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

MOTION PLANNING

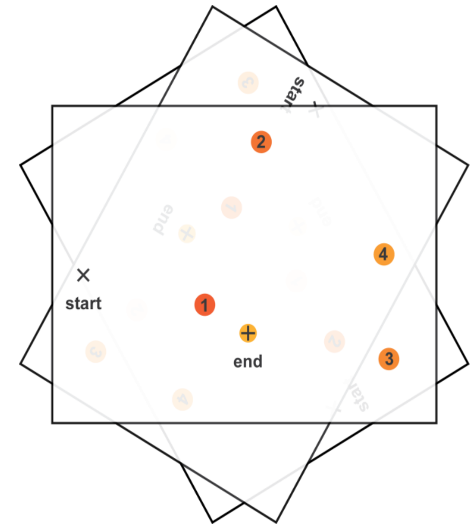
- complex actions need to be planned in advance, for example to intercept a ping-pong ball
- it is not possible to use only feedback, because of the large sensory delays and the time to perform actions
- planning has to integrate sensory information during movement
- what is planned, what is modified during movement?

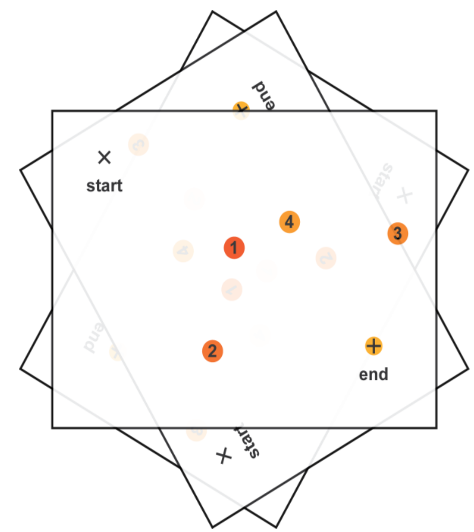
EVIDENCE OF A PLANNING STAGE

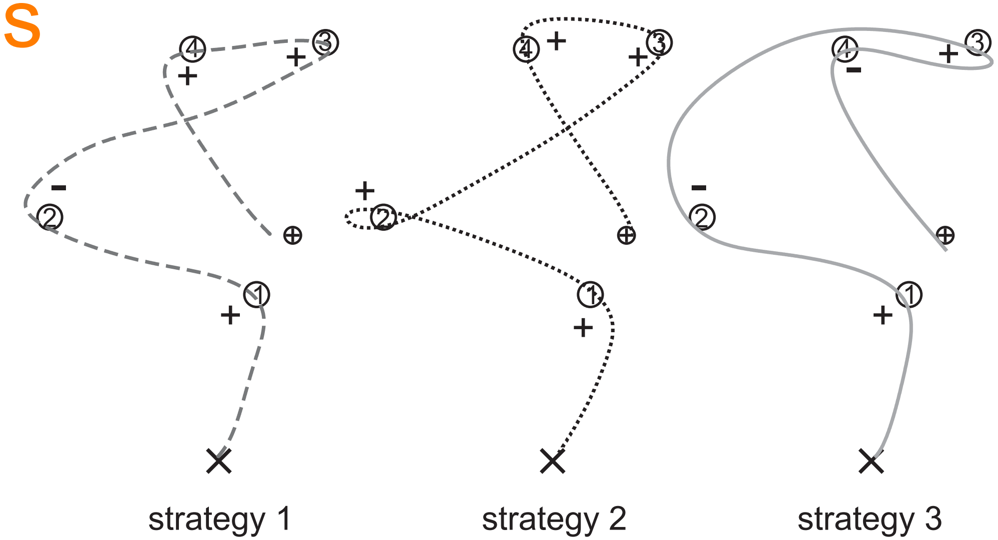
- task: go through a sequence of via-point "as fast and accurate as possible"

- 2 setups in 3 orientations

- subjects randomly use multiple strategies



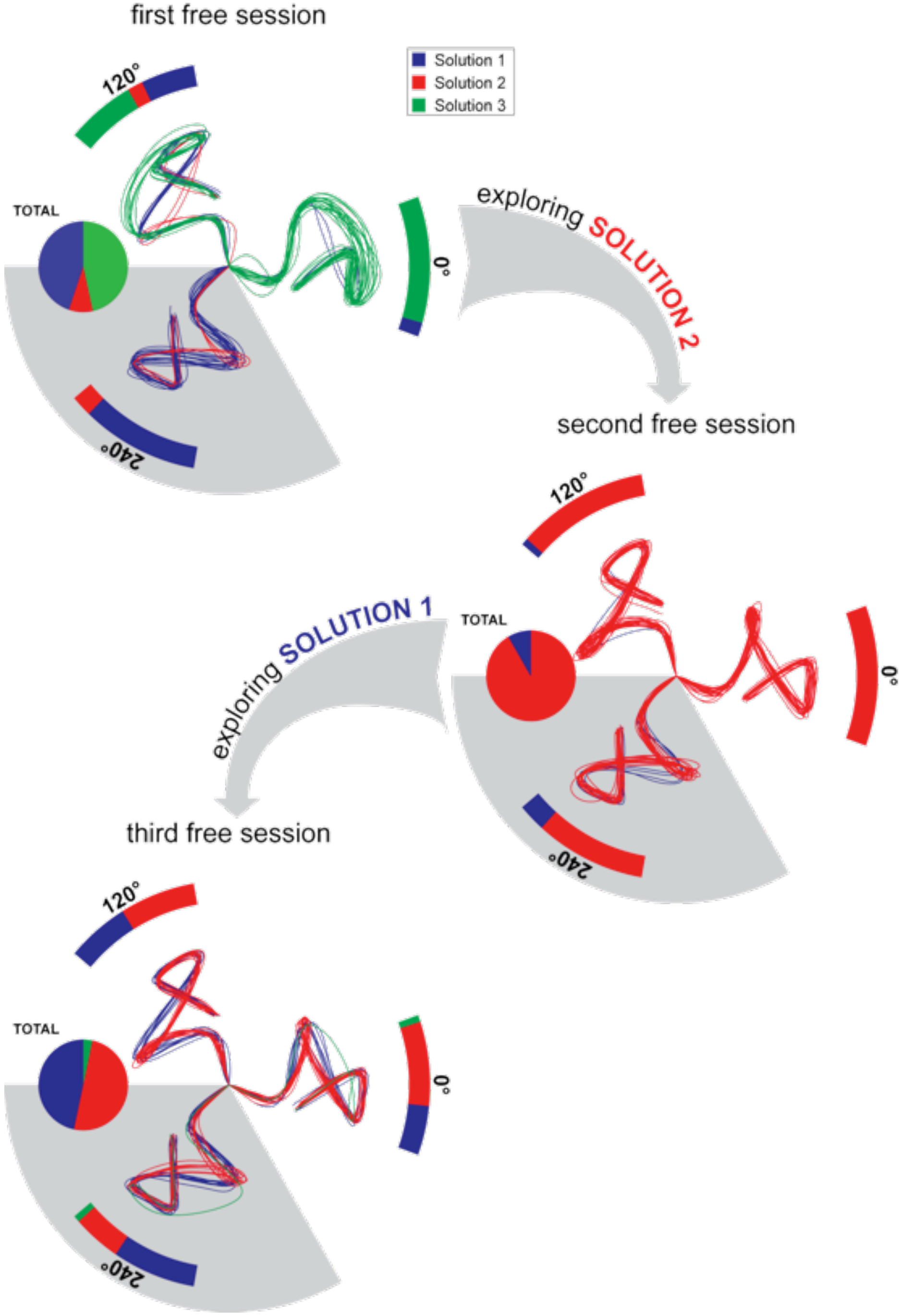




[Kodl et al., PLoS ONE 2011]

EVIDENCE OF A PLANNING STAGE

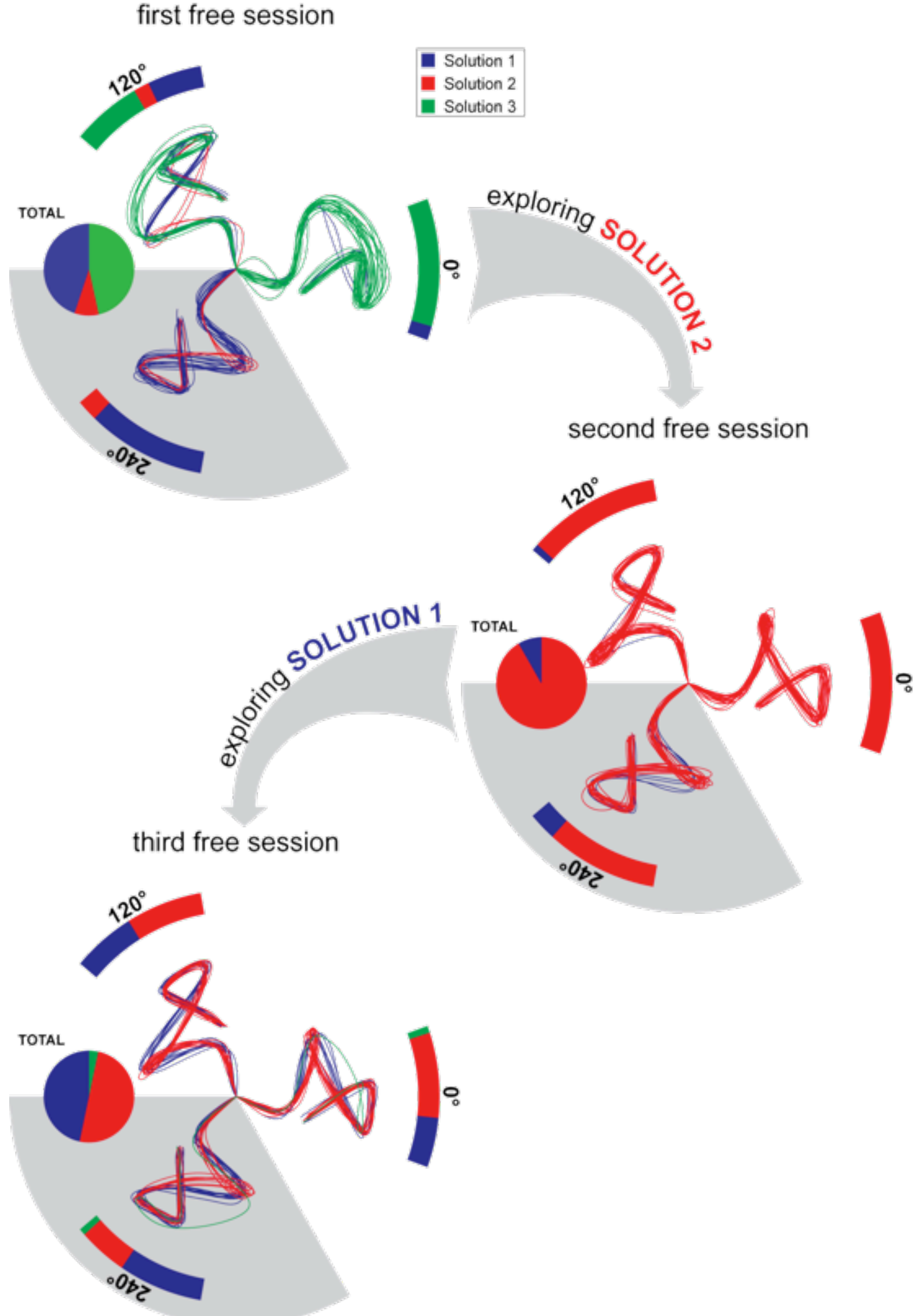
- subjects spontaneously use multiple strategies
- show a specific solution in 2 directions
- subjects increase the probability of using this solution in all directions
- but less in the untrained direction



[Kodl et al., PLoS ONE 2011]

EVIDENCE OF A PLANNING STAGE

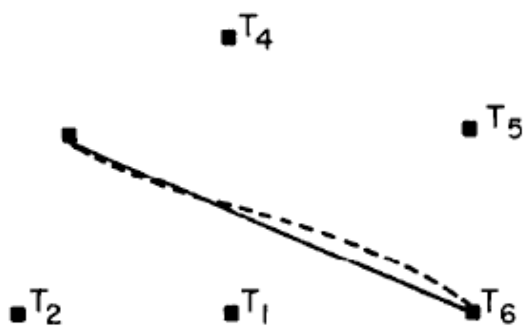
- evidence of a plan prior to motion execution
- show a specific solution in 2 directions
- subjects increase the probability of using this solution in all directions
- but less in the untrained direction

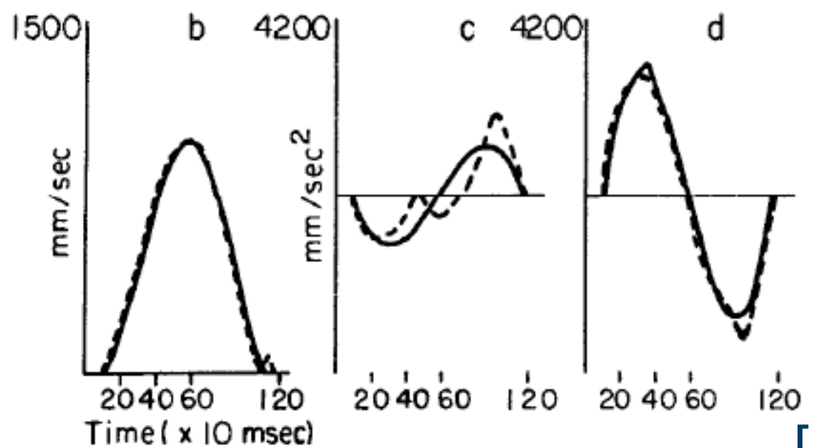


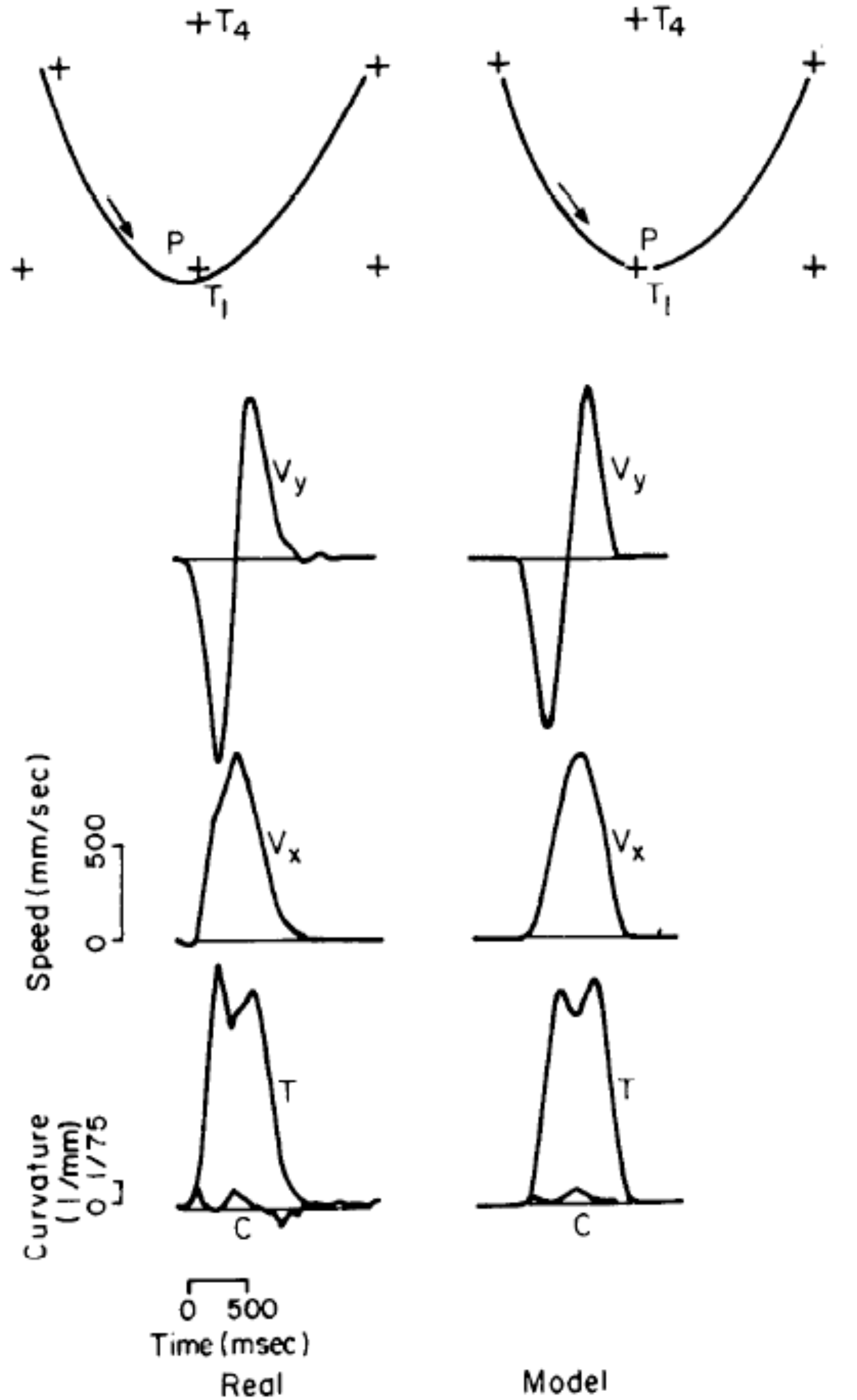
[Kodl et al., PLoS ONE 2011]

MINIMAL JERK MODEL

the CNS generates smooth motion, minimising e.g. the jerk $\int \left(\frac{d^3\mathbf{x}}{dt^3} \right)^2 dt$

