# HUMAN ROBOTICS

- muscle mechanics and control
- single-joint neuromechanics
- multi-joint multi-muscle kinematics
- multi-joint dynamics and control
- motor learning and memory
- interaction control
- motion planning and online control
- integration and control of sensory feedback
- applications in neurorehabilitation and robotics

# INTEGRATION AND CONTROL OF SENSORY FEEDBACK

- We perceive the environment from our many senses, which are subjected to noise, and from which our brain has to decide on the situation
- sensing is not formed of passive sensors with fixed properties: In contrast the CNS can adapt the sensors' properties to the task and conditions
- the motor function and sensing are closely connected

# INTEGRATION AND CONTROL OF SENSORY FEEDBACK

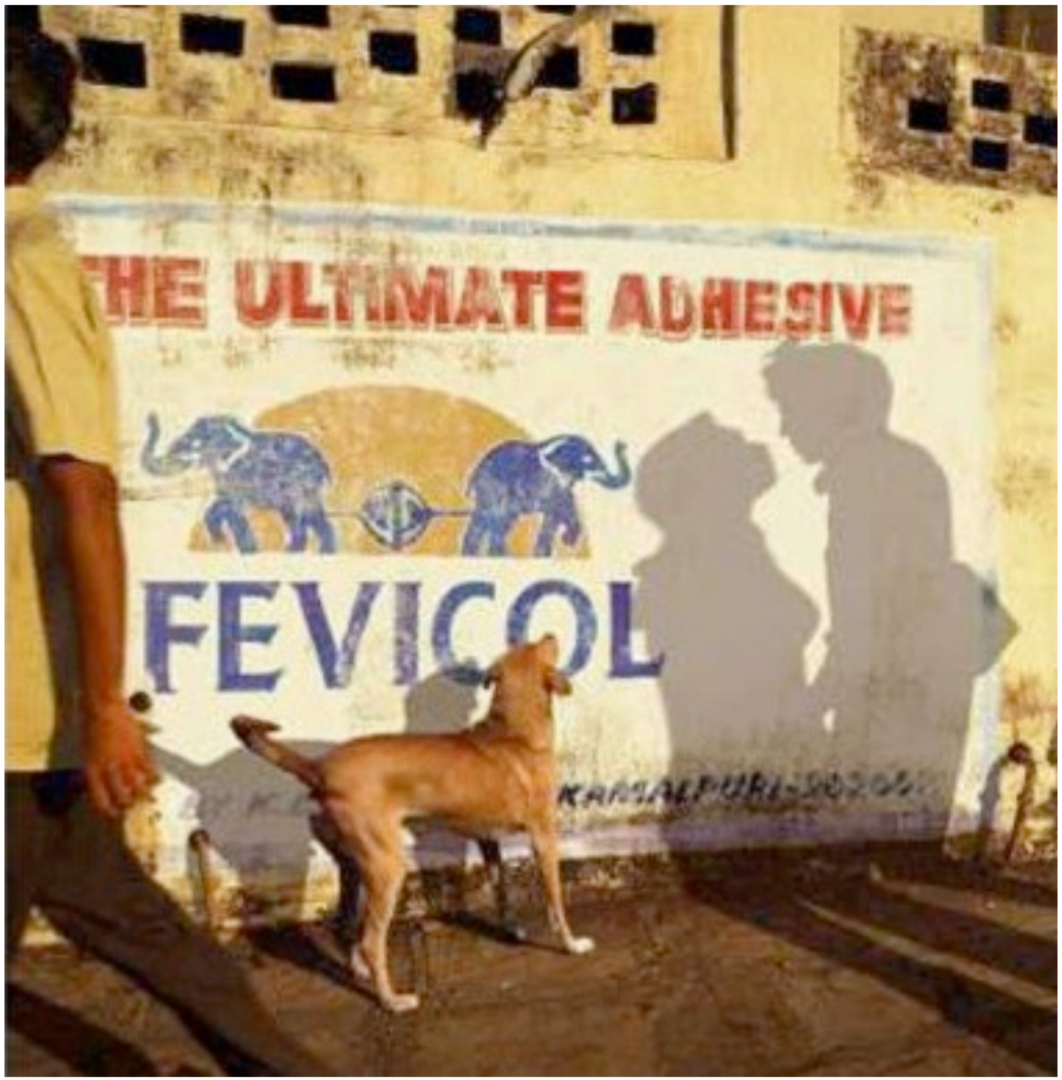
- both sensor resolution and noise vary in the state space (e.g. by skin sensors)
- noise in sensory feedback depends on limb state and location in space
- proprioception (from skin, joint and muscle afferents) is more accurate in the direction away from the body as laterally, the converse for vision

# INTEGRATION AND CONTROL OF SENSORY FEEDBACK

- sensory information is delayed due to transduction (within the receptors), transmission of the sensation (due to neural conduction and synaptic transmission) and processing

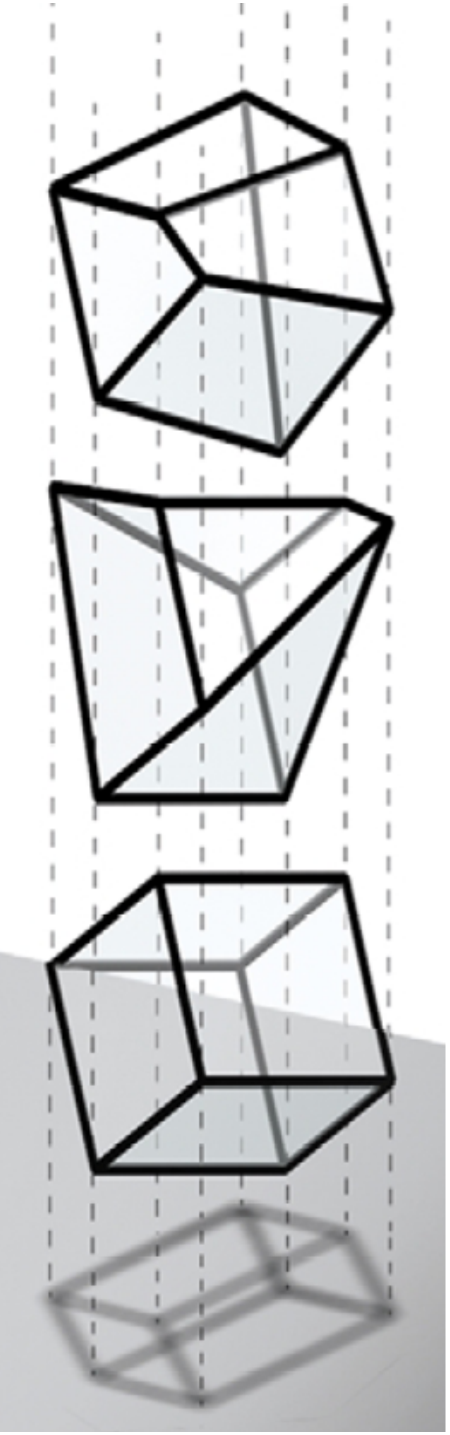
- the sensorimotor system must operate with the inherent noise, delays and uncertainty in the sensory feedback

- the CNS deals with these issues by using Bayesian integration, forward models, active sensing and adaptive feedback

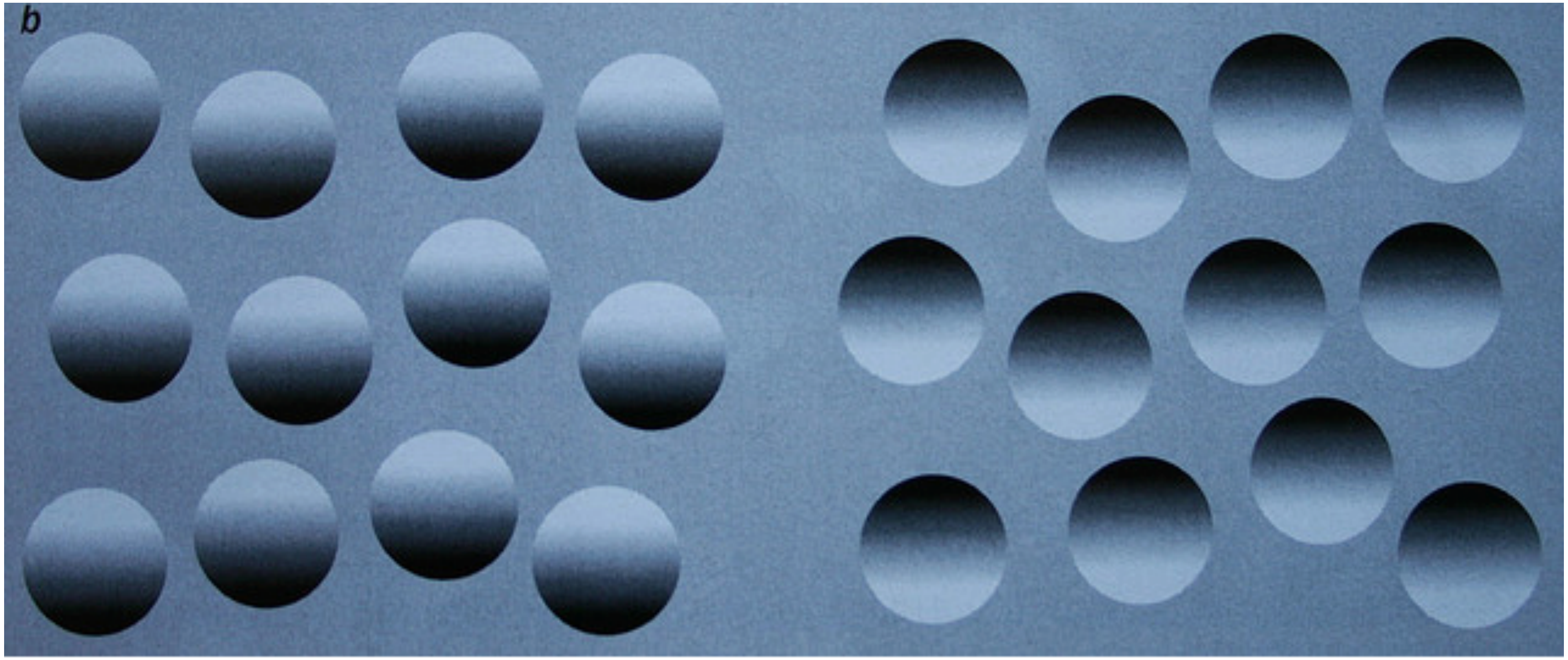

THE ULTIMATE ADHESIVE
FEVICOL

# BAYESIAN INTEGRATION

- sensory information can be ambiguous (e.g. same retinal signal for distinct objects)
- in many cases we have to decide on an action before our senses can provide a complete interpretation



# BAYESIAN INTEGRATION




- how can your brain decide (without touching) that the shapes on the left side are convex?
- it assumes that light comes from above, as with the sun, and in this context the shapes could only be convex

