HUMAN ROBOTICS

robotics of human
robotics for humans

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HUMAN MOTOR LEARNING

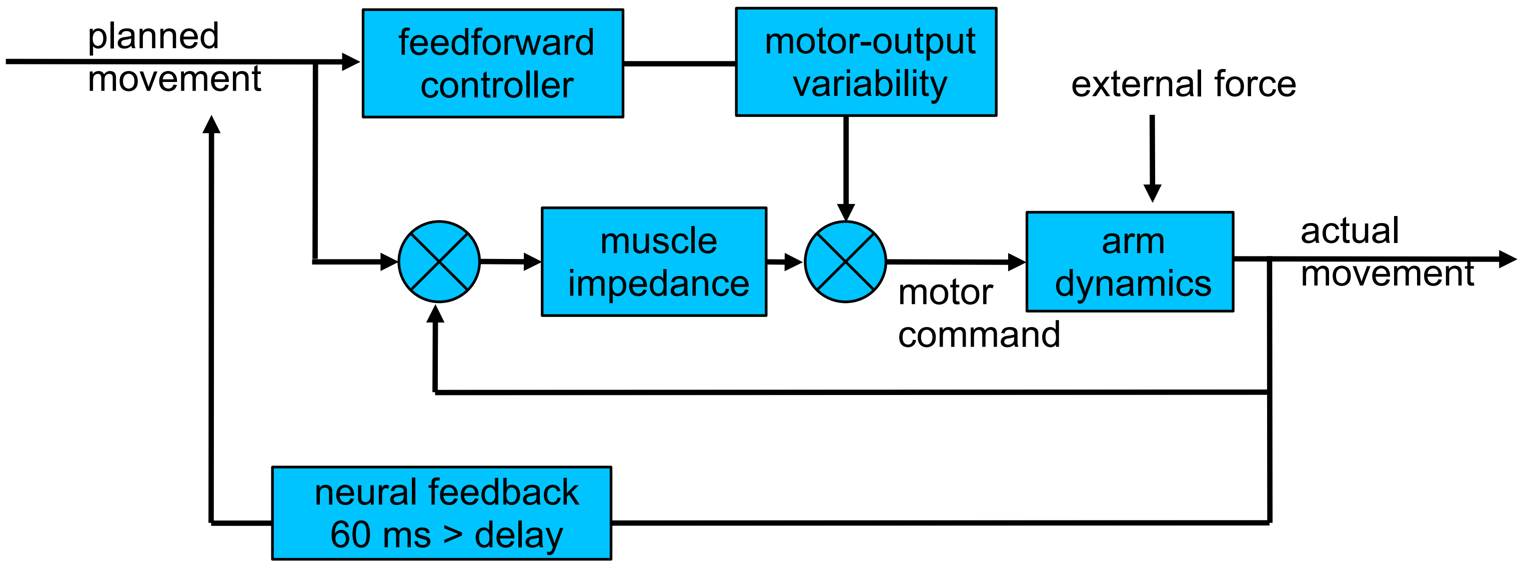
- we constantly need to learn new tasks and adapt to changing conditions, e.g. during infancy or with ageing

- similarities between rehabilitation and motor learning in healthy subjects as a tool to develop efficient rehabilitation strategies

MOTOR ADAPTATION & MOTION OPTIMISATION

- motor adaptation
- learning of tasks with multiple solutions
- skill learning
- motor learning

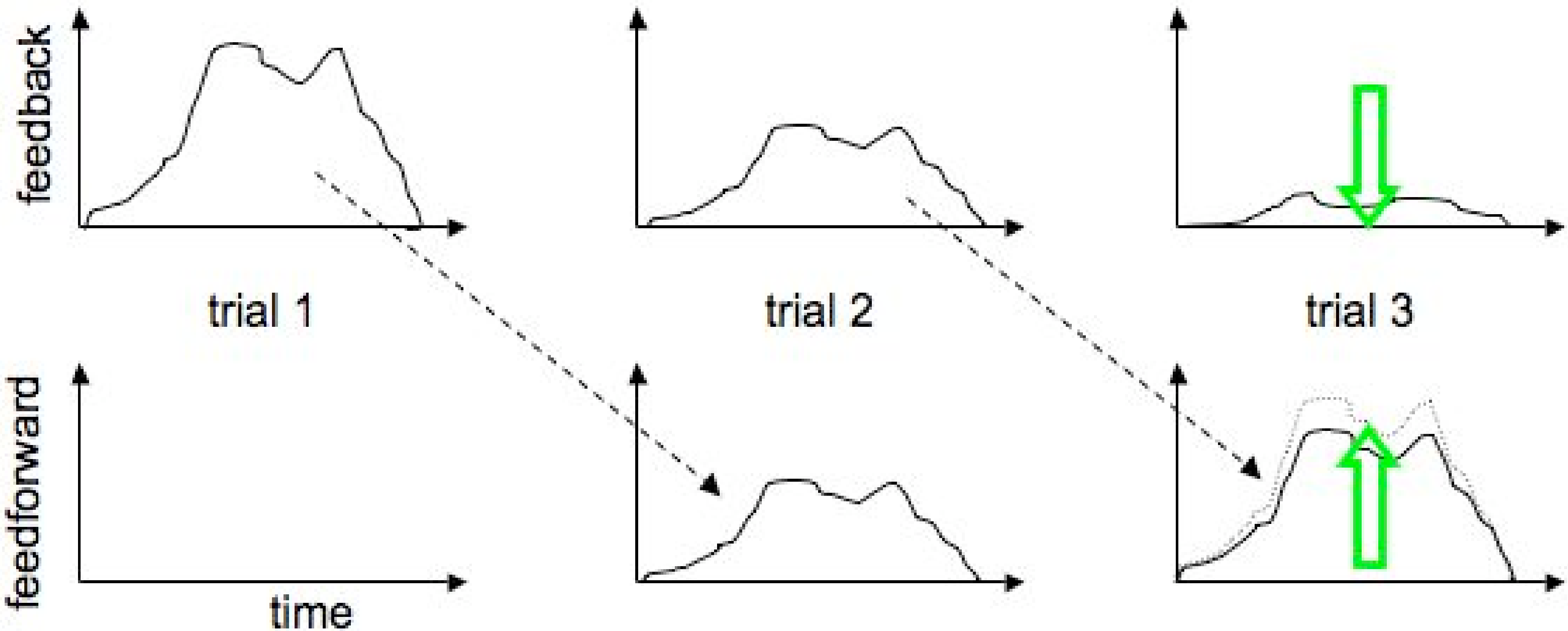
CONTROL OF HUMAN ARM



- muscle impedance provides stability
- reflexes generally also contributes to stability
- neural feedback is too slow and weak to explain fast motion

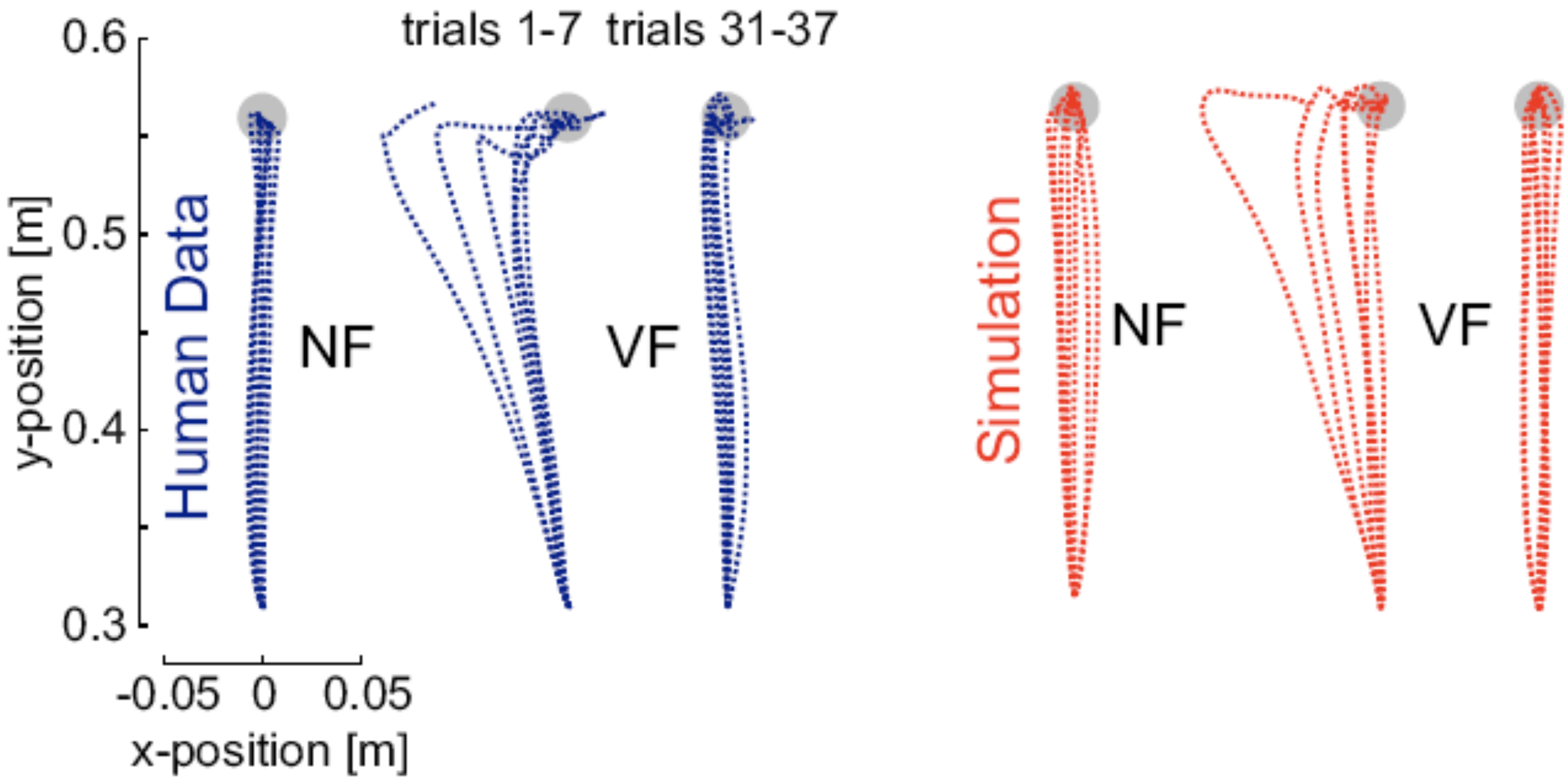
-> feedforward controller using an inverse model, which allows suitable commands to be executed

FEEDFORWARD ADAPTATION THROUGH ITERATIVE CONTROL



- to repeat a single movement
- feedback enables to follows the trajectory, thus is indicative of the task dynamics
- $\tau_{FF}^{k+1}(t) = \tau_{FF}^{k}(t) + \alpha\,\tau_{FB}^{k}(t)$, $0<\alpha<1$

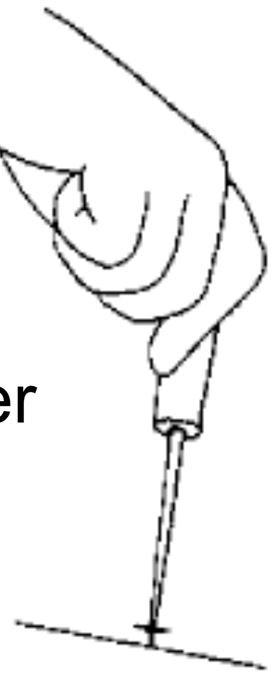
ITERATIVE CONTROL IN HUMANS



- an efficient computational model of motor learning with good predictions
- valid for a single repeated movement

[Tee et al. 2010 Biological Cybernetics]

ADAPTATION IN UNSTABLE DYNAMICS



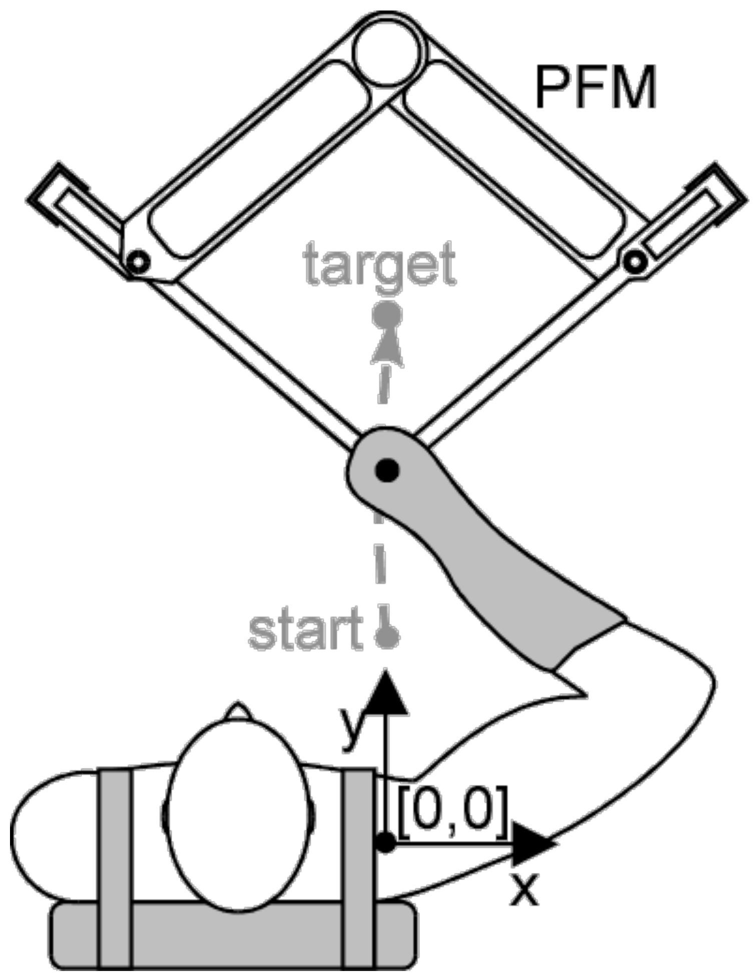
screwdriver

chiseling, carving

- in unstable tasks typical of tool use, motor variability leads to errors and unpredictability
- this requires to compensate for the interaction force and instability

TO INVESTIGATE ADAPTATION IN UNSTABLE DYNAMICS

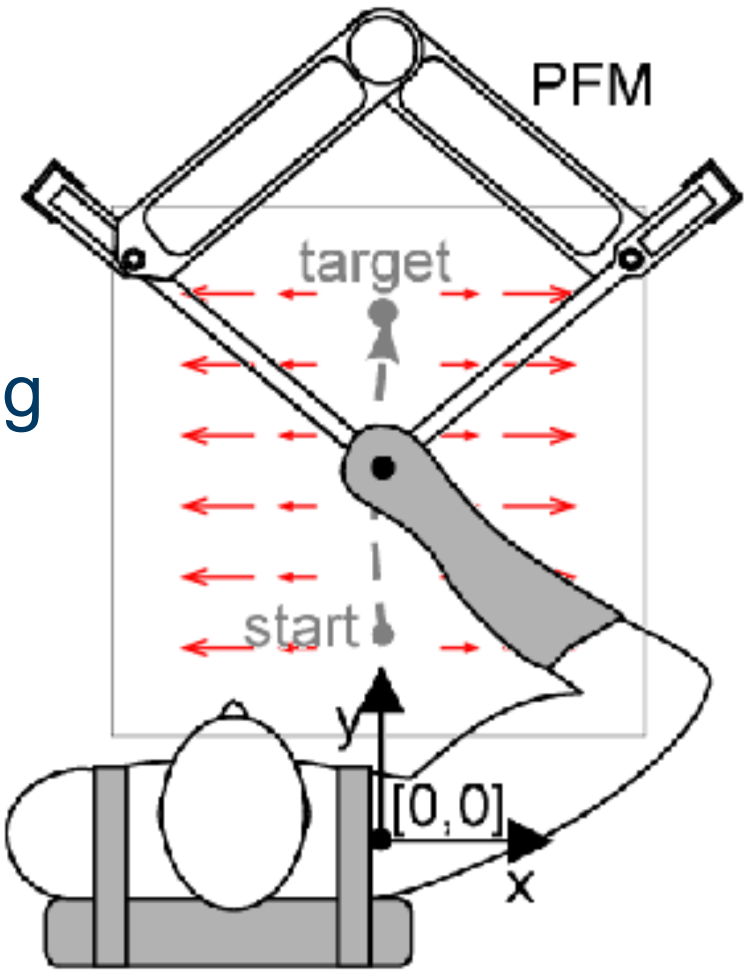
- human subjects perform point to point movements with the hand attached to a powerful robotic interface