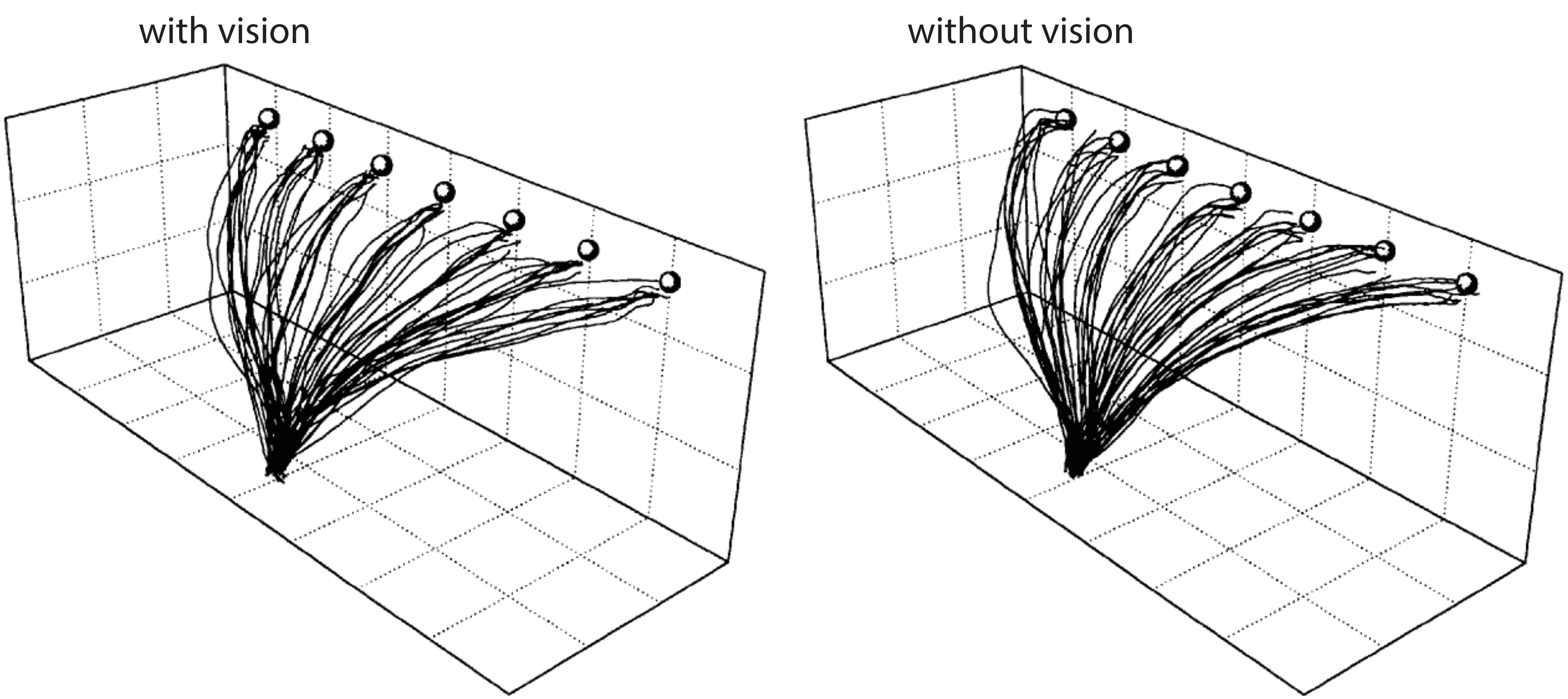






[Flash and Hogan, J Neuroscience 1985]

MOVEMENTS ARE NOT ALWAYS STRAIGHT



- vertical movements are curved
- the trajectory depends on the task, e.g. varies with the end conditions

[Day et al., Brain 1988]

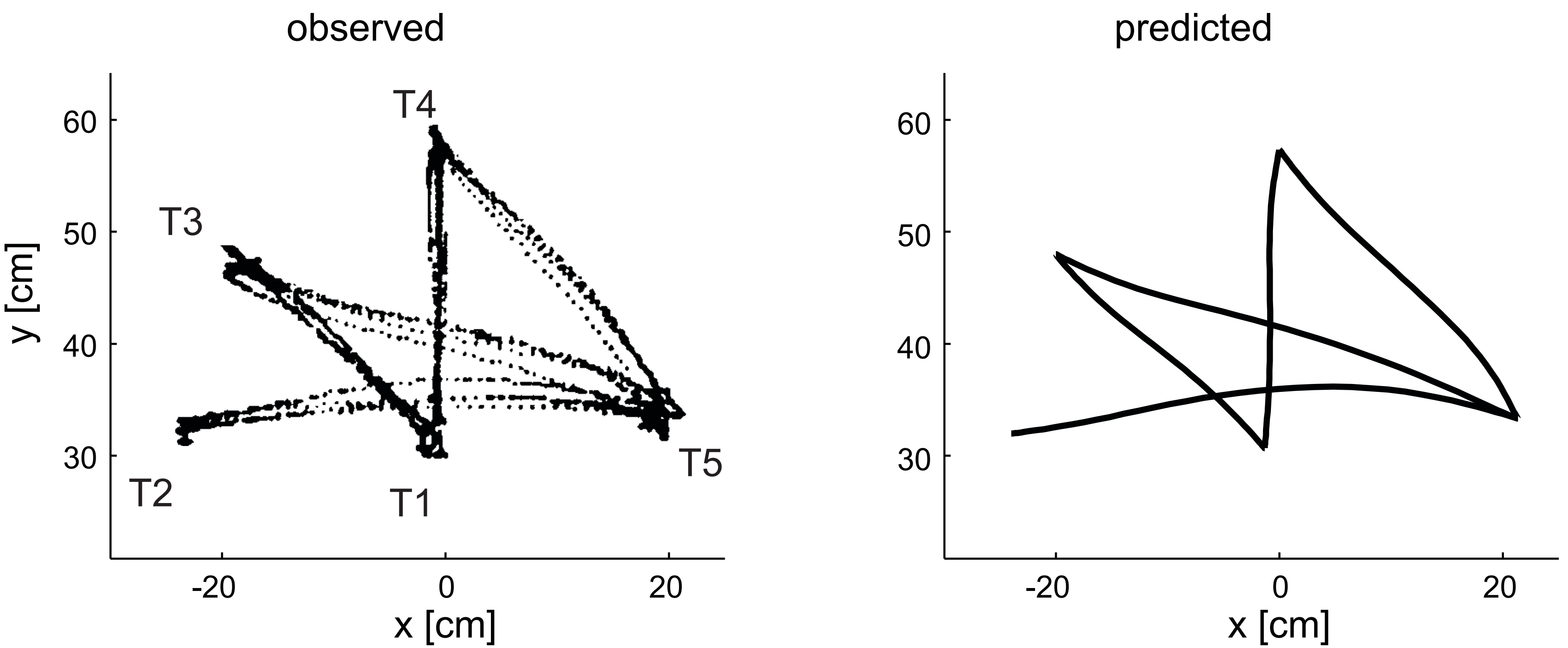
MINIMISATION OF INTRINSIC PROPERTIES

- maximal smoothness yields good trajectory prediction for horizontal arm movements, but...
- which functional advantage could this have?
- how could the CNS compute quantities such as jerk, using the noisy sensory signals?

- goal: to minimise the deviation at movement end
- with signal dependent noise, this corresponds to minimising effort during movement

[Harris and Wolpert, Nature 1998]

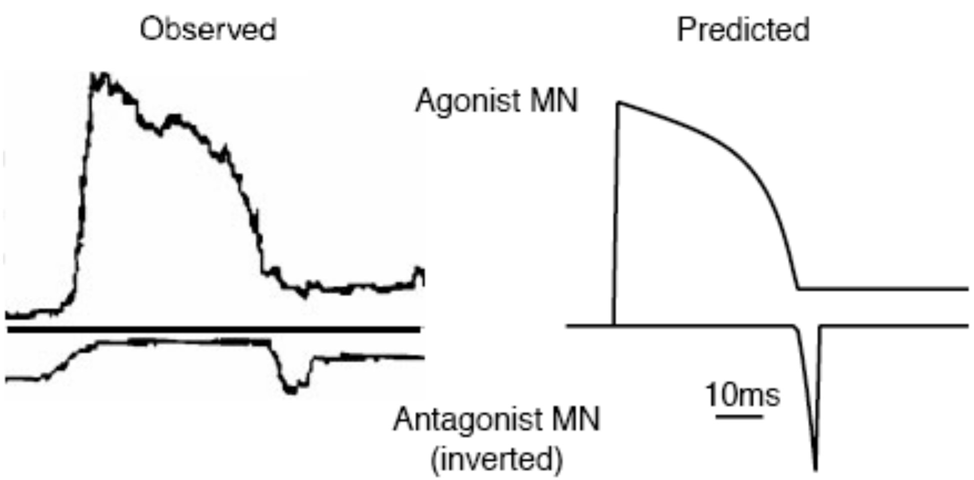
MINIMISATION OF INTRINSIC PROPERTIES

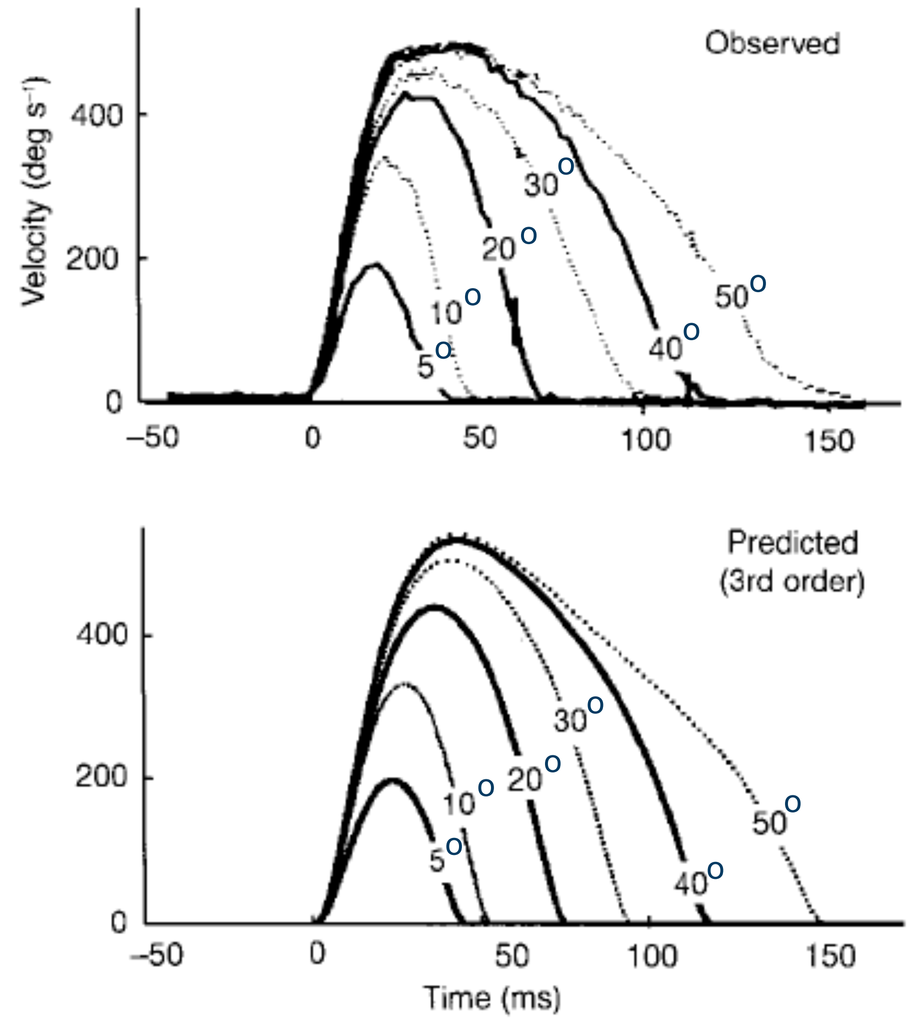


- linear dynamic model or arm and muscle dynamics
- good prediction of goal directed movements

[Harris and Wolpert, Nature 1998]

MINIMISATION OF INTRINSIC PROPERTIES

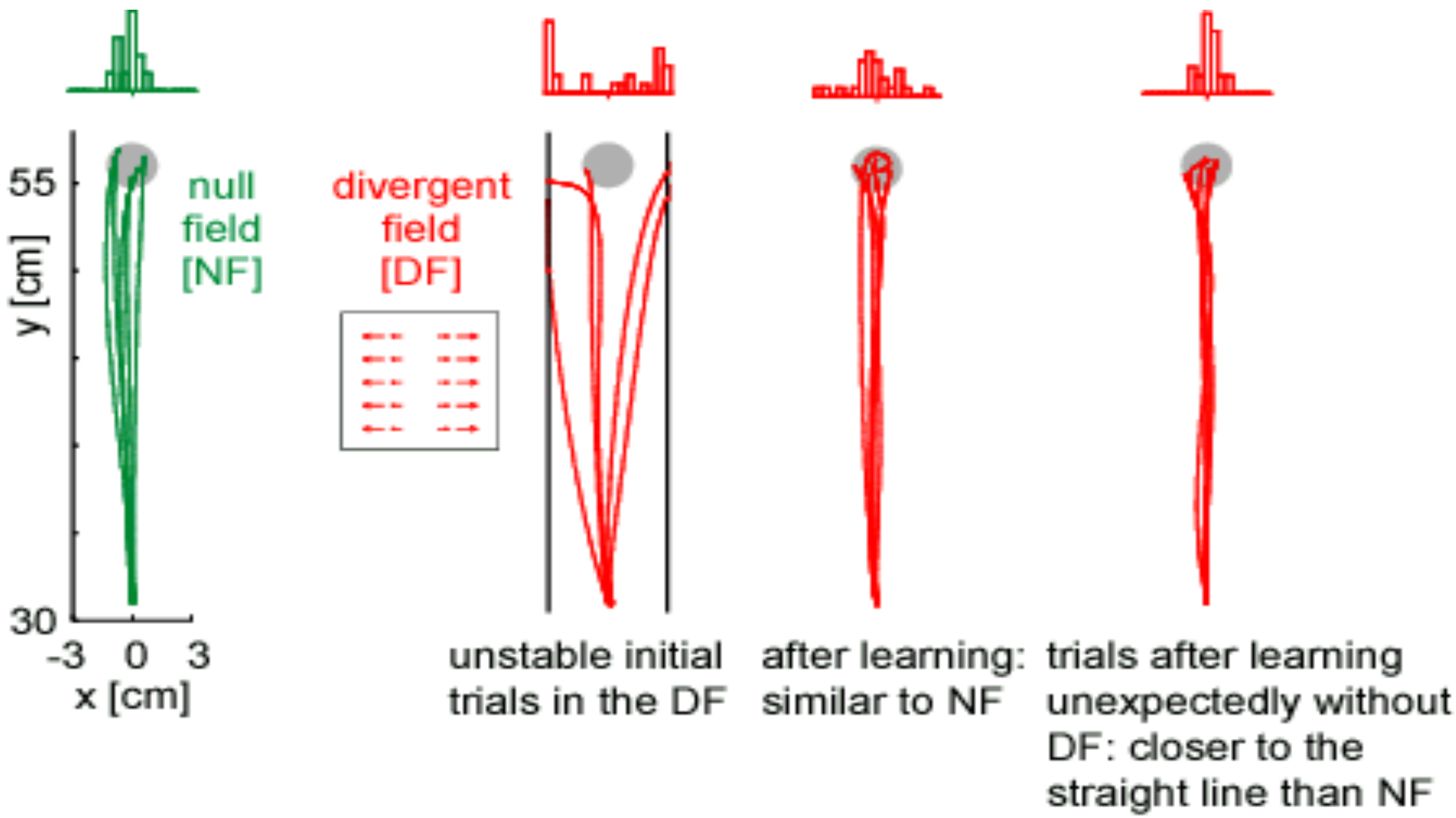




excellent prediction of eye motorneurons activity and velocity during saccades

[Harris and Wolpert, Nature 1998]

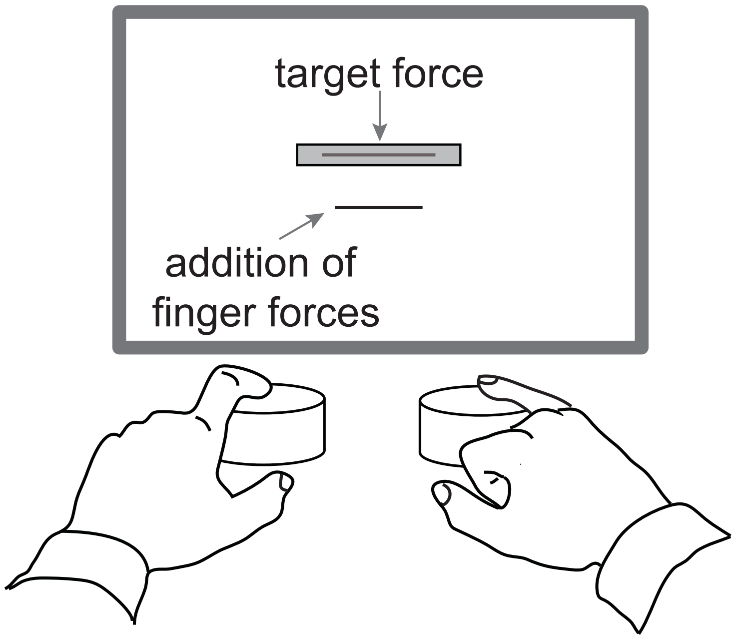
EFFORT OR ERROR MINIMISATION?

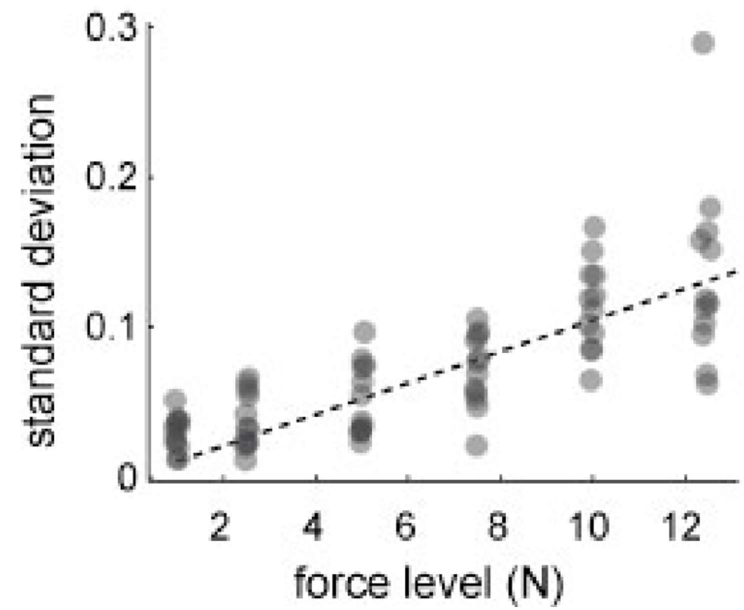


- after-effects -> selective co-contraction can decrease deviation
- this suggests minimisation of (at least) effort

[Burdet et al. Nature 2001]

EFFORT OR ERROR MINIMISATION?