# BAYESIAN INTEGRATION

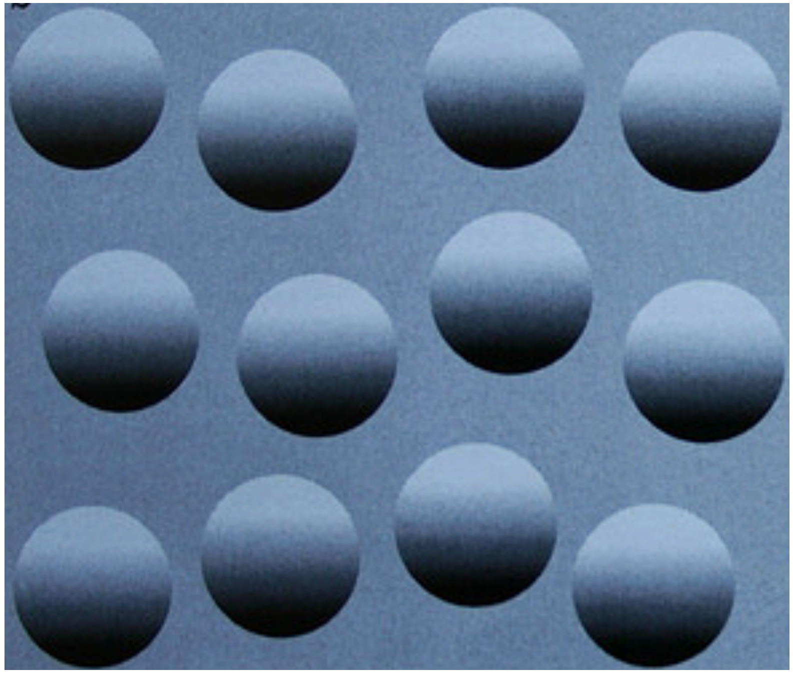
Bayesian statistics

a framework for interpreting situations in which the brain decides on an action by relying on a-priori information

Bayes rule:

$$P(A|B) = \frac{P(B|A)}{P(B)}\, P(A)$$

posterior likelihood prior

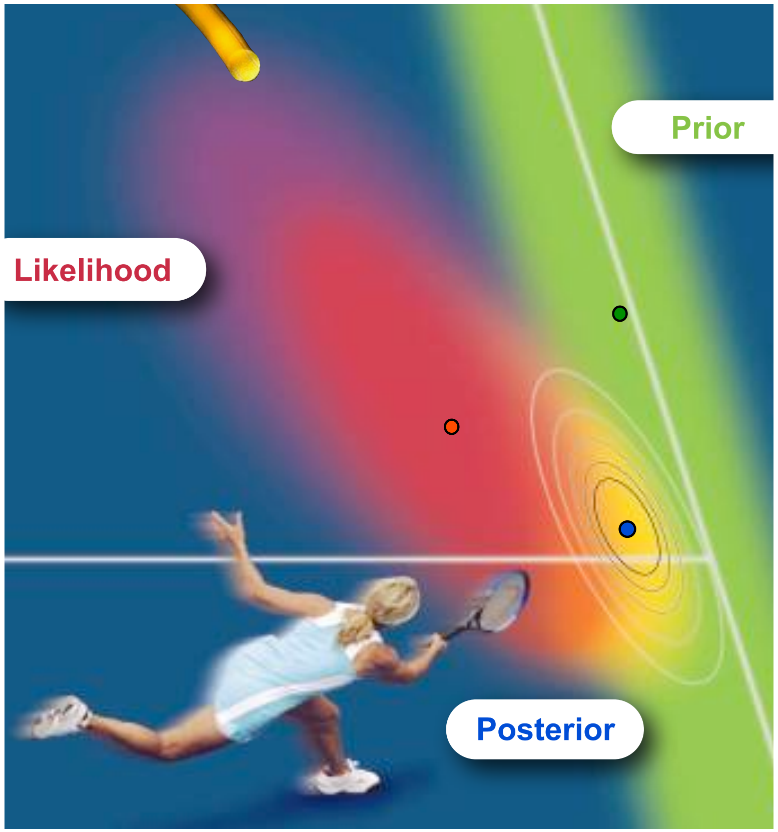


A=shape (convex/concave: P(A)=1/2)

B=illumination (top/bottom: P(B)=1/2)

from daily experience:
P(B|A) ~ 1 when A=convex & B=top

# SENSORIMOTOR INTEGRATION




- when playing tennis, should one estimate the ball from incoming sensory information or from experience?
- to deal with wind, it would be better to rely on sensory information, however when there is fog or at dusk, it would be necessary to rely on previous experience

*x*: "true" position
*s*: position from sensors

$$P(x|s) = \frac{P(s|x)\,P(x)}{P(s)}$$

posterior likelihood prior

[Kording and Wolpert, Nature 2004]

# MAXIMUM LIKELIHOOD (GAUSSIAN DISTRIBUTION)

$$P(x|s) = \frac{P(s|x)\,P(x)}{P(s)} = \frac{\frac{1}{\sigma_s\sqrt{2\pi}} e^{-\frac{(x_s-x)^2}{2\sigma_s^2}} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\overline{x})^2}{2\sigma^2}}}{P(s)}$$

$$0 \equiv \frac{dP(x|s)}{dx}$$

$x$: "true" position

$s$: position from sensors

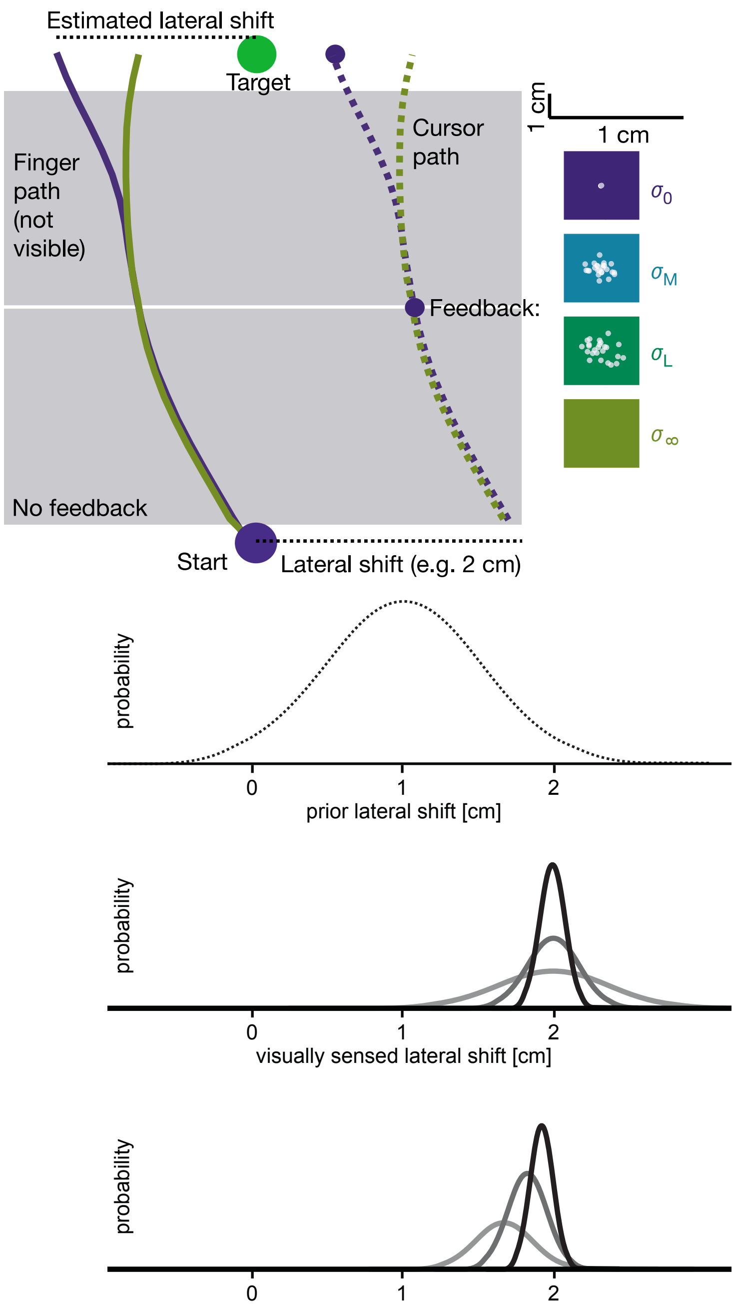
$$0 = \frac{d}{dx}\left[\frac{(x_s - x)^2}{2\sigma_s^2} + \frac{(x-\overline{x})^2}{2\sigma^2}\right] = \frac{x - x_s}{\sigma_s^2} + \frac{x - \overline{x}}{\sigma^2}$$

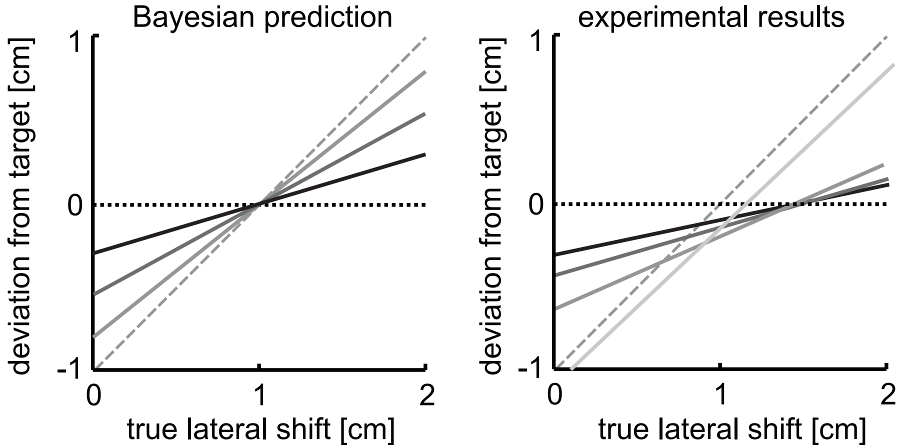
$$0 = \left(\sigma^2 + \sigma_s^2\right) x - \sigma^2 x_s - \sigma_s^2 \overline{x}$$

$$\widehat{x} = \frac{\sigma^2 x_s + \sigma_s^2 \overline{x}}{\sigma^2 + \sigma_s^2}, \qquad \hat{\sigma} = \frac{\sigma^2\,\sigma_s^2}{\sigma^2 + \sigma_s^2}$$

# SENSORIMOTOR INTEGRATION

- repeat trials with feedback (at midpoint) shifted right of 1*cm* in average
- then observe the deviation when shifted right of 2*cm*
- Bayesian combination of sensory information and prior

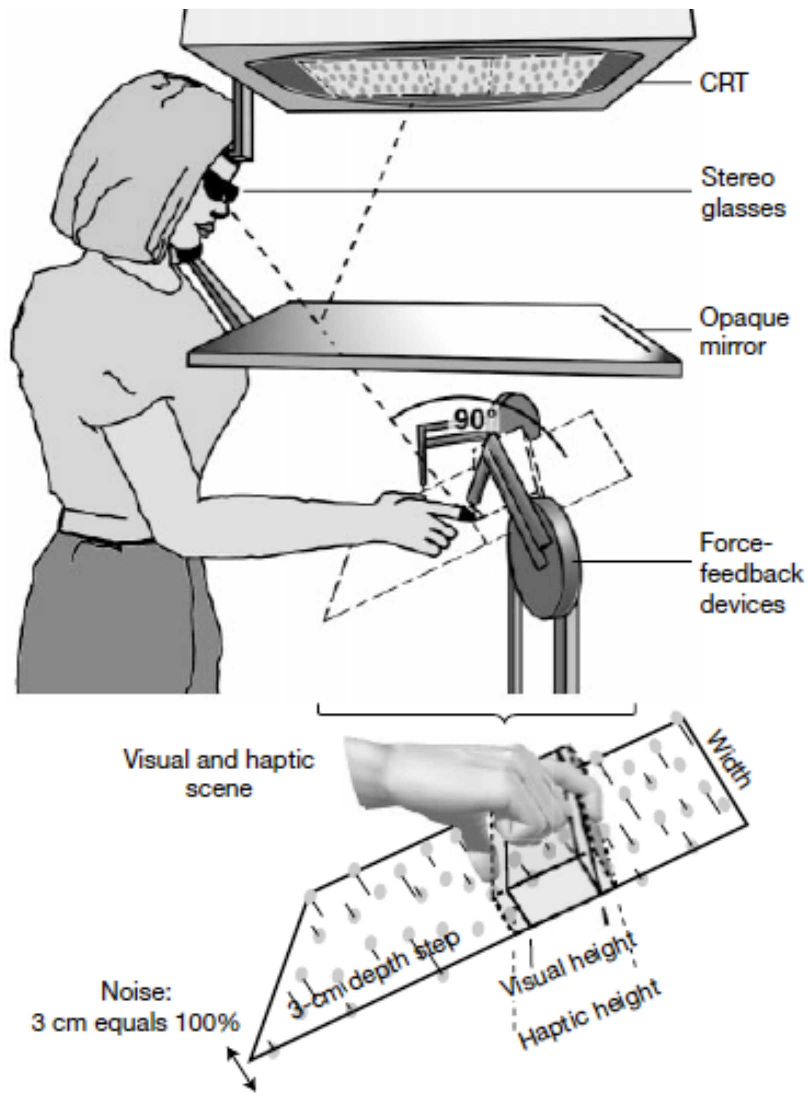



[Kording and Wolpert, Nature 2004]