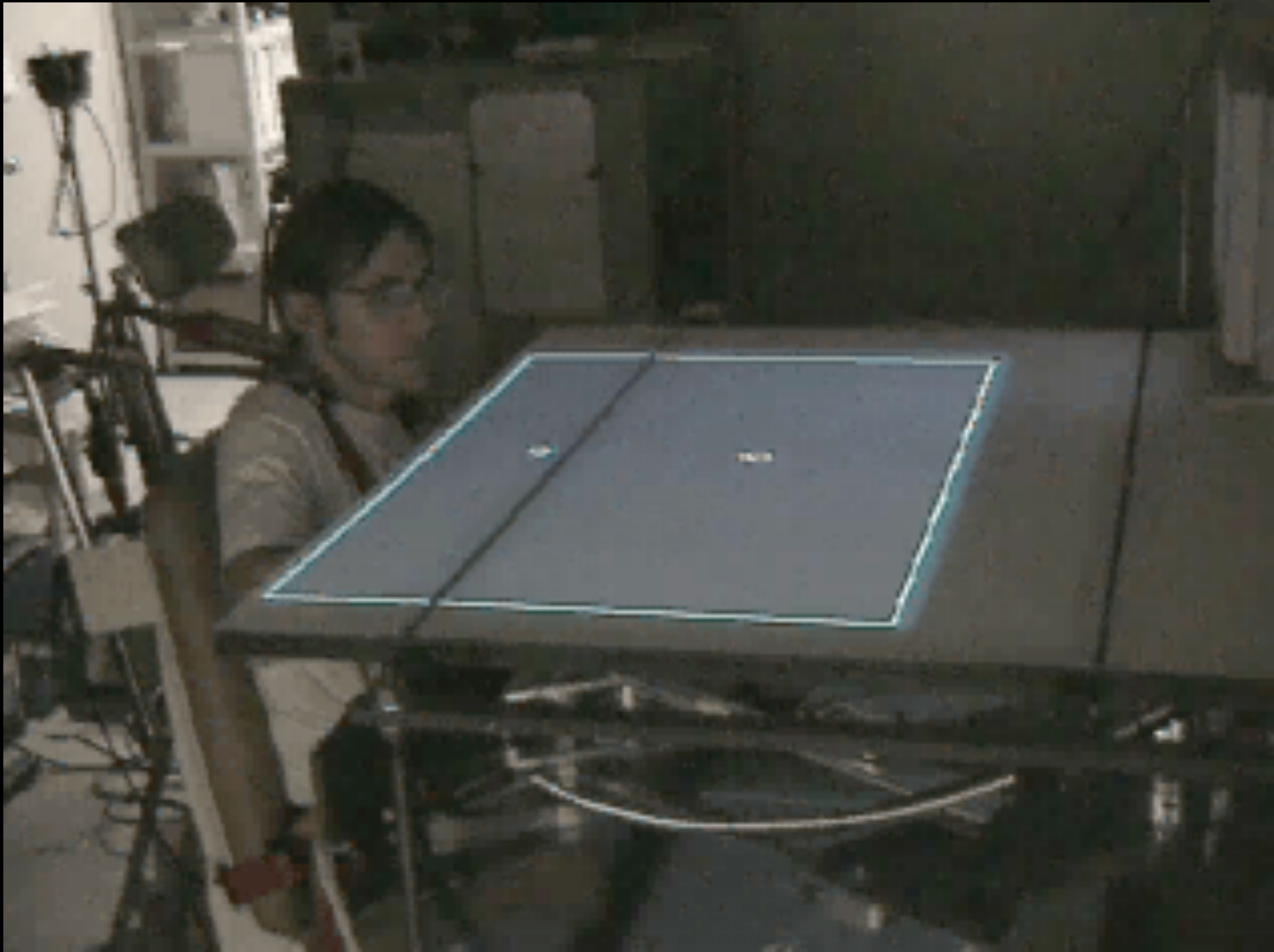


TO INVESTIGATE ADAPTATION IN UNSTABLE DYNAMICS

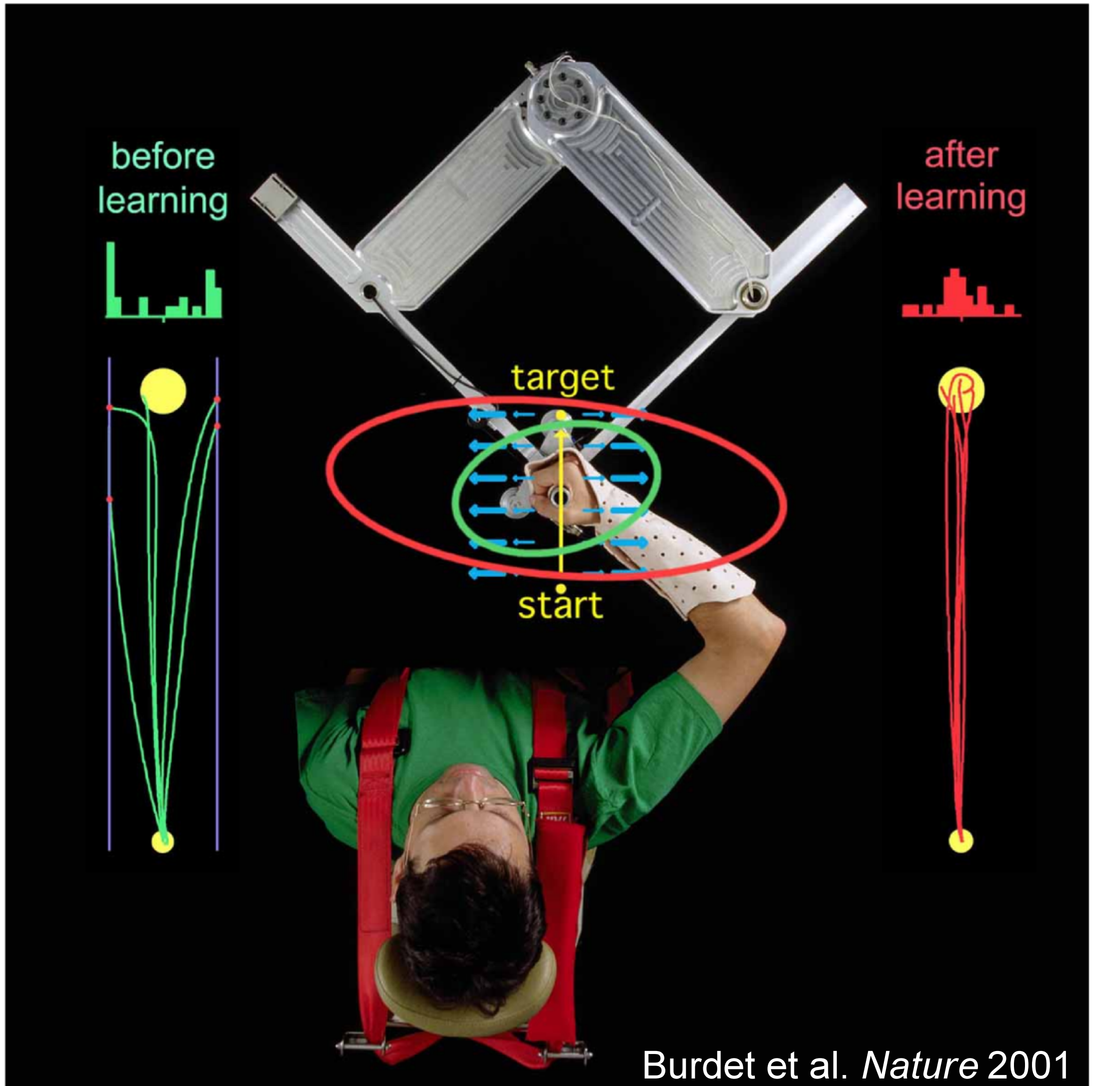
• human subjects perform point to point movements with the hand attached to a powerful robotic interface

• forces diverting to left or to right





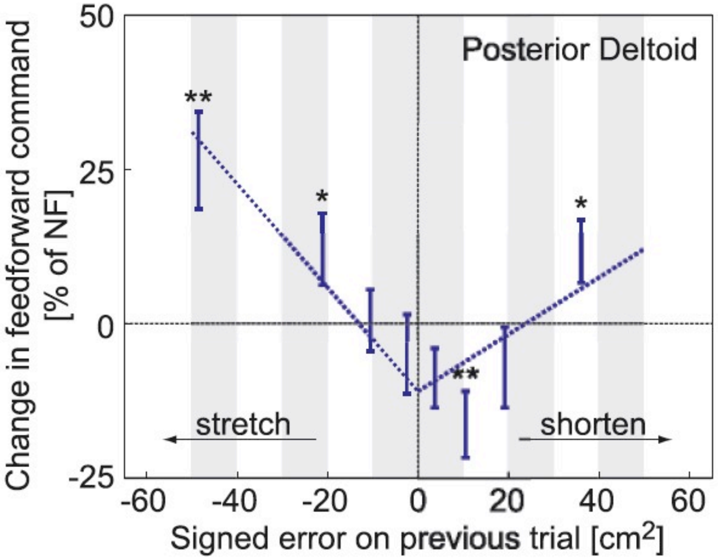
LEARNING OF FORCE AND ELASTICITY

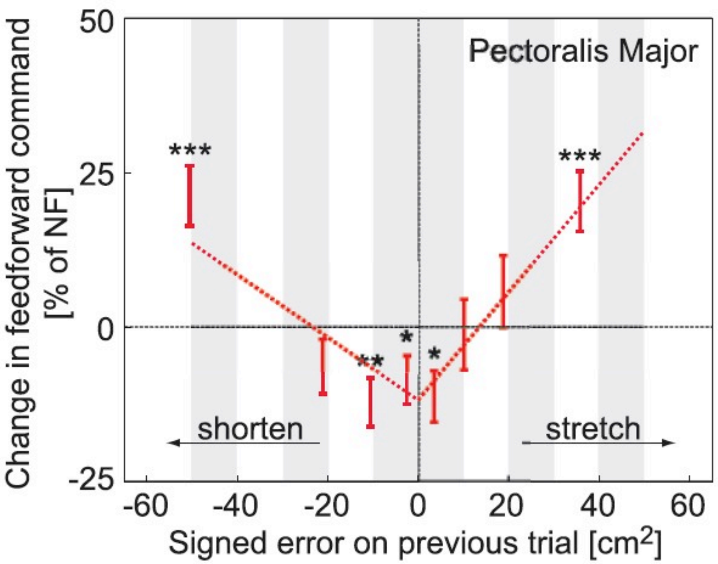


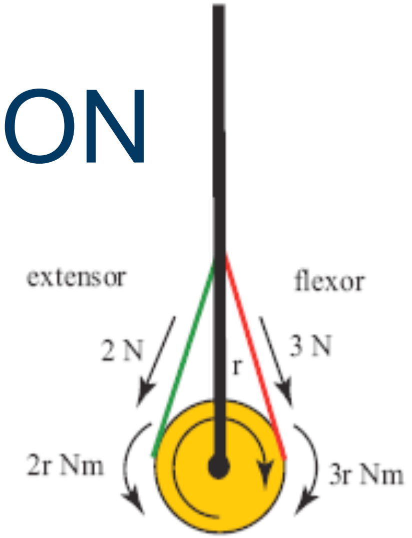
with learning:

- feedforward compensates for the interaction with the environment
- stiffness increases to counteract the instability

PRINCIPLES OF MOTOR ADAPTATION



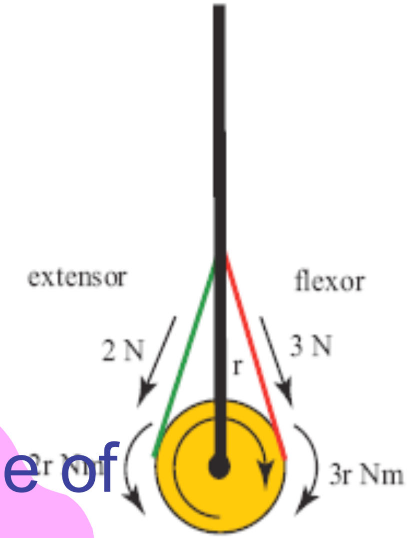


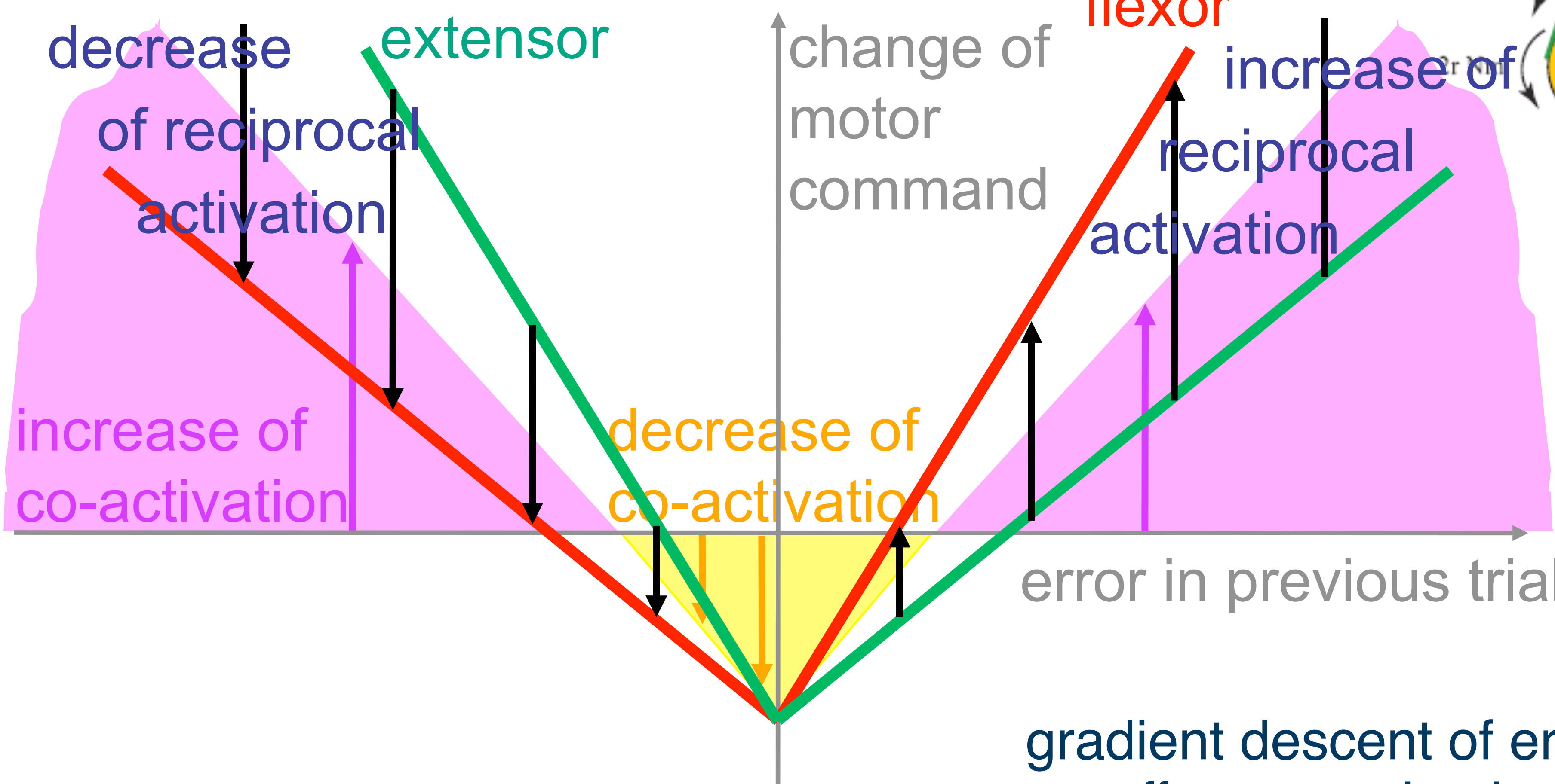


- learning in a muscle space
- feedforward increases with the muscle stretch in previous trial
- it also increases with antagonist muscle stretch
- and decreases when the error is small

[Franklin et al. 2008 J Neuroscience]

ALGORITHM FOR TRIAL-BY-TRIAL LEARNING





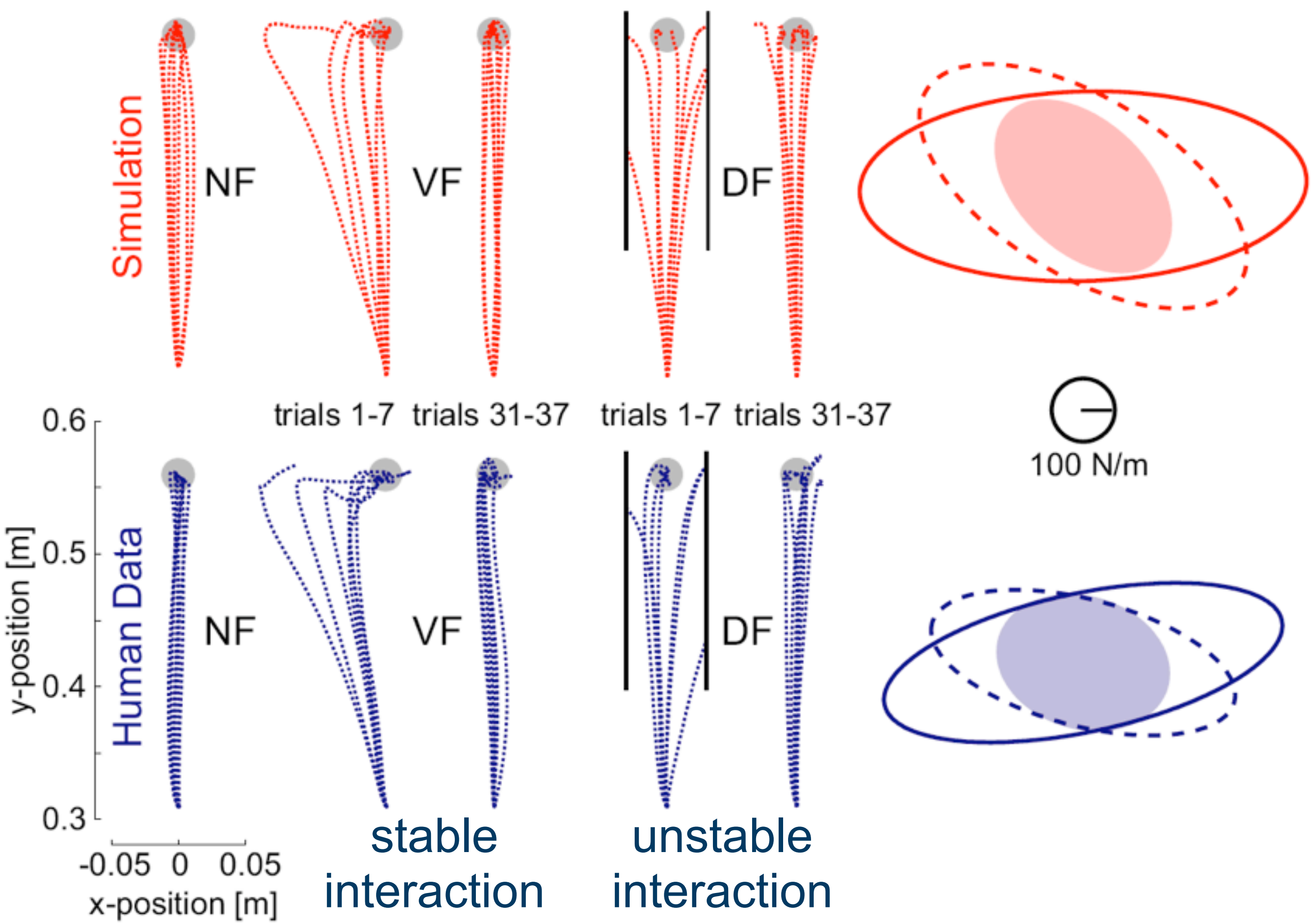
gradient descent of error and
effort to maintain stability

