Wolpert, JNP, 2004, Haruno & Wolpert 05 JNP , Harris & Wolpert Biol Cyb 2006)

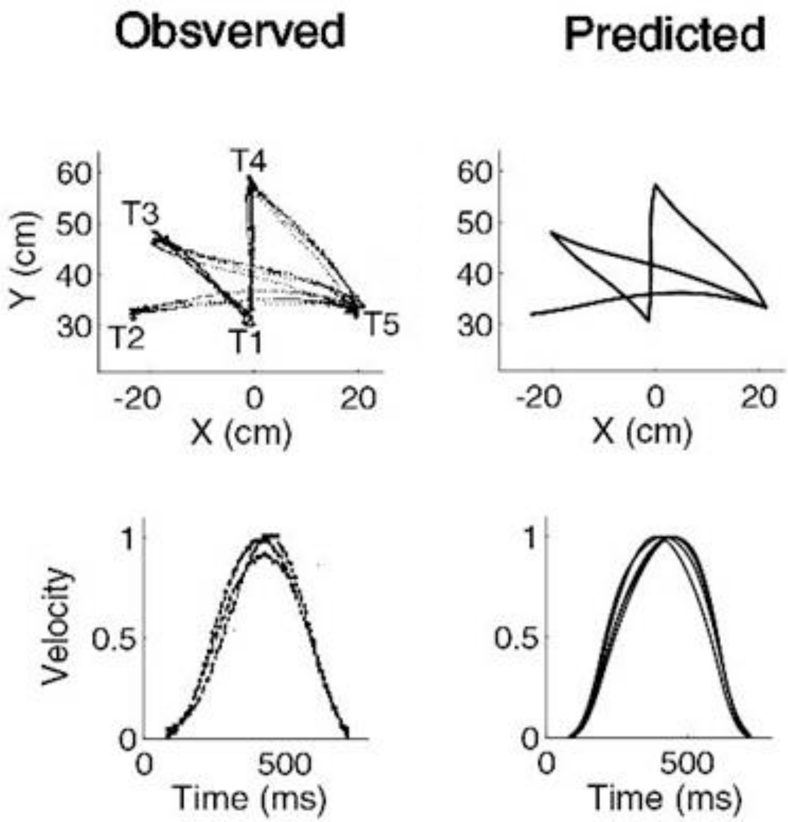
Pointing movements: minimises variance

$$u(t) = \frac{k_1 e^{\frac{(t-M)}{\tau_1}} + k_2 e^{\frac{(t-M)}{\tau_2}} + k_3 e^{\frac{(t-M)}{\tau_3}}}{(\tau_2 - \tau_3)\tau_1 e^{\frac{t-T}{\tau_1}} + (\tau_3 - \tau_1)\tau_2 e^{\frac{t-T}{\tau_2}} + (\tau_1 - \tau_2)\tau_1 e^{\frac{t-T}{\tau_3}}}$$

Eye movements

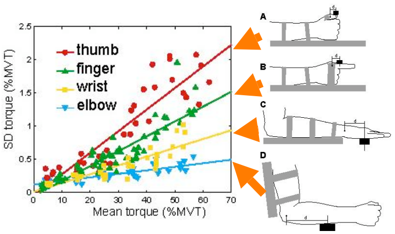


Arm movements



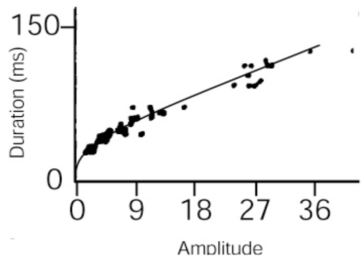
Eye, head, arm & wrist movements

Sources of SDN noise



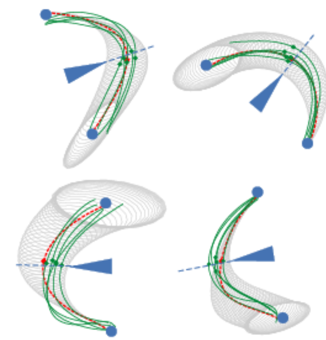
(Jones, Hamilton & Wolpert, JNP, 2002)
Hamilton, Jones & Wolpert, EBR, 2004)

Saccades main sequence



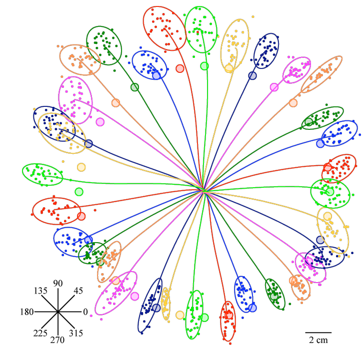
(Harris & Wolpert Biol Cyb.2006)