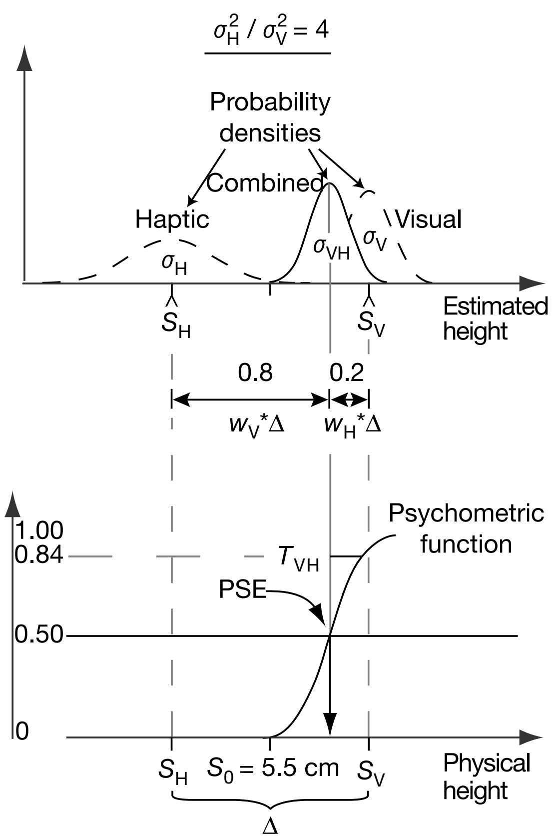
# MULTISENSORY INTEGRATION

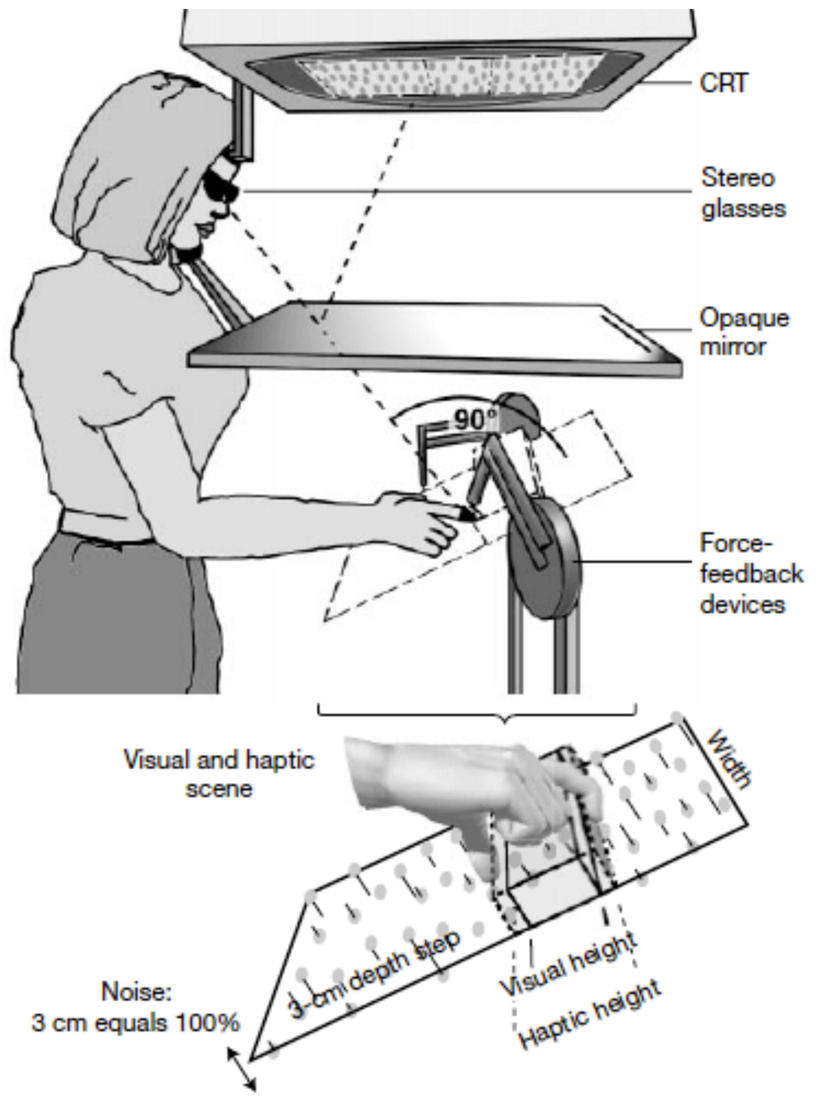
- how does the brain combine information from multiple sensors, which provide inaccurate and perhaps conflicting estimations?
- example: estimation of an object's size using visual and haptic information




[Ernst and Bank, Nature 2002]

# MULTISENSORY INTEGRATION




[Ernst and Bank, Nature 2002]

# MULTISENSORY INTEGRATION

probability of the object's size = $x$ given independent, Gaussian visual and haptic information:

$$P(v \cap h) = P(v)\,P(h) = \frac{e^{-\frac{(x-\overline{x}_v)^2}{2\sigma_v^2}}}{\sigma_v\sqrt{2\pi}}\;\frac{e^{-\frac{(x-\overline{x}_h)^2}{2\sigma_h^2}}}{\sigma_h\sqrt{2\pi}}$$

$$0 \equiv \frac{dP(v \cap h)}{dx}$$

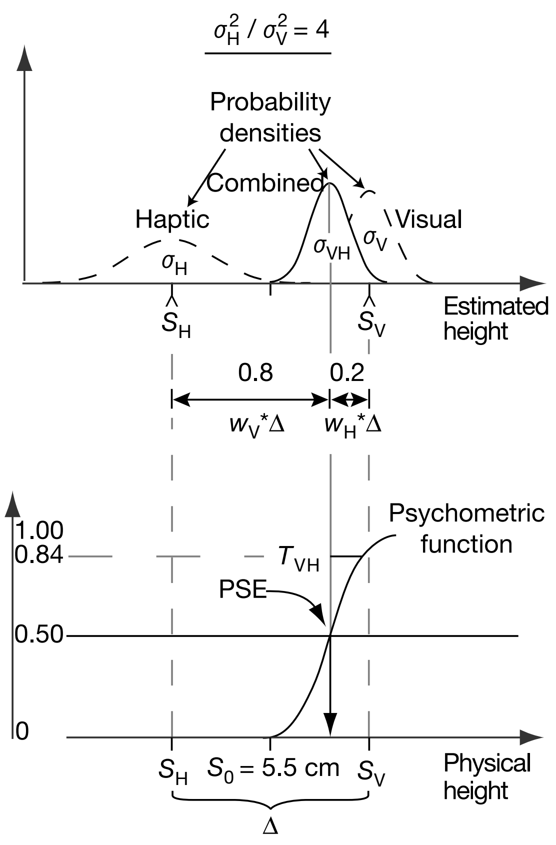
$$0 = \frac{d}{dx}\left[\frac{(x-\overline{x}_v)^2}{2\sigma_v^2} + \frac{(x-\overline{x}_h)^2}{2\sigma_h^2}\right] = \frac{x-\overline{x}_v}{\sigma_v^2} + \frac{x-\overline{x}_h}{\sigma_h^2}$$

$$0 = \left(\sigma_h^2 + \sigma_v^2\right) x - \sigma_h^2\,\overline{x}_v - \sigma_v^2\,\overline{x}_h$$

$$\hat{x} = \frac{\sigma_h^2\,\overline{x}_v + \sigma_v^2\,\overline{x}_h}{\sigma_v^2 + \sigma_h^2}, \qquad \hat{\sigma} = \frac{\sigma_v^2\,\sigma_h^2}{\sigma_v^2 + \sigma_h^2}$$

# BAYESIAN MODEL PREDICTION

$$\hat{x} = \frac{\sigma_v^2}{\sigma_h^2 + \sigma_v^2} x_h + \frac{\sigma_h^2}{\sigma_h^2 + \sigma_v^2} x_v \qquad \sigma_b^2 = \frac{\sigma_v^2 \, \sigma_h^2}{\sigma_v^2 + \sigma_h^2}$$




[Ernst and Bank, Nature 2002]

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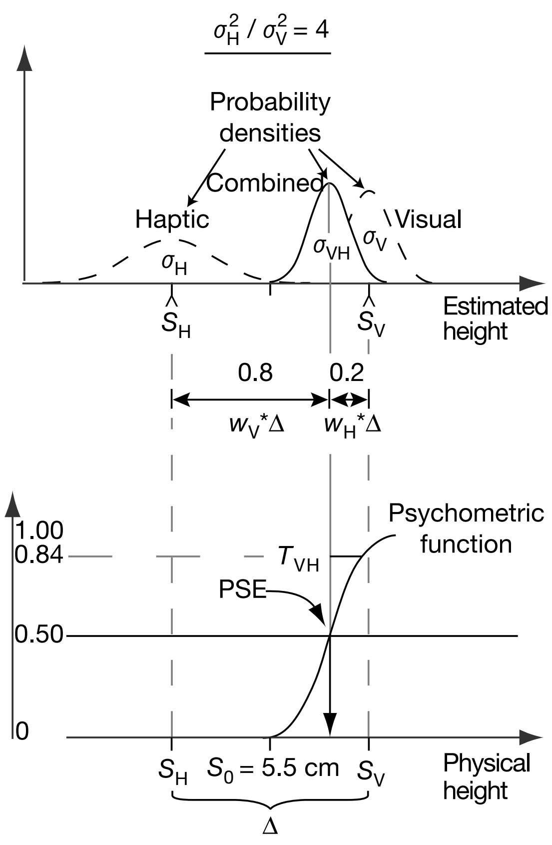
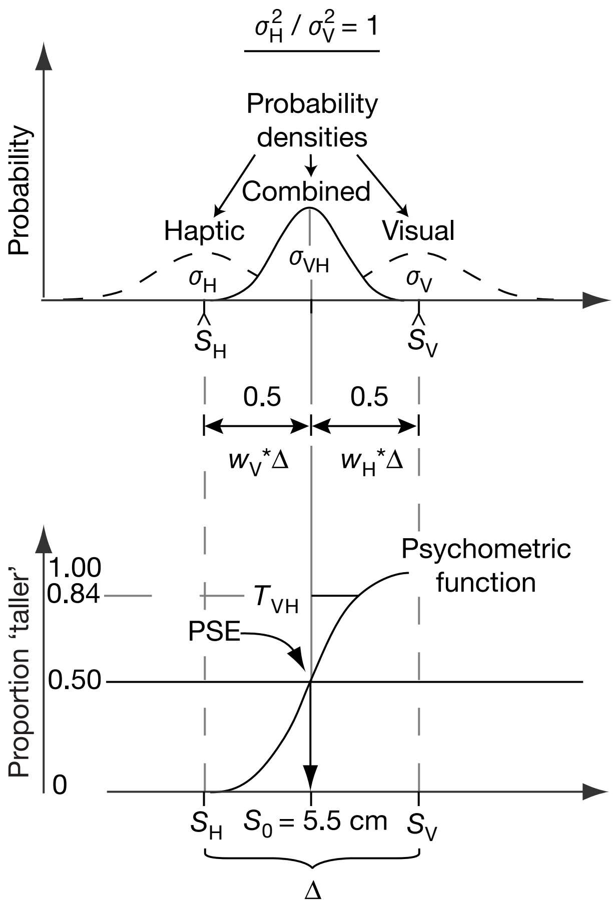
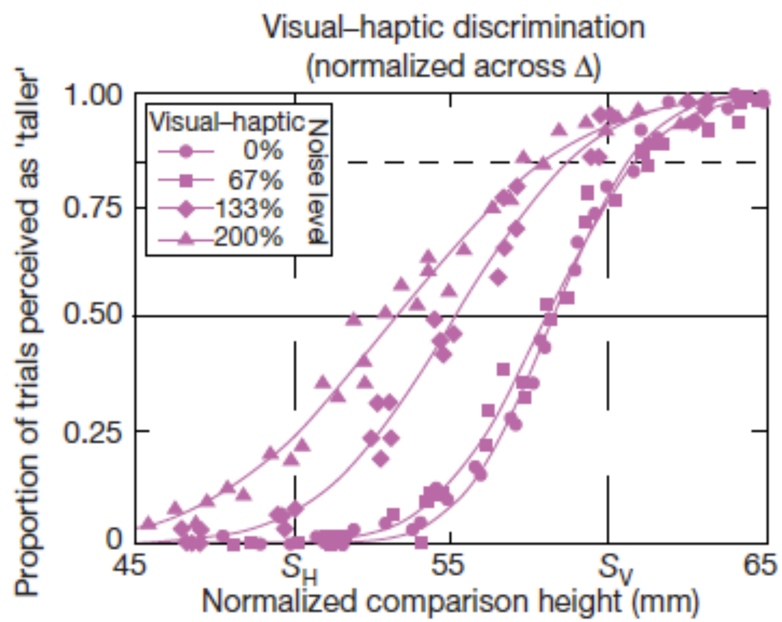