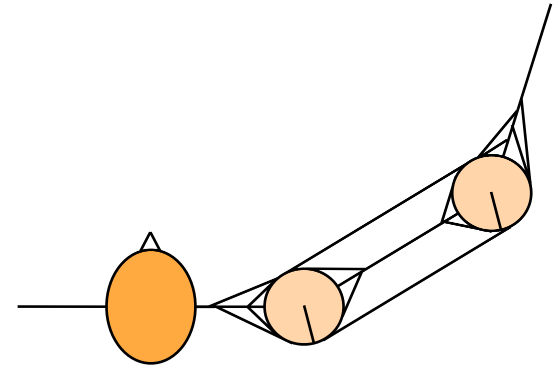
$$V(t) \equiv \alpha e^2(t) + \beta u^2(t)\,,\ \ \alpha, \beta > 0$$

[Franklin et al. 2008 J Neuroscience]

[Yang, Ganesh et al. 2011 IEEE T Robotics]

COMPUTATIONAL MODEL



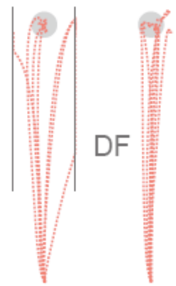


simulation with a 2-joint 6-muscles model

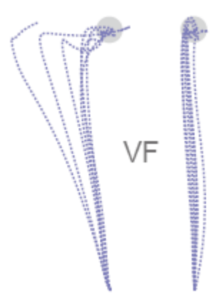
this simple algorithm can stabilise unstable dynamics and reproduce the adaptation observed in experiments

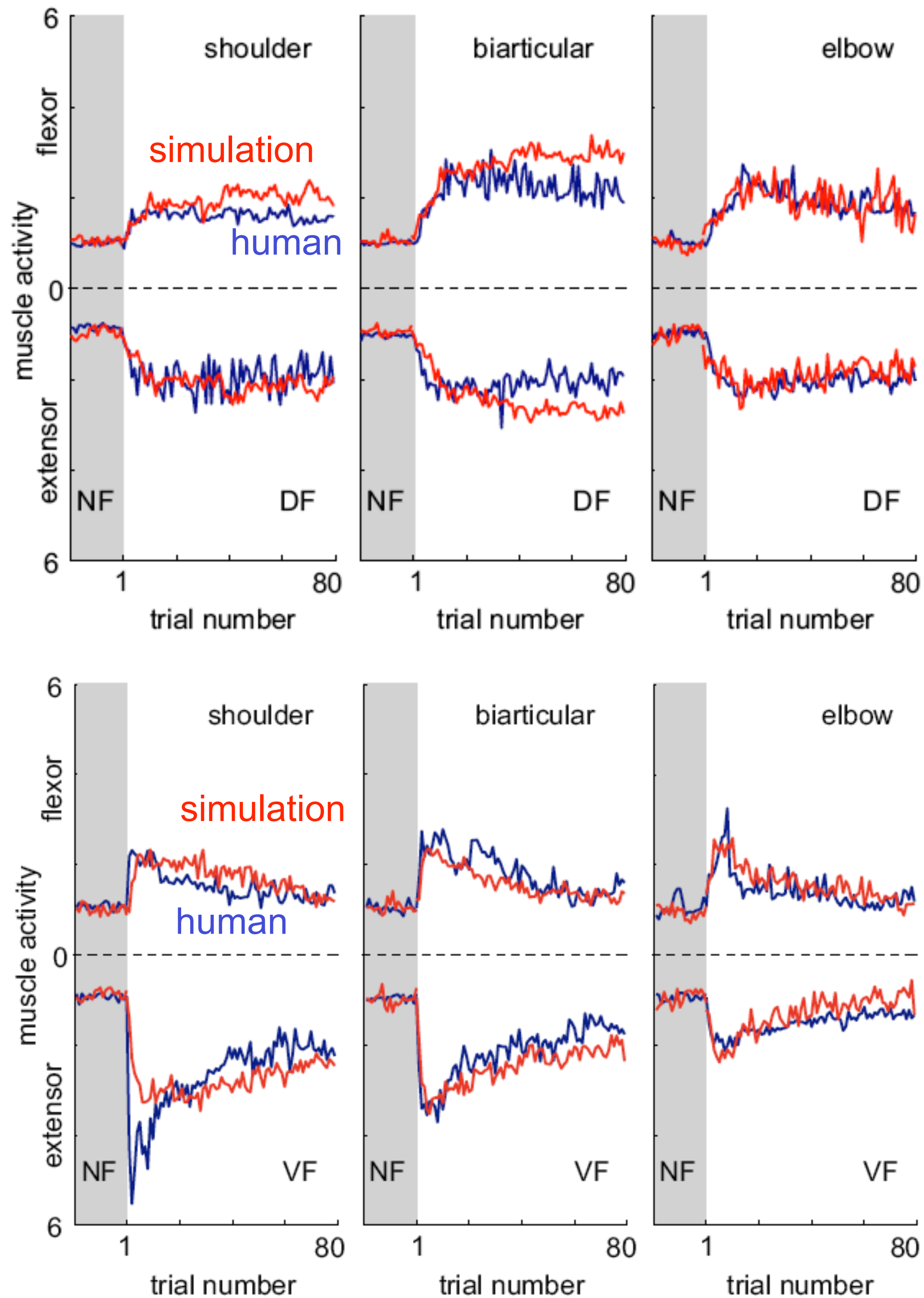
[Franklin et al. 2008 J Neuroscience]

EVOLUTION OF ACTIVATION



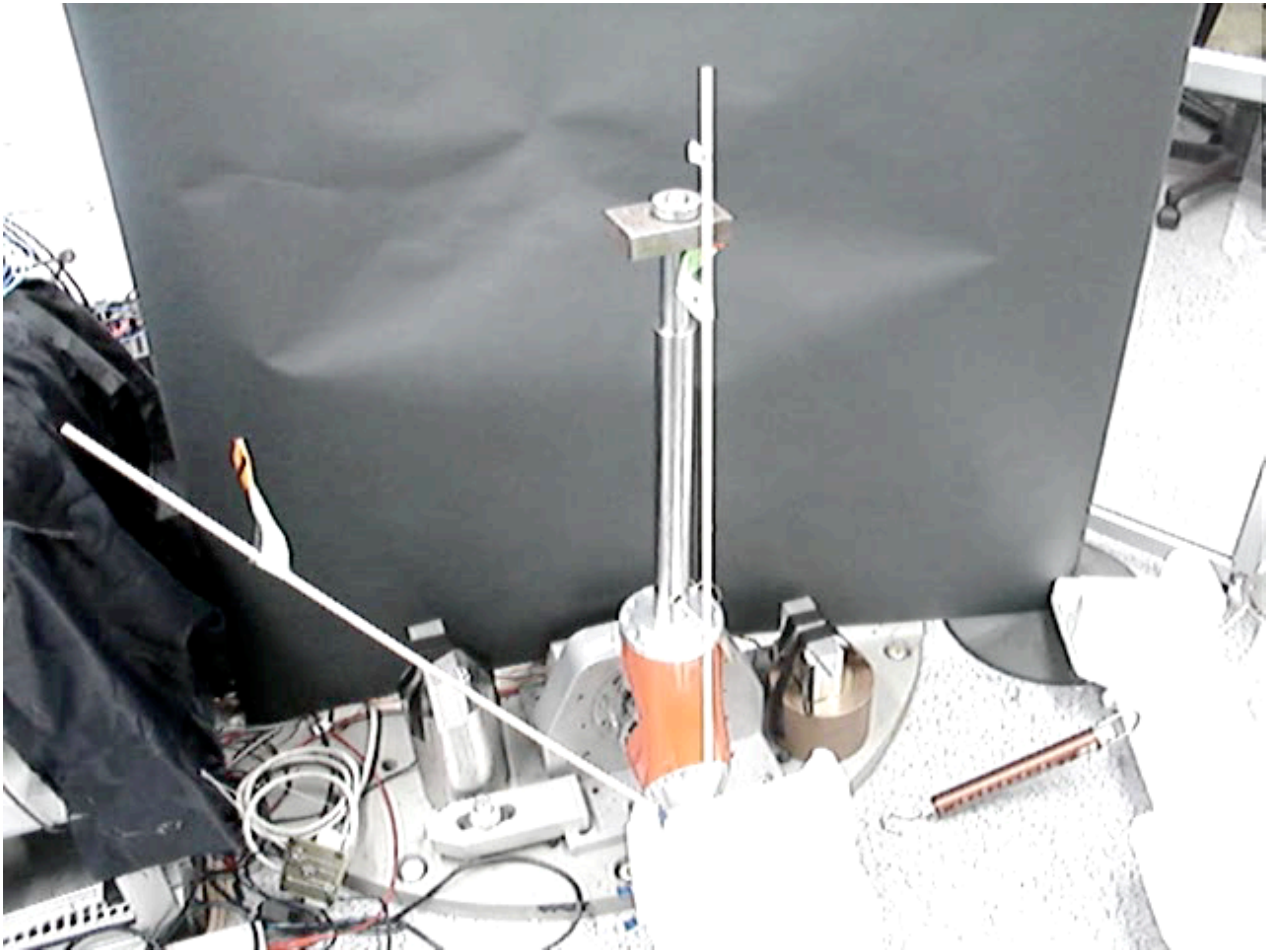
the model predicts the trial-by-trial changes of muscle activation





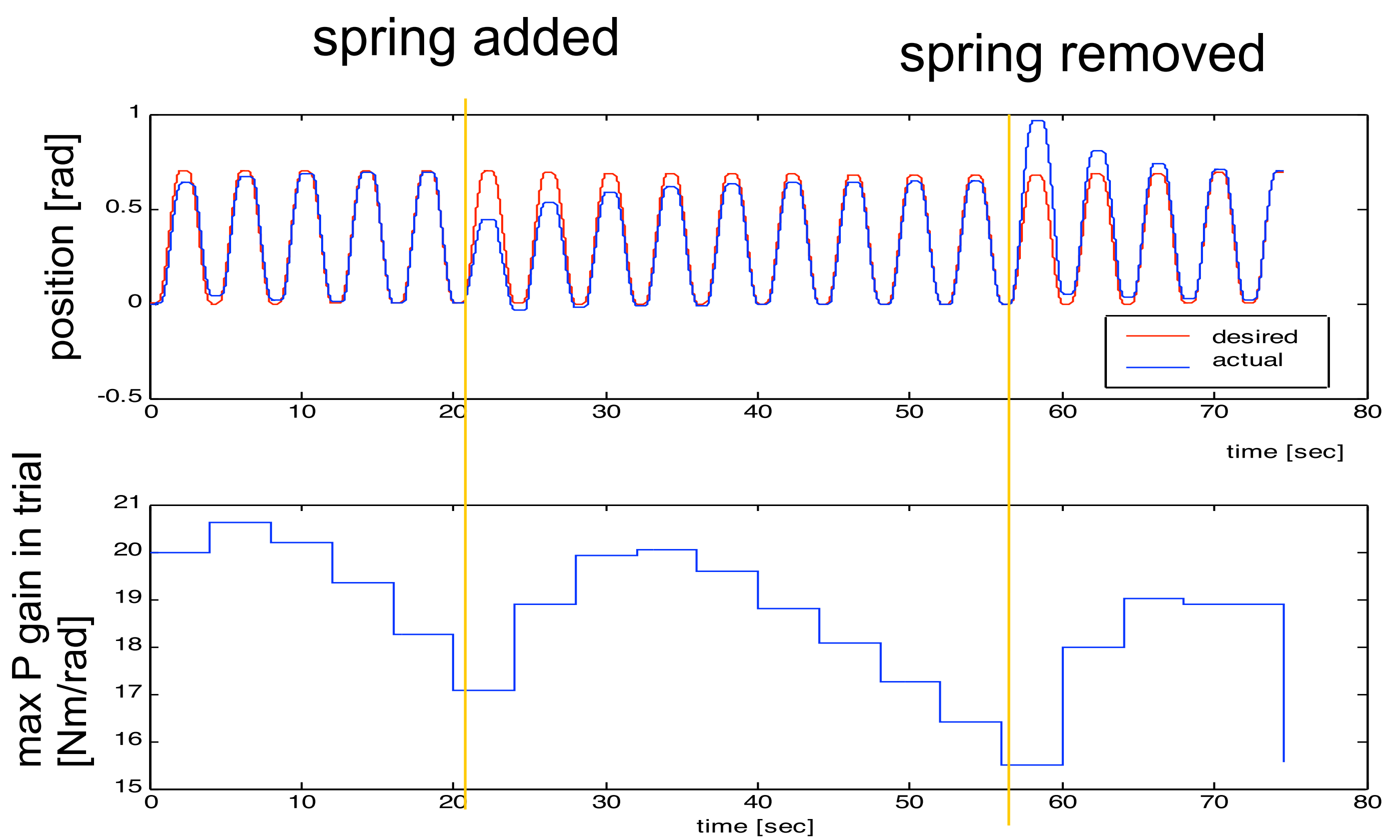
[Franklin et al. J Neuroscience 2008]

LEARNING: FROM HUMAN TO ROBOT



[Yang, Ganesh et al. 2011 IEEE T Robotics]

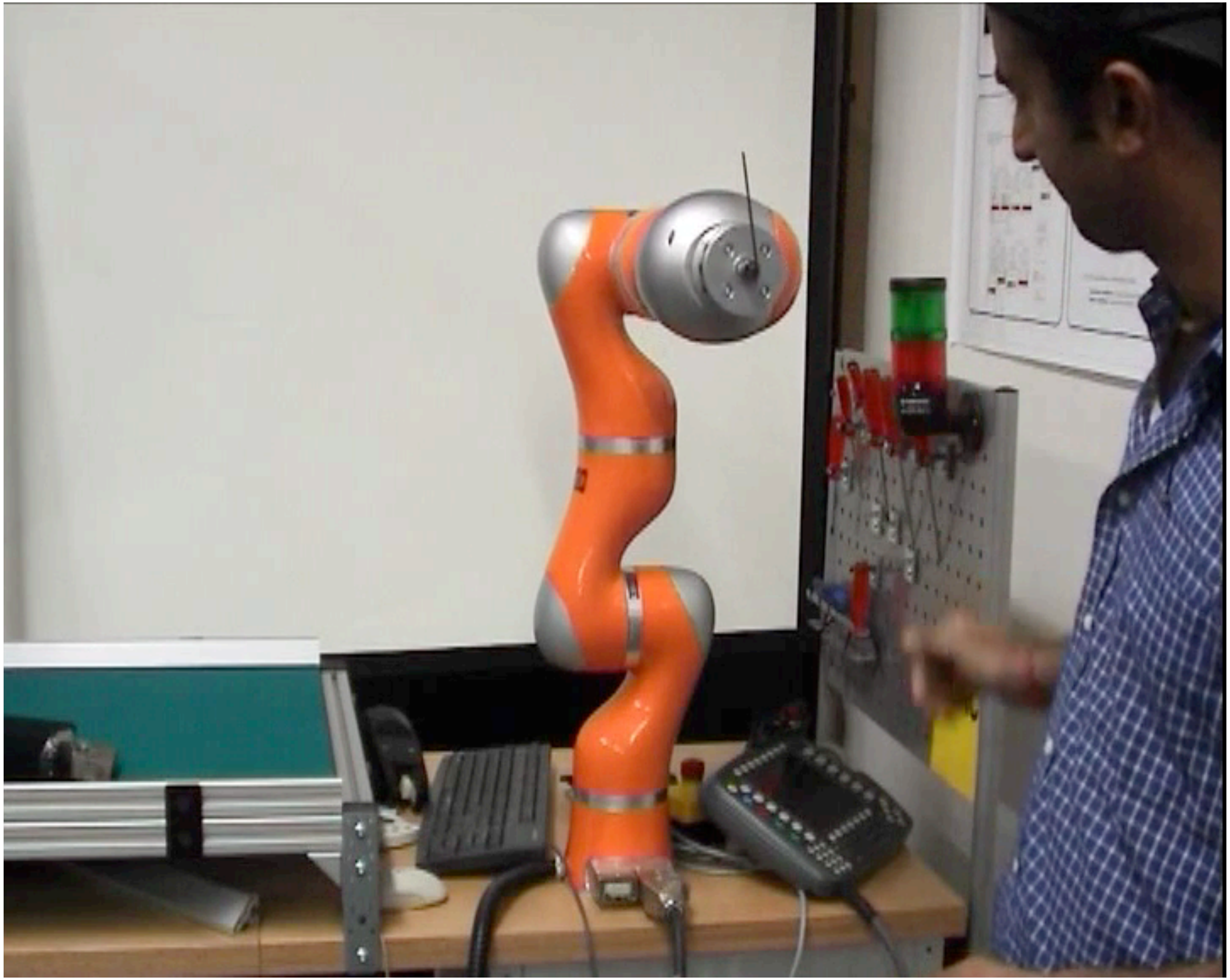
BIOMIMETIC STIFFNESS EVOLUTION



in the presence of external disturbance the robot increases its impedance, learns and then reduces the impedance again

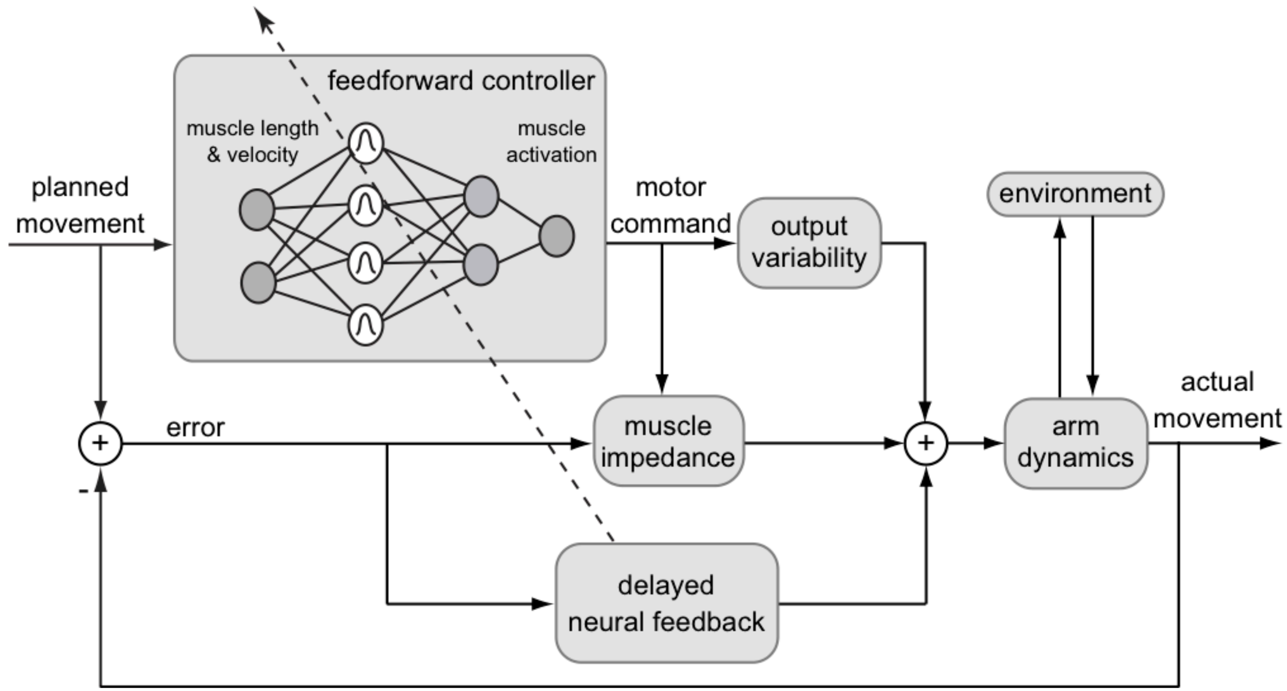
[Yang, Ganesh et al. 2011 IEEE T Robotics]