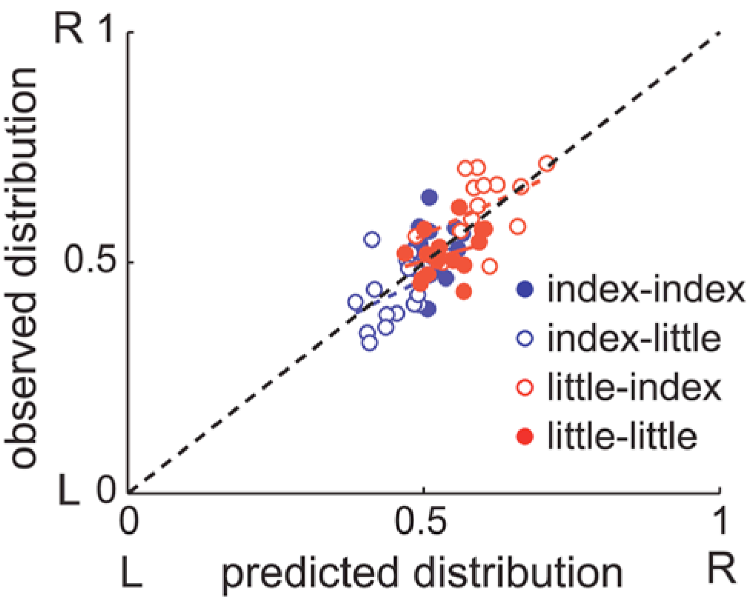


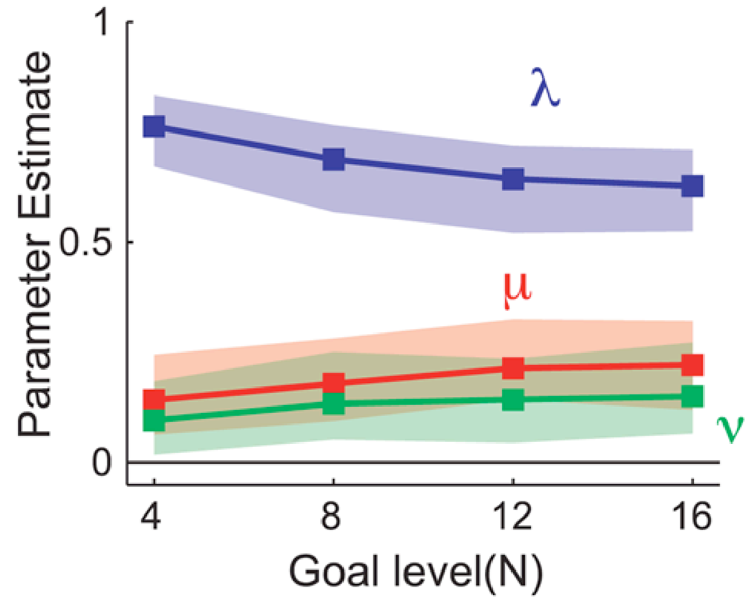
- press against force sensors with the left index/little finger and right little/index finger
- noise increases linearly in each finger, with different slopes for the four fingers
- do we share the force to minimise error or effort?

[O’Sullivan et al. Plos Computational Biology 2009]

EFFORT AND ERROR MINIMISATION

$$J = \nu \underbrace{E\left[(F_r + F_l - F_g)^2\right]}_{\text{Expect squared-error}} + \lambda \underbrace{(u_r^2 + u_l^2)}_{\substack{\text{Non-normalized}\\ \text{effort}}} + \mu \underbrace{\left(\left(\frac{u_r}{MVC_r}\right)^2 + \left(\frac{u_l}{MVC_l}\right)^2\right)}_{\text{Normalized effort}}$$





- less noisy finger contributes more to total force
- but less noisy finger is often the stronger
- both effort and error are considered in the control, but effort is more important

[O'Sullivan et al. Plos Computational Biology 2009]

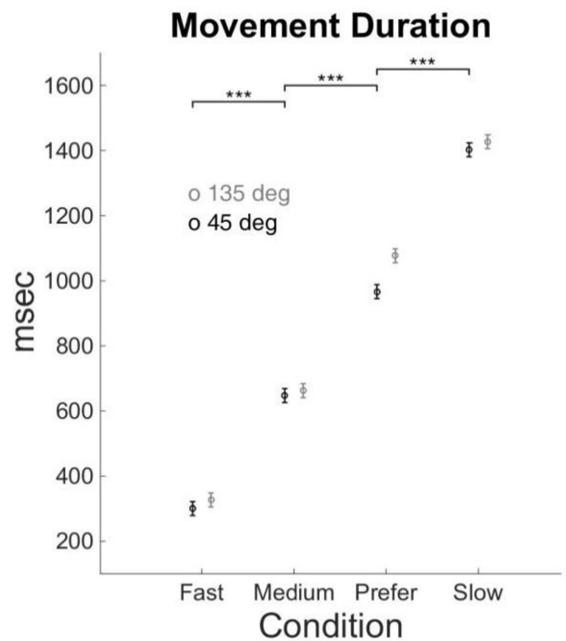
HOW LONG SHOULD TAKE A MOVEMENT?

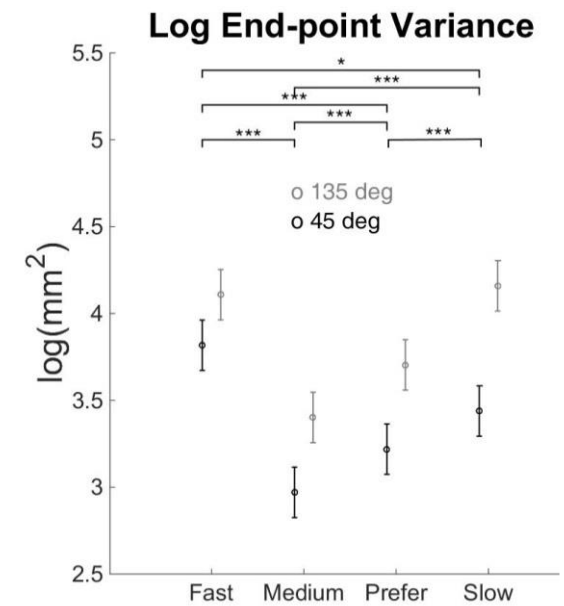
$$V \equiv \int dt\, \mathbf{u}^T \mathbf{R}^T \mathbf{R}\, \mathbf{u}$$

- the acceleration decreases in a quadratic fashion with a linear increase in movement duration
- to minimise effort (or signal dependent noise), a reaching movement should be as long as possible

EFFORT AND ERROR MINIMISATION

endpoint variability of reaching arm movements at different duration conditions





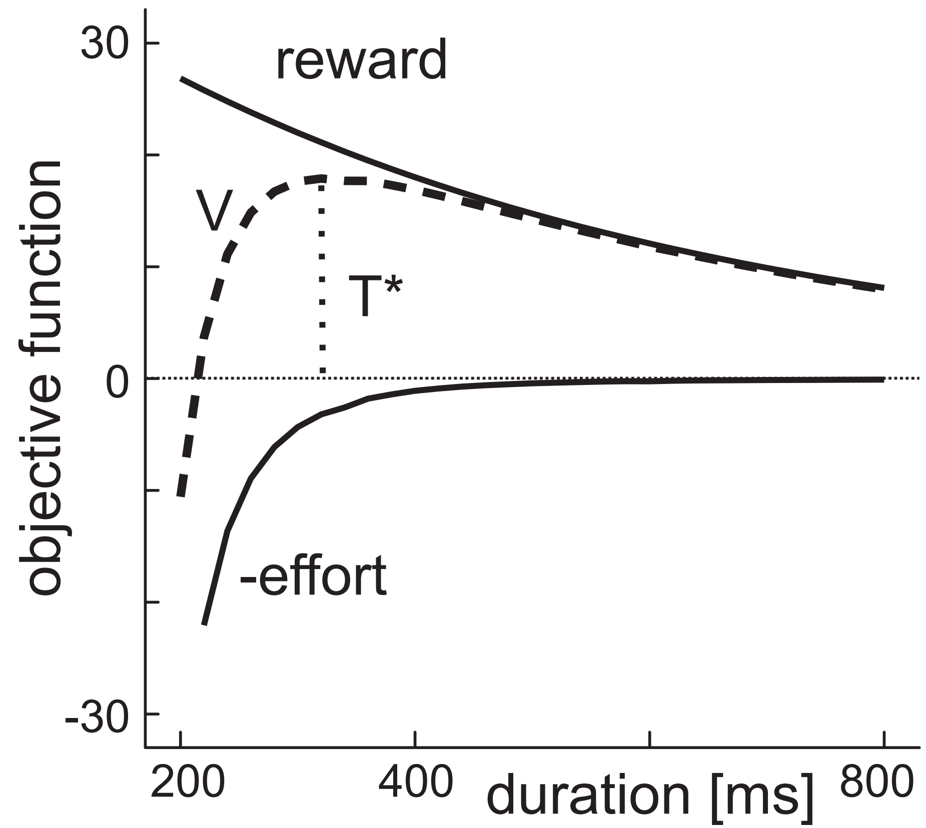
- there is a minimum of deviation
- minimisation of variability: signal dependent noise lengthens movement & constant noise shortens it
- however subjects use a longer movement time than variability minimum, suggesting consideration of effort

[Wang et al. J Neurophysiology 2016]

REWARD-BASED OPTIMAL CONTROL

$$V \equiv \int_0^\infty dt\, e^{-t/\varsigma} \left[\begin{matrix}\text{success}\\ \text{reward}\end{matrix} - \mathbf{u}^T \mathbf{R}^T \mathbf{R}\, \mathbf{u} \right]$$

- it might be of advantage to take an apple or a cup as quickly as possible
- trade-off between fast movements to satisfy a need rapidly and the resulting increase of effort



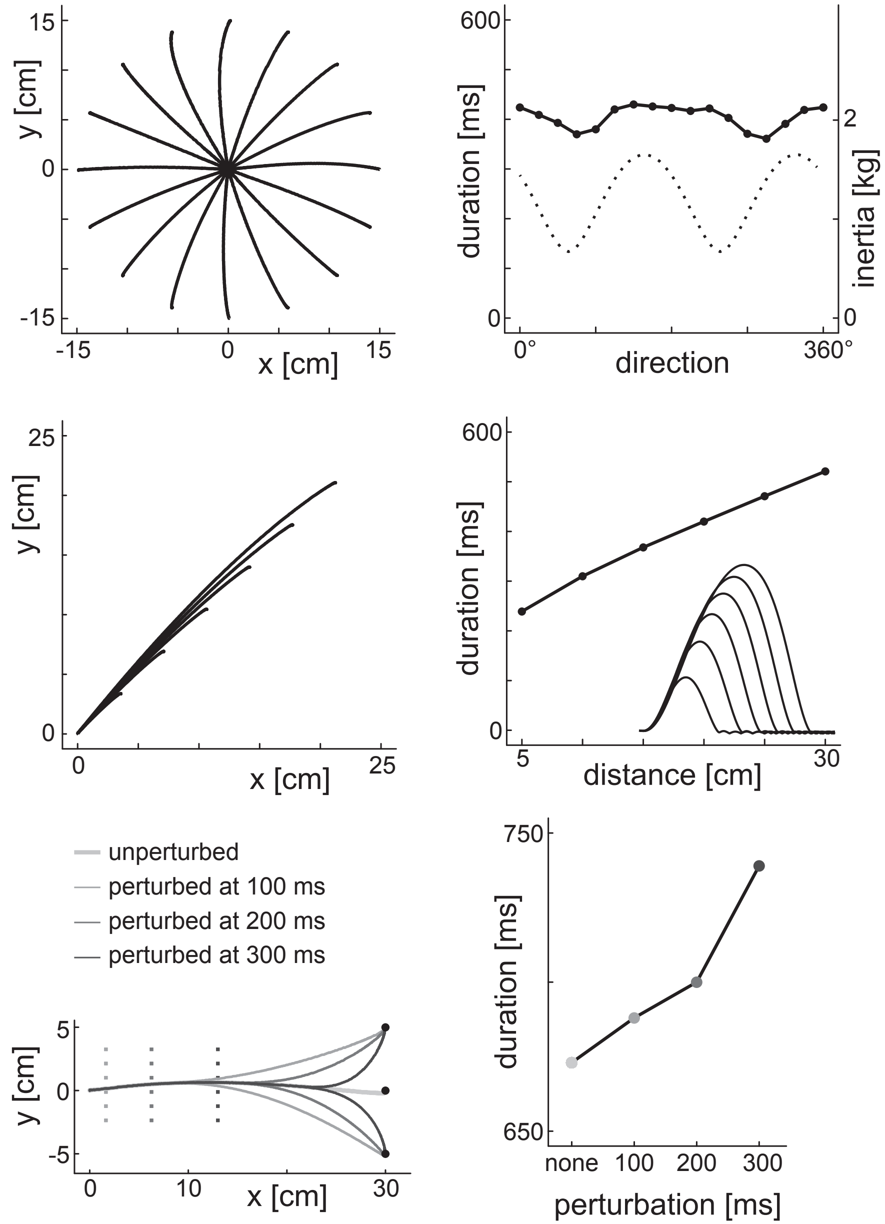
[Rigoux and Guigon, PLoS Computational Biology 2012]

REWARD-BASED OPTIMAL CONTROL

- reaching in all directions

- of various amplitude

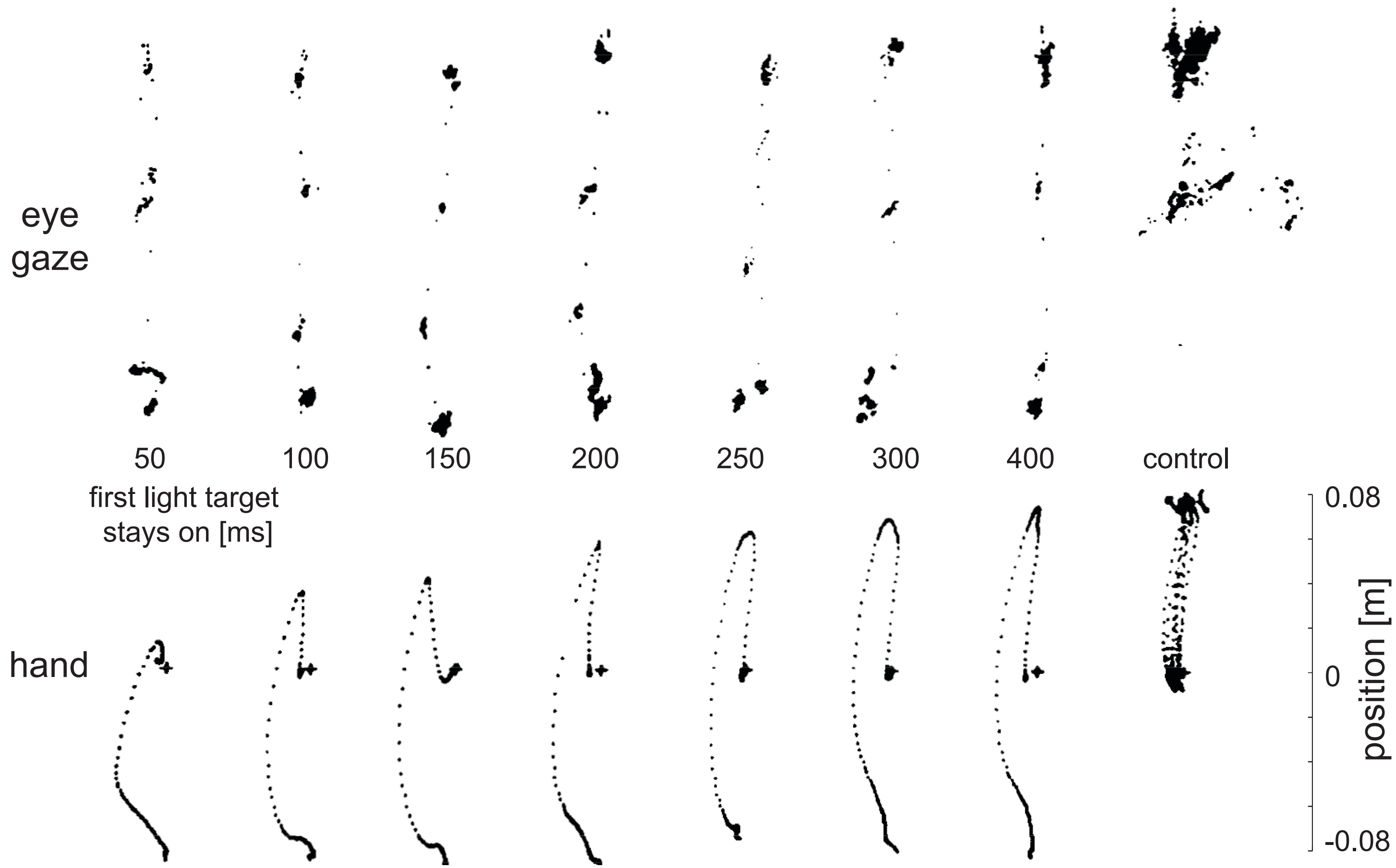
- target jump



[Rigoux and Guigon, PLoS Computational Biology 2012]

SENSOR-BASED MOTION CONTROL

- eyes jump to first then to second target and precede the movement
- arm movement is smoothly redirected towards target



- constant reaction time to target jump
- reaction time = 100-250*ms* from trajectory change

[Georgopoulos et al., J Neurophysiology 1981]

OPTIMAL CONTROL

system equation
in discrete time $k\Delta t$

$$\mathbf{z}_{k+1} = \mathbf{A}_k \mathbf{z}_k + \mathbf{B}_k \mathbf{u}_k$$

$\mathbf{z}_k$ state vector

$\mathbf{u}_k$ motor command

$$\mathbf{z}_{k+1} \equiv \begin{bmatrix} x_{k+1} \\ \dot{x}_{k+1} \\ \mu_{k+1} \\ \vartheta_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & \dfrac{\Delta t}{m} & 0 \\ 0 & 0 & 1 - \dfrac{\Delta t}{\varsigma_\mu} & \dfrac{\Delta t}{\varsigma_\mu} \\ 0 & 0 & 0 & 1 - \dfrac{\Delta t}{\varsigma_\vartheta} \end{bmatrix} \begin{bmatrix} x_k \\ \dot{x}_k \\ \mu_k \\ \vartheta_k \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \dfrac{\Delta t}{\varsigma_\vartheta} \end{bmatrix} u_k$$

1DOF pointmass with muscle dynamics

OPTIMAL CONTROL

to determine a series of motor commands $\{\mathbf{u}_k\}$ that brings the hand from $\mathbf{0}$ to the target $\mathbf{x}^*$ at time $K\Delta t$ with minimal effort:

$$V = \mathbf{e}_K^T \mathbf{Q} \mathbf{e}_K + \sum_{k=0}^{K-1} \mathbf{u}_k^T \mathbf{R}_k \mathbf{u}_k \qquad \mathbf{e}_K \equiv \mathbf{x}^* - \mathbf{x}_K$$

Linear Quadratic Regulator (LQR)