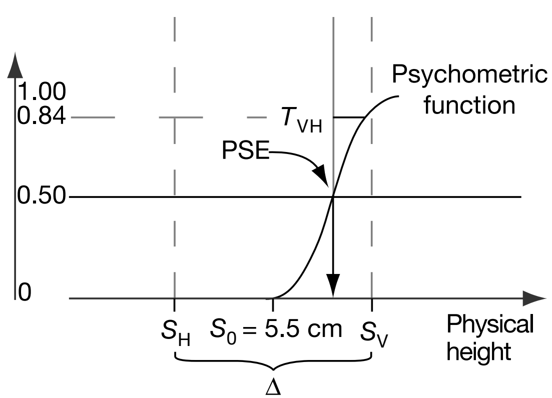

blurred vision

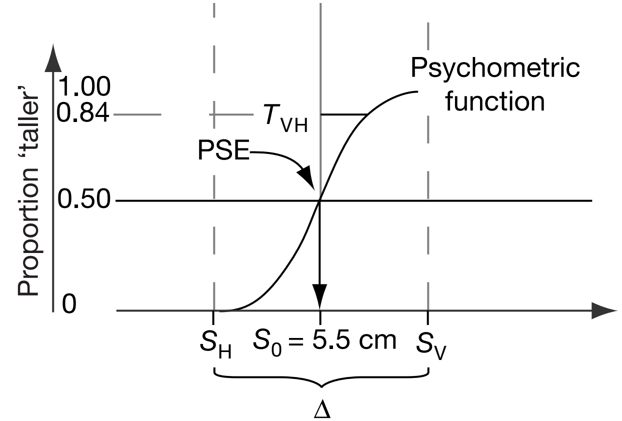
[Ernst and Bank, Nature 2002]

# BAYESIAN MODEL PREDICTION




experiment



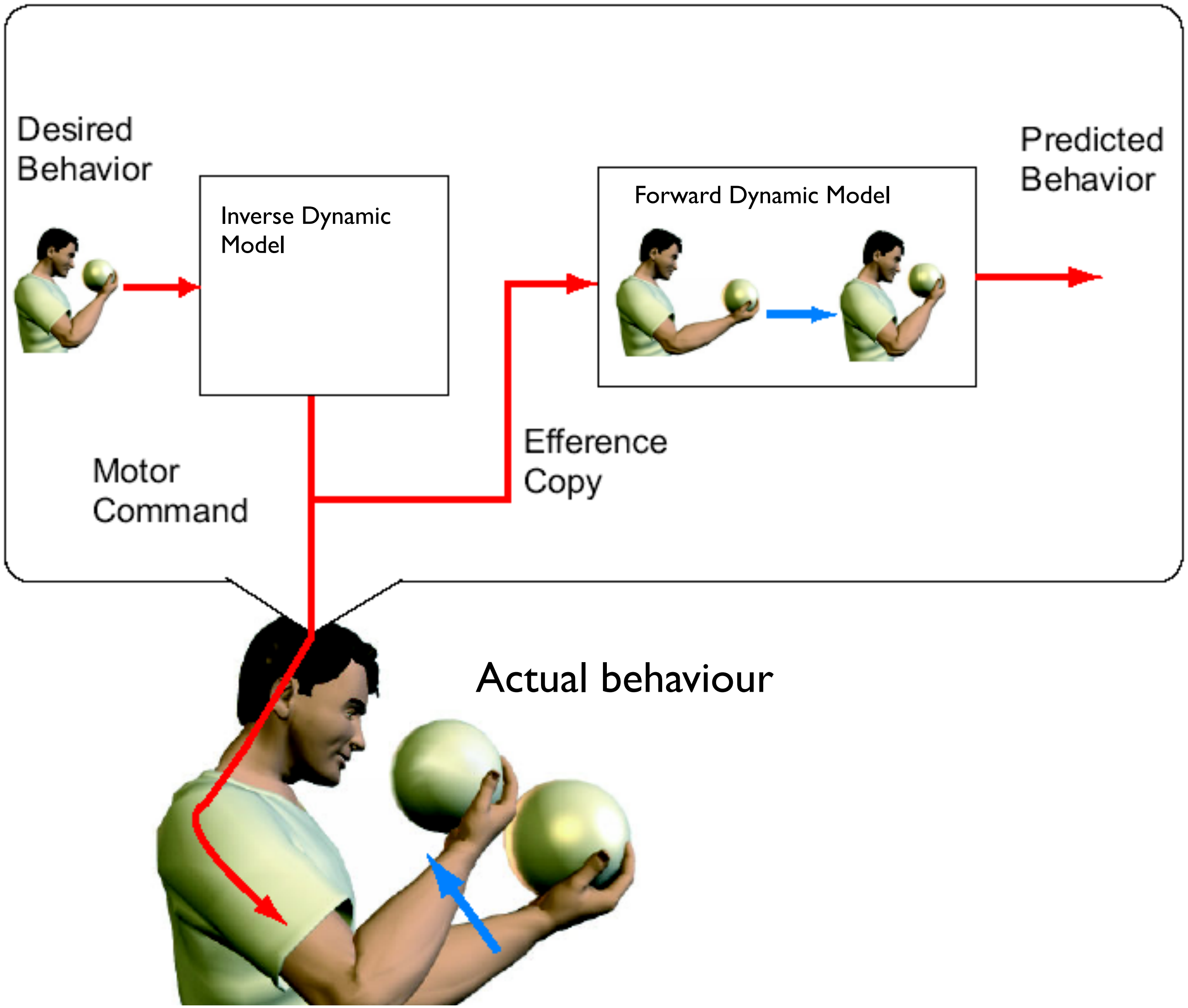

blurred vision

[Ernst and Bank, Nature 2002]

# INTERNAL FORWARD MODEL

- before: combination of a few discrete cues
- wanted now: framework for sensorimotor acting continually in a dynamic and evolving environment
- our sensing cannot provide accurate estimate of our current body state during movement as sensory feedback is delayed and noisy -> stochastic prediction
- prior: distribution of the most likely limb states given our motor command and the movement history, provided by a forward model

# INTERNAL FORWARD MODEL




[Wolpert and Flanagan, Current Biology 2001]

# KALMAN FILTER AS FORWARD MODEL

linear forward model with Gaussian noise:

$$\mathbf{z}_{k+1} = \mathbf{A}_k \mathbf{z}_k + \mathbf{B}_k \mathbf{u}_k + \boldsymbol{\eta}_k$$ : system equation

$$\mathbf{y}_{k+1} = \mathbf{C}_k \mathbf{z}_k + \boldsymbol{\omega}_k$$ : linear observation equation

sensing with Gaussian noise

$$\hat{\mathbf{z}}_{k+1} = \mathbf{A}_k \hat{\mathbf{z}}_k + \mathbf{B}_k \mathbf{u}_k + \mathbf{K}_k (\mathbf{y}_k - \mathbf{C}\hat{\mathbf{z}}_k)$$

LQE = Kalman Filter minimising $E[\| \mathbf{z}_k - \hat{\mathbf{z}}_k \|^2]$

$$\mathbf{K}_k = \mathbf{A}_k \mathbf{P}_k \mathbf{C}_k^T (\mathbf{C}_k \mathbf{P}_k \mathbf{C}_k^T + \mathrm{E}(\mathbf{y}_k \mathbf{y}_k^T))^{-1} \quad \hat{\mathbf{z}}_0 = E[\mathbf{z}_0] \quad \mathbf{P}_0 = E(\mathbf{z}_0 \mathbf{z}_0^T)$$

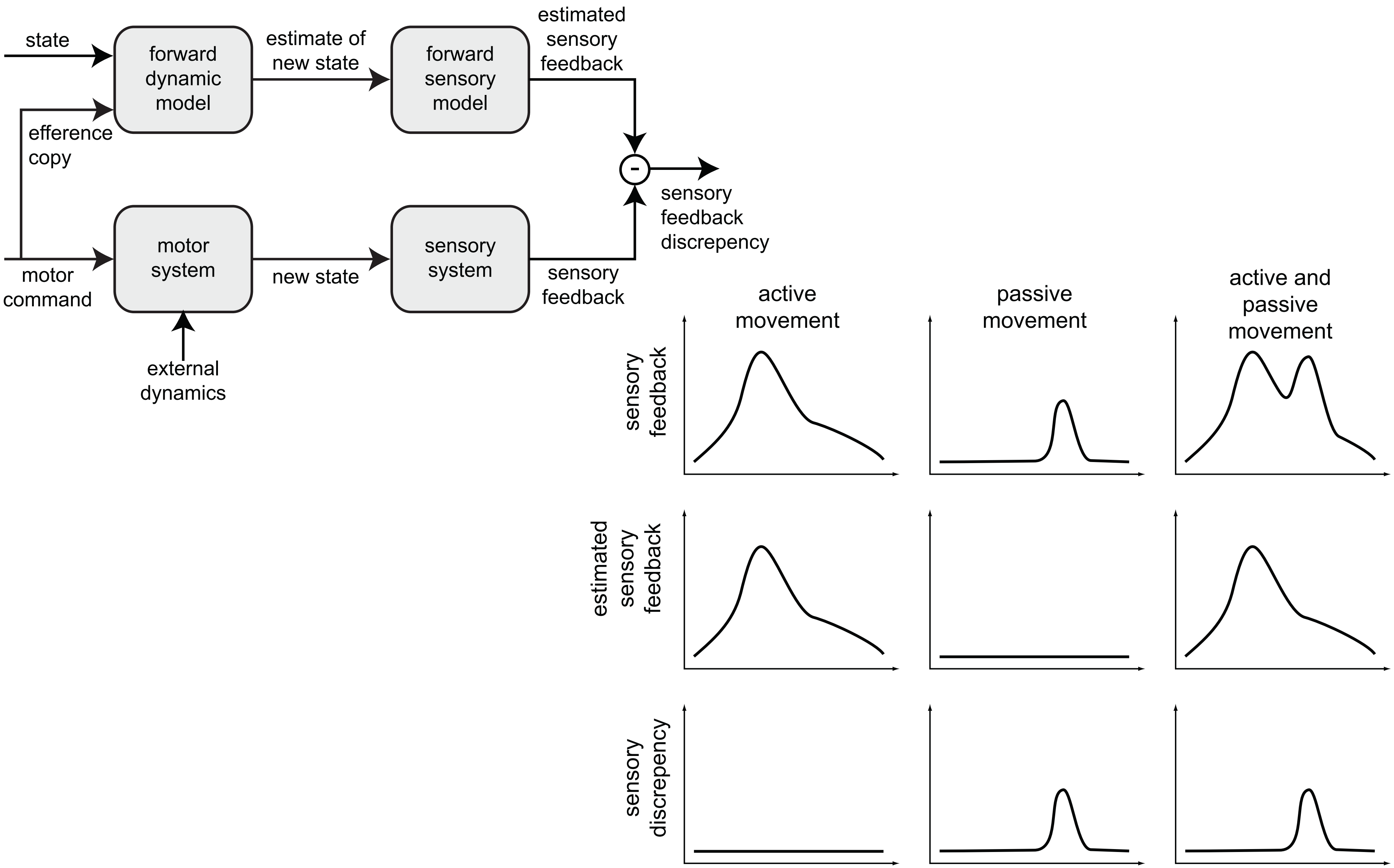
$$\mathbf{P}_{k+1} = \mathbf{A}_k (\mathbf{P}_k - \mathbf{P}_k \mathbf{C}_k^T (\mathbf{C}_k \mathbf{P}_k \mathbf{C}_k^T + E(\mathbf{z}_k \mathbf{z}_k^T))^{-1} \mathbf{C}_k \mathbf{P}_k) \mathbf{A}_k^T + E(\mathbf{y}_k \mathbf{y}_k^T)$$