LEARNING: FROM HUMAN TO ROBOT



[Yang, Ganesh et al. 2011, IEEE T Robotics]

GENERALISATION



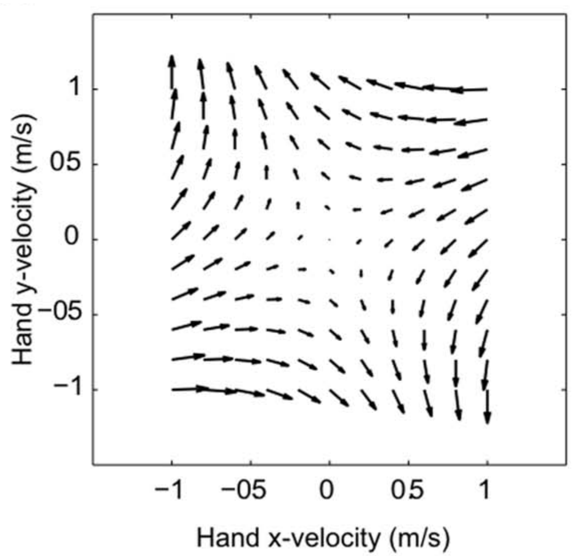
• iterative control can learn only along a single trajectory

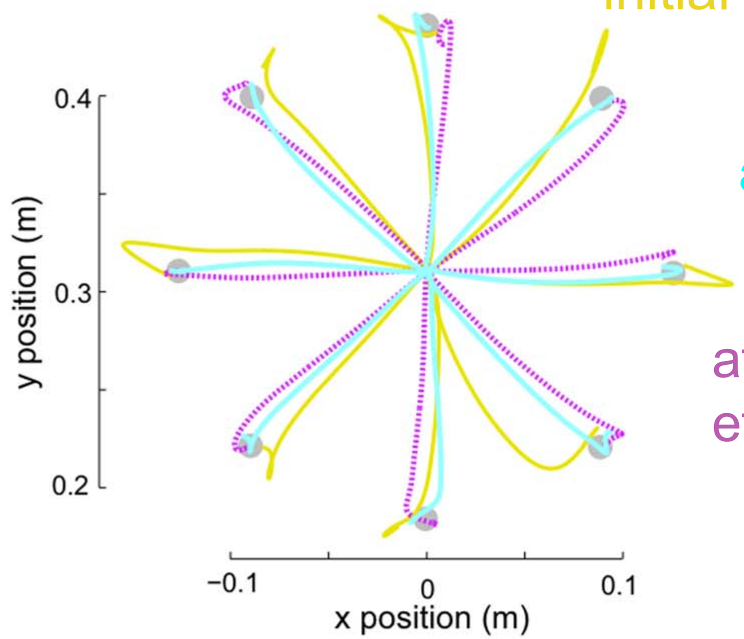
• to learn performing several distinct movements, use as inverse model a mapping of the state

• artificial neural network to map the state to the required muscle activations

[Kadiallah et al., PLoS ONE 2012]

GENERALISATION





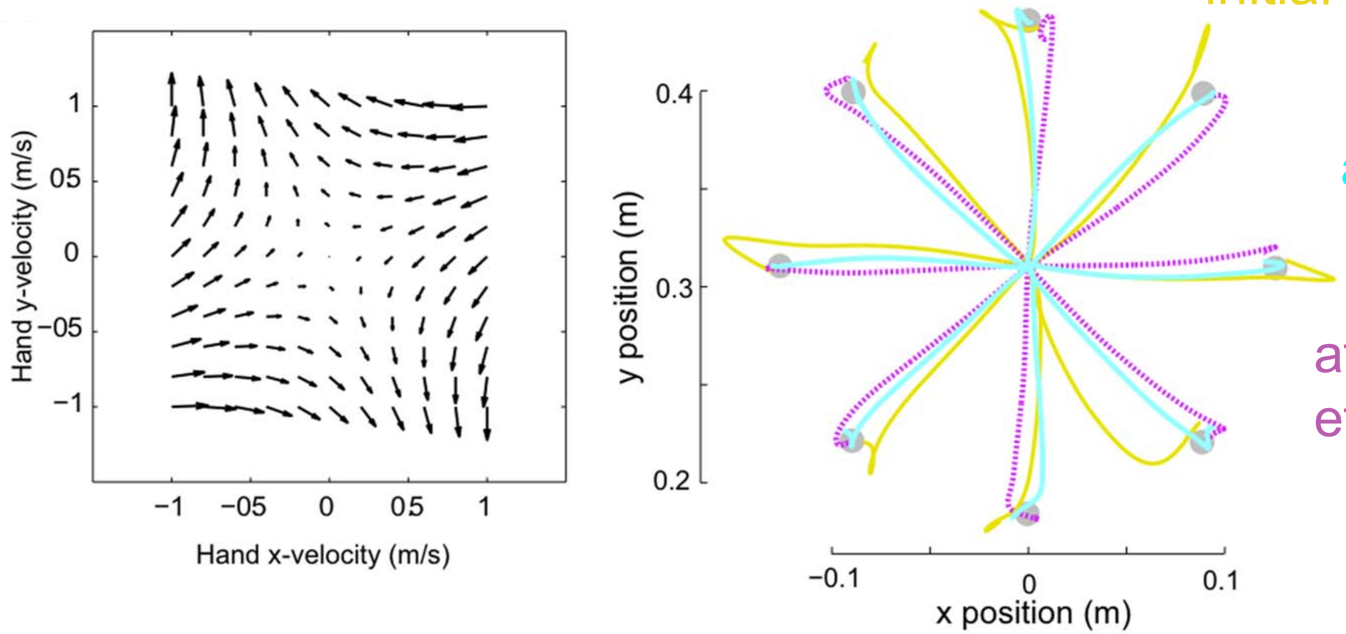
before-effects trials:
initial effect of force field

after learning trials

after-effects trials:
effect of motor memory

[Kadiallah et al., PLoS ONE 2012]

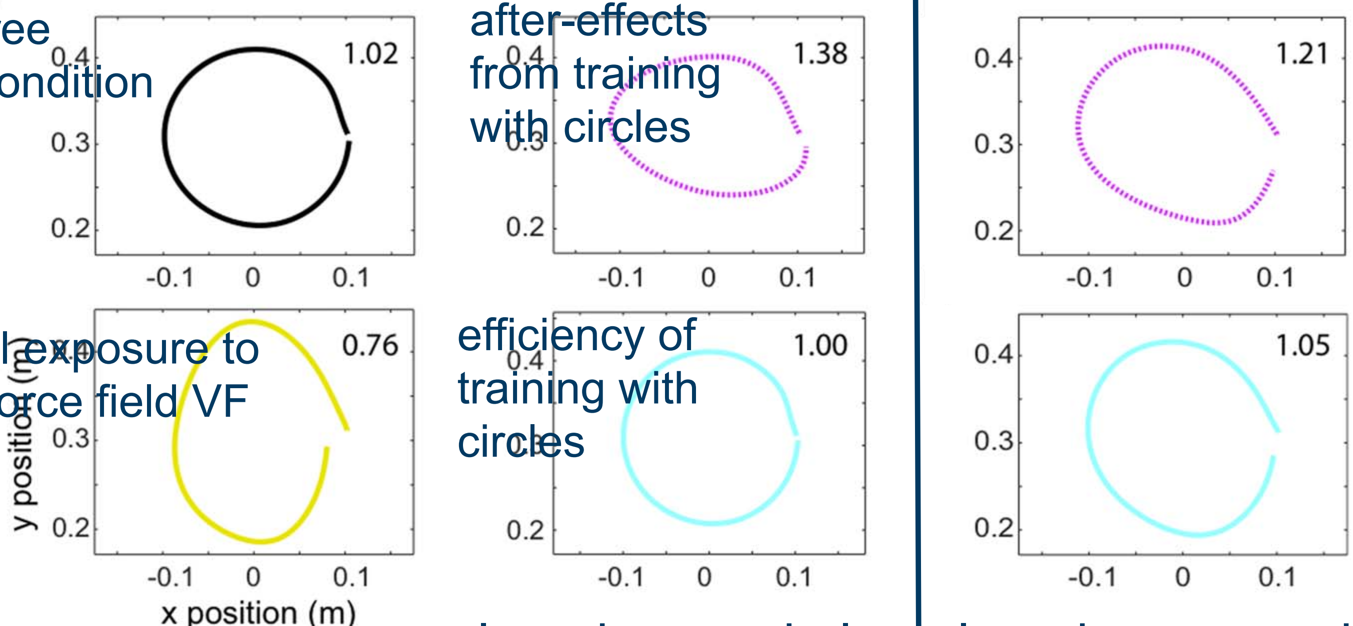
GENERALISATION



before-effects trials: initial effect of force field

after learning trials

after-effects trials: effect of motor memory



free condition

after-effects from training with circles

after-effects from training with reaching movements

initial exposure to the force field VF

efficiency of training with circles

transfer of learning from reaching movements

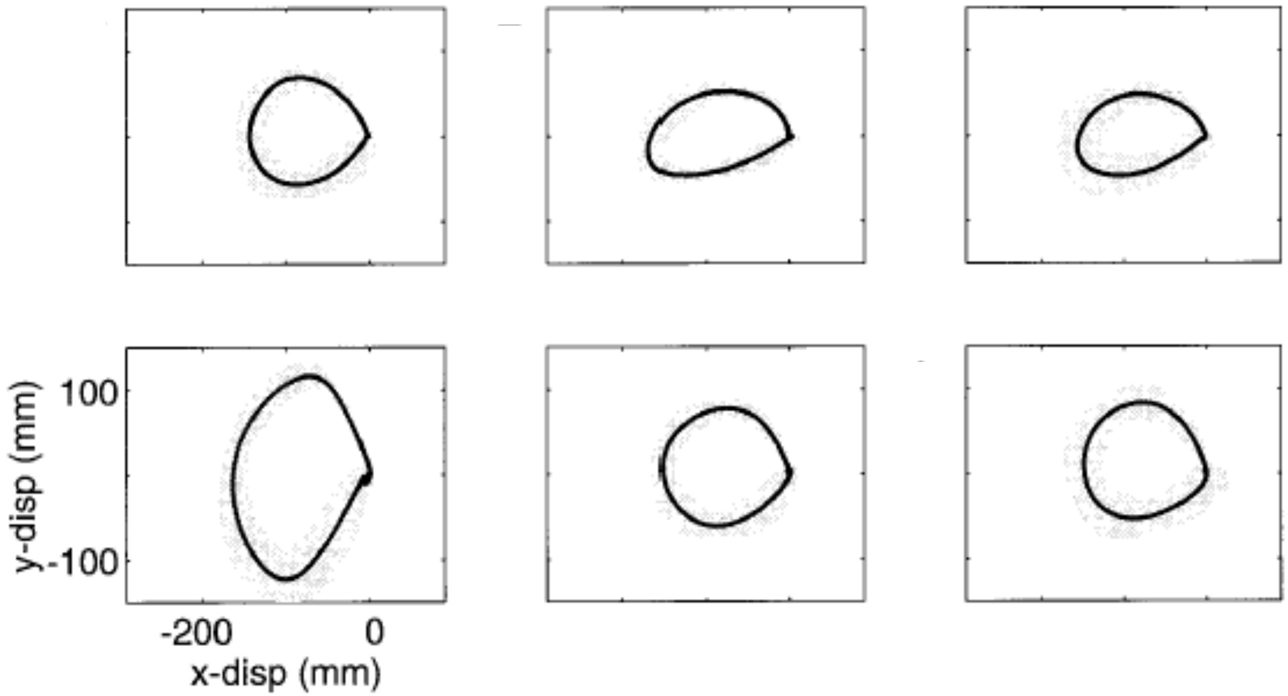
learning on circle

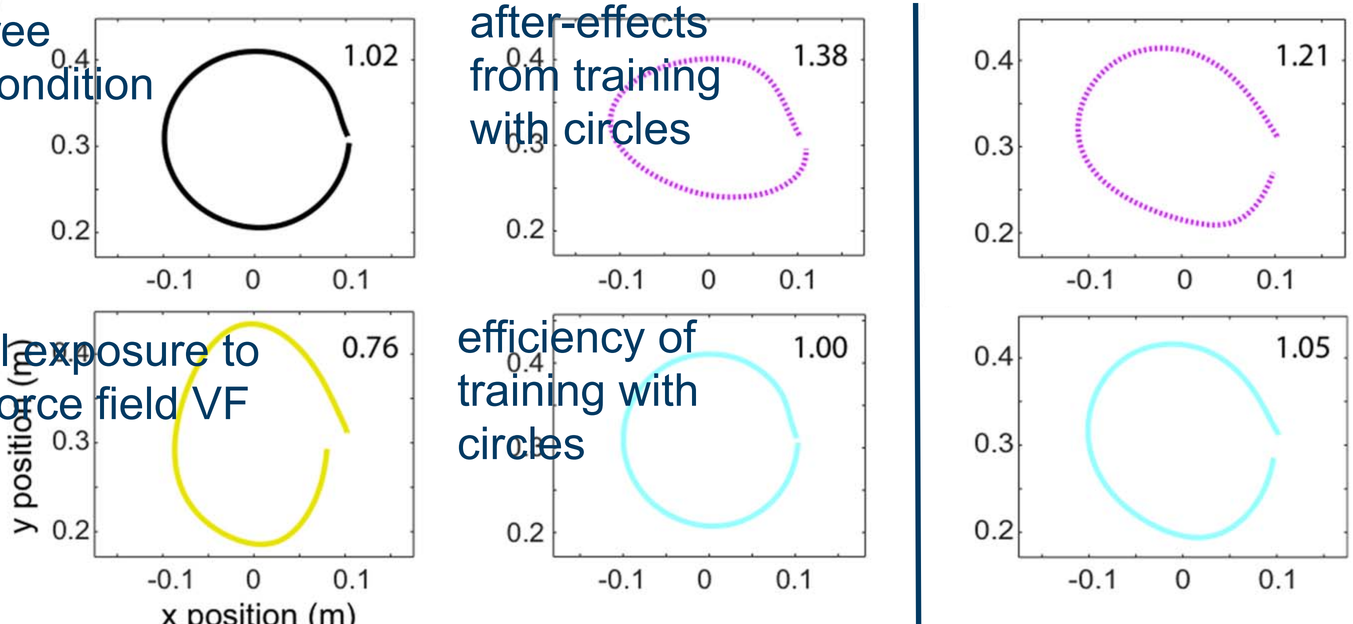
learning on reaching

[Kadiallah et al., PLoS ONE 2012]

GENERALISATION

[Conditt et al. 1998 J Neurophysiology]





free condition

after-effects from training with circles

after-effects from training with reaching movements

initial exposure to the force field VF

efficiency of training with circles

transfer of learning from reaching movements

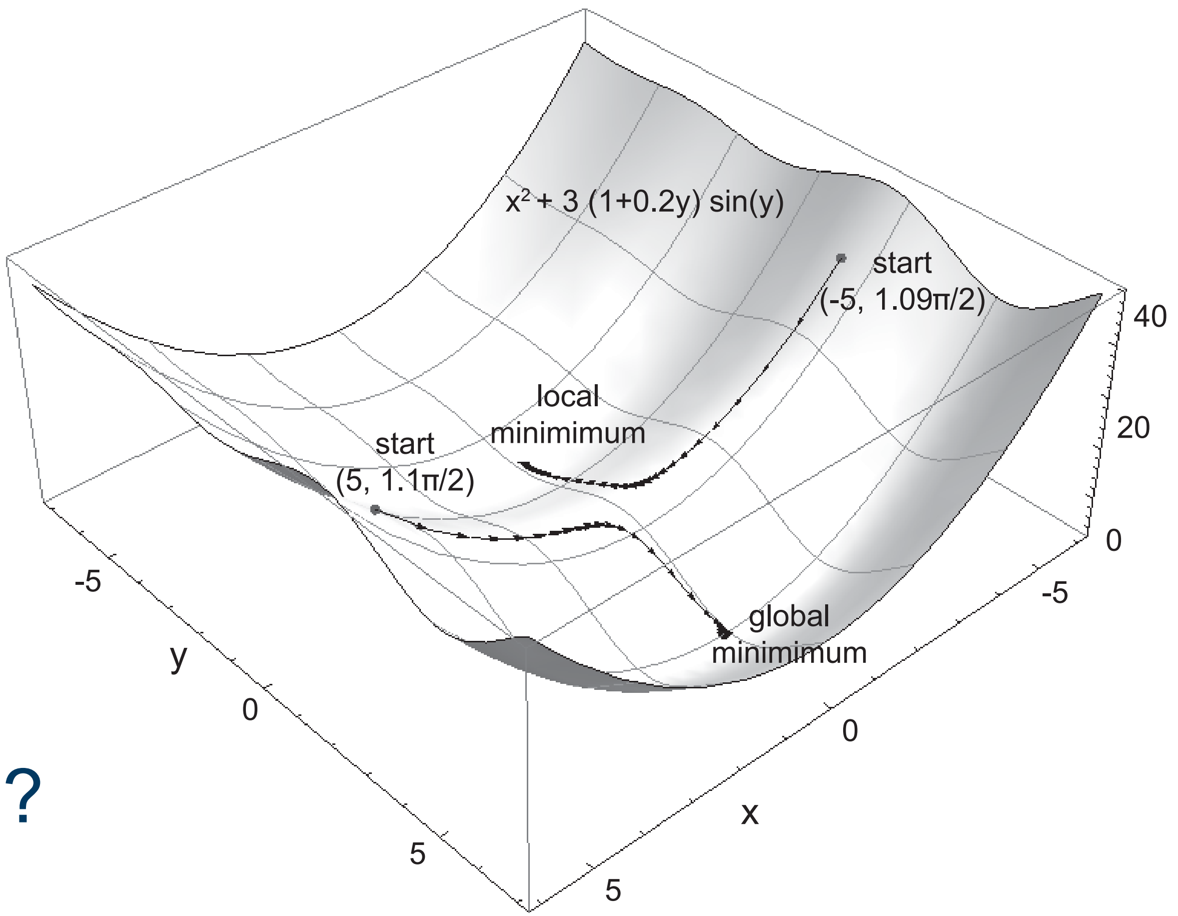
learning on circle

learning on reaching

[Kadiallah et al., PLoS ONE 2012]

We have described human motor adaptation

- which happens in an automatic way
- both in healthy and (some) impaired subjects
- this corresponds to local optimisation



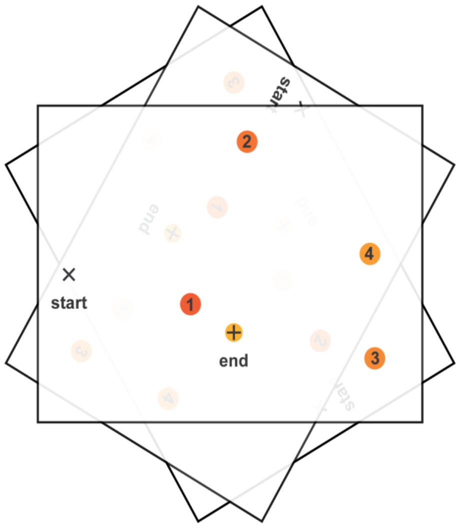
How do humans deal with global optimisation?