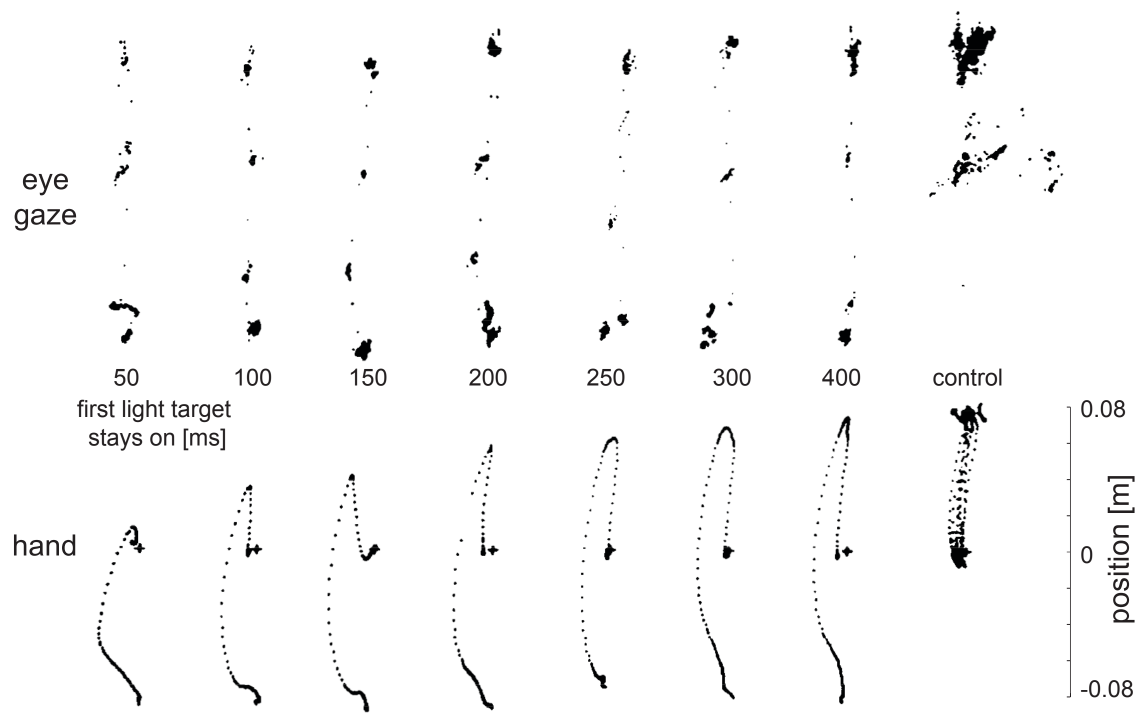
$$\mathbf{S}_K = \mathbf{Q}_K \qquad \mathbf{L}_k = (\mathbf{B}_k^T \mathbf{S}_{k+1} \mathbf{B}_k + \mathbf{R}_k)^{-1} \mathbf{B}_k^T \mathbf{S}_{k+1} \mathbf{A}_k$$

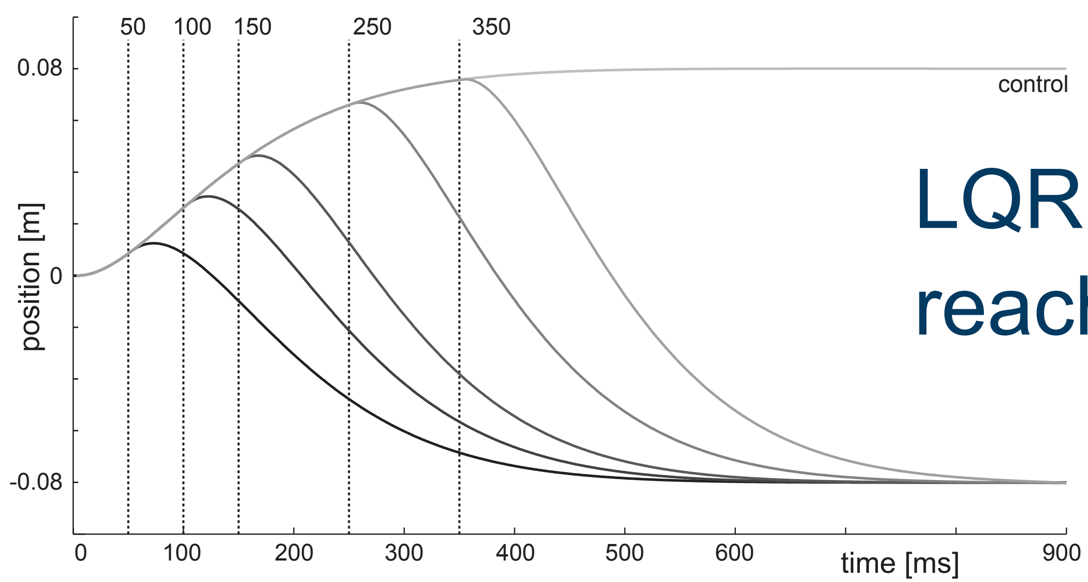
$$\mathbf{S}_k^T = \mathbf{A}_k^T (\mathbf{S}_{k+1} - \mathbf{S}_{k+1} \mathbf{B}_k (\mathbf{B}_k^T \mathbf{S}_{k+1} \mathbf{B}_k + \mathbf{R}_k)^{-1} \mathbf{B}_k^T \mathbf{S}_{k+1}) \mathbf{A}_k$$

$$\mathbf{u}_k = -\mathbf{L}_k \mathbf{z}_k$$

iterative solution backward in time

SENSOR-BASED MOTION CONTROL





LQR modelling of reaching with target jump

LINEAR SENSOR FUSION

- how can you locate your telephone on the bedside table using audition and vision?
- how can the CNS combine different sources of sensory information, each delayed and with inherent noise, to estimate movement?

discrete time $k\Delta t$:

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

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

$\mathbf{z}_k$ state vector $\mathbf{u}_k$ motor command

$\boldsymbol{\eta}_k$ system noise $\boldsymbol{\omega}_k$ sensor noise

LINEAR SENSOR FUSION WITH LQE

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

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

to minimise prediction error $E[\| \mathbf{z}_k - \hat{\mathbf{z}}_k \|^2]$

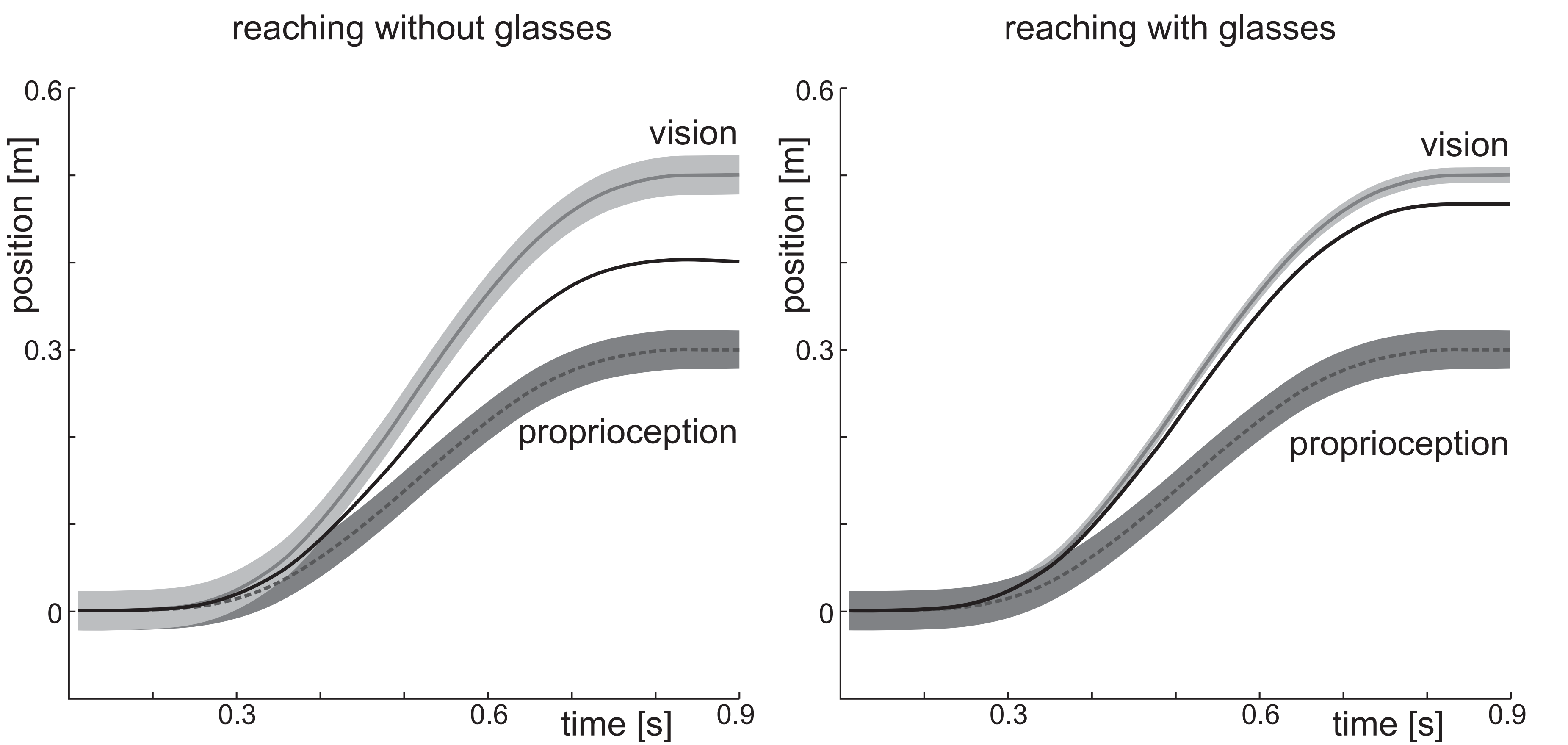
Linear Quadratic Estimator (LQE, Kalman Filter)

$$\hat{\mathbf{z}}_{k+1} = \mathbf{A}_k \hat{\mathbf{z}}_k + \mathbf{B}_k \mathbf{u}_k + \mathbf{K}_k (\mathbf{y}_k - \mathbf{C} \hat{\mathbf{z}}_k) \qquad \hat{\mathbf{z}}_0 = E[\mathbf{z}_0]$$

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

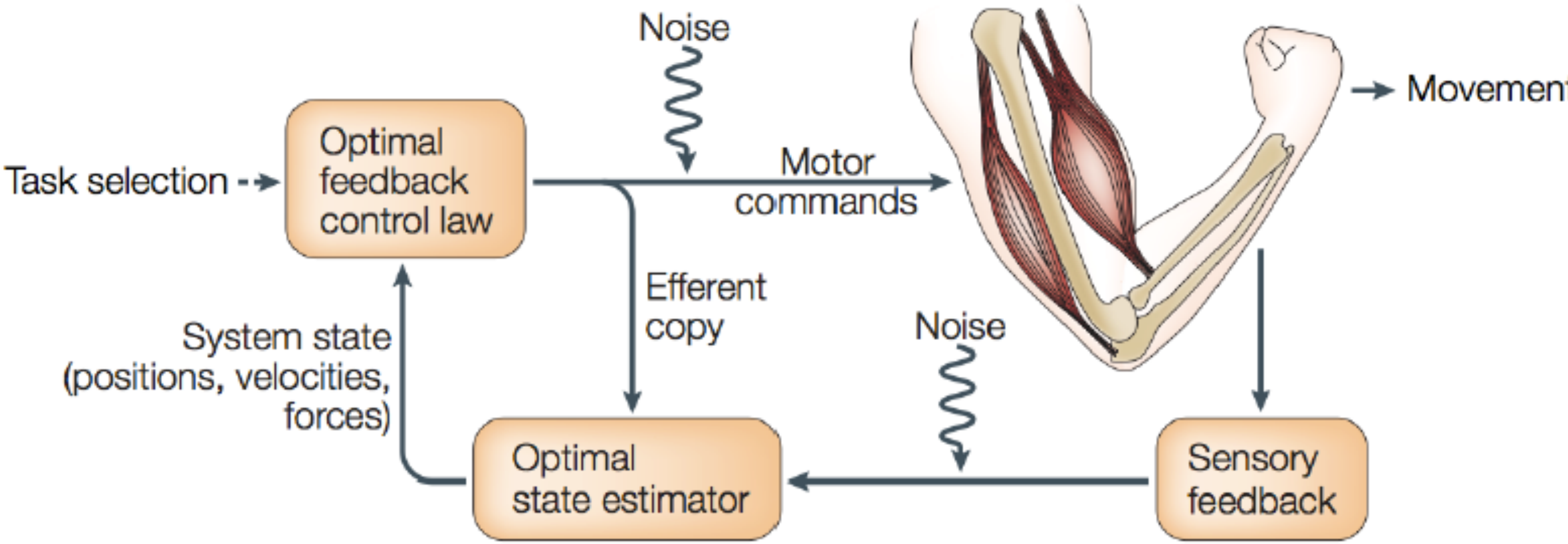
$$\mathbf{P}_{k+1} = \mathbf{A}_k (\mathbf{P}_k - \mathbf{P}_k \mathbf{C}_k^T (\mathbf{C}_k \mathbf{P}_k \mathbf{C}_k^T + E(\mathbf{z}_k \mathbf{z}_k^T))^{-1} \mathbf{C}_k \mathbf{P}_k) \mathbf{A}_k^T + E(\mathbf{y}_k \mathbf{y}_k^T)$$

LINEAR SENSOR FUSION WITH LQE



the estimation “trusts more”, i.e. weights more the more accurate sensing source

STOCHASTIC OPTIMAL CONTROL



- motion planning including feedback as optimal solution of a cost function
- cost function: typically task error and effort

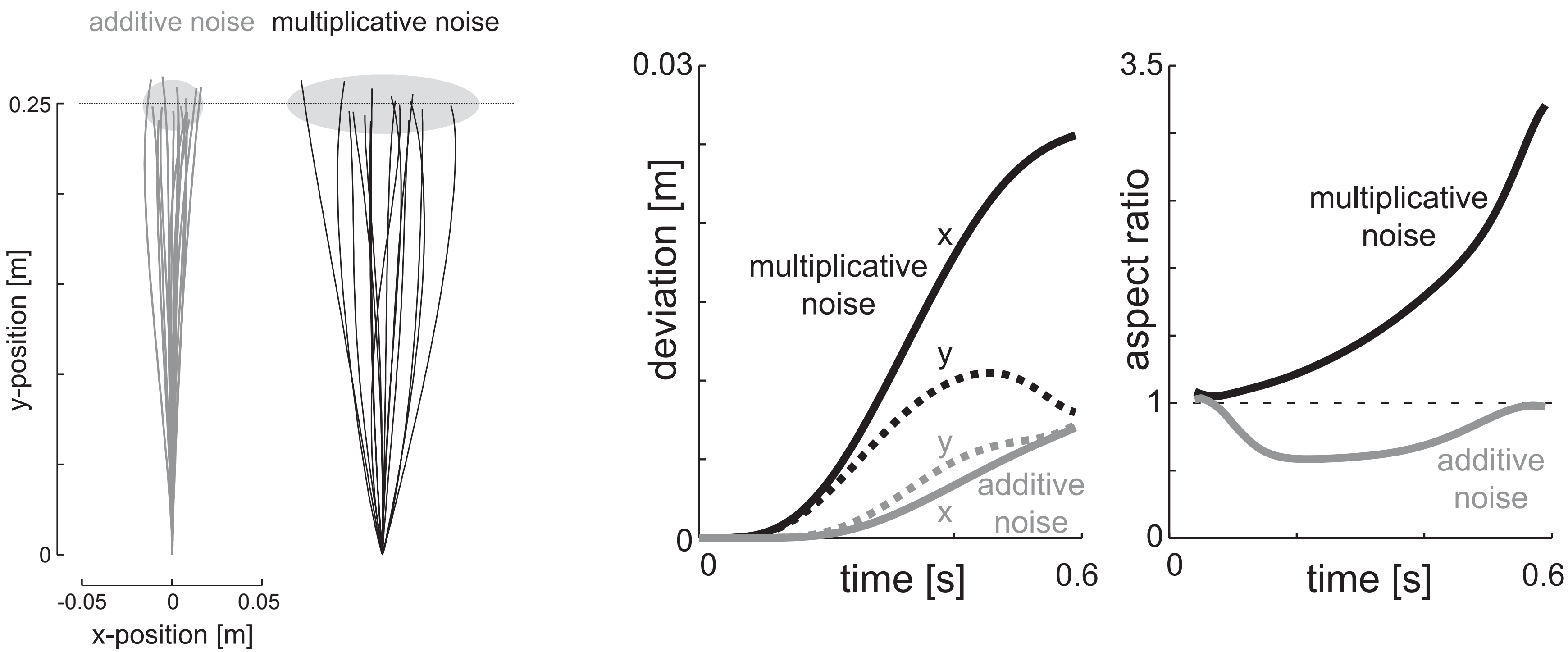
STOCHASTIC OPTIMAL CONTROL

- if a linear system with additive Gaussian white noise uses a linear sensor process with additive Gaussian white noise in order to perform optimal control relative to a quadratic cost function, then regulation and state estimation are independent

- Linear Quadratic Gaussian control (LQG) can be obtained by using LQR and LQE together

- $\mathbf{u}_k = -\mathbf{L}_k \hat{\mathbf{z}}_k$ with $\hat{\mathbf{z}}_k$ from LQE and $\mathbf{L}_k$ from LQR

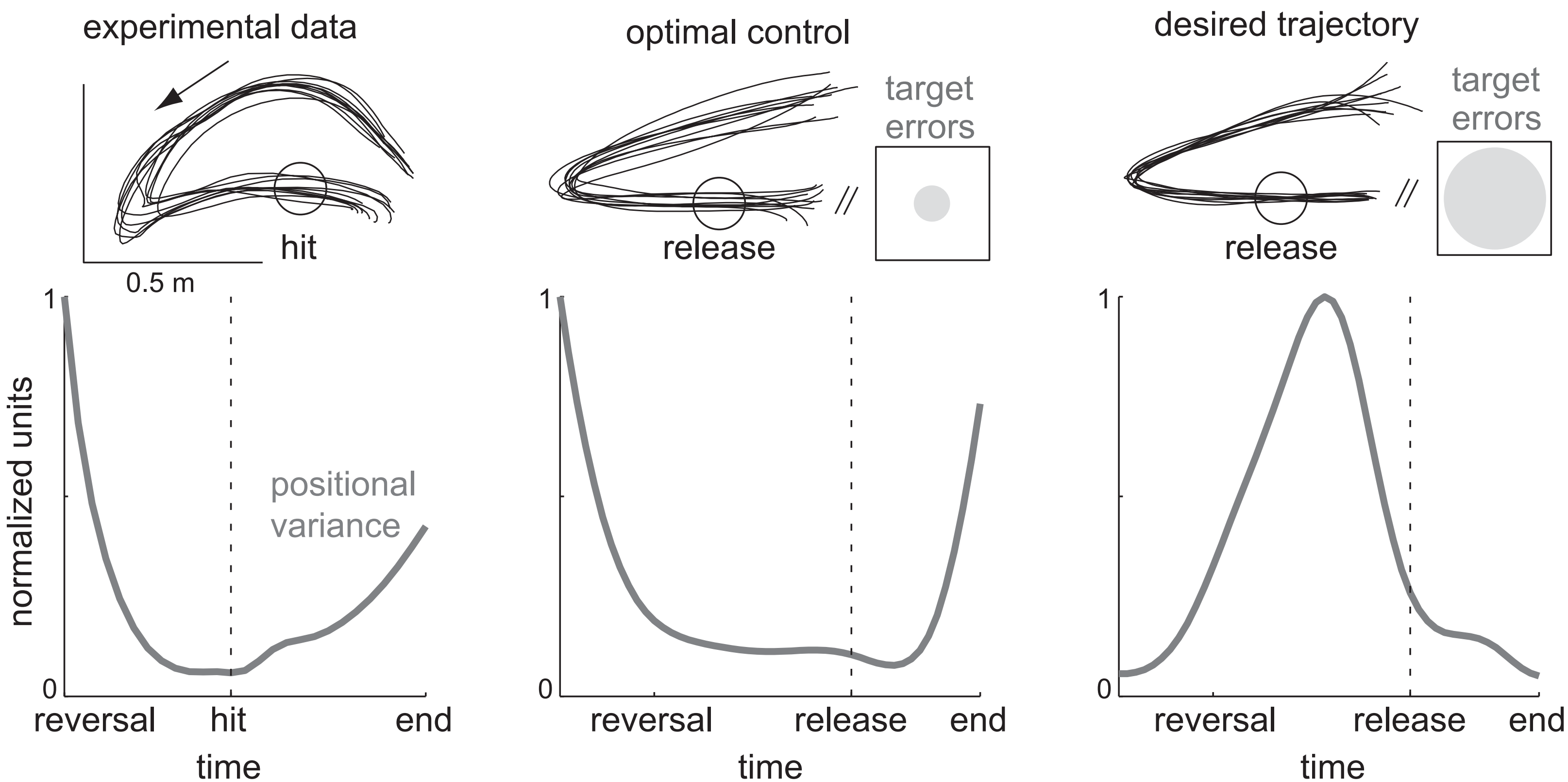
STOCHASTIC OPTIMAL CONTROL



- *x*: movements to a line are not curved towards the normal as it would cost effort to bend the trajectory
- *y*: multiplicative noise puts pressure to reduce deviation and enables the system to prevent noise