# STATE ESTIMATION

to localise an object relative to your head, you need to know:

- its location on the retina
- the eyes’ orientation from their motoneurons’ activity

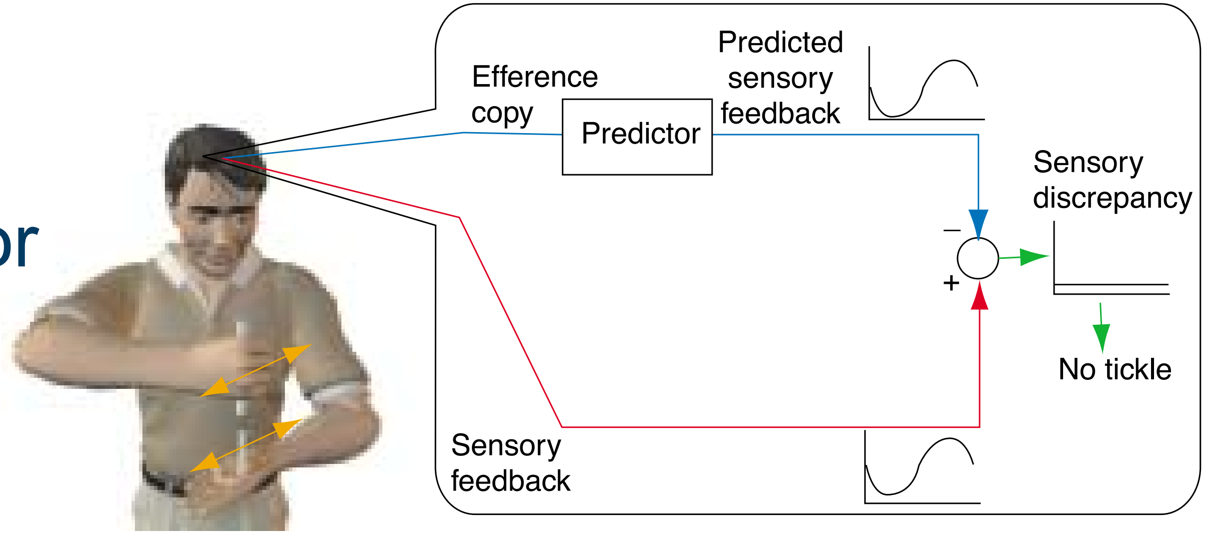
# SENSORY PREDICTION

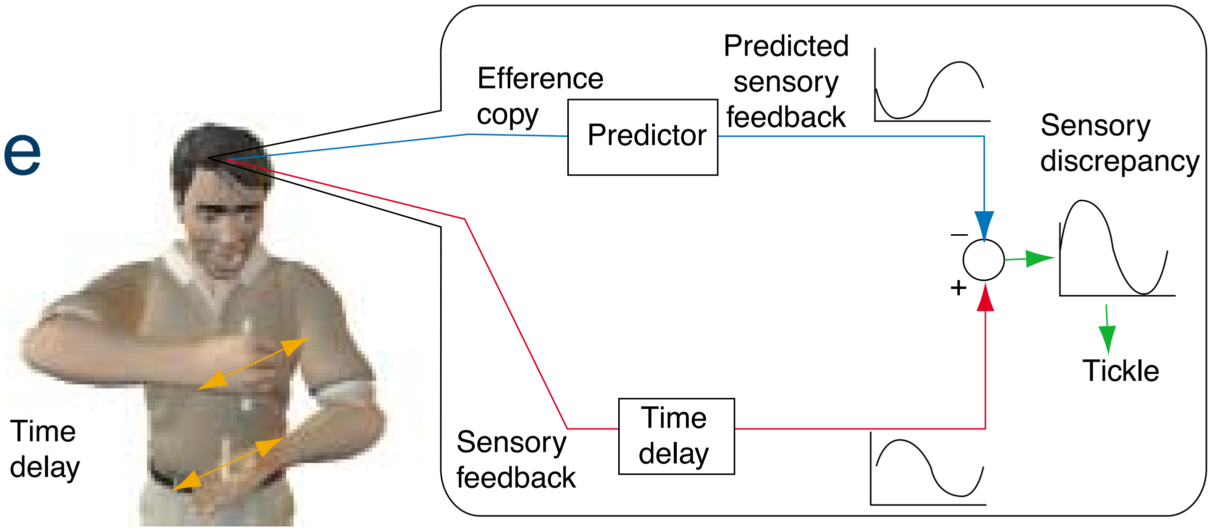



[Wolpert and Flanagan, Current Biology 2001]

# WHY ONE CANNOT TICKLE ONESELF

- robot to control the stimulus
- if the robot is delayed or moving in another direction the signal becomes ticklish
- the prediction mechanism used for the sensory cancellation is both temporally and spatially precise

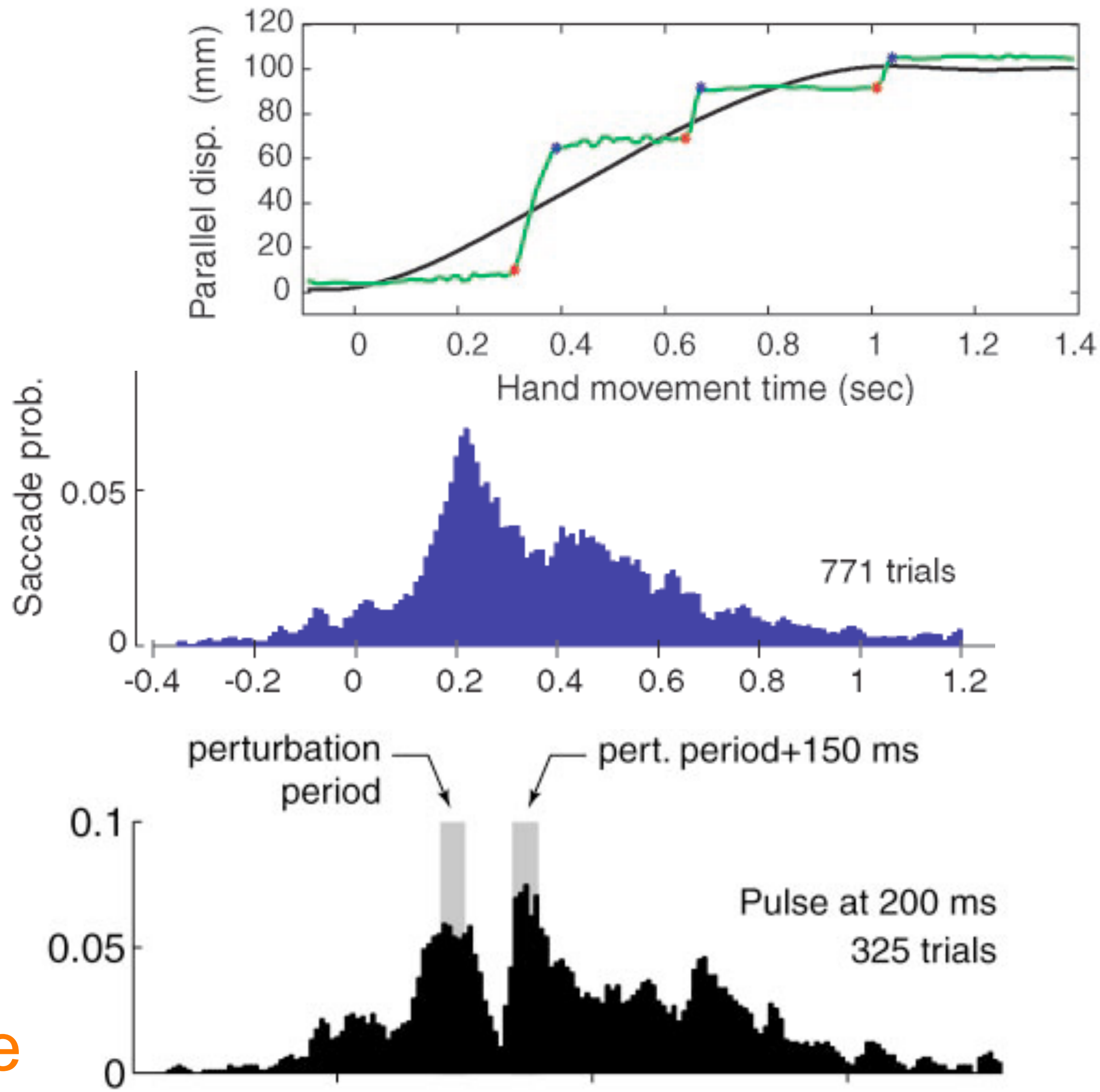



[Wolpert and Flanagan, Current Biology 2001]