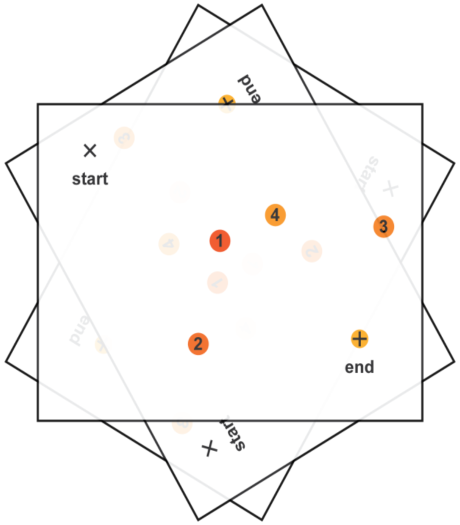
LEARNING IN TASKS WITH MULTIPLE SOLUTIONS

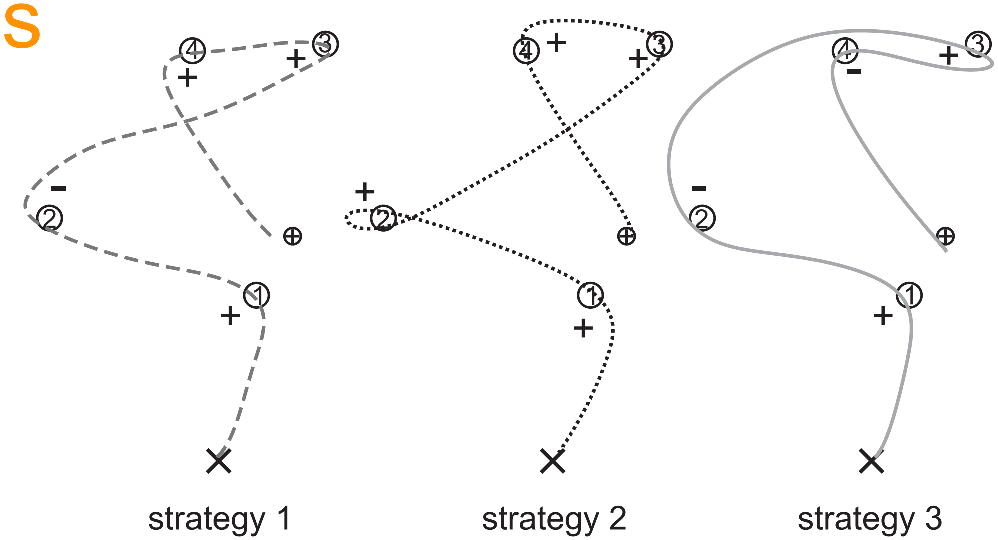
- tasks of daily life can be carried out using several strategies
- however motor control research has focused on tasks with a single minimum of error and effort
- how do human deal with tasks with multiple solutions?

A TASK WITH MULTIPLE SOLUTIONS

- task: go through a sequence of via-point “as fast and accurate as possible”
- 2 setups in 3 orientations
- subjects randomly use multiple strategies

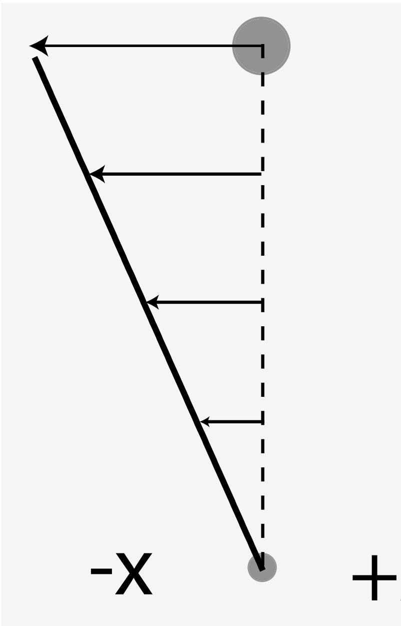






[Kodl et al., PLoS ONE 2011]

EVEN SIMPLE TASKS HAVE MULTIPLE SOLUTIONS



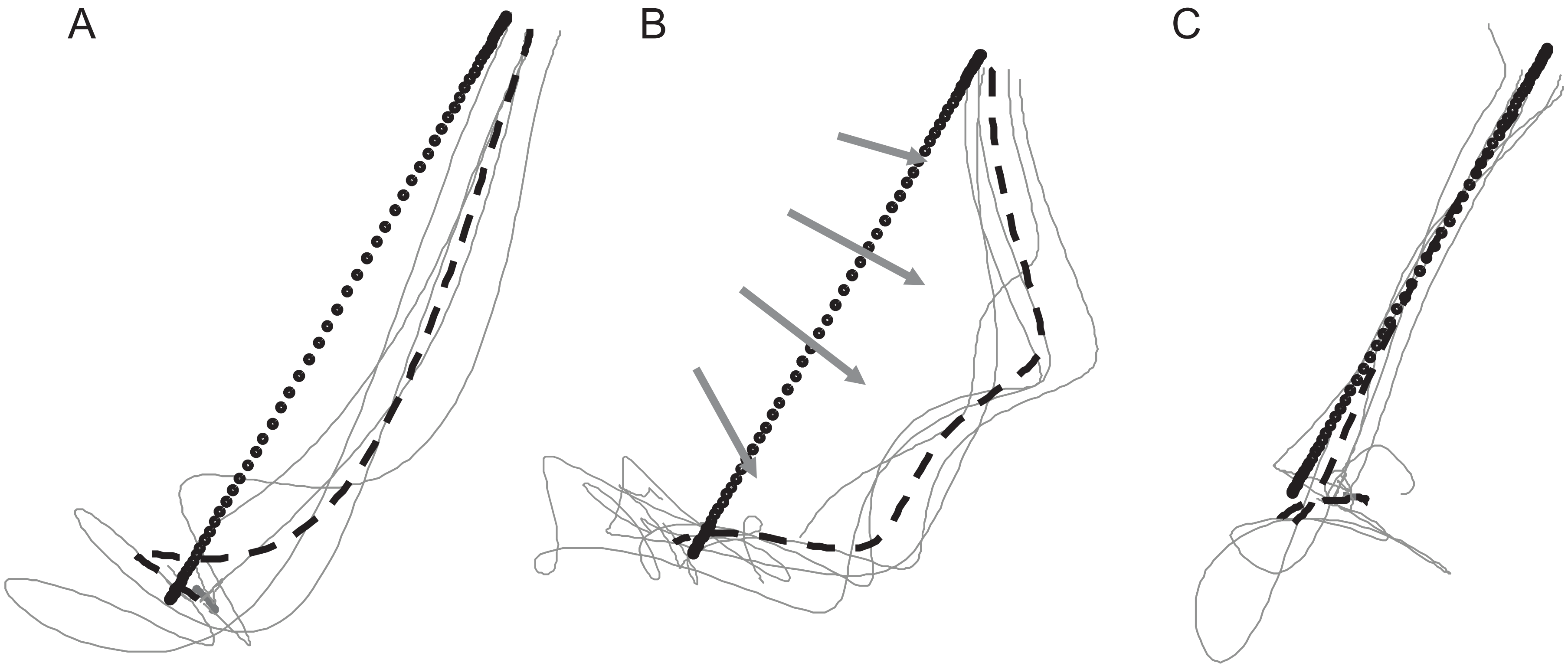
$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} 0 & 2 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

free movements

the two strategies
can be & are used !

[Ikezami et al. unpublished]

EVEN SIMPLE TASKS HAVE MULTIPLE SOLUTIONS



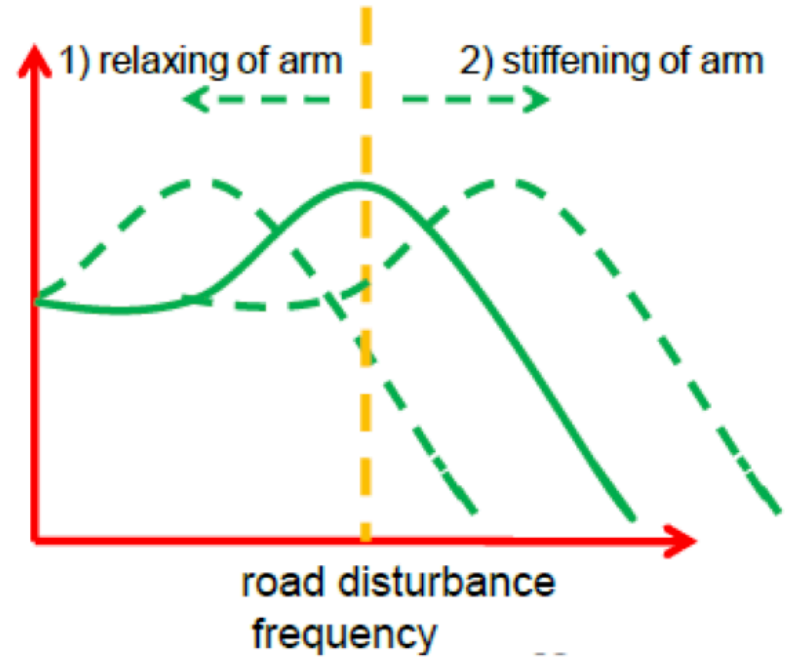
before learning

the two strategies can be & are used !

after learning

[Patton et al. 2006 J Rehabilitation]

A "REAL" TASK WITH MULTIPLE SOLUTIONS

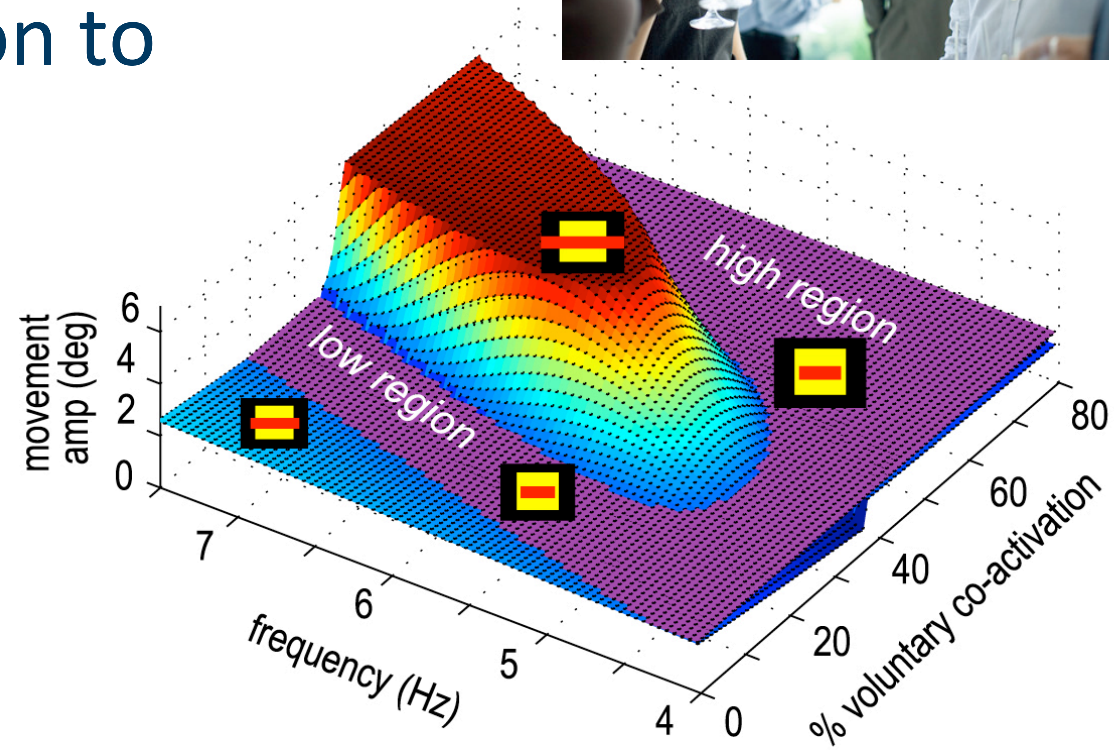


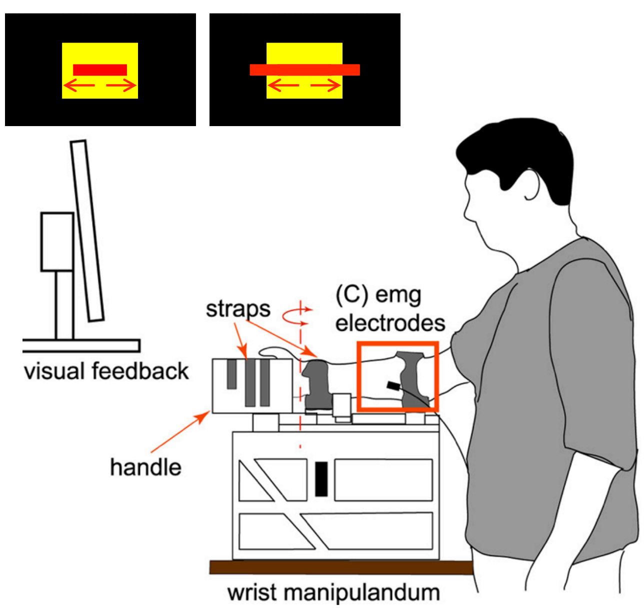
- how to attenuate disturbances from road?
- one can stiffen or relax the arms to stay away from the resonance frequency

[Ganesh et al J Neurophysiology 2010]

HOW DO HUMANS SELECT A STRATEGY?