Obstacle avoidance



(Hamilton & Wolpert JNP 2002)

Other noise sources



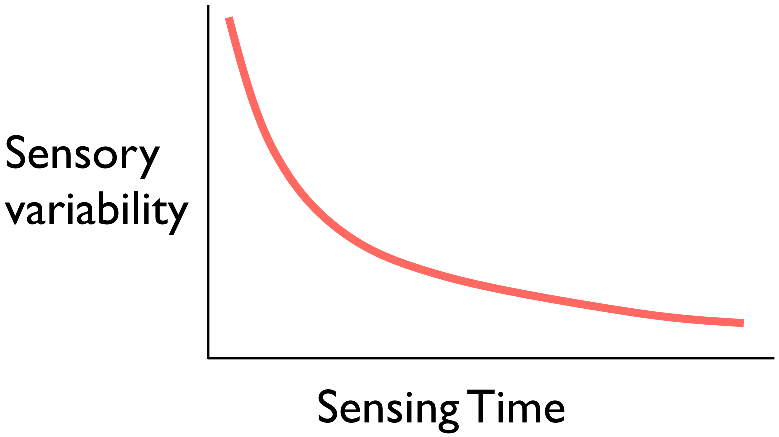
(Van Beers, Haggard & Wolpert, JNP, 2004)

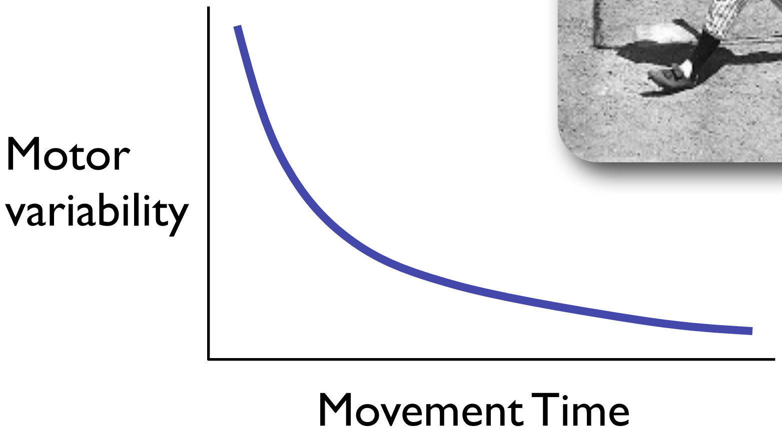
- Biologically plausible underpinning for eye, arm and wrist movements
- Noise lead to statistics of movement
- We can control the statistics by choosing different ways to move