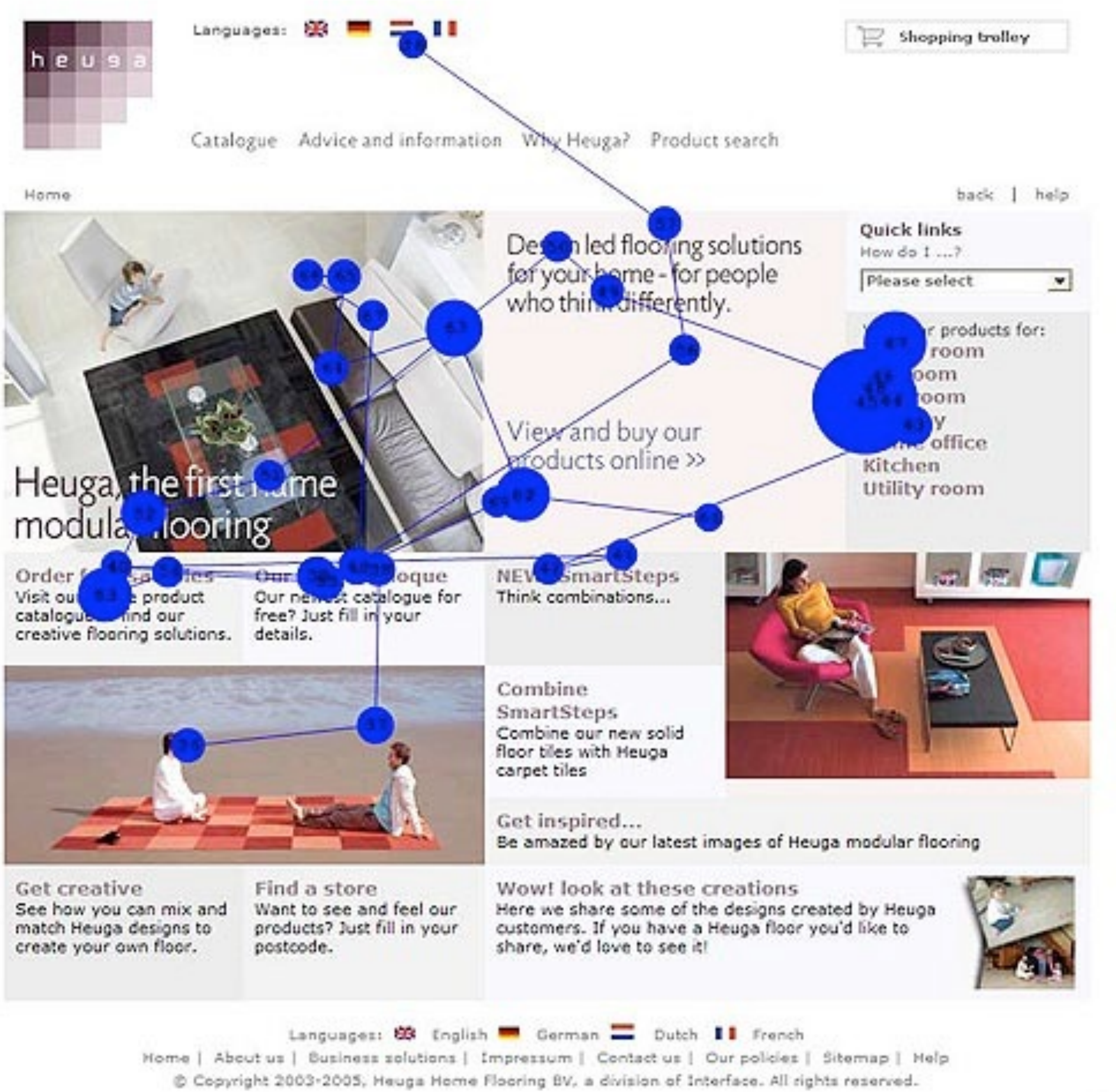
# PREDICTIVE CONTROL

- subjects are asked to track their hand during reaching
- hand is not visible
- gaze saccades are directed to a position advanced by an average of 200*ms*
- after the hand is disturbed, it takes ~100*ms* without saccades before they again move ahead of the hand
- this provides evidence for a forward model



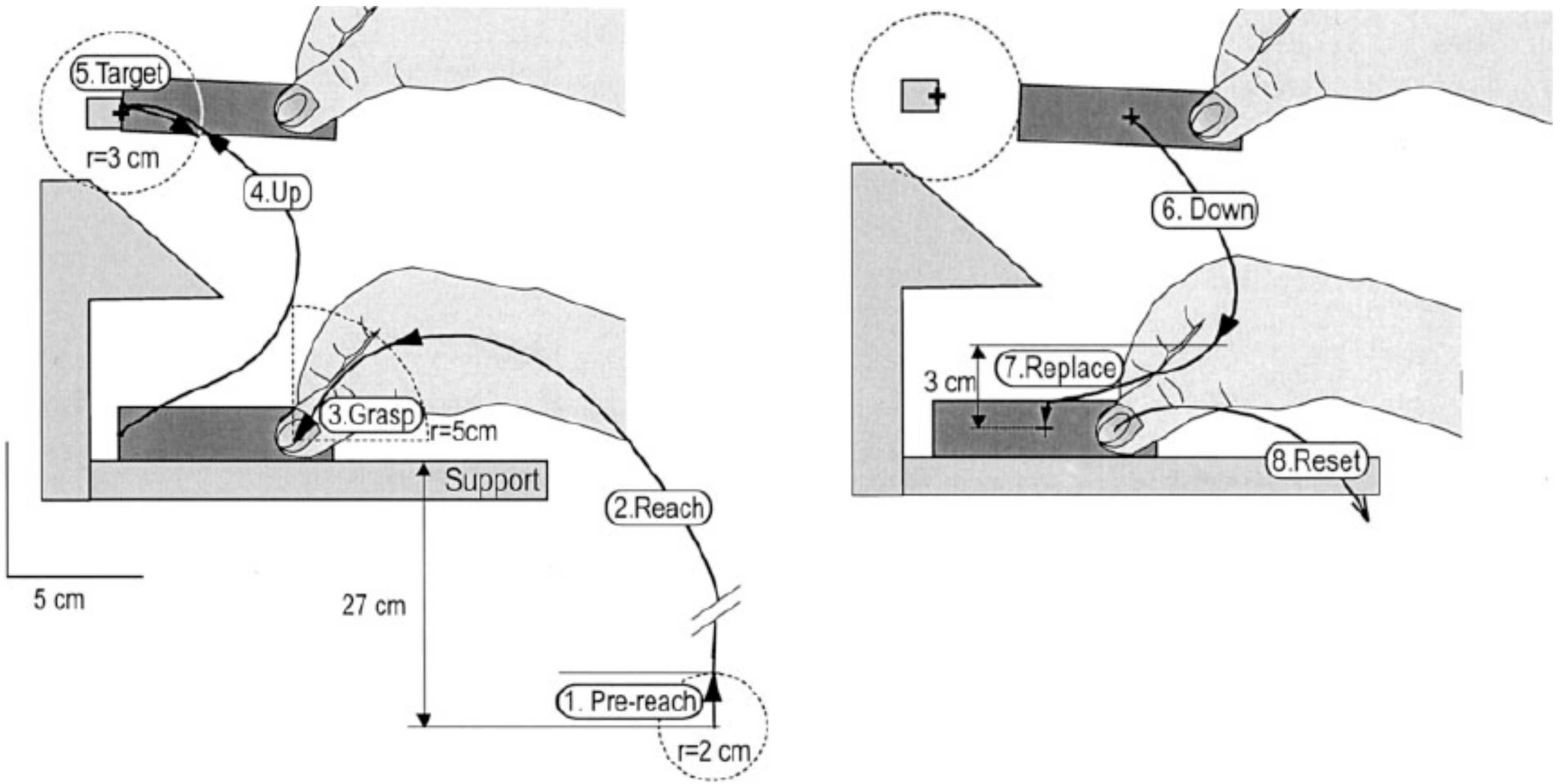

[Ariff et al., J Neuroscience 2002]

# PURPOSEFUL, ACTIVE VISION




- fovea has highest resolution and sensitivity
- gaze to improve visual sensing

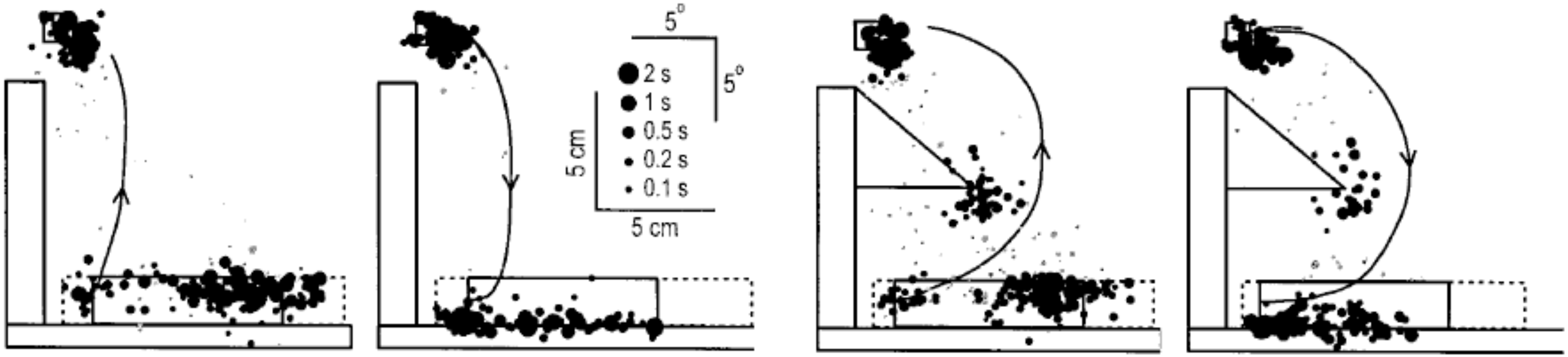
# VISUO-MOTOR COORDINATION




- subjects reach for and grasp a bar and move it to press a target-switch
- hand, object and gaze movements were analysed

[Johansson et al., J Neuroscience 2001]

# VISUO-MOTOR COORDINATION




- subjects never fixated the hand or the moving bar
- subjects fixated landmarks critical for the control of the task, obstacles in the movement path were optional landmarks
- gaze movement lead hand/bar movements, such that subjects planned and monitored critical kinematic events for verification of subgoal completion

[Johansson et al., J Neuroscience 2001]

# FEEDBACK ADAPTATION

- if the sensorimotor control system functions similarly to optimal control, then involuntary responses should have similar characteristics to voluntary commands as both are produced by the same neural structures

- involuntary responses would be expected to adapt to the physical requirements of the task as voluntary commands

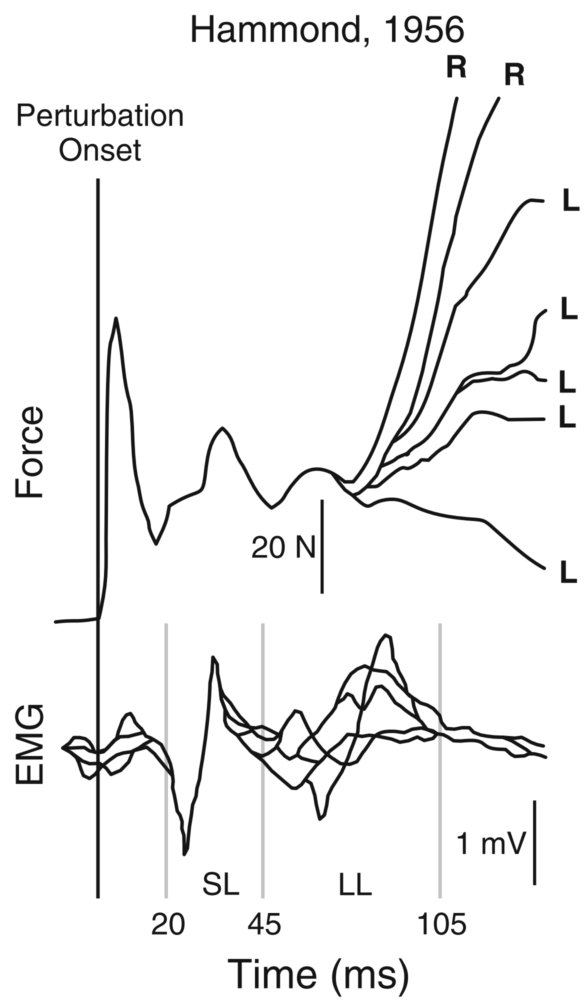
- the feedback system has access to predictive models of the environment, allowing rapid control that takes into account the dynamics of the limbs

[Pruszynski and Scott, Experimental Brain Research 2012]

# LONG LATENCY STRETCH REFLEX

voluntary movements to a small stretch with negligible reflexes start after 105*ms*