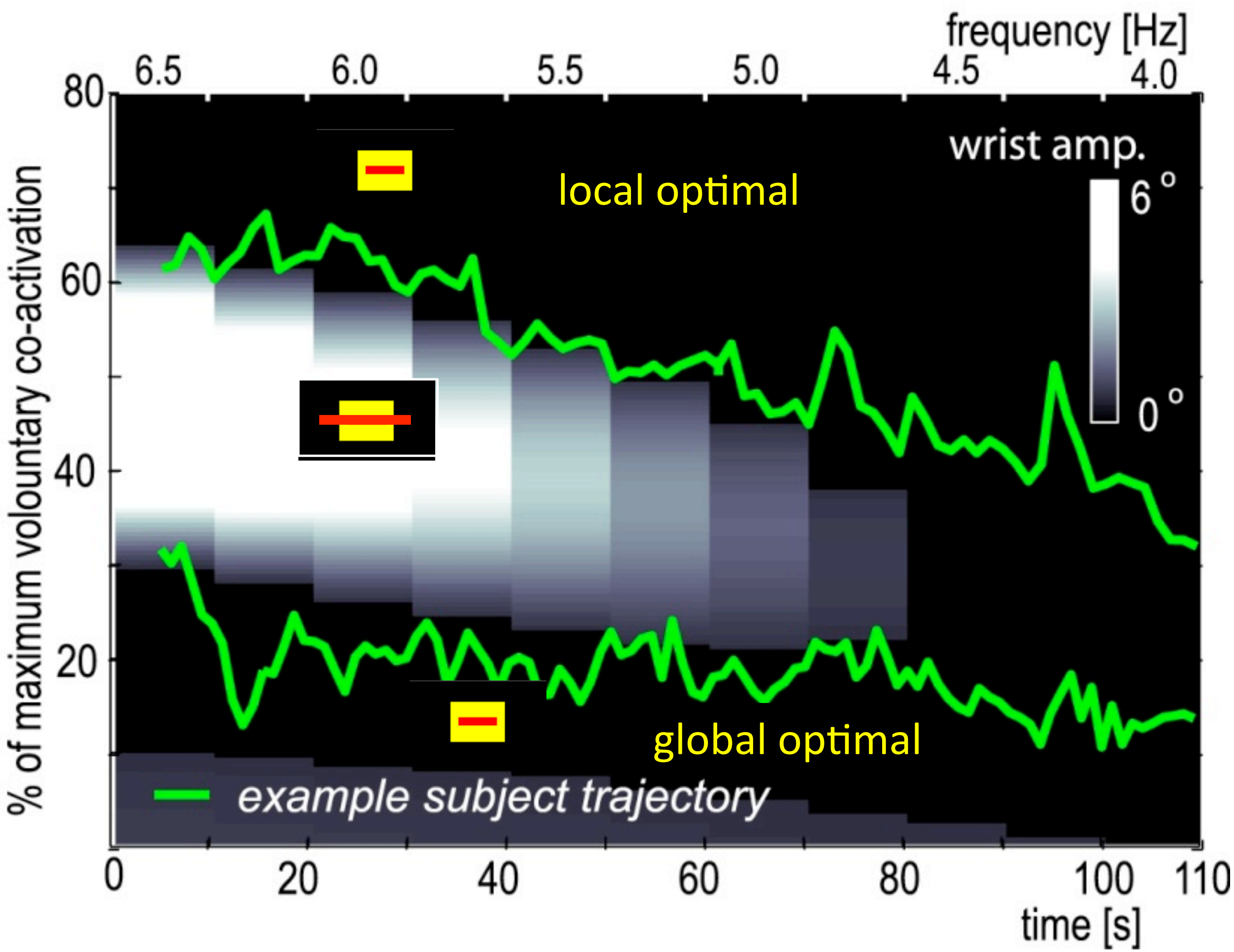
task: control co-activation to attenuate the effect of a sinusoidal disturbance

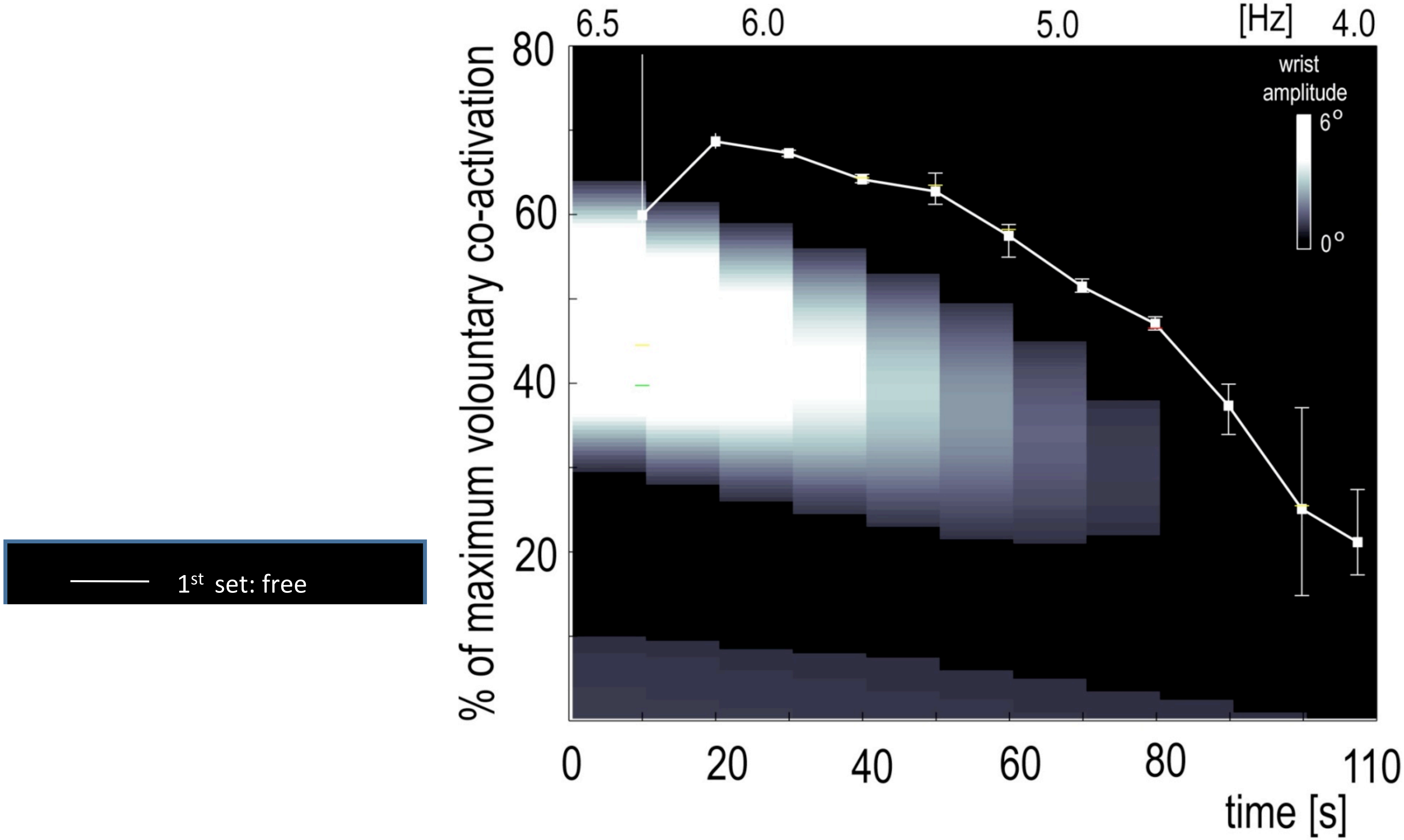




[Ganesh et al. 2010 J Neurophysiology]

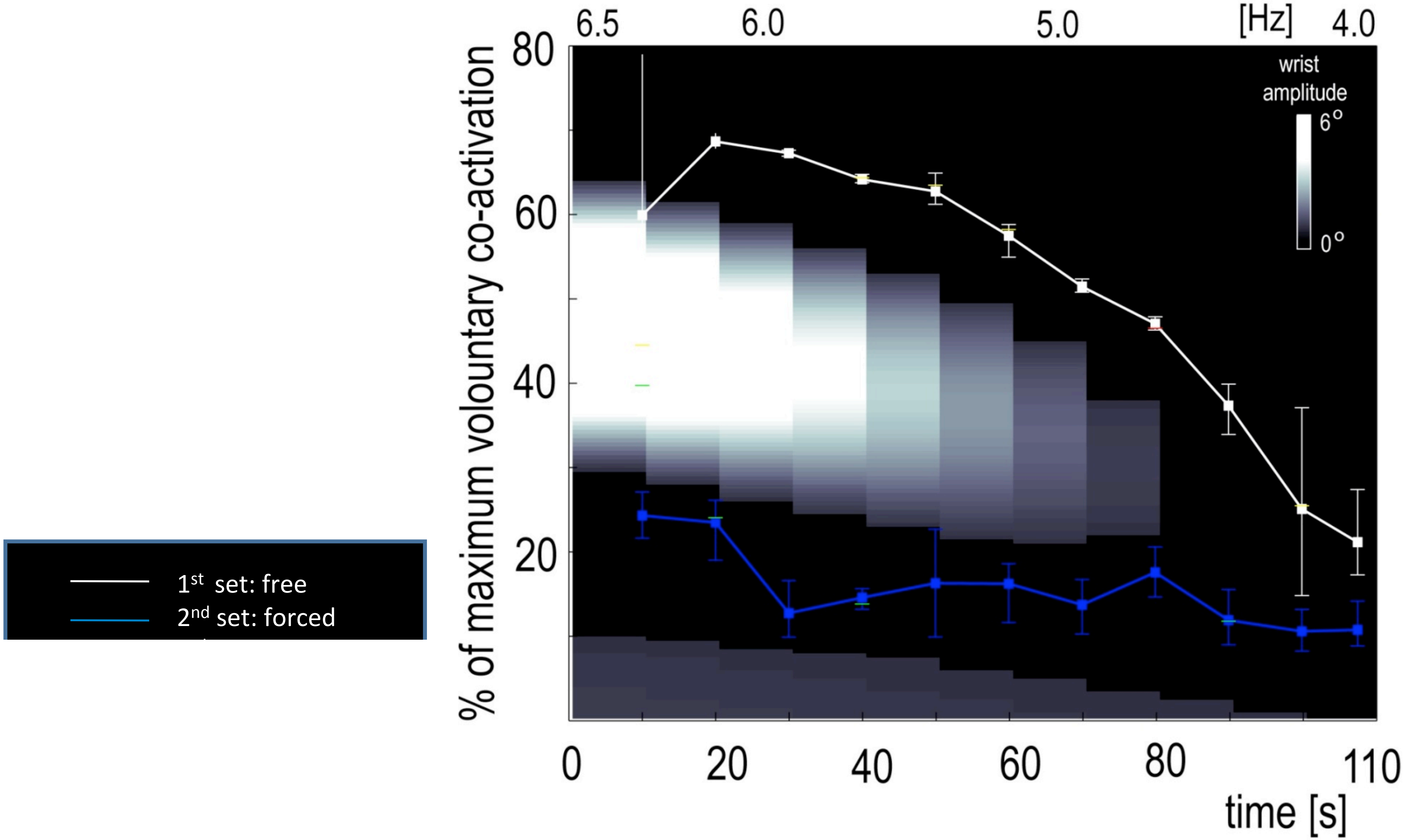
HOW DO HUMANS SELECT A STRATEGY?





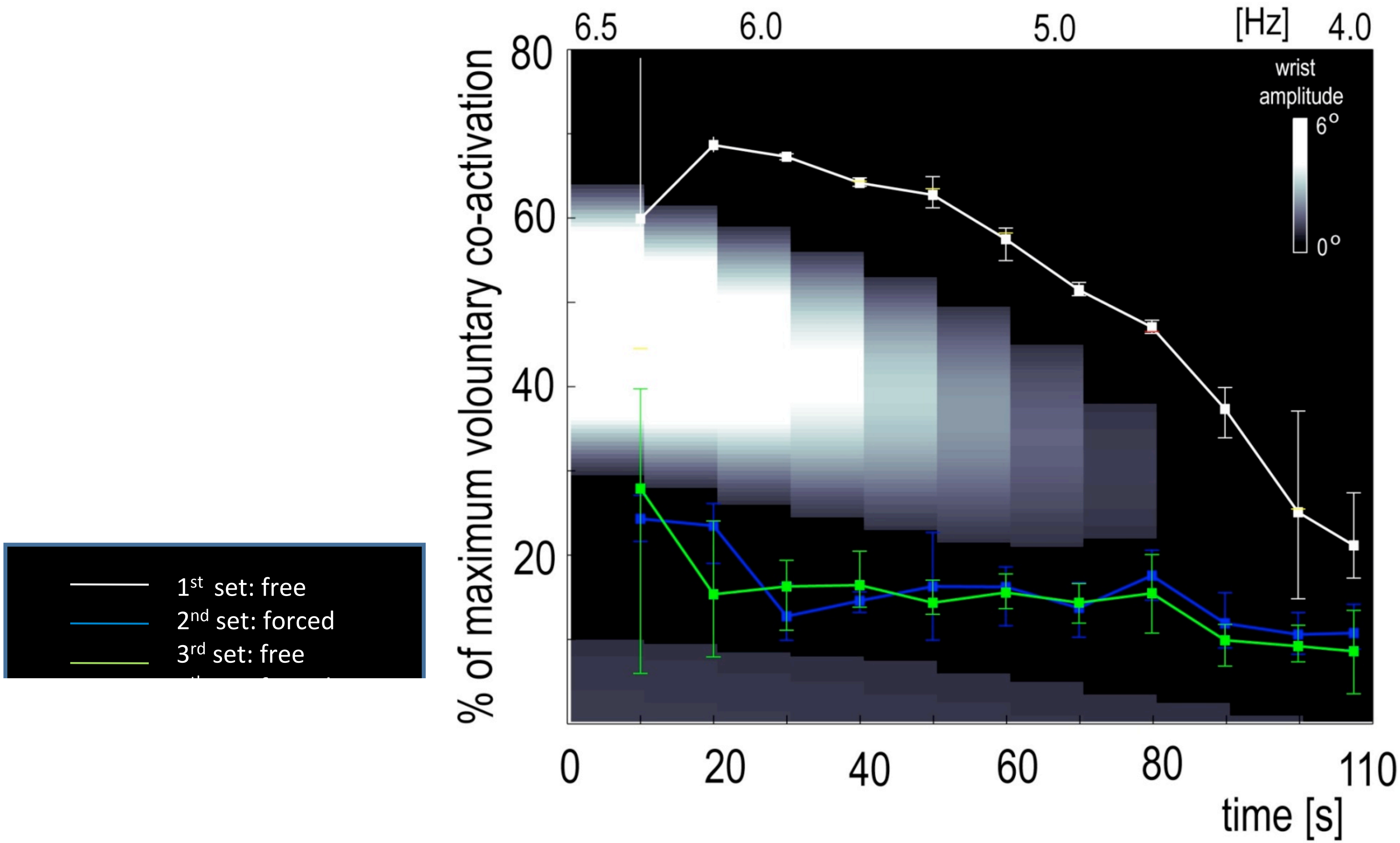
- in the first trial (white line), 5 subjects prefer the low stiffness area and 5 the high area

[Ganesh et al. 2010 J Neurophysiology]



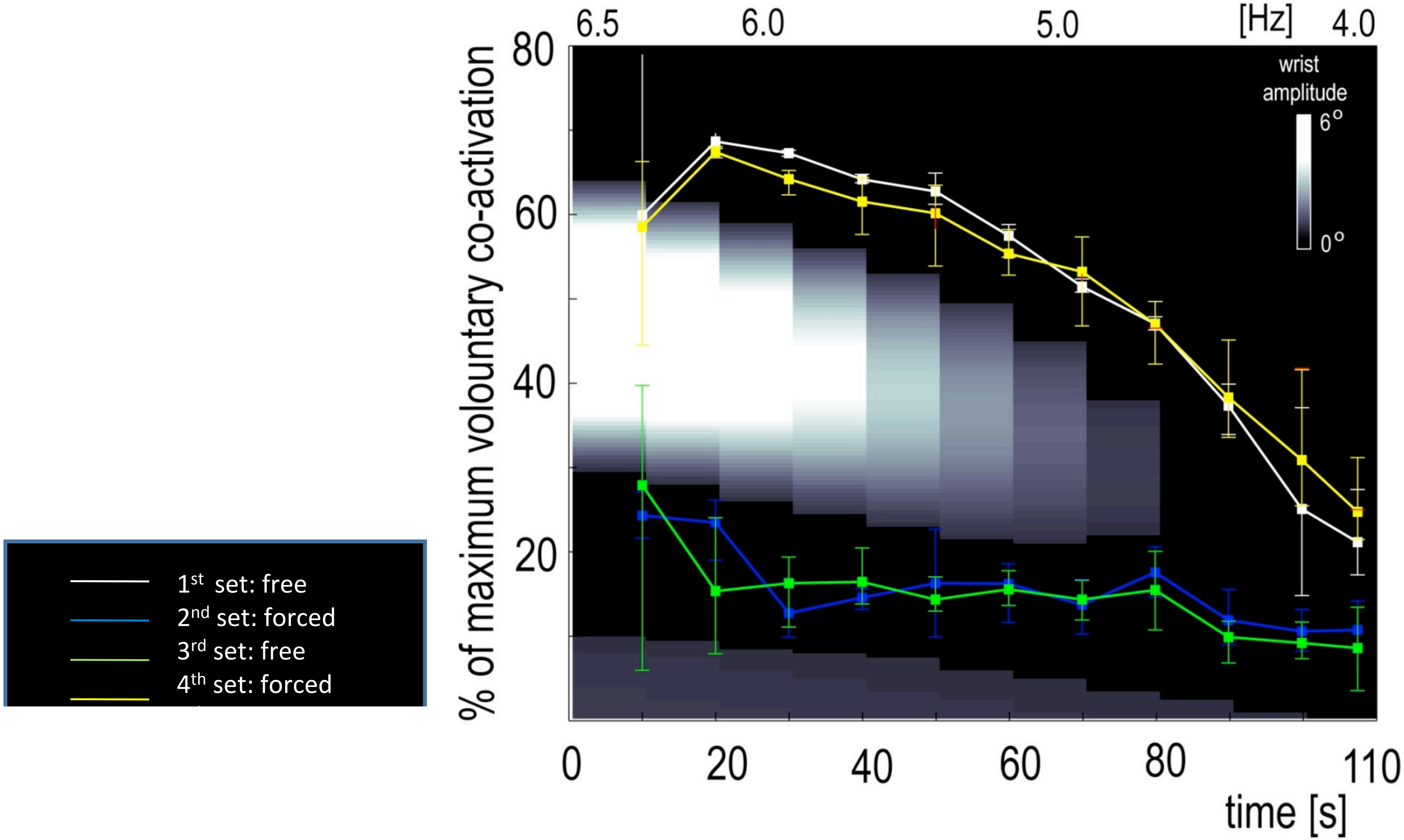
- when ‘forced’ to the other region (blue) they change their preference

[Ganesh et al. 2010 J Neurophysiology]