[Todorov and Jordan, Nature Neuroscience 2002]

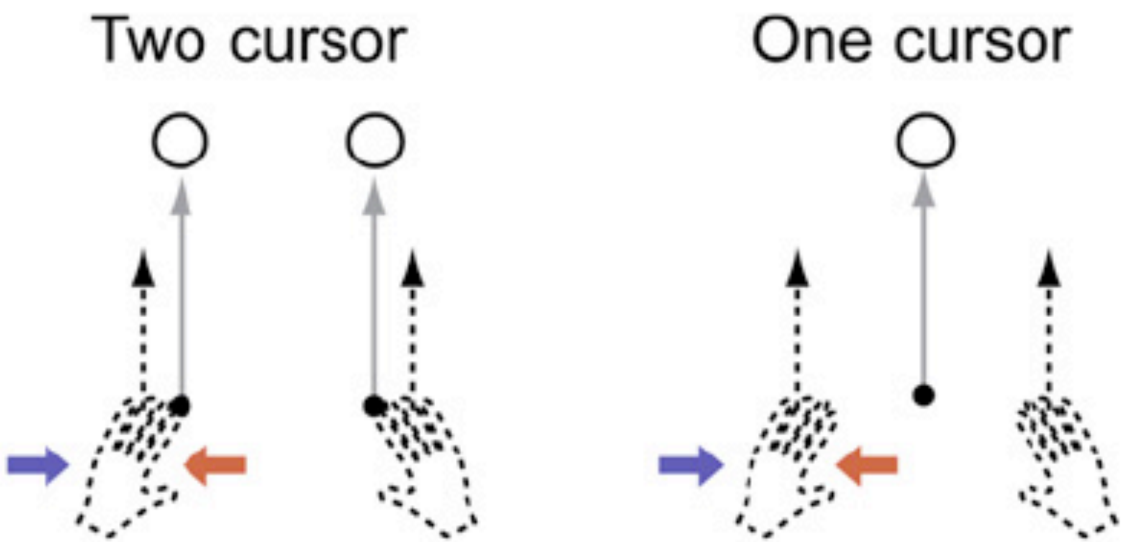
STOCHASTIC OPTIMAL CONTROL



- similar variability with optimal control as in data
- the control focuses on the task, in contrast to control along a desired trajectory

[Todorov and Jordan, Nature Neuroscience 2002]

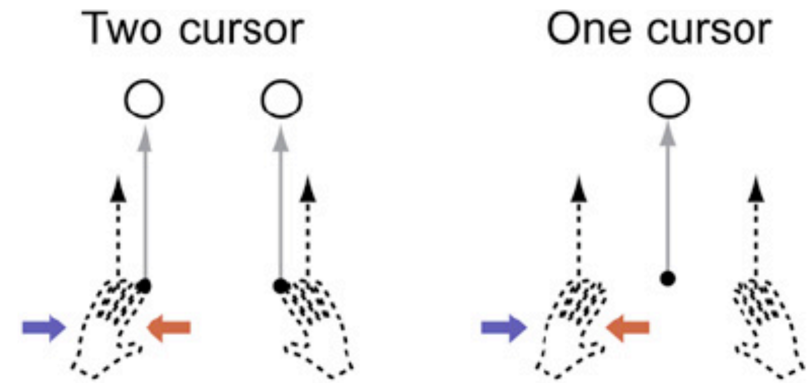
BIMANUAL CONTROL

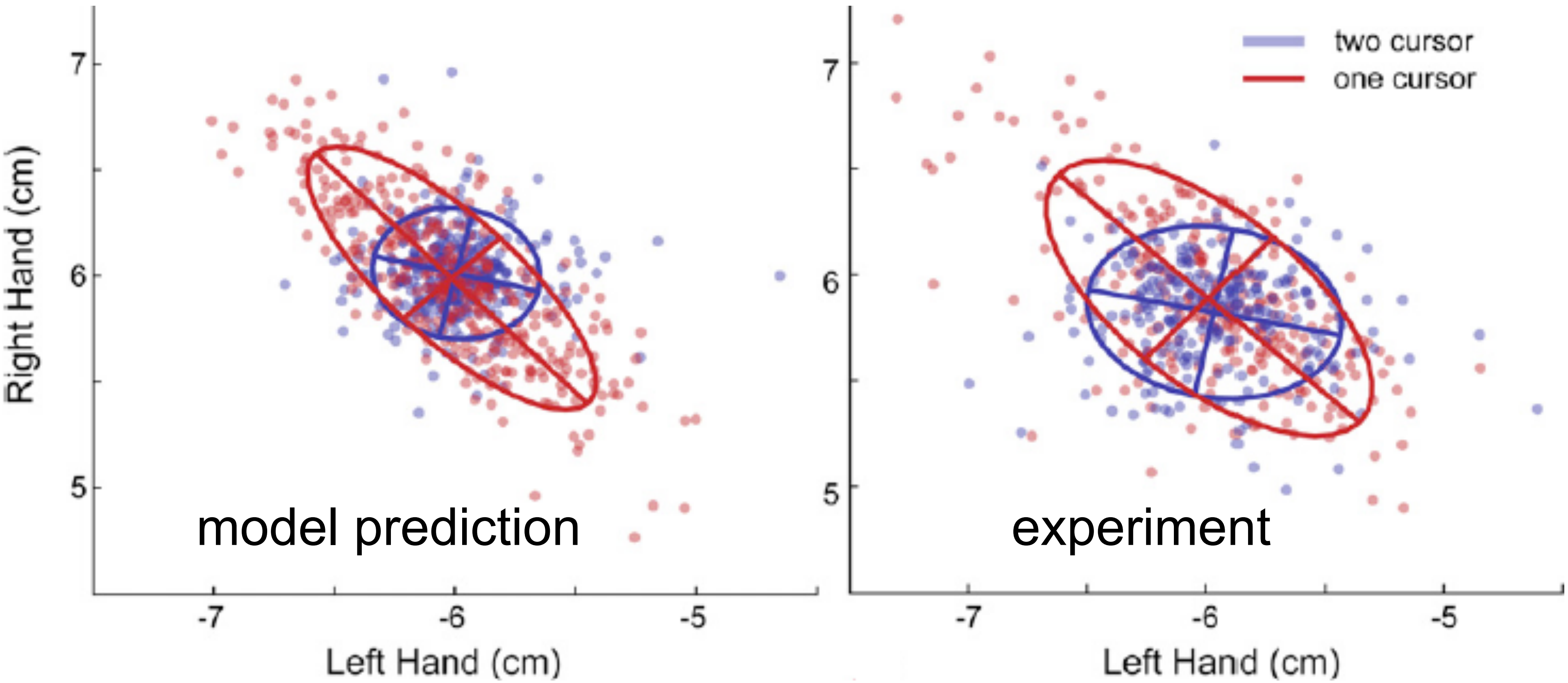


- redundant task
- cost: end distance + effort
- effort: sum of individual efforts
- two cursors: distance for each hand
- one cursor: distance of the mean

[Diedrichsen, Current Biology 2007]

BIMANUAL CONTROL





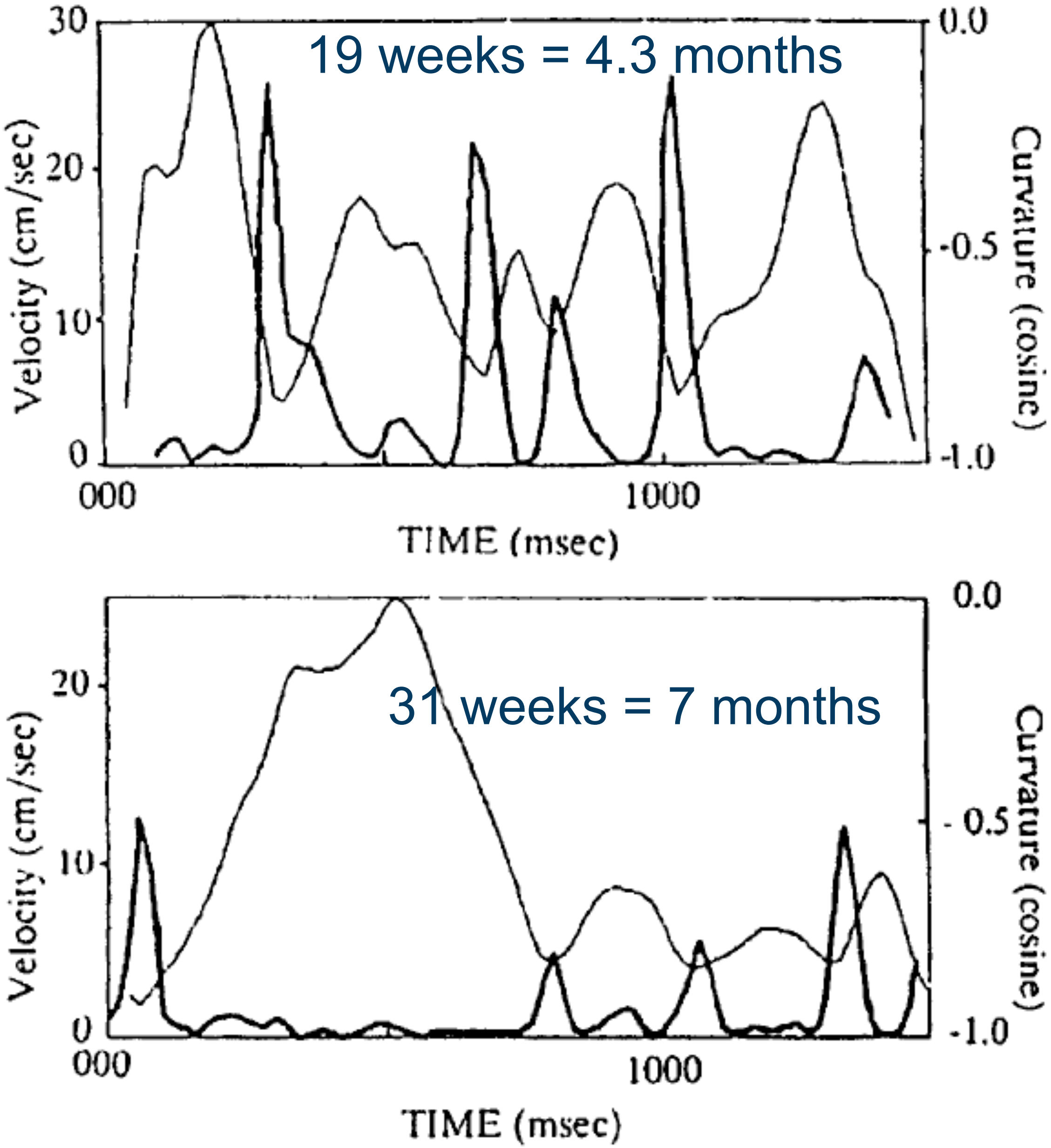
- minimum intervention principle along task-irrelevant dimensions

[Diedrichsen, Current Biology 2007]

SUBMOVEMENT PRIMITIVES

- optimisation can, in principle, be used to coordinate the system of the limbs and muscles
- practically it may be difficult to learn complex behaviours with a system that has as much redundancy as the human neuromuscular system
- biomechanical and neural constraints may impose constraints and thus reduce the redundancy
- a popular idea is that the nervous system uses sensorimotor building blocks or primitives to facilitate motor control and learning

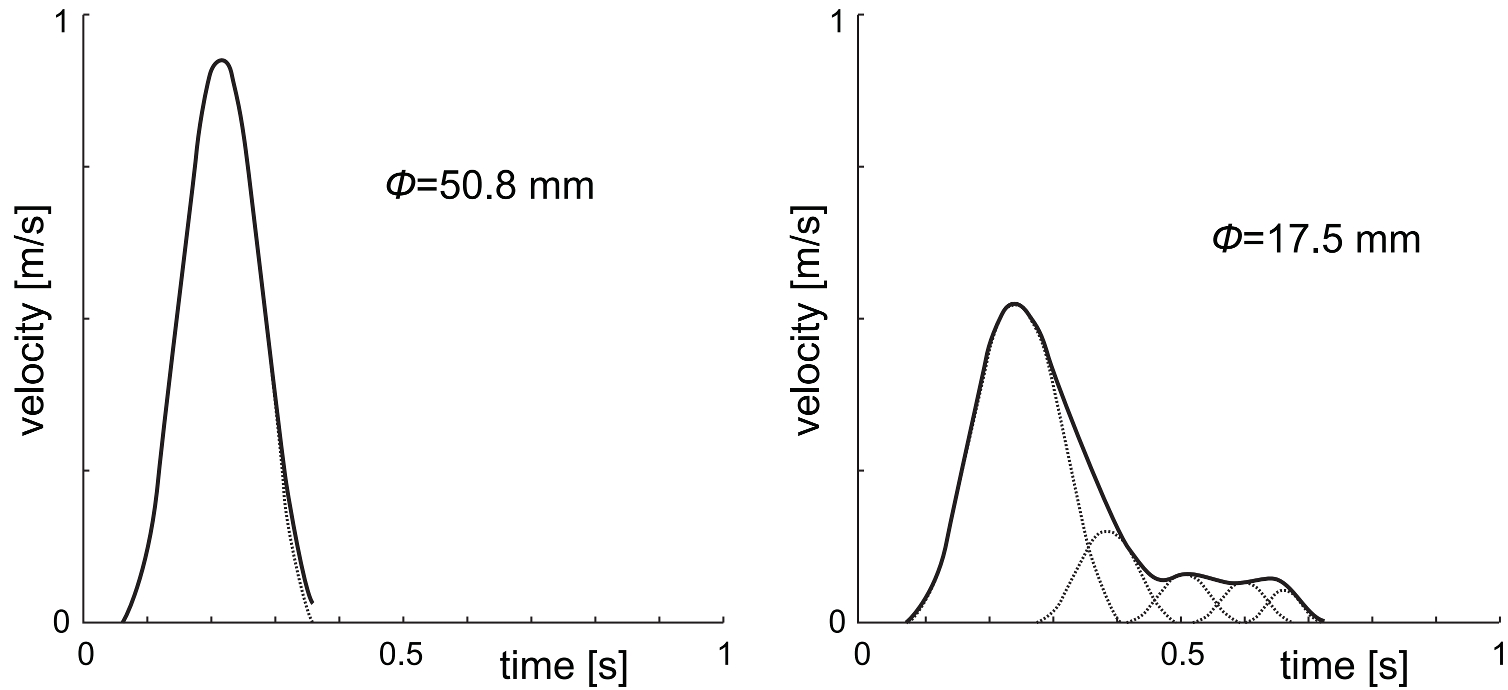
SUBMOVEMENT PRIMITIVES



- at about 6 months, babies change from a strategy with a series of submovements
- ... to a smoother movement with asymmetric velocity profile and large initial submovement

[von Hofsten and Roennqvist, Child Development 1993]

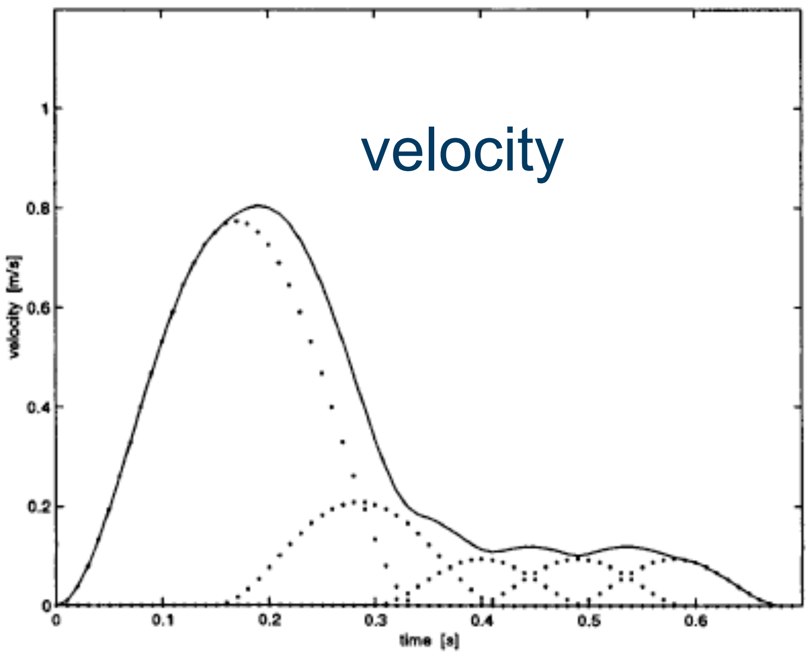
SUBMOVEMENT PRIMITIVES

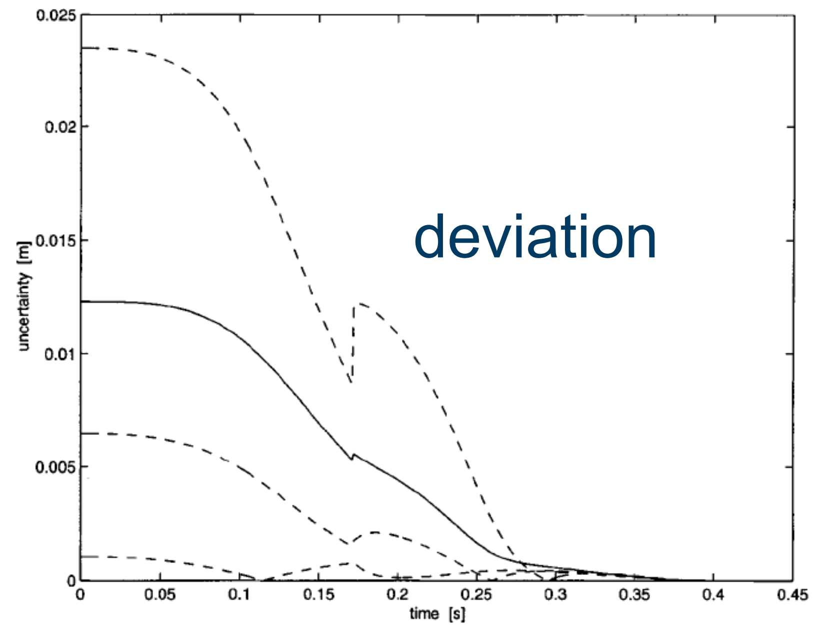


- placing a peg into holes of different diameters
- the peak velocity decreases and the movement becomes more asymmetric as accuracy increases
- fluctuations corresponding to direction change can be interpreted as submovement primitives