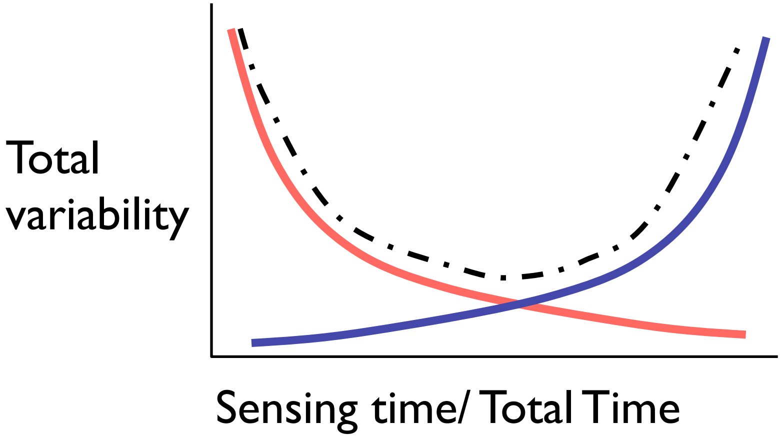
V. Transition from perception to action

In limited time tasks how do subjects trade-off time for

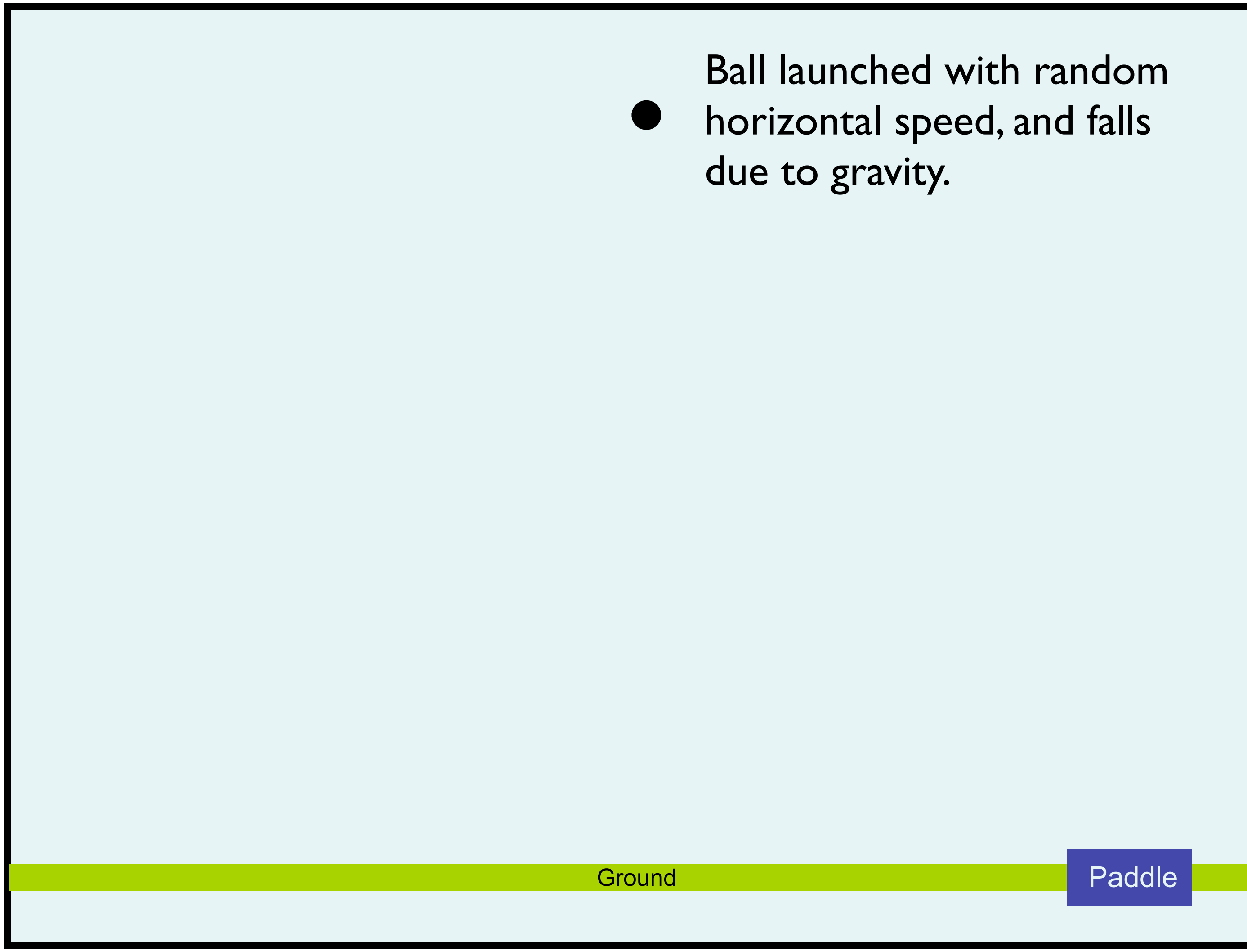
- sensory perception
- motor action