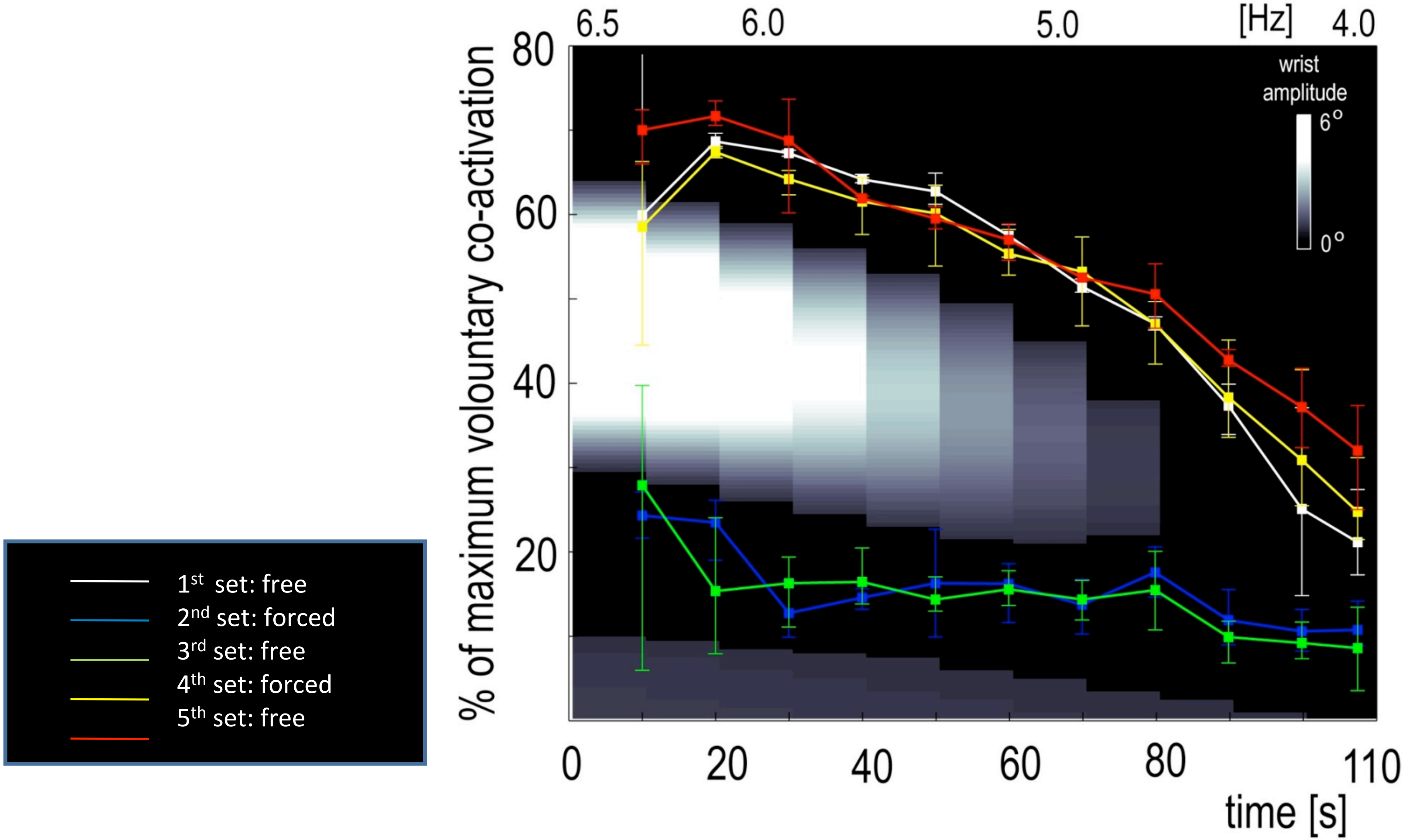
- when ‘forced’ to the other region (blue) they change their preference
- …and **all** the successive ‘free’ trials (green) then follow the ‘forced’ trajectory

[Ganesh et al. 2010 J Neurophysiology]



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

[Ganesh et al. 2010 J Neurophysiology]



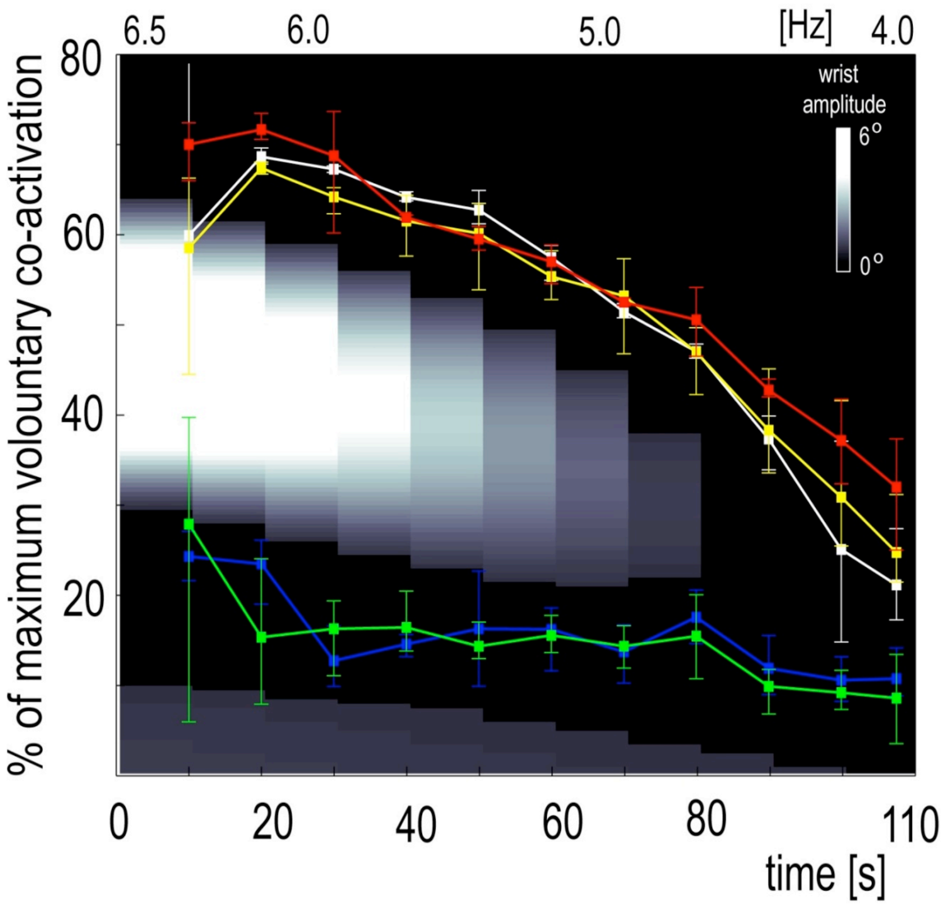
- on being ‘forced’ back (yellow), their movements return to the original trajectory
- **all** the next ‘free’ trials (red) follow the ‘forced’ trajectory

[Ganesh et al. 2010 J Neurophysiology]

Memory > error > energy

- no global minimisation: the subjects do not use the global minimum of error-effort

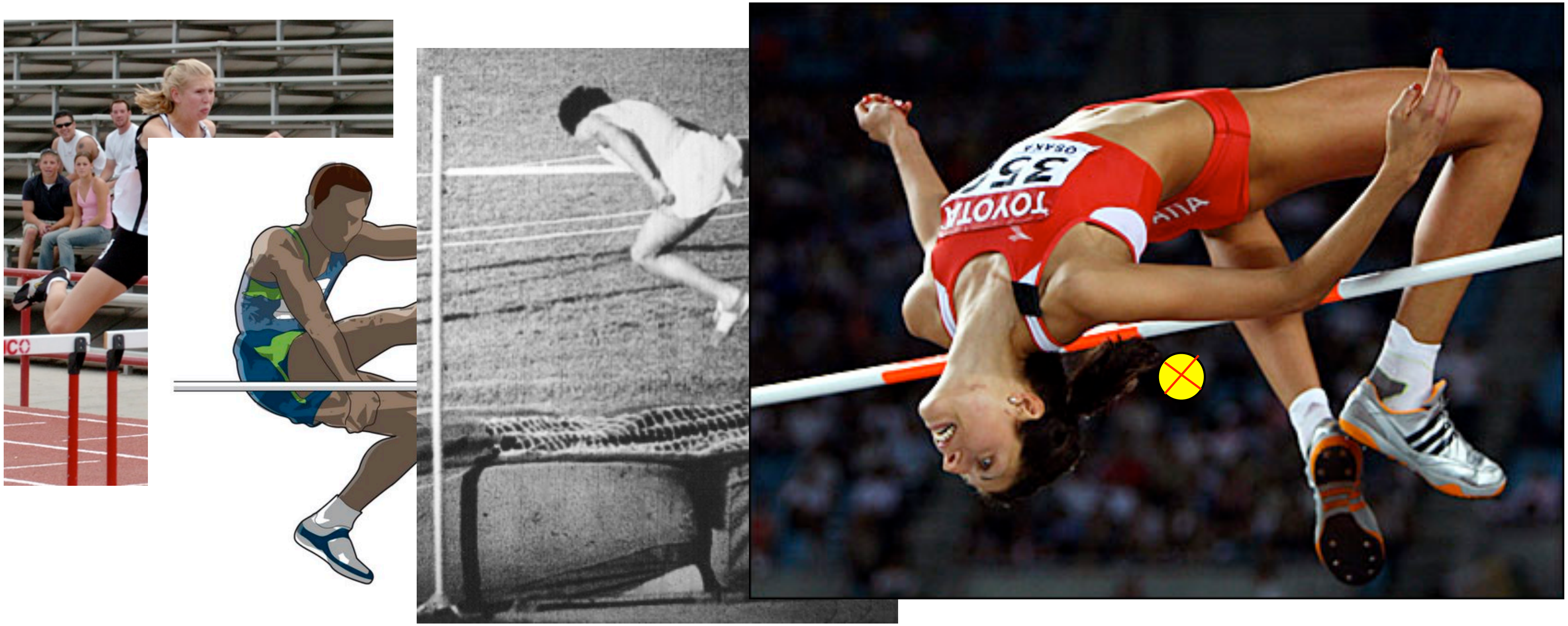
- however, there is some local minimisation



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

[Ganesh et al. 2010 J Neurophysiology]

Optimisation in real tasks?



- no mechanism for global optimisation
- culture and imitation can push us using a better solution, which is memorised (i.e. imitation learning)
- local optimisation around this solution

[Burdet, Franklin & Milner 2013, MIT Press]

SKILL LEARNING

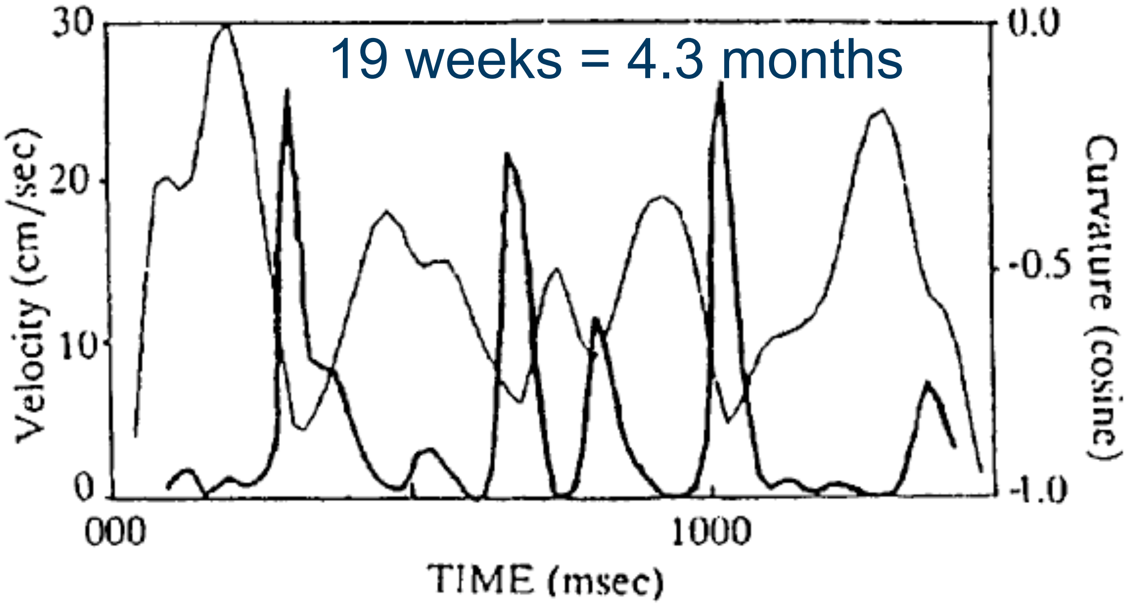
Human motor learning appears to involve:

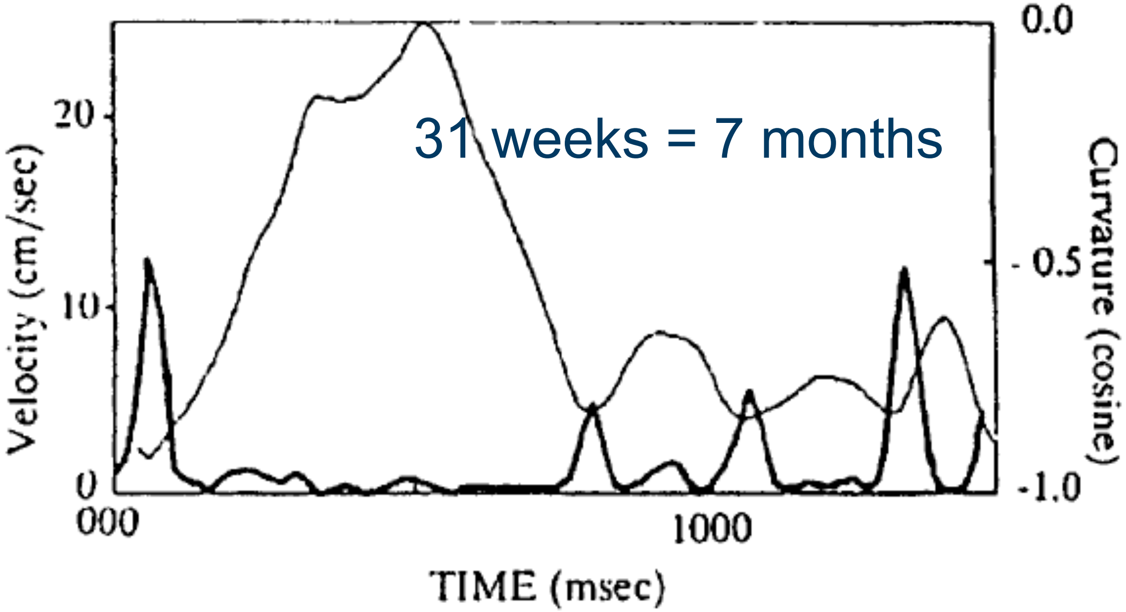
- conscious processes and memorisation (imitation learning)
- automatic motor adaptation

This is not sufficient to explain learning in many cases:

- accurate reaching by infants
- complex tasks?
- neurorehabilitation has probably more to do with the learning of infants then with motor adaptation

REACHING LEARNING BY INFANTS

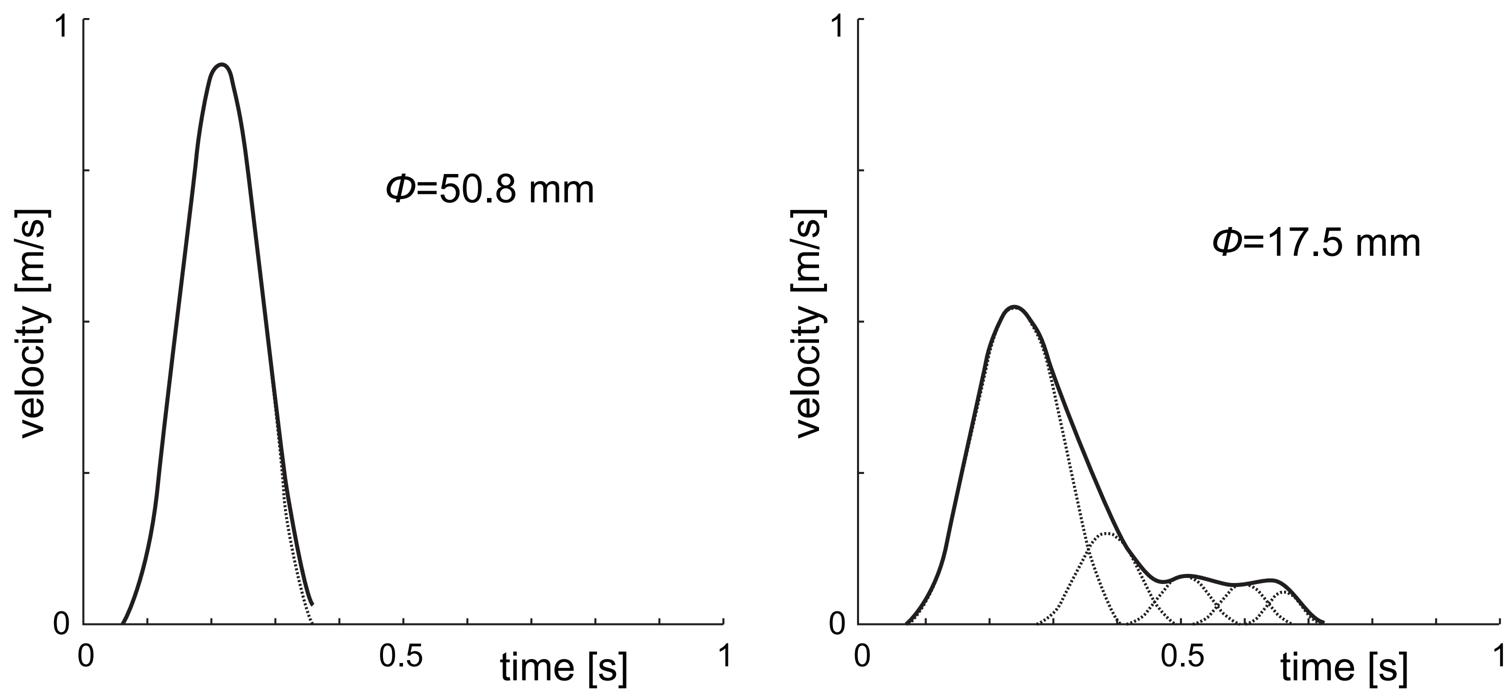




- at about 6 months, babies change from a strategy with a series of submovements
- ... to a smoother movement with asymmetric velocity profile and large initial submovement

[von Hofsten and Roennqvist 1993, Child Development]