[Milner, Neuroscience 1992]

MODEL VISUO-MOTOR COORDINATION

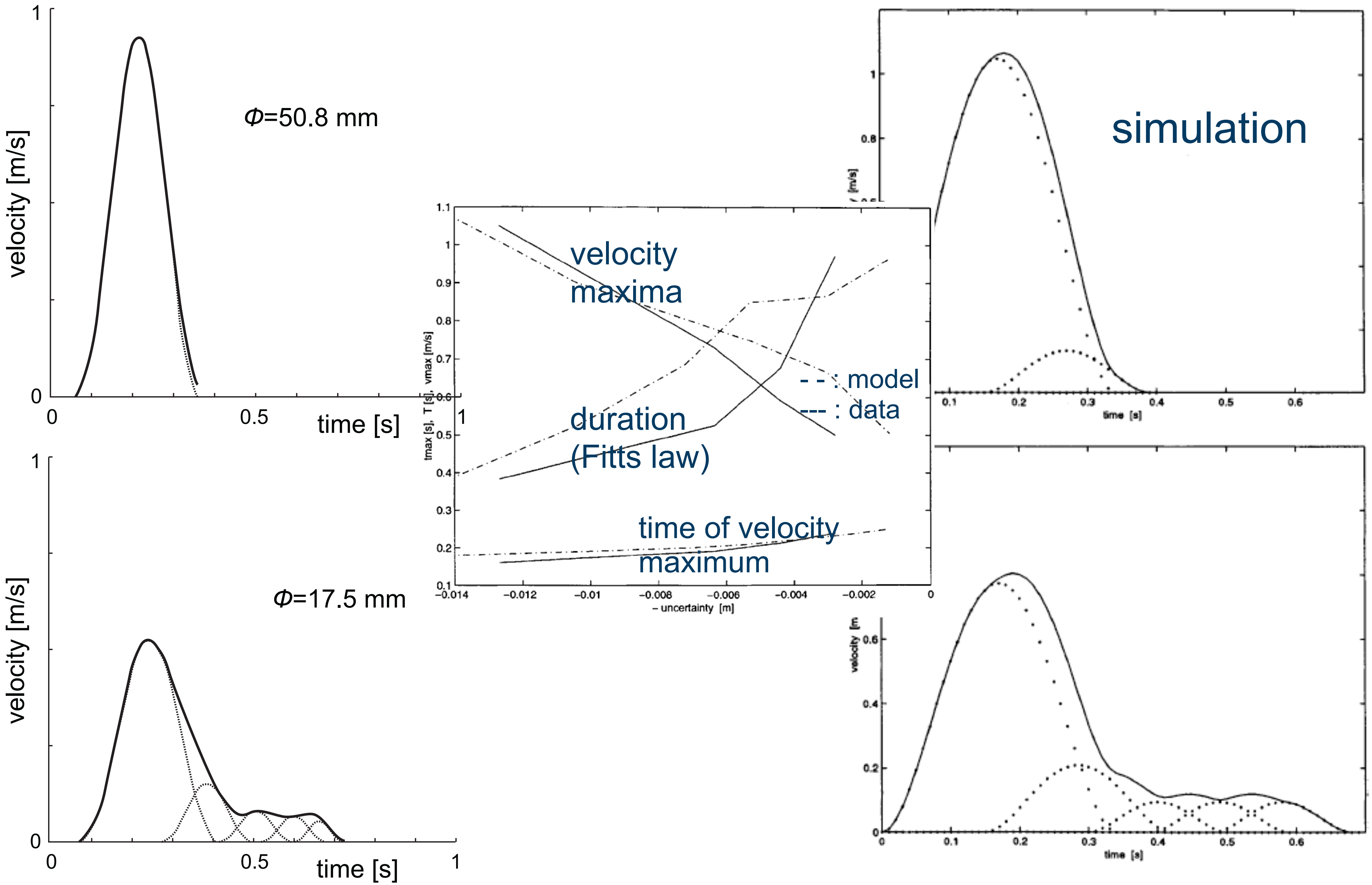




- motion as a series of ballistic submotions
- each submotion has noise proportional to its mean speed, thus slower submotions are more accurate but take longer
- forward model to detect where the actual movement is going to, based on the subject specific submotion shape
- learn submotions with minimal time for a required accuracy

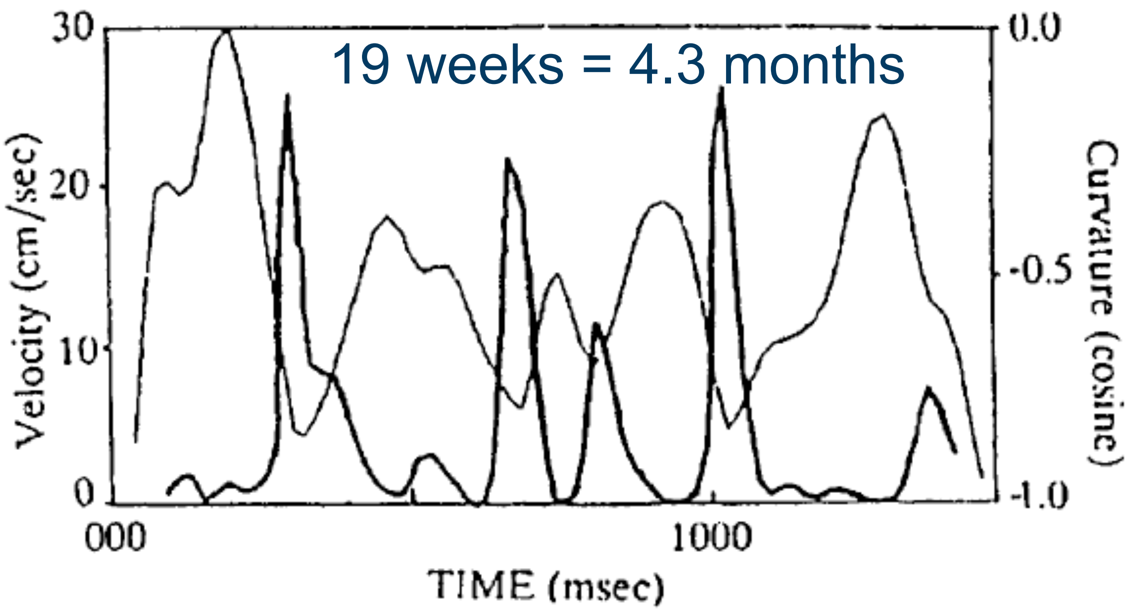
[Burdet and Milner, Biological Cybernetics 1998]

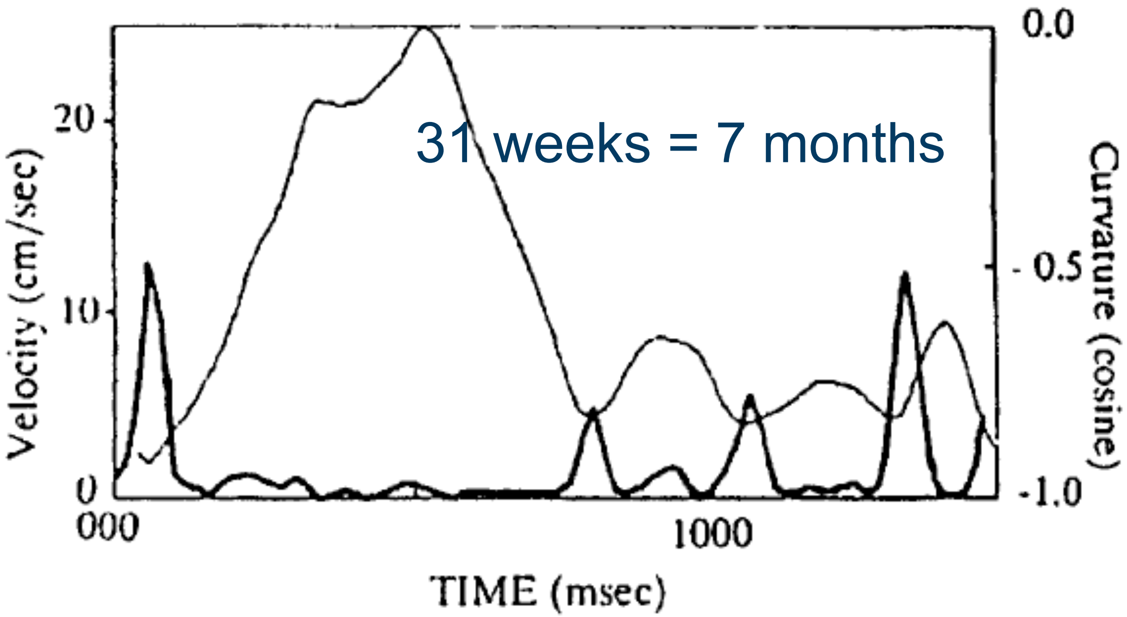
MODEL VISUO-MOTOR COORDINATION



[Burdet and Milner, Biological Cybernetics 1998]

MODEL VISUO-MOTOR COORDINATION



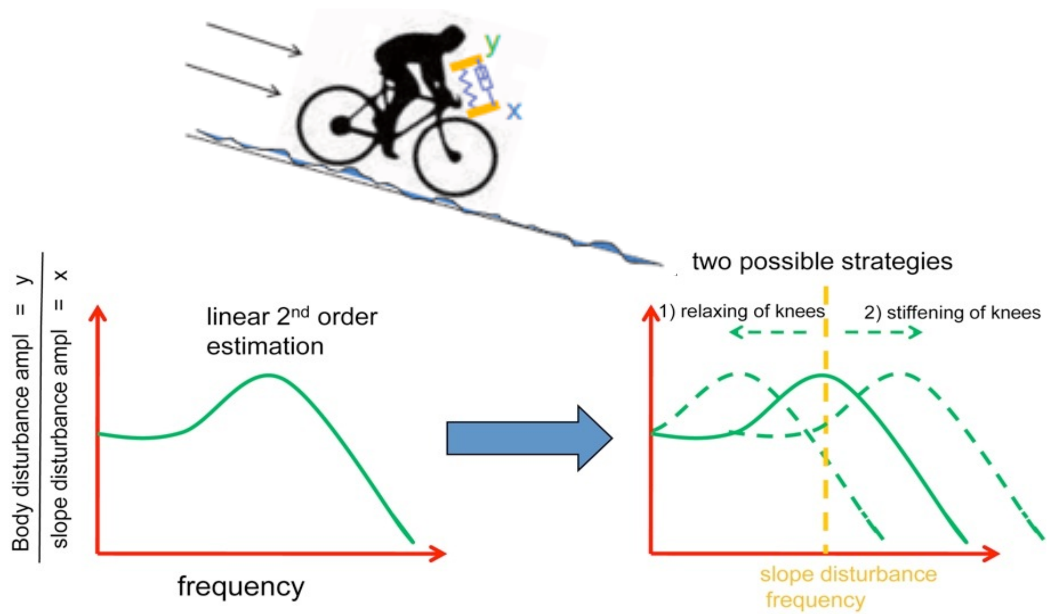


- at about 6 months, babies learn to perform coordinated reaching movements
- this may correspond to their increasing memory capabilities

[von Hofsten and Roennqvist, Child Development 1993]

LOW VS HIGH STIFFNESS STRATEGIES

to attenuate disturbances (e.g. to prevent water in a glass from spilling), one can stiffen the arm, or relax it



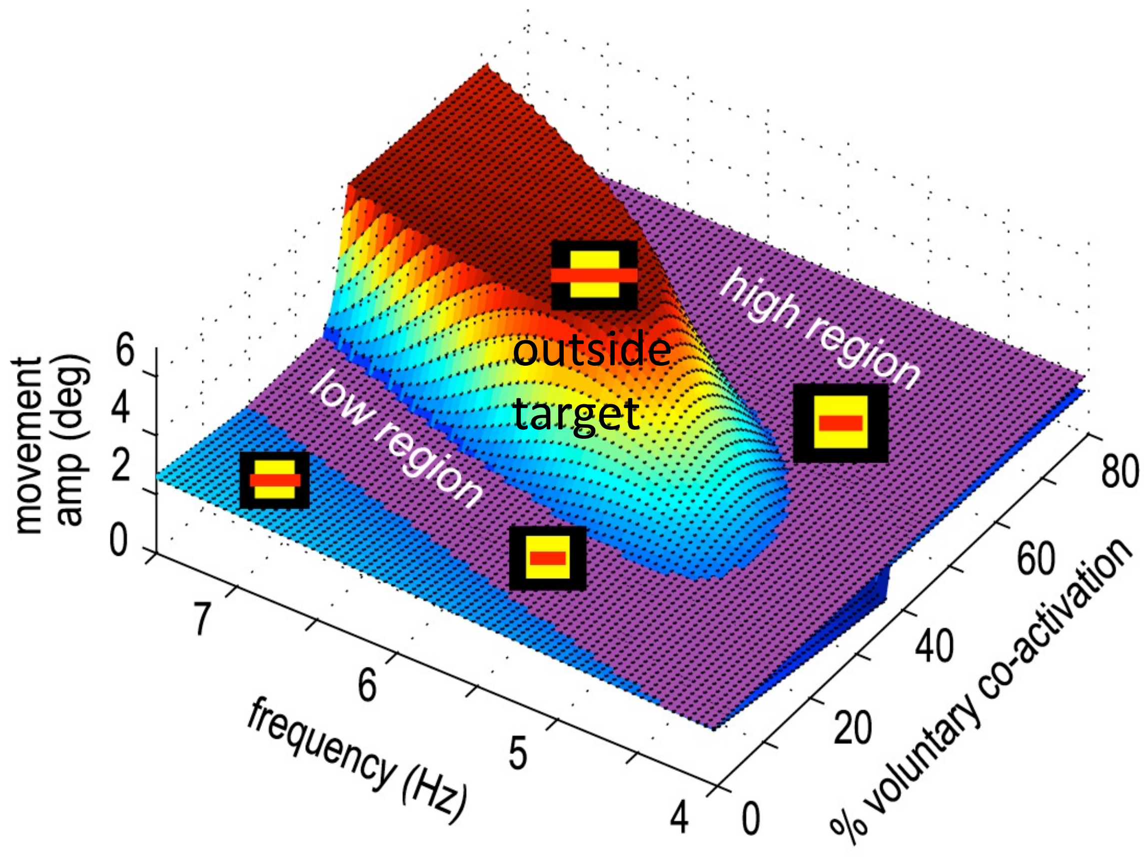
[Ganesh et al. J Neurophysiology 2010]

LOW VS HIGH STIFFNESS STRATEGIES

- 1DOF wrist flexion/extension
- sinusoidal perturbation
- EMG recorded from wrist (ECRB and FCR) muscles, to set the wrist amplitude
- to maintain the wrist amplitude (red bar) below 3º (yellow band) by co-activating the wrist muscles in a suitable way

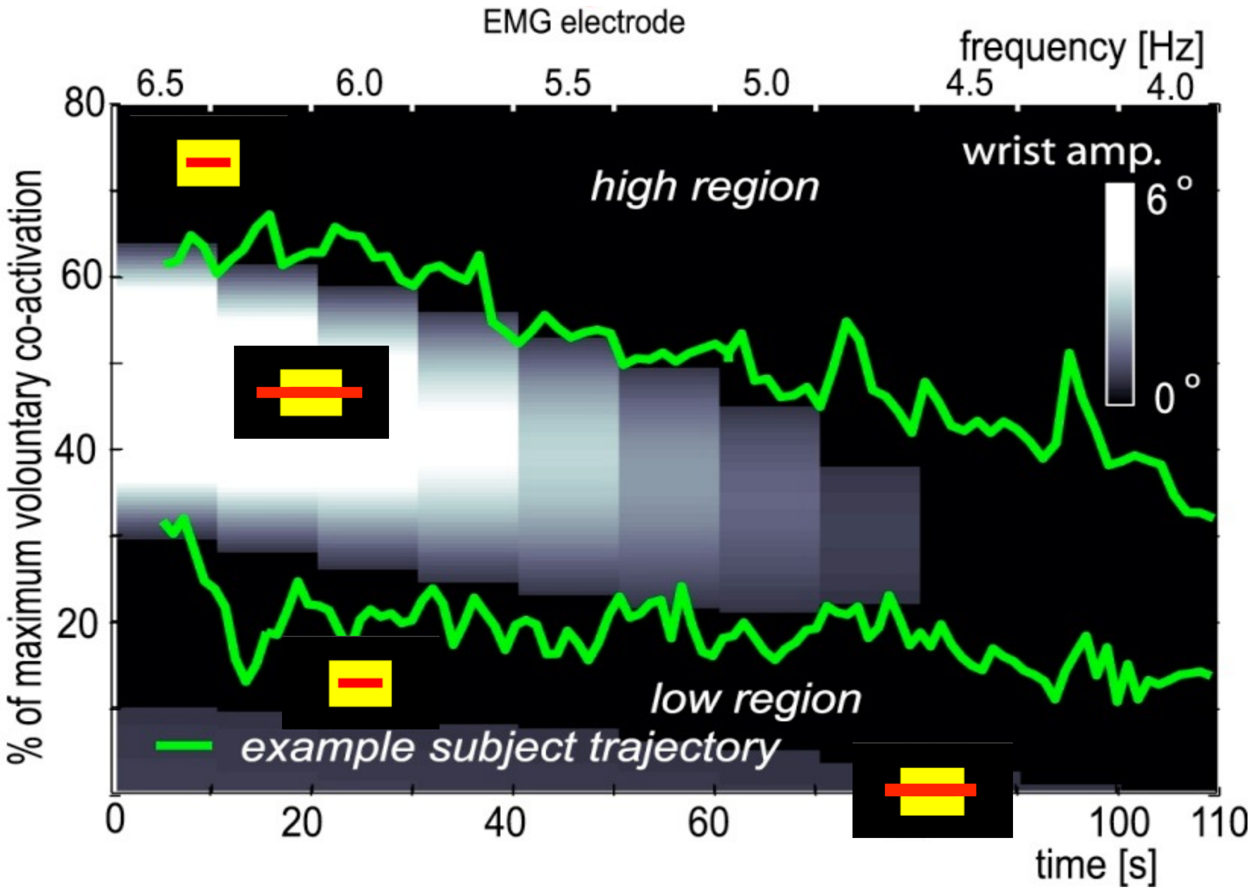
[Ganesh et al. J Neurophysiology 2010]