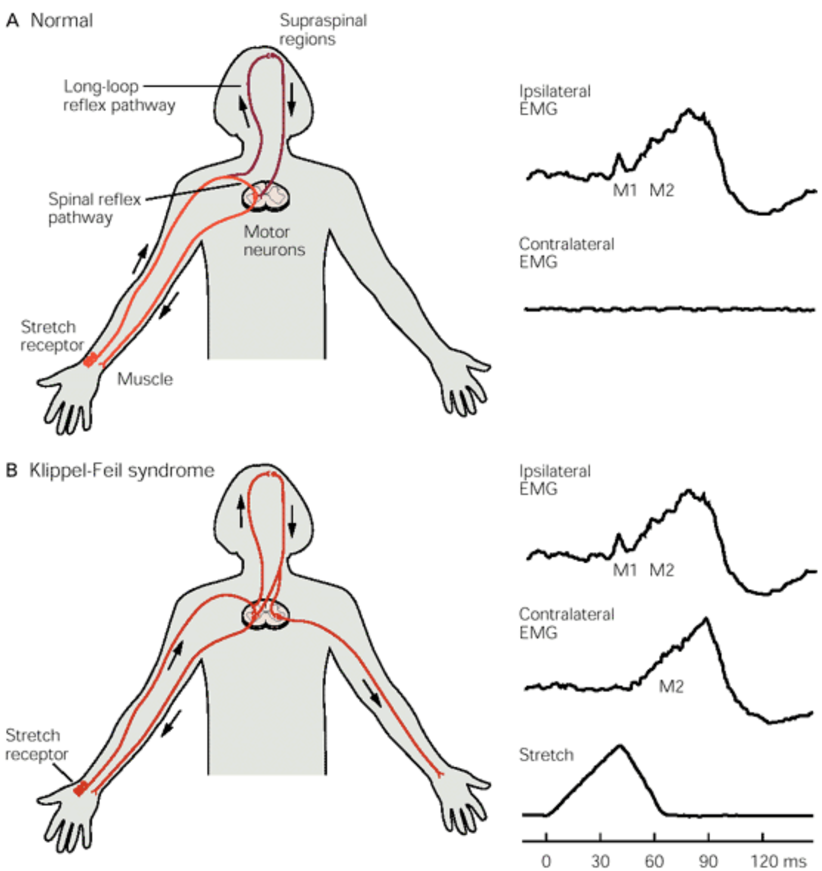
long latency reflexes influenced by instruction to "resist" vs. "let go"

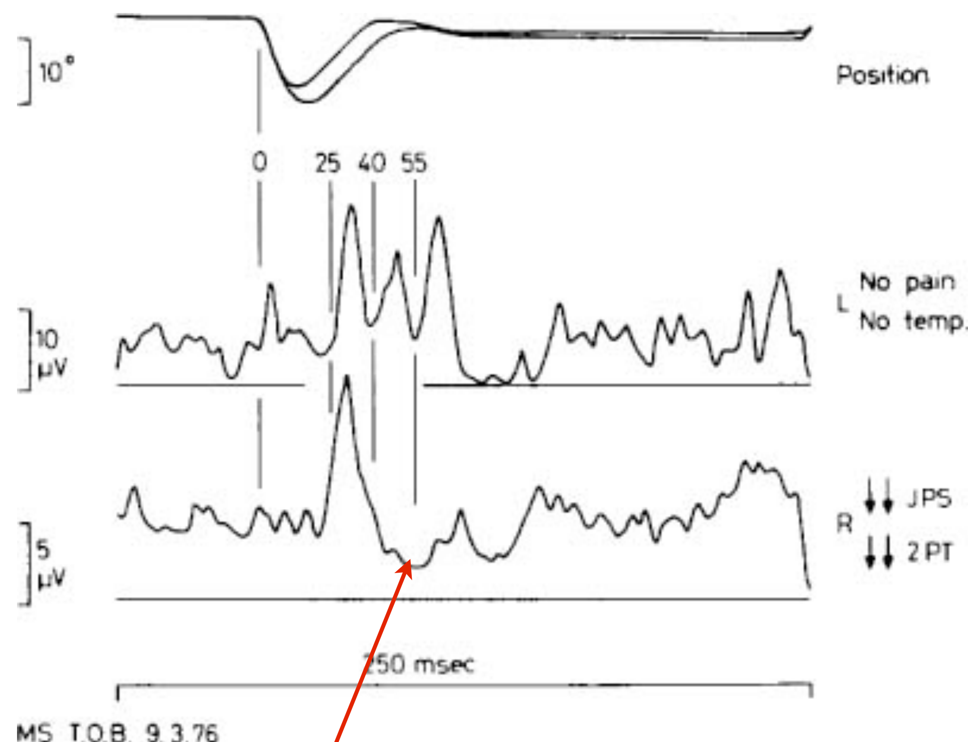



long latency stretch reflexes elicit a graded response

# LONG LATENCY STRETCH REFLEX

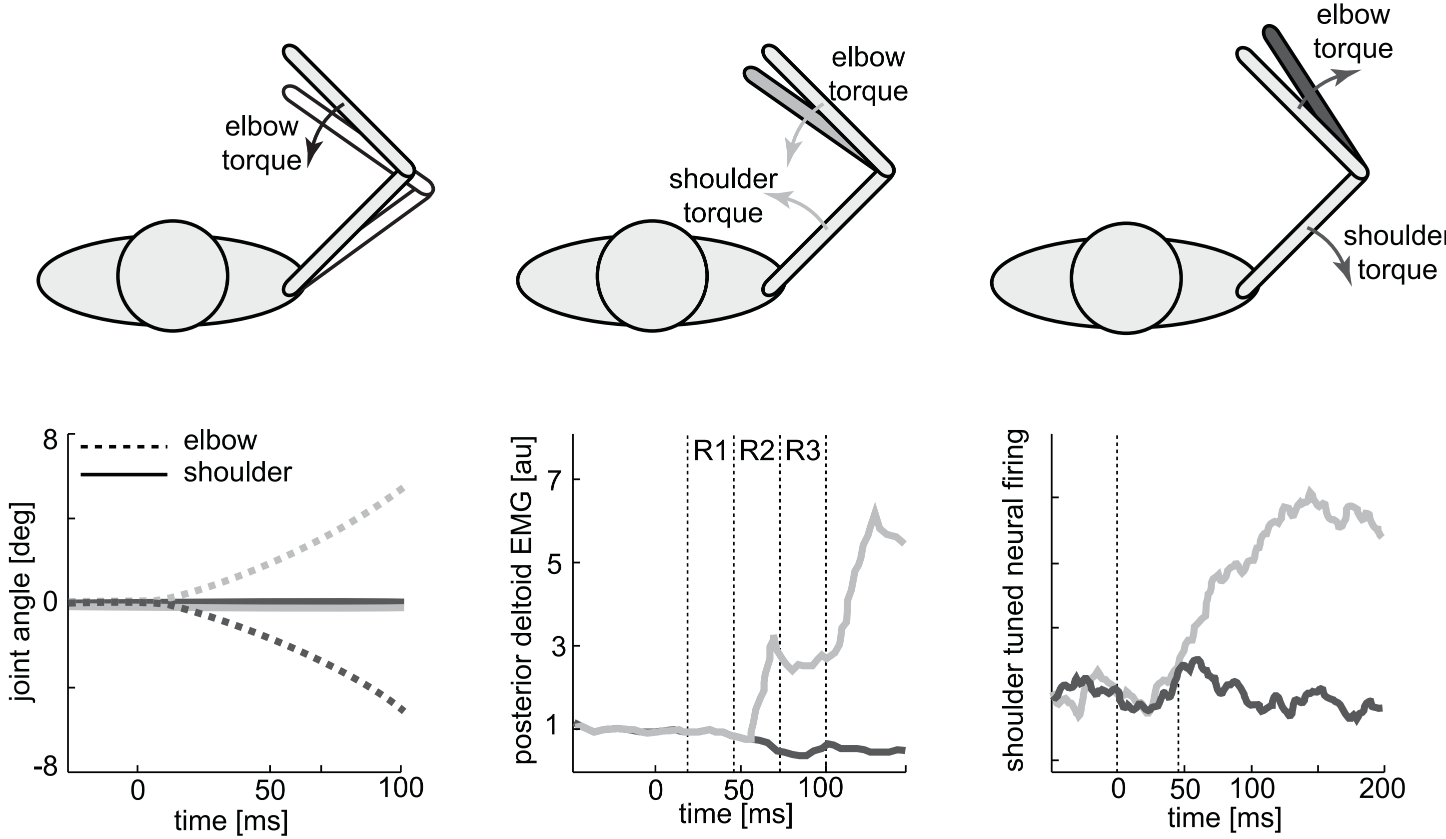
– short latency reflex response (M1) is monosynaptic
– longer latency components (M2, M3) have cortical components




Due to brain stem damage from stroke

# FEEDBACK ADAPTATION

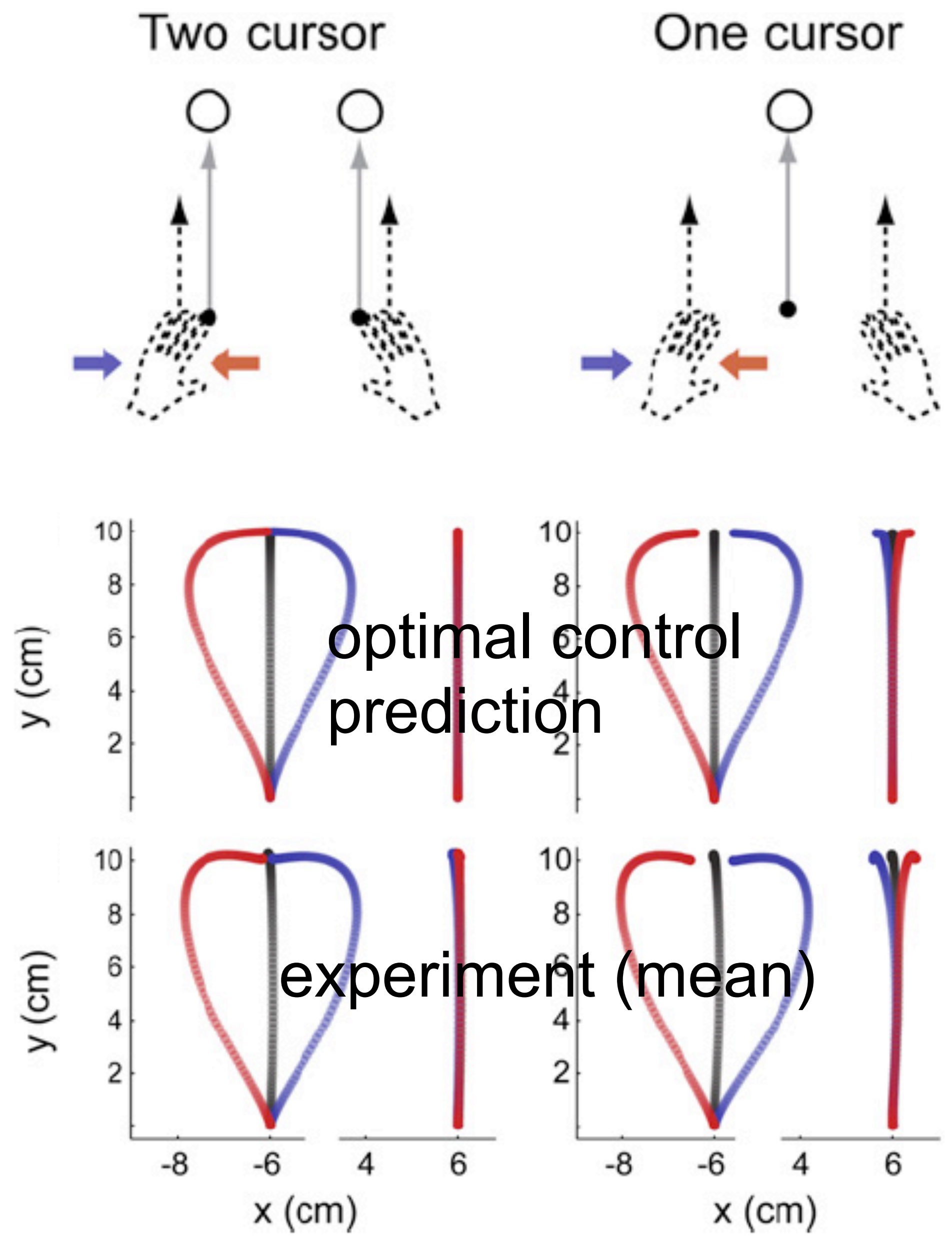



- when the elbow flexes, the CNS expects the shoulder to extend
- if the shoulder is prevented to move, this is reflected in long latency stretch reflexes