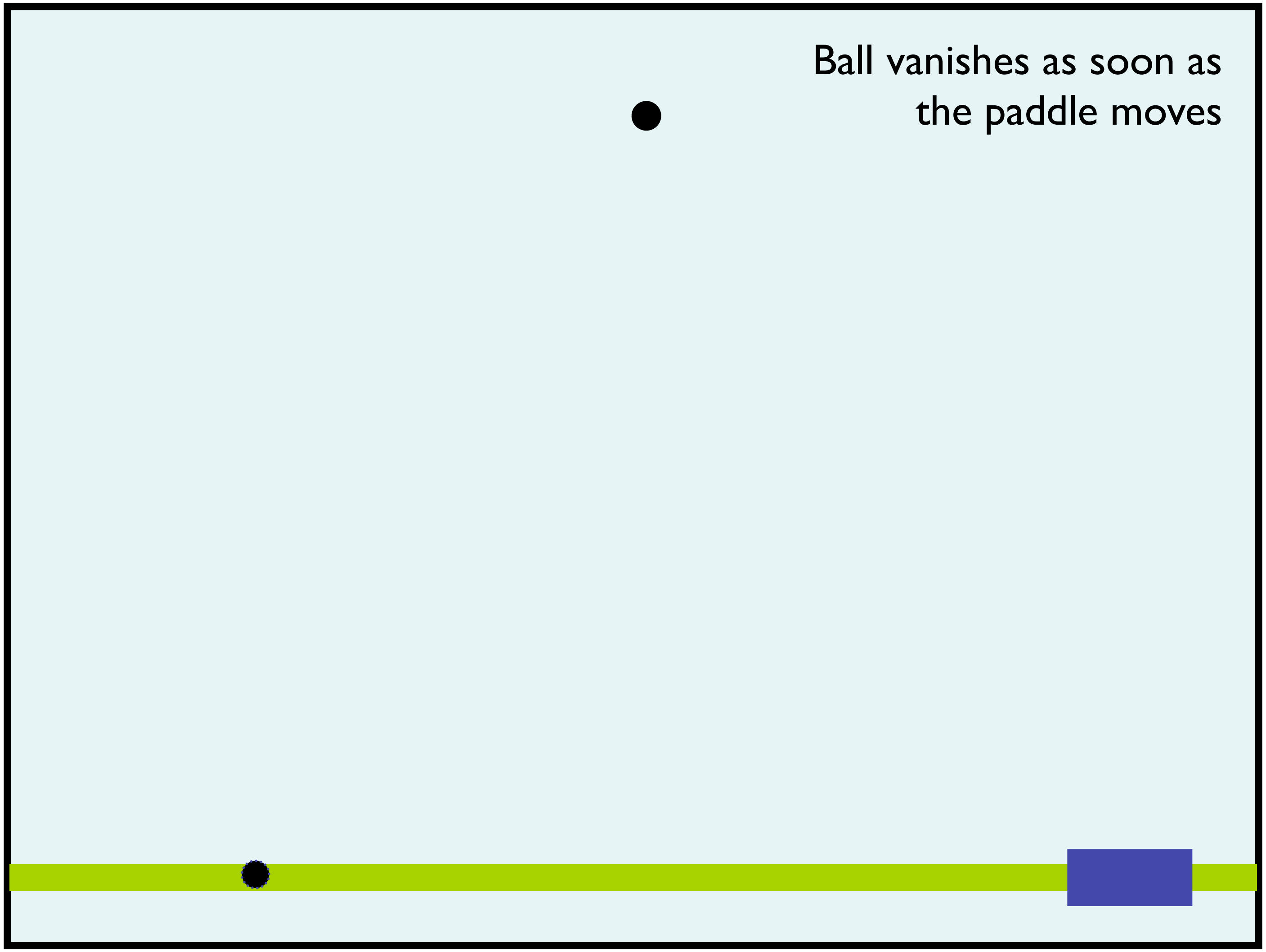


Catch the ball with the paddle

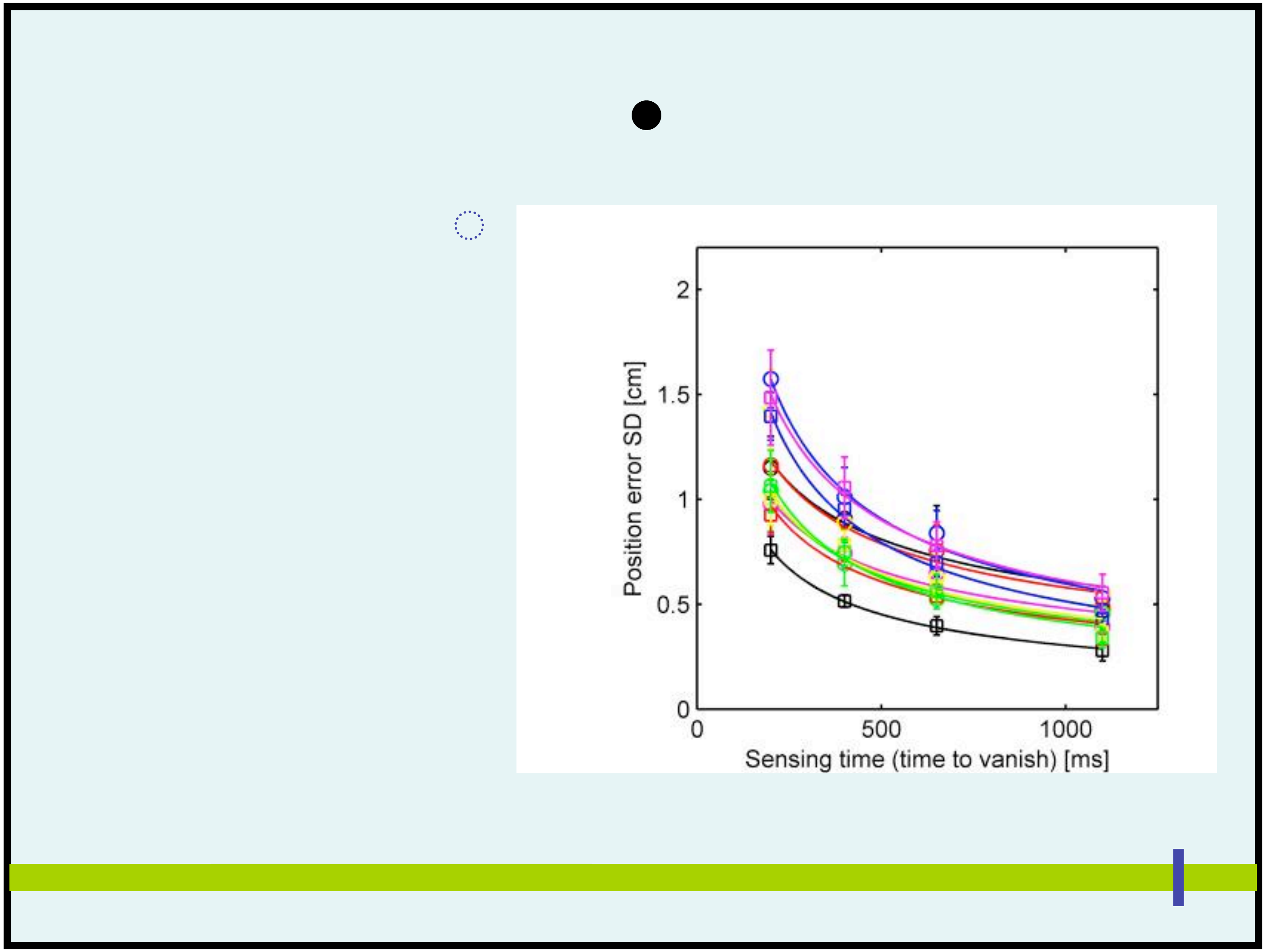


(Faisal & Wolpert)