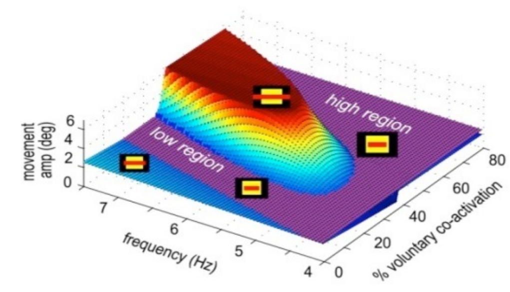
pert. amplitude(frequ,stiffness)



[Ganesh et al. J Neurophysiology 2010]

BI-SOLUTION PARADIGM

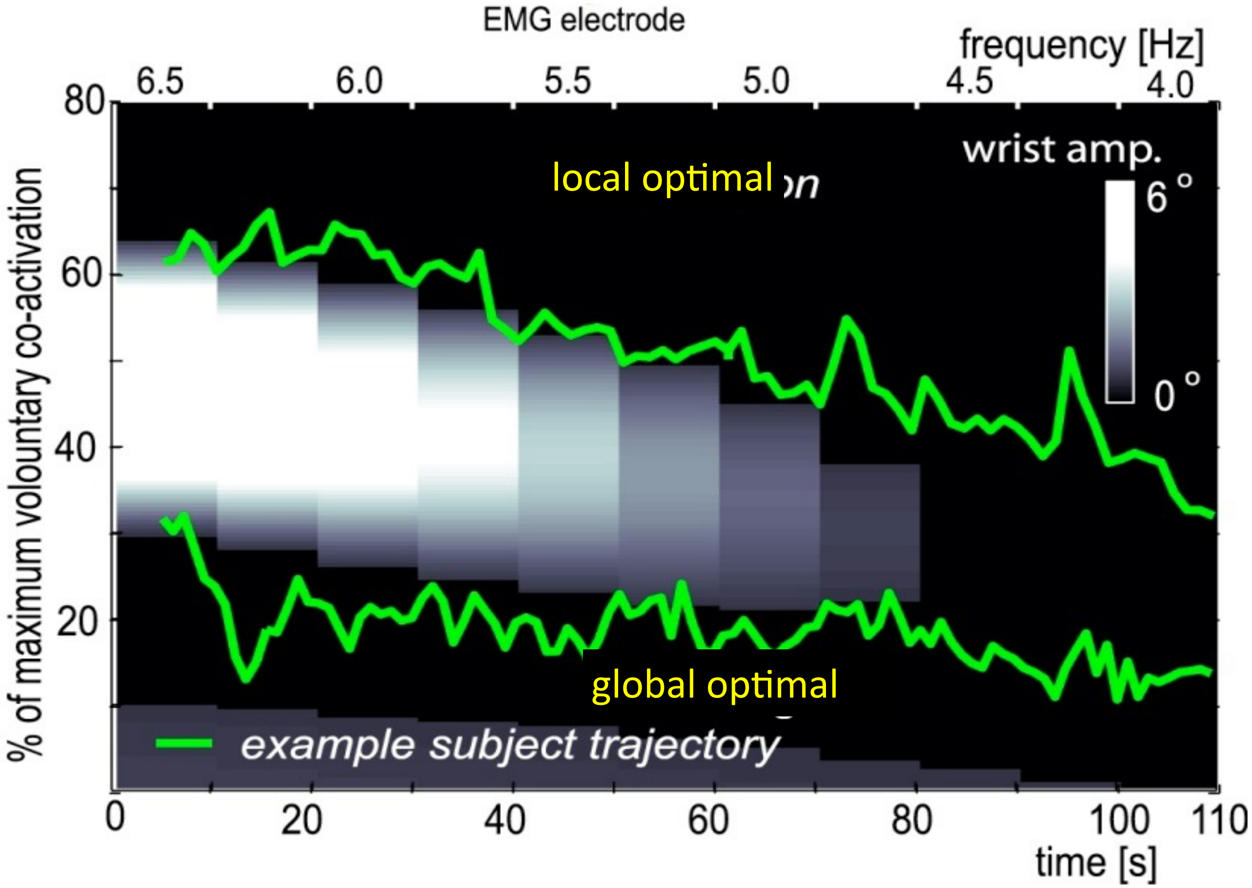


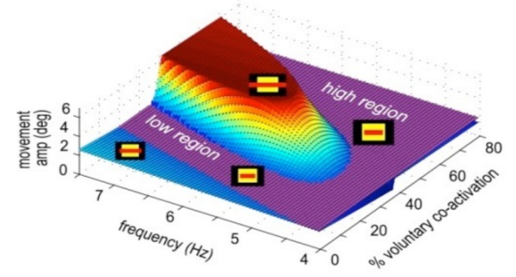


- perturbation amplitude as a function of its frequency and the subject co-contraction level
- the perturbation frequency changes from *7Hz* down to 4*Hz* in steps of 0.25*Hz* (10 seconds each)

[Ganesh et al. J Neurophysiology 2010]

BI-SOLUTION PARADIGM



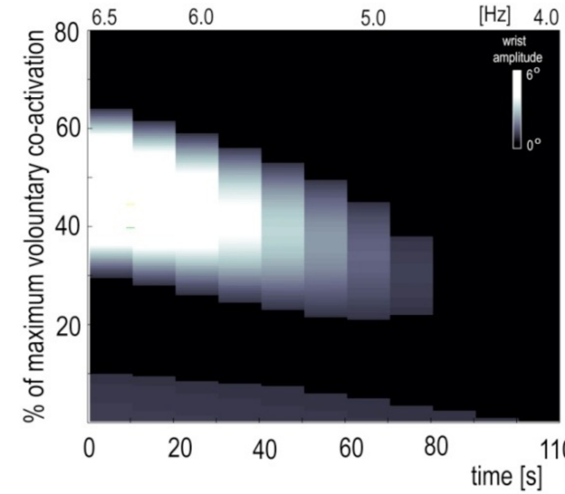


cost = ε(error) + μ(effort)

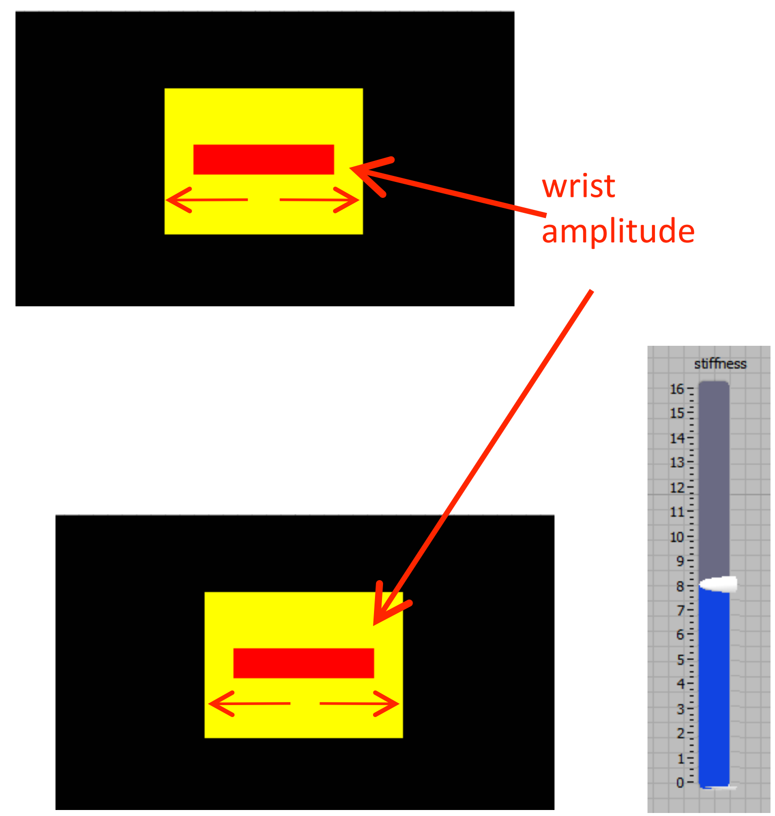
ε,μ: monotonically increasing positive functions

[Ganesh et al. J Neurophysiology 2010]

EXPERIMENT



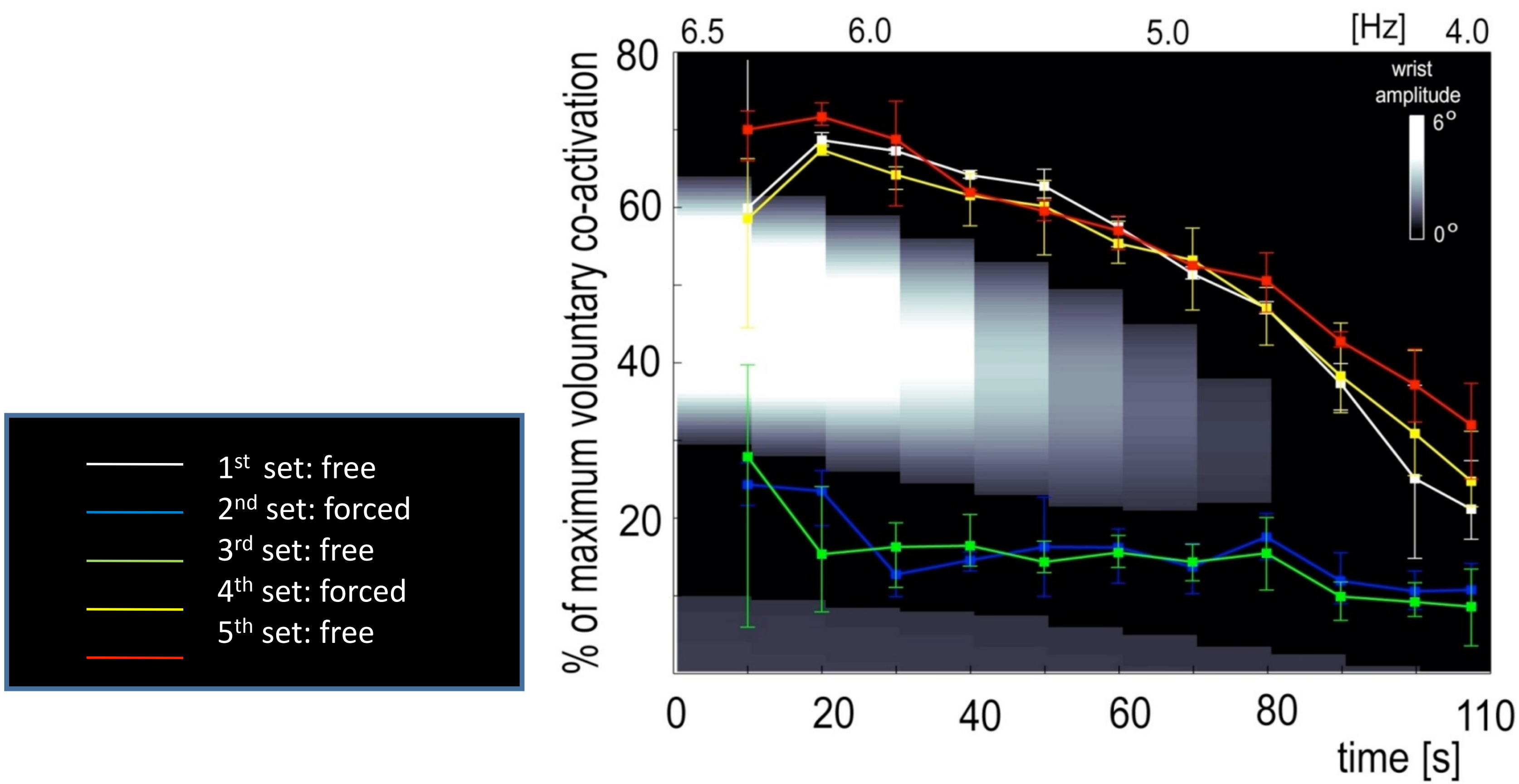
- alternance of sets with 3 trials
- subjects informed that higher stiffness may not lead to low amplitude
- free sessions
- forced sessions: subjects forced to start in the low or in the high stiffness area by giving them feedback of their stiffness (only first 5-7 seconds)



stiffness indicator

[Ganesh et al. J Neurophysiology 2010]

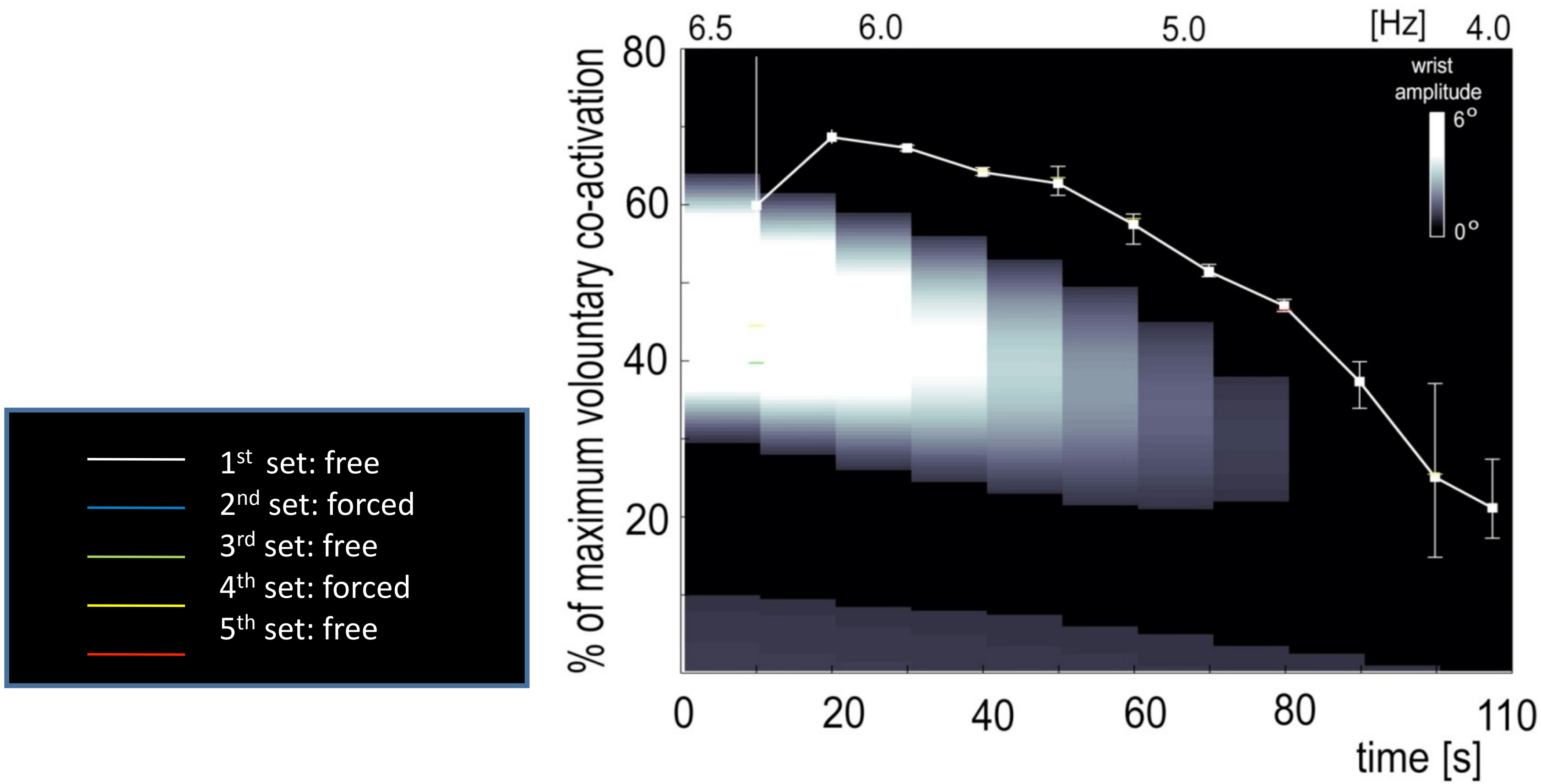
RESULTS (1)



- the subjects do not necessarily adopt the ‘high stiffness’ strategy

[Ganesh et al. J Neurophysiology 2010]

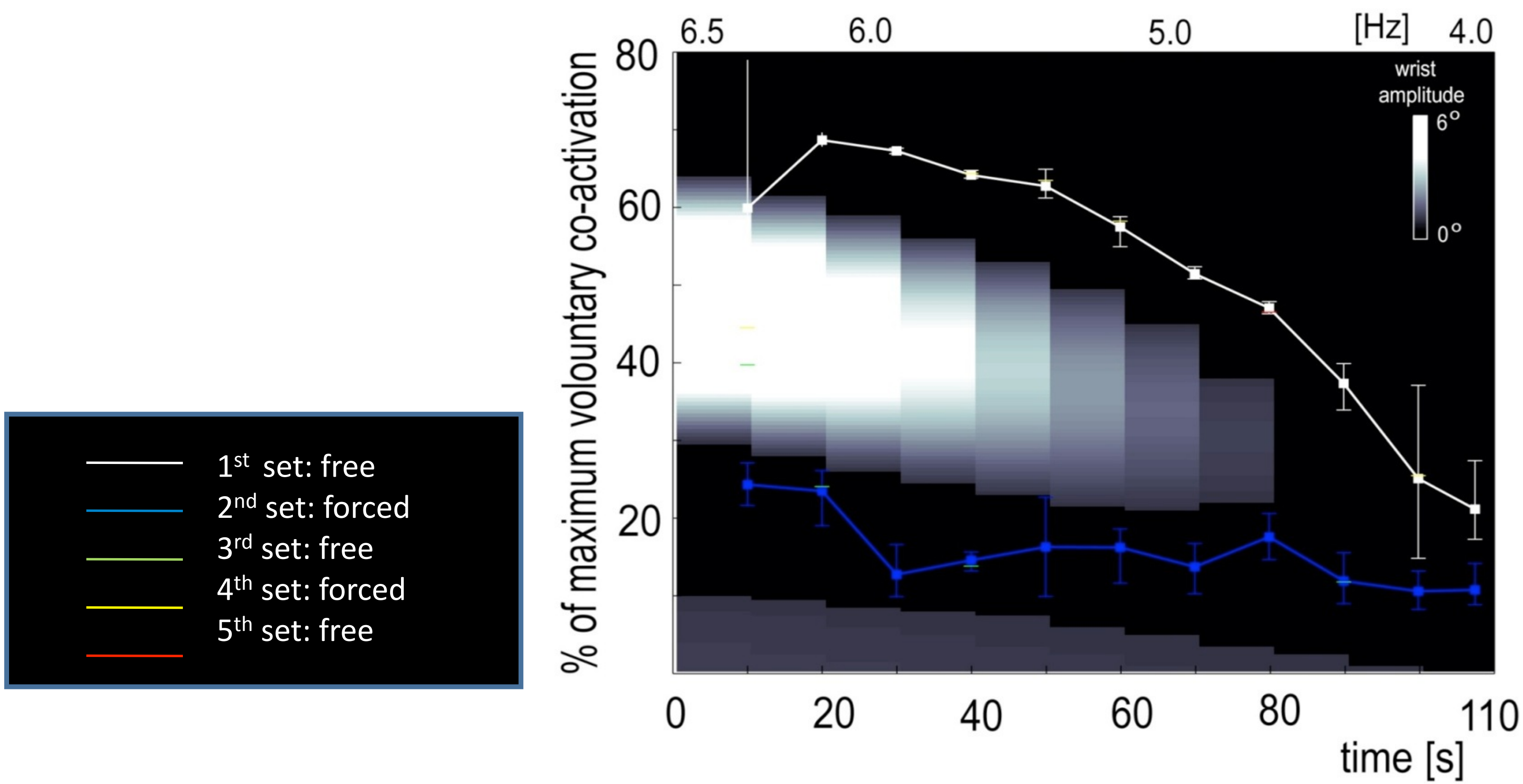
RESULTS (2)