[Kurtzer et al., Current Biology 2008, J Neurophysiology 2009, Nature 2011]

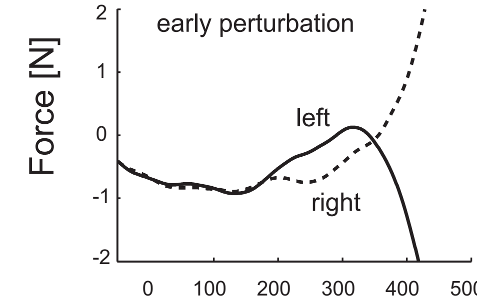
# FEEDBACK ADAPTATION

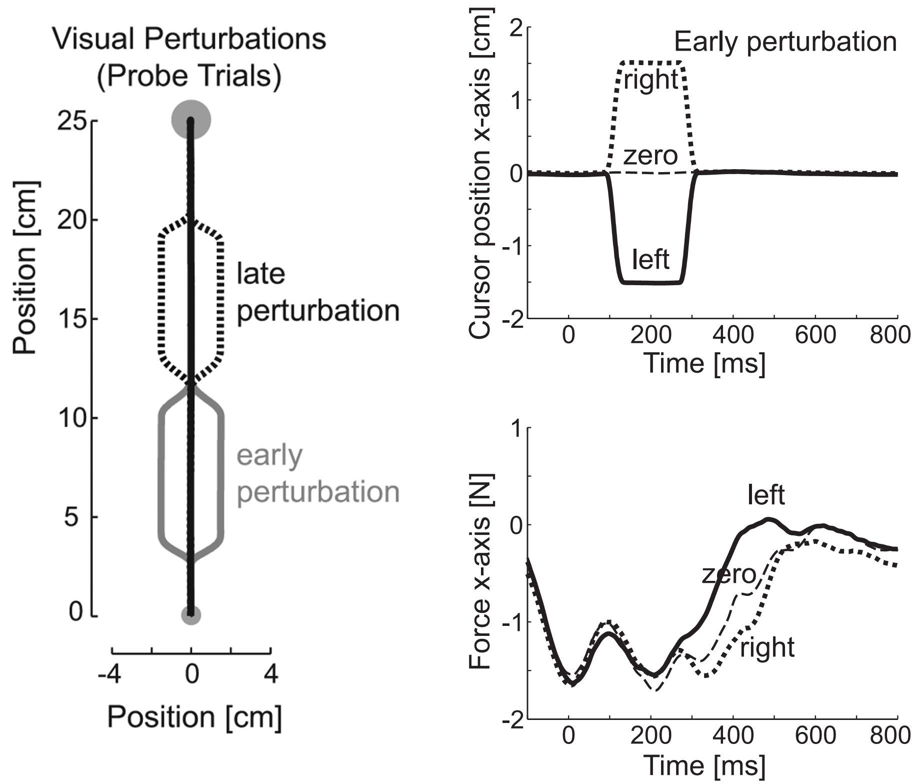
- optimal control modelling of this redundant task
- cost: end distance + effort
- effort: sum of individual efforts
- two cursors: distance for each hand
- one cursor: distance of the mean

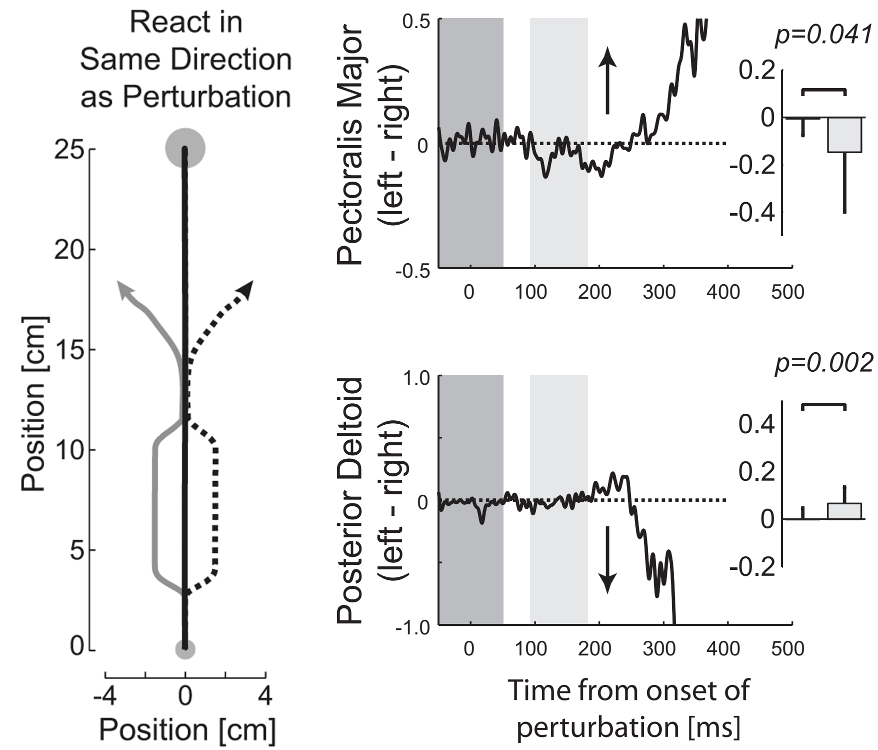



[Diedrichsen, Current Biology 2007]

# VISUOMOTOR REFLEXES



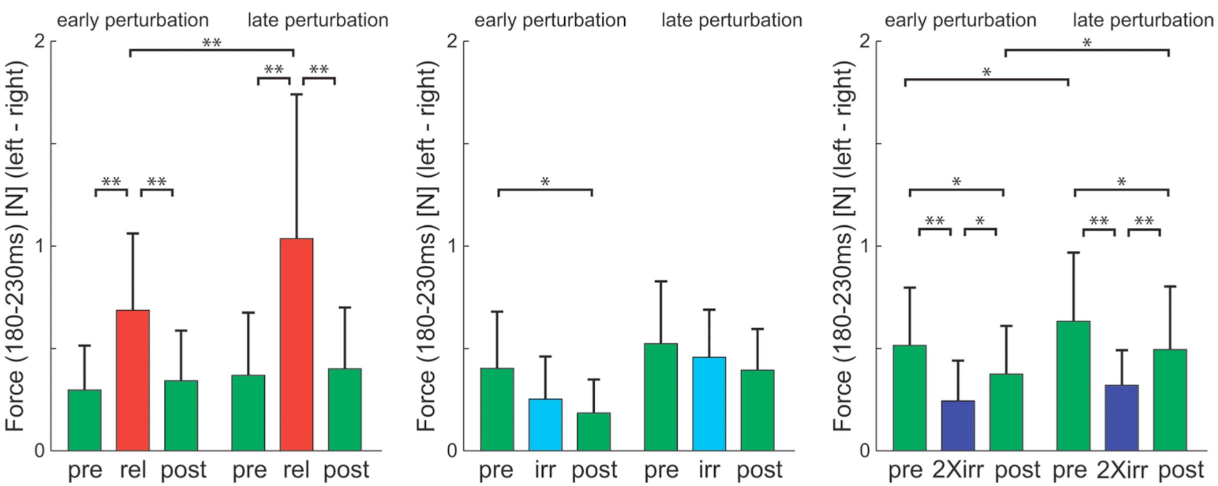




response to visual perturbation detected after 110*ms* in muscle and 150*ms* in the hand force

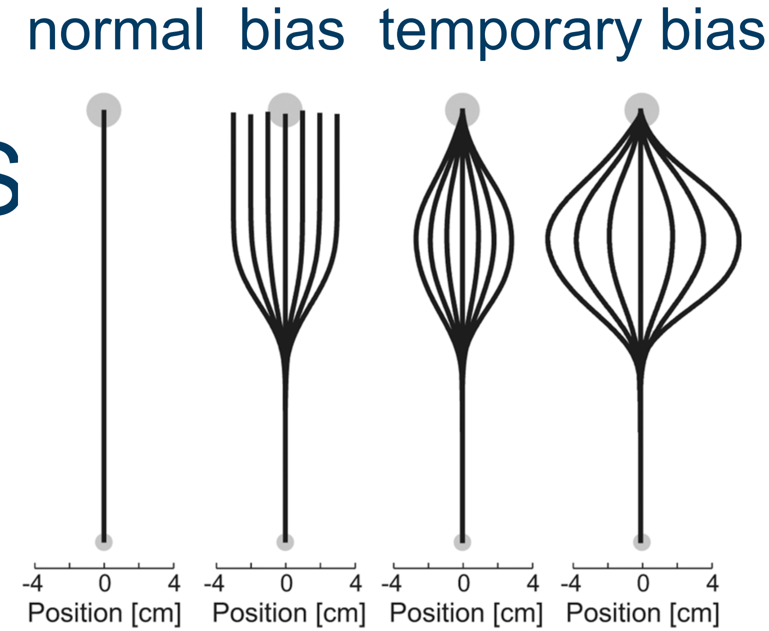
occurs >100ms before voluntary corrections

requires knowledge of the limb state

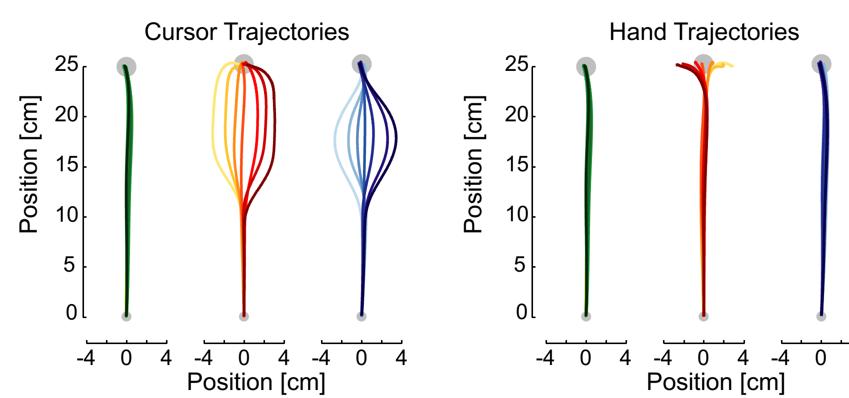
# ADAPTATION OF VISUOMOTOR REFLEXES




- gain of visuomotor reflexes adapted to the task demands
- feedback has access to predictive models of the limb state and internal models of the task dynamics




- visual bias interfering with the task
- action changes only when needed



# INTEGRATION AND CONTROL OF SENSORY FEEDBACK

- sensing is not a fixed process, but adapts to the neuro-muscular system, the environment and the task demands
- the brain combines delayed, noisy sensory information from multiple modalities in a statistically optimal way, weighting the information by its reliability, in order to produce an estimate with the minimum variability
- the sensorimotor control system combines the efferent copy of the motor command with a model of the body and environment to produce a predictive estimate of the current and future state of the body

# INTEGRATION AND CONTROL OF SENSORY FEEDBACK

- the sensorimotor control system produces motor outputs designed to increase the sensitivity of afferent feedback, yielding high-resolution information about only a few key elements relating to the task
- sensory feedback is adaptive to the environment, demonstrating adaptive responses to perturbations that vary depending on the task-relevance of the information
- the whole sensory-motor function has to be considered as a system, which is optimised with practice and learned during infancy and adulthood