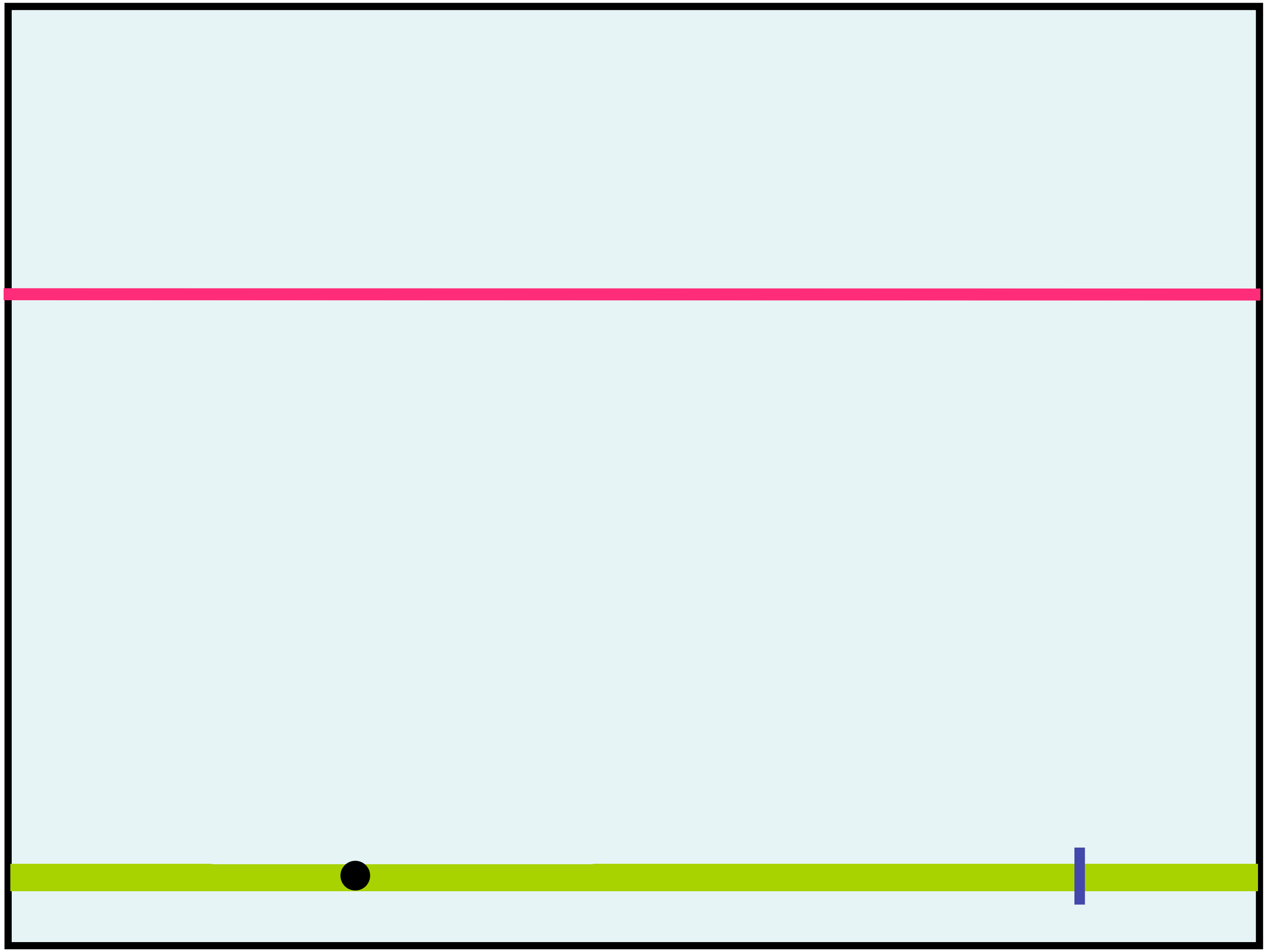
Catch the ball with the paddle



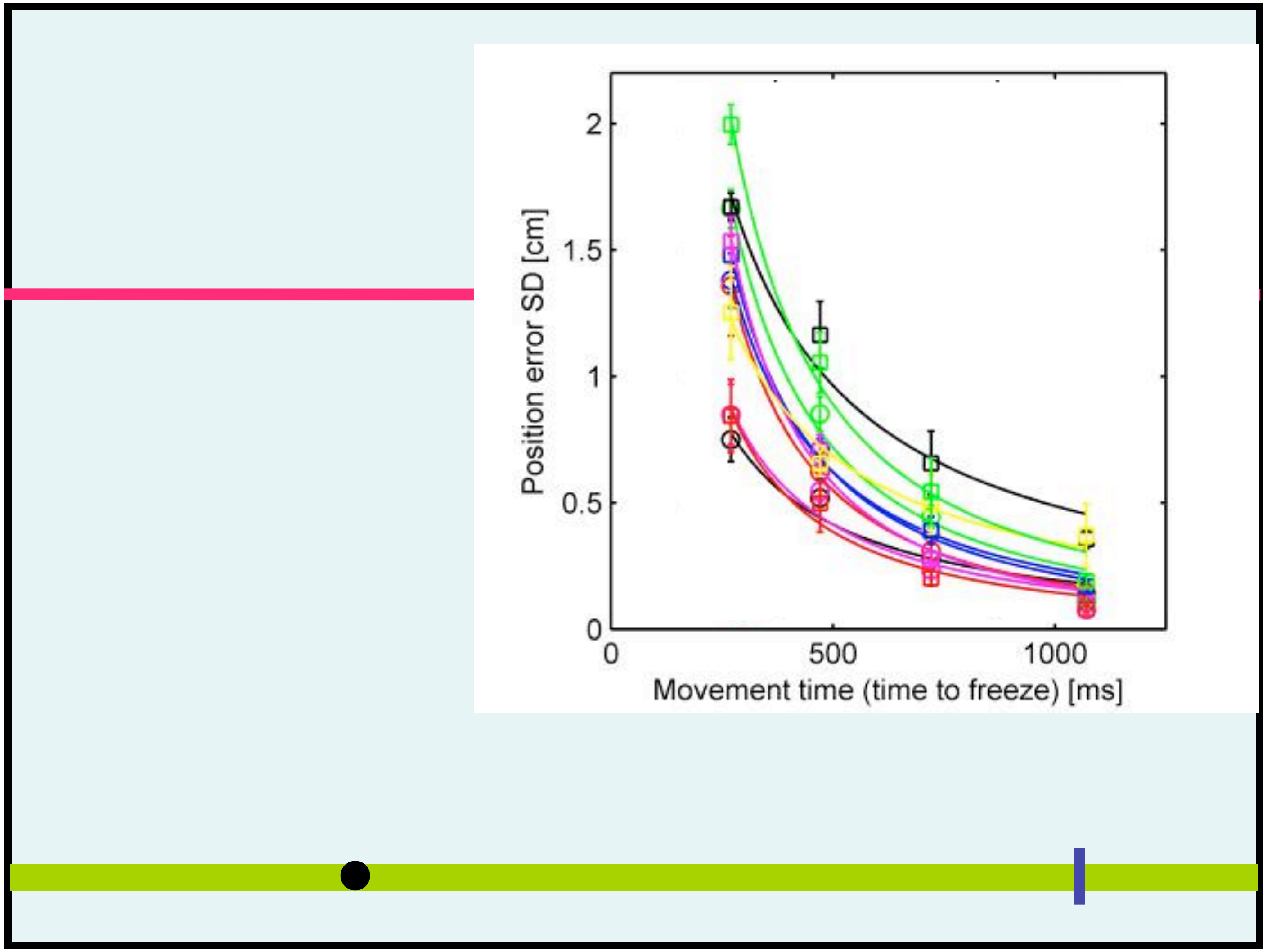
Sensory variability



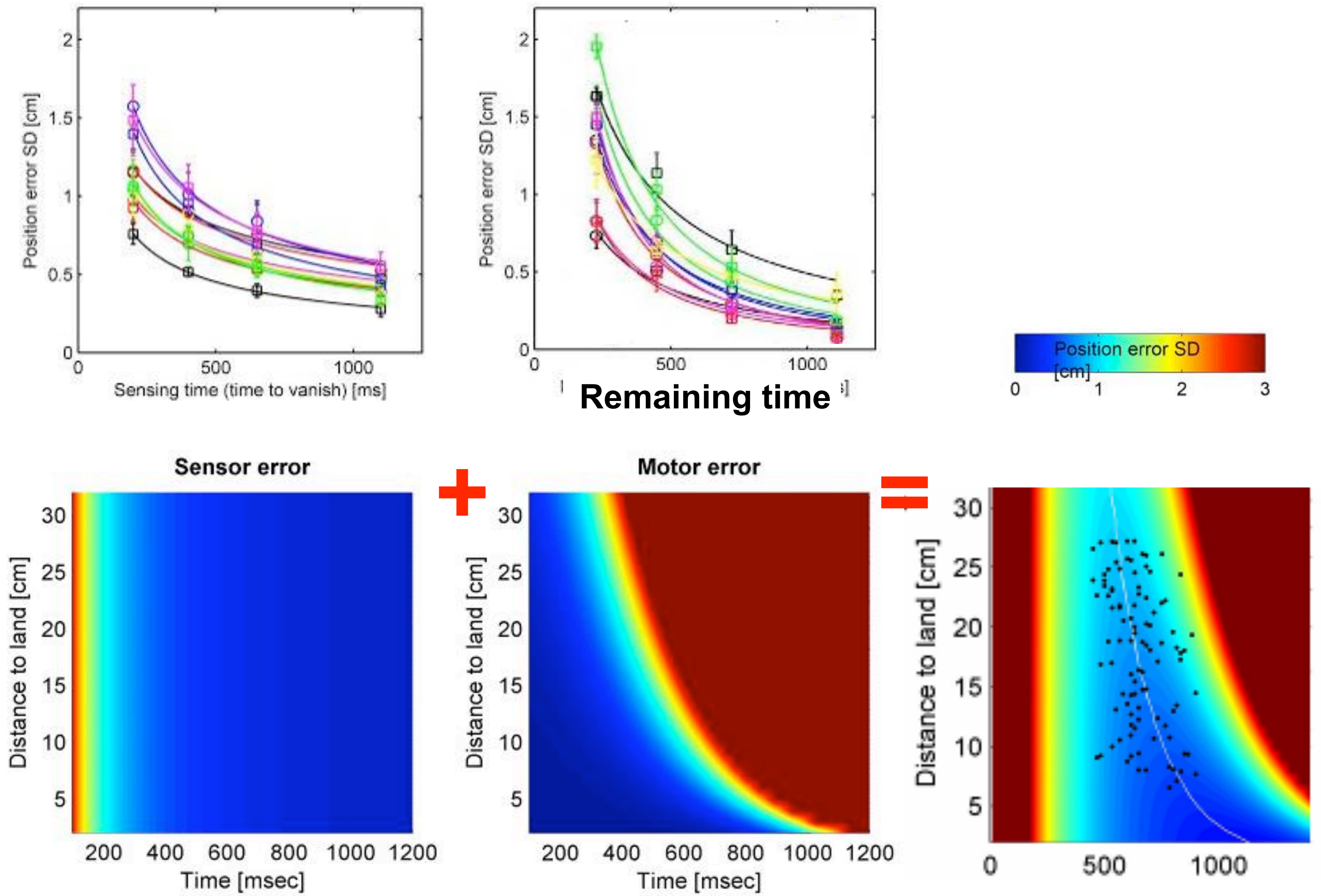
Motor variability