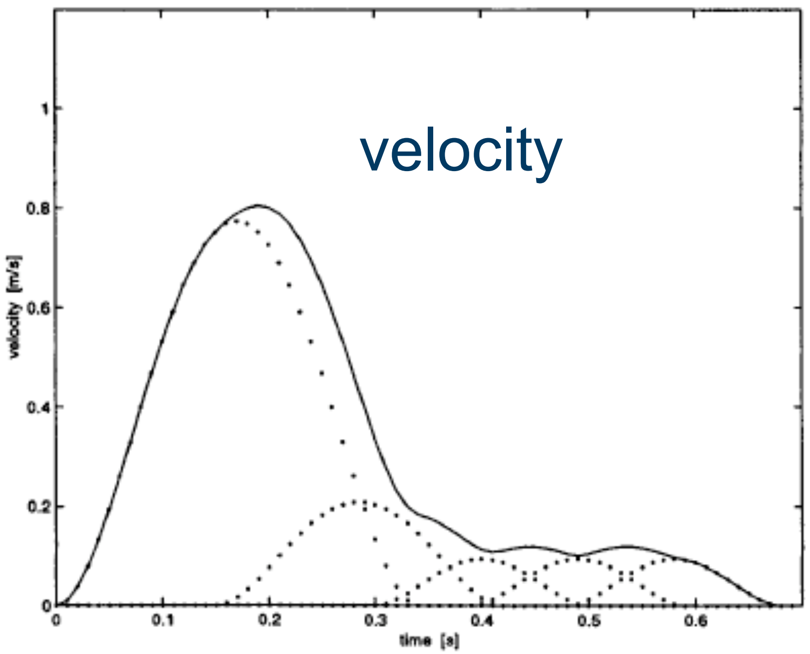
ACCURATE REACHING IN ADULTS

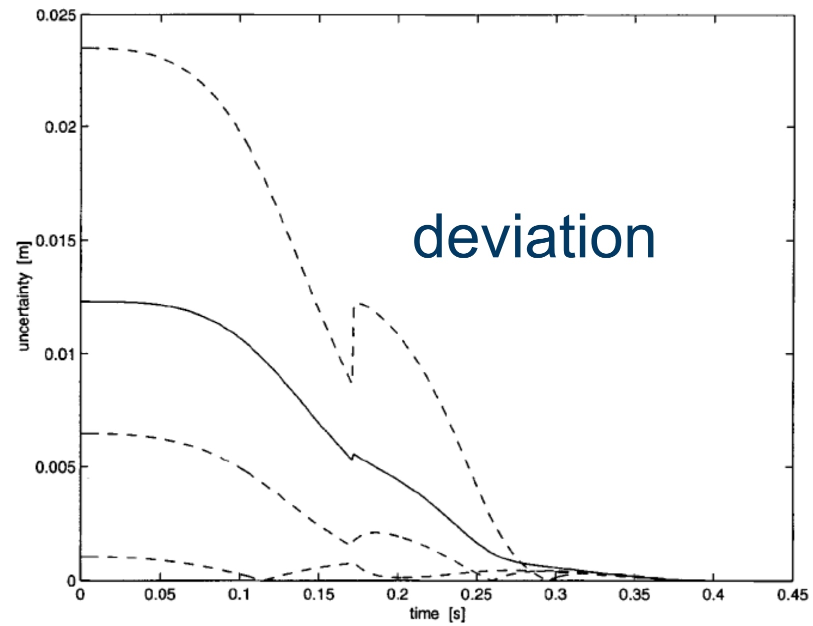


- placing a peg into holes of different diameters
- the peak velocity decreases and the movement becomes more asymmetric as accuracy increases
- fluctuations corresponding to direction change can be interpreted as submovement primitives

[Milner 1992, Neuroscience]

LEARNING OF REACHING IN ADULTS

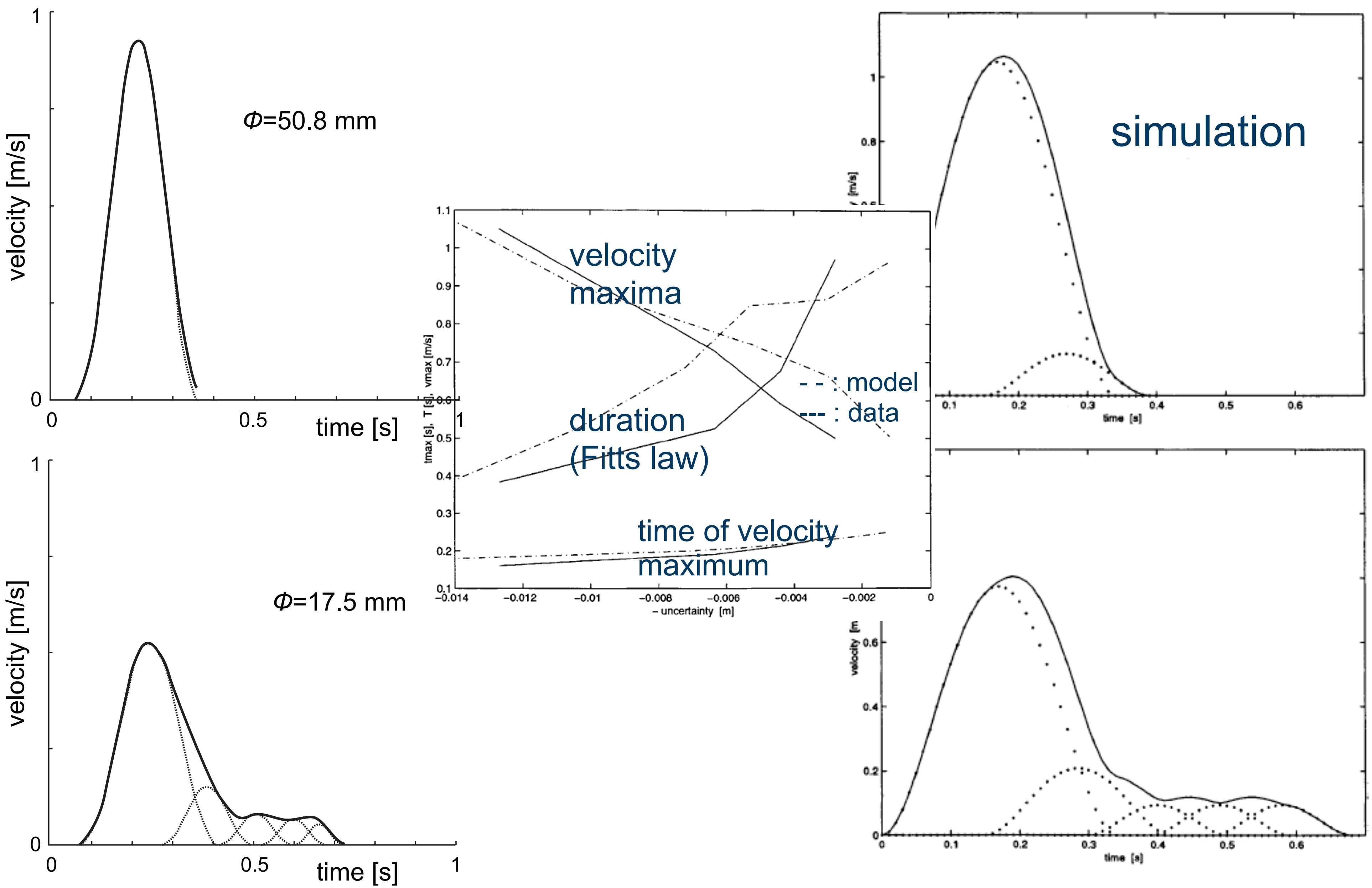




- motion as a series of ballistic submotions
- each submotion has noise proportional to its mean speed, thus slower submotions are more accurate but take longer
- forward model to detect where the actual movement is going to, based on the subject specific submotion shape
- learn submotions with minimal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

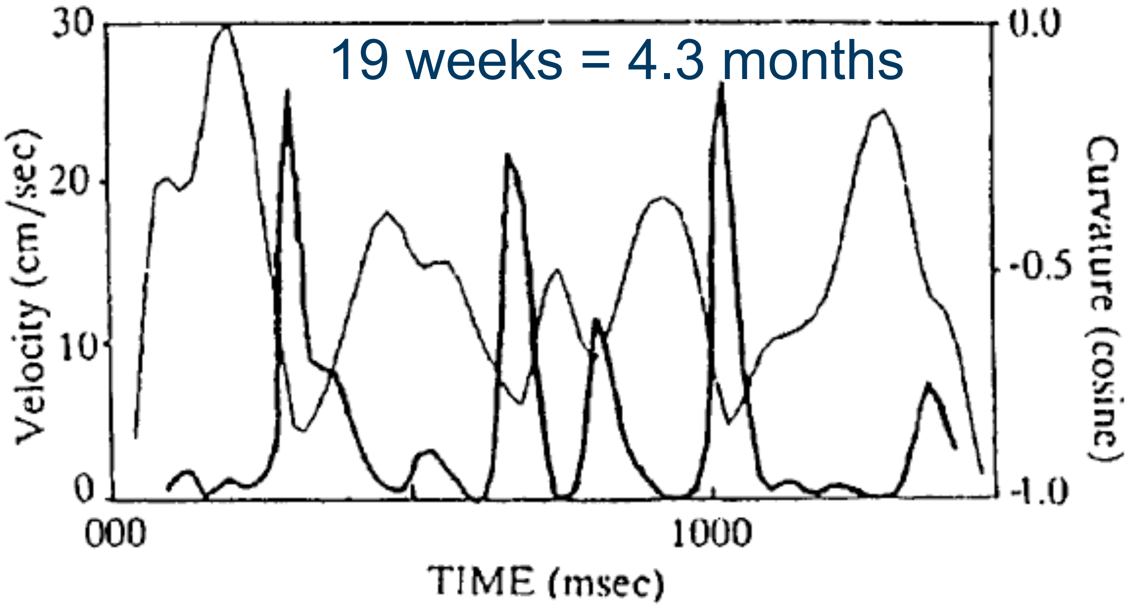
[Burdet & Milner 1998, Biological Cybernetics]

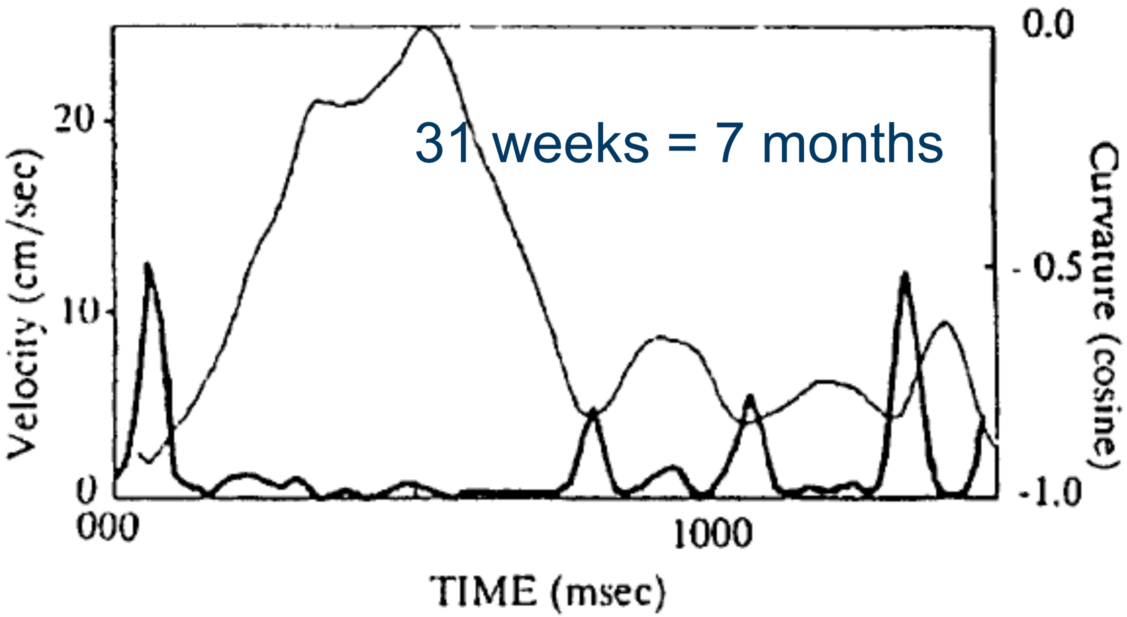
LEARNING OF REACHING IN ADULTS



[Burdet & Milner 1998, Biological Cybernetics]

LEARNING OF REACHING IN INFANTS





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

[von Hofsten and Roennqvist 1993, Child Development]

MOTOR LEARNING

- involves three kinds of learning: memorisation, gradient descent minimisation of error and effort, reinforcement learning

- what do we miss?

- relevance to neurorehabilitation?

WHAT DO WE MISS?

- identification of structures facilitating learning, e.g. PCA, submotions

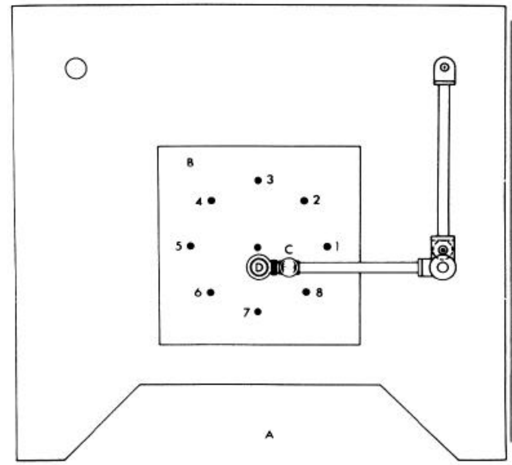
- methods of reinforcement learning

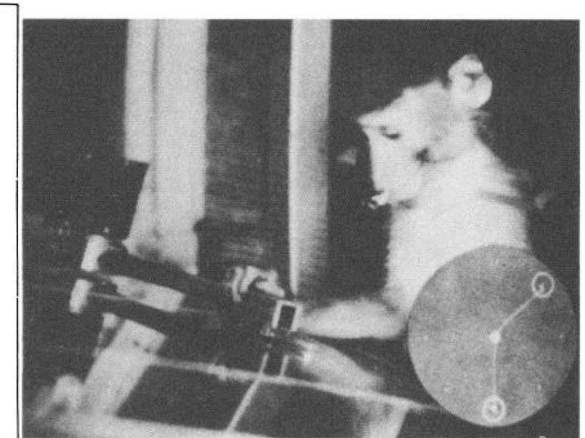
- underlying feedback driving learning was not addressed in this lecture, neither reactive motion planning -> next talk

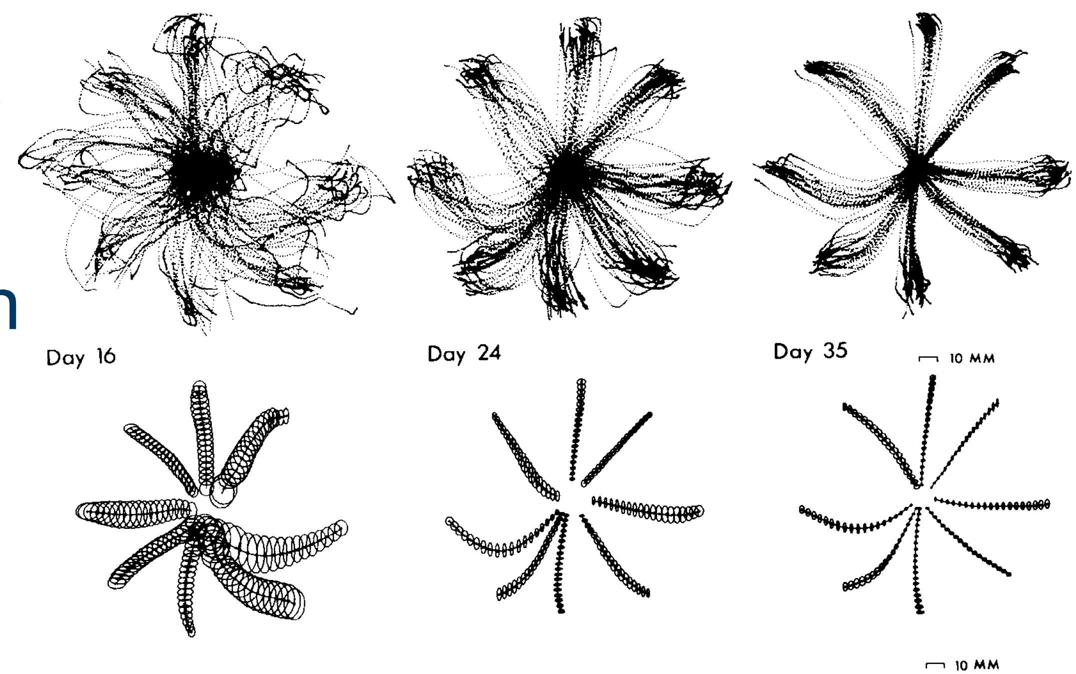
- how should motion variability adaptation & exploration be modelled?

HOW SHOULD VARIABILITY ADAPTATION AND EXPLORATION BE MODELLED?

- motor learning is charac-terised by a decrease of variability
- this means that both mean and deviation are adapted by motor learning, i.e. stochastic optimisation
- what is relationship between variability and exploration in presence of reduced feedback?







[Georgopoulos et al. 1981, J Neurophysiology]

RELEVANCE TO NEUROREHABILITATION ?

- not straightforward, e.g. rehabilitation based mainly on motor adaptation (Patton&Mussa-Ivaldi) does not seem to provide stable benefits (but may still be a good model for modification of brain activity)

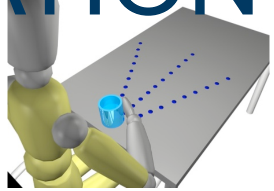
- most rehabilitation seems to rely on memorisation and reinforcement learning

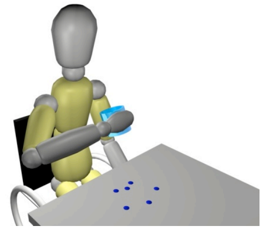
- integrated methods considering several aspects of learning, e.g. memorisation and augmented feedback

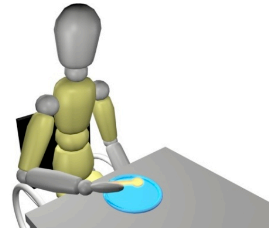
- focus on suitable sensory feedback

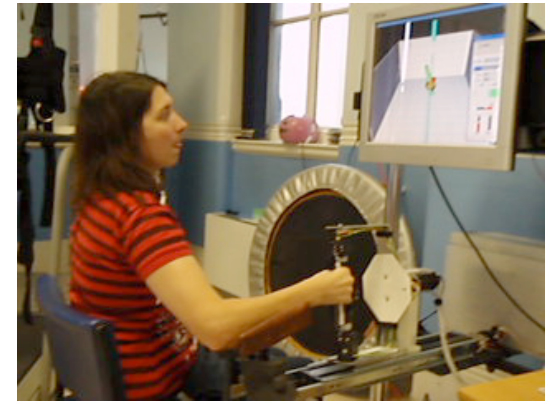
- optimal scheduling can be/is studied with similar methods

NEUROSCIENCE OF REHABILITATION

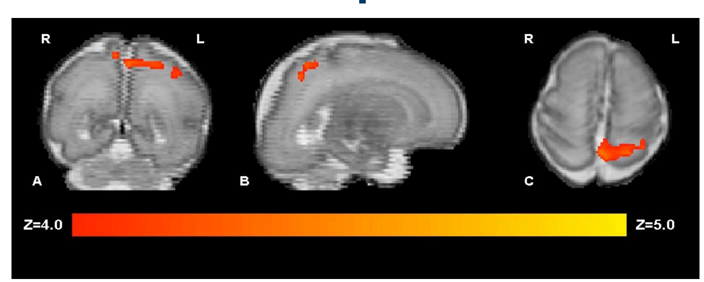