- in the first trial (white line), 5 subjects prefer the low stiffness area and 5 the high area

[Ganesh et al. J Neurophysiology 2010]

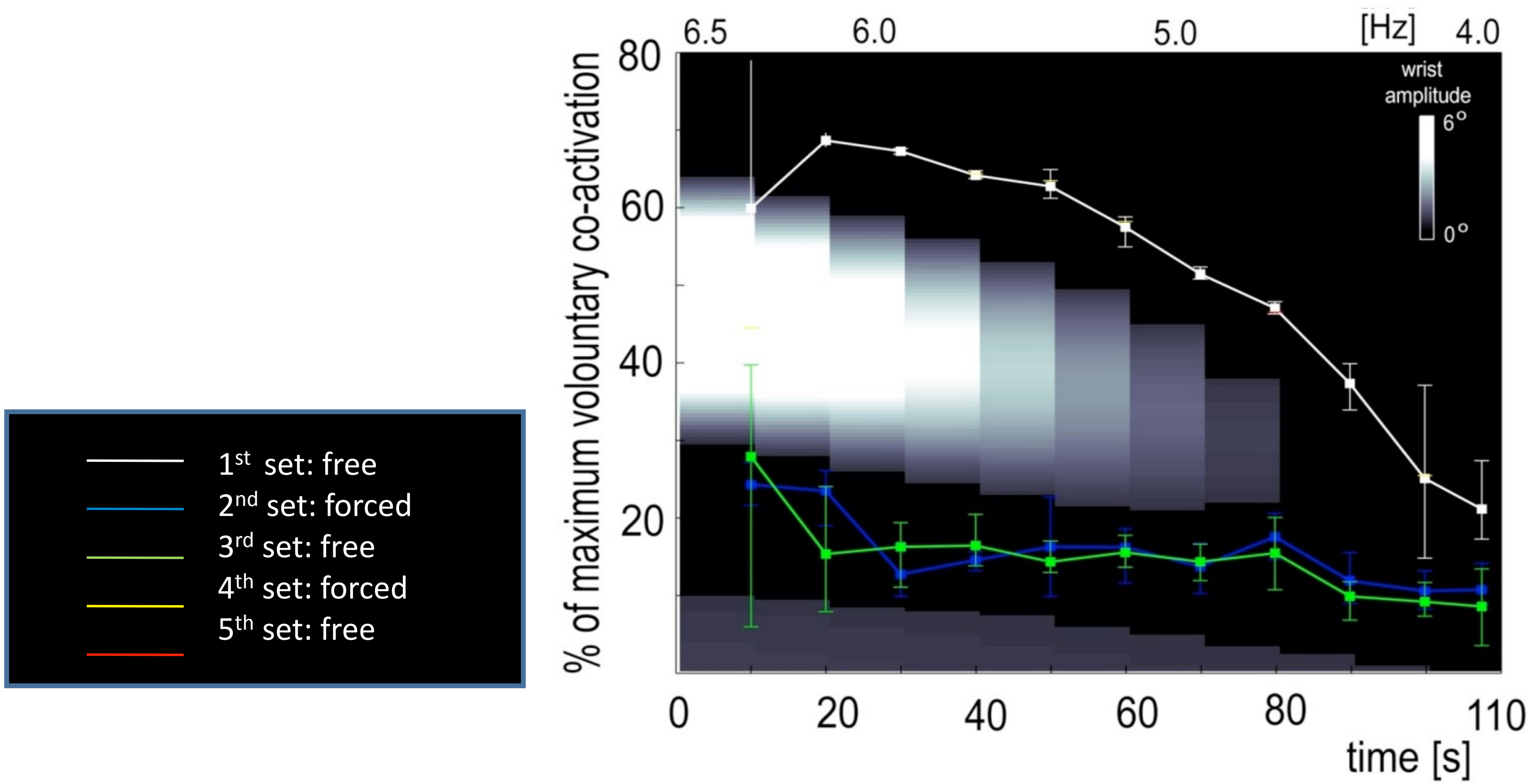
RESULTS (3)



- when ‘forced’ to the other region (blue) they change their preference

[Ganesh et al. J Neurophysiology 2010]

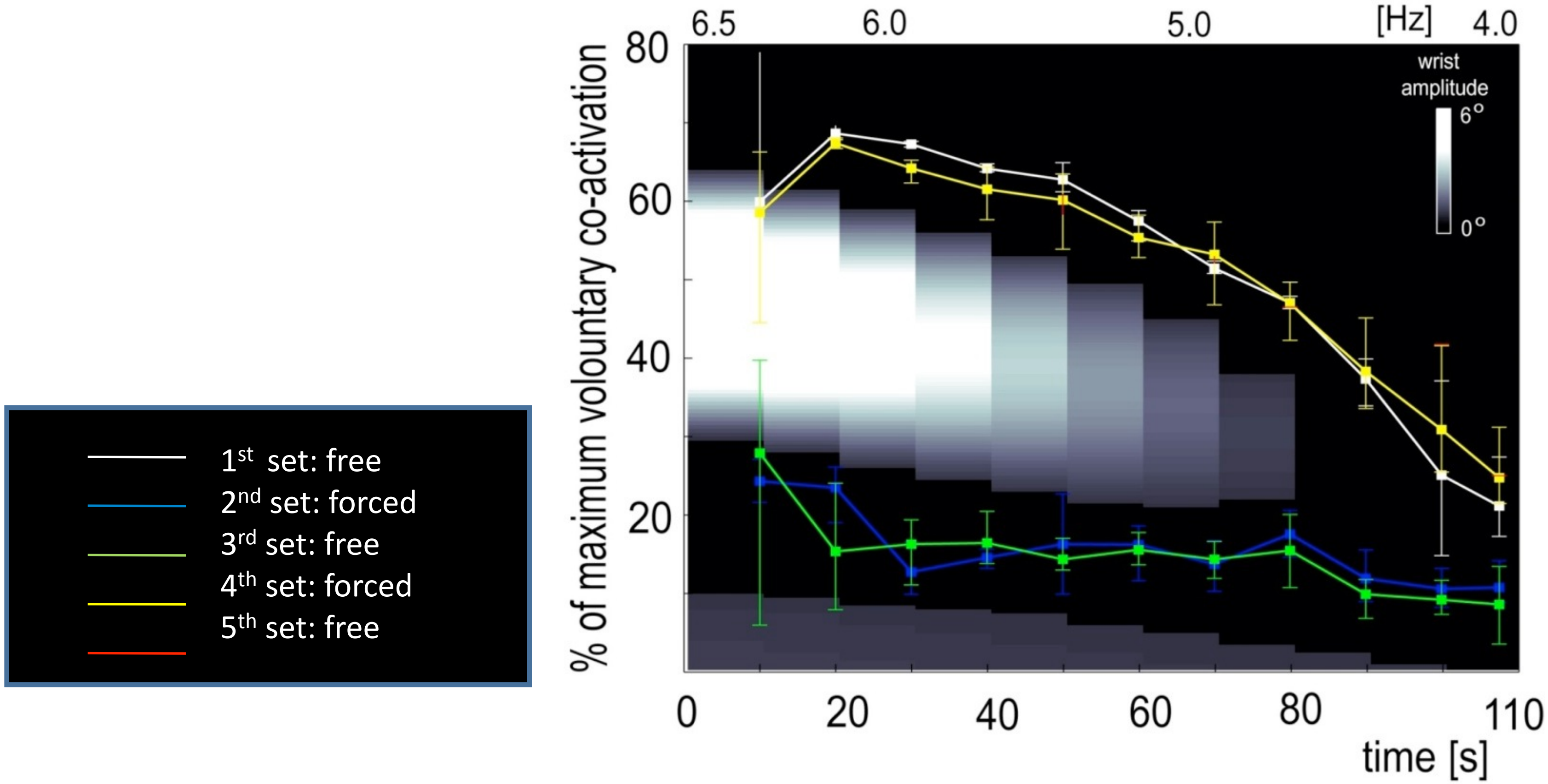
RESULTS (3)



- …and all the successive 'free' trials (green) then follow the 'forced' trajectory

[Ganesh et al. J Neurophysiology 2010]

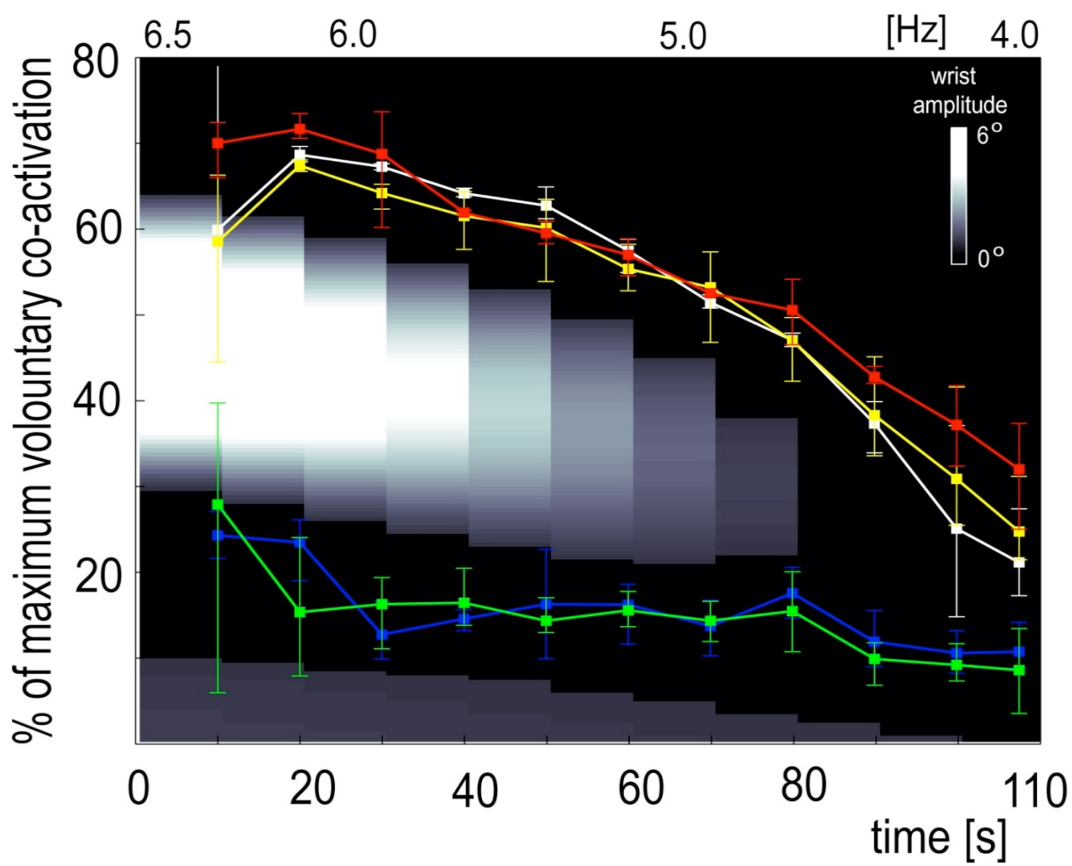
RESULTS (4)



- on being ‘forced’ back (yellow), their movements return to the original trajectory

[Ganesh et al. J Neurophysiology 2010]

RESULTS (4)



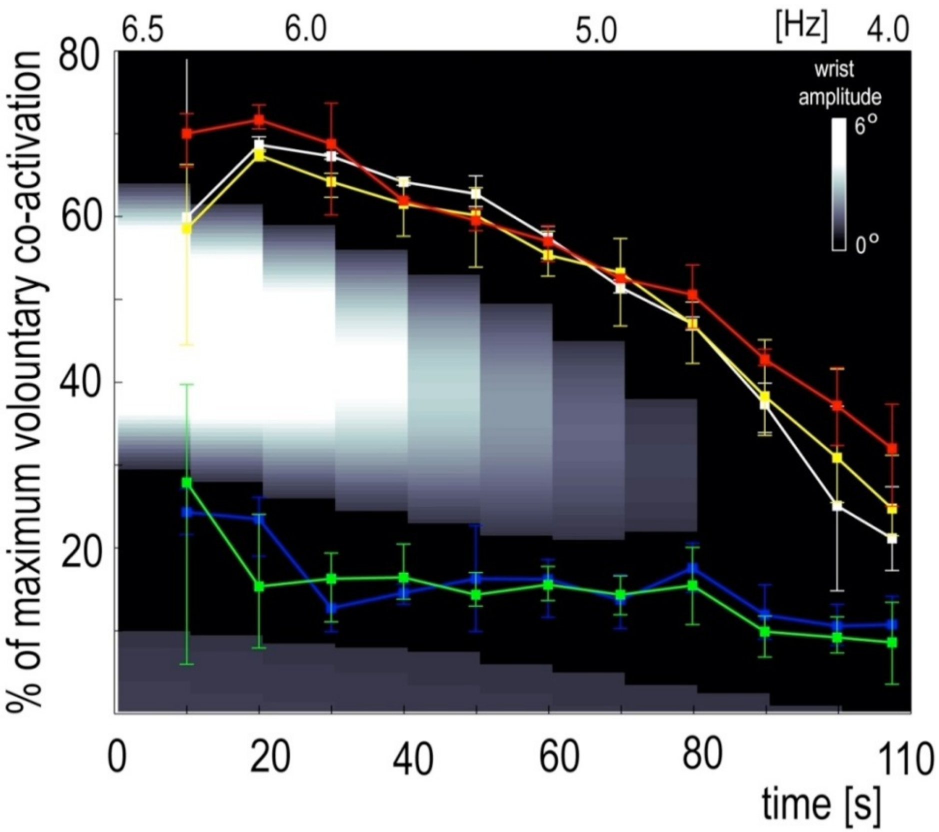
1st set: free
2nd set: forced
3rd set: free
4th set: forced
5th set: free

- **all** the next ‘free’ trials (red) follow the ‘forced’ trajectory

[Ganesh et al. J Neurophysiology 2010]

LEARNING IN MULTIPLE SOLUTIONS

- no global minimisation: The subjects were unable to realise the global minimum of error-effort
- however, there was local energy minimisation in the selected stiffness area

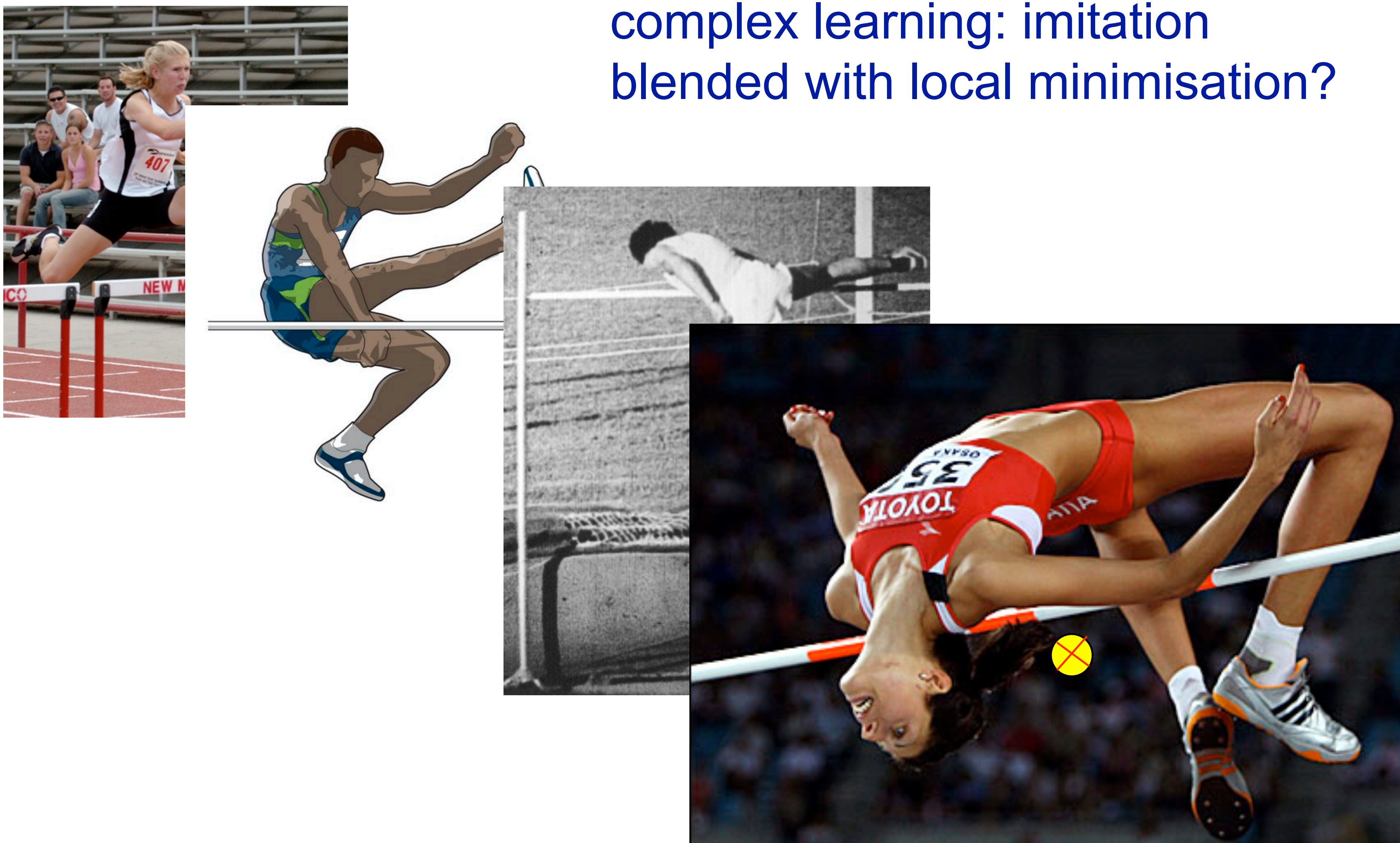


- memory: subjects tend to repeat what they are forced to do

[Ganesh et al. J Neurophysiology 2010]

LEARNING IN MULTIPLE SOLUTIONS

complex learning: imitation
blended with local minimisation?



[Ganesh et al. J Neurophysiology 2010]