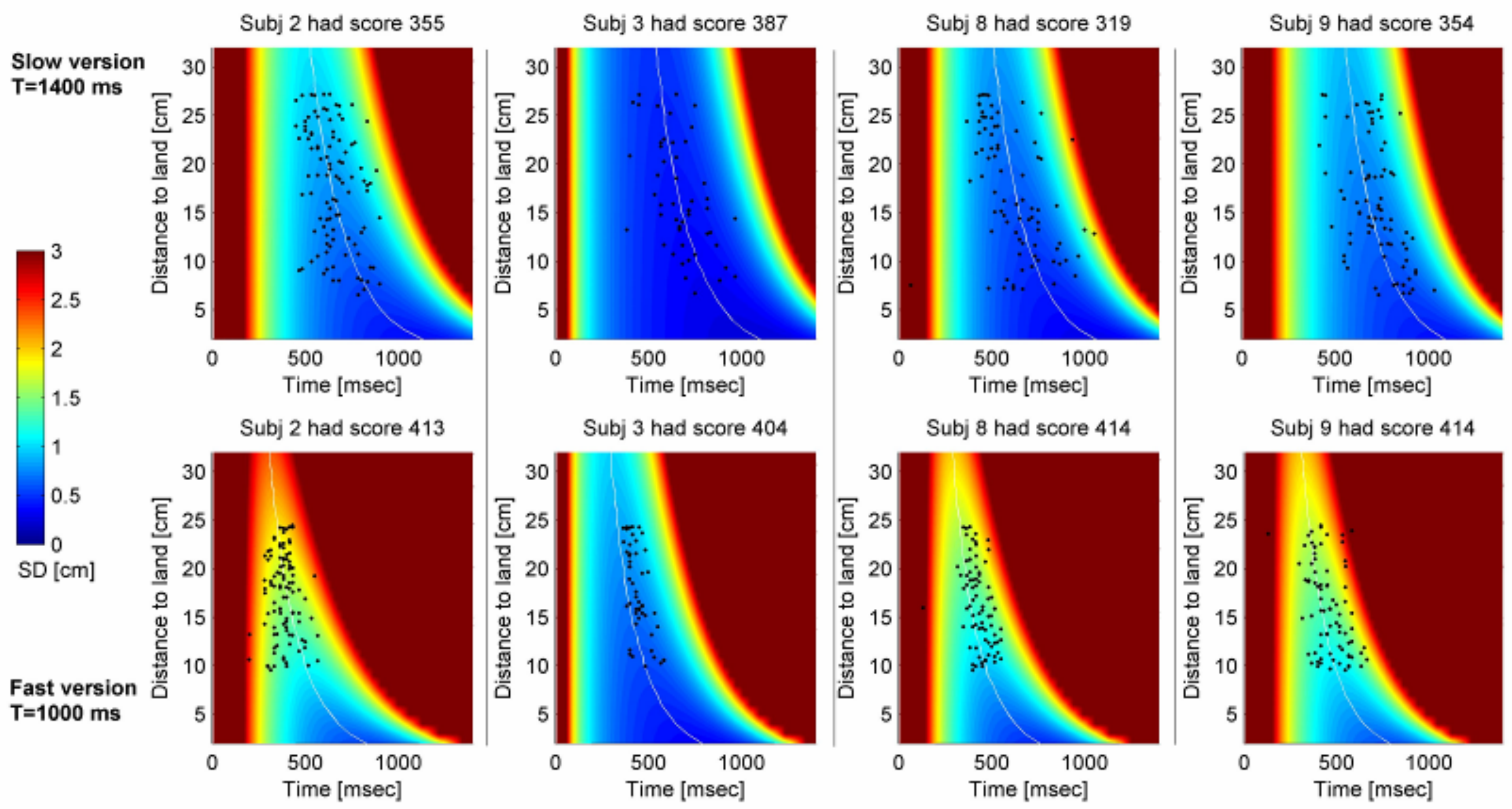
Motor variability



Optimal transition time



Subjects are close to optimal



Summary

Brain

- Evolved to control movement
- Devotes a great deal of effort to minimise uncertainty through
  - Bayesian estimation
  - Predicting consequences of actions
  - Controlling statistics of action through planning
- Optimal transition form perception to action

www.wolpertlab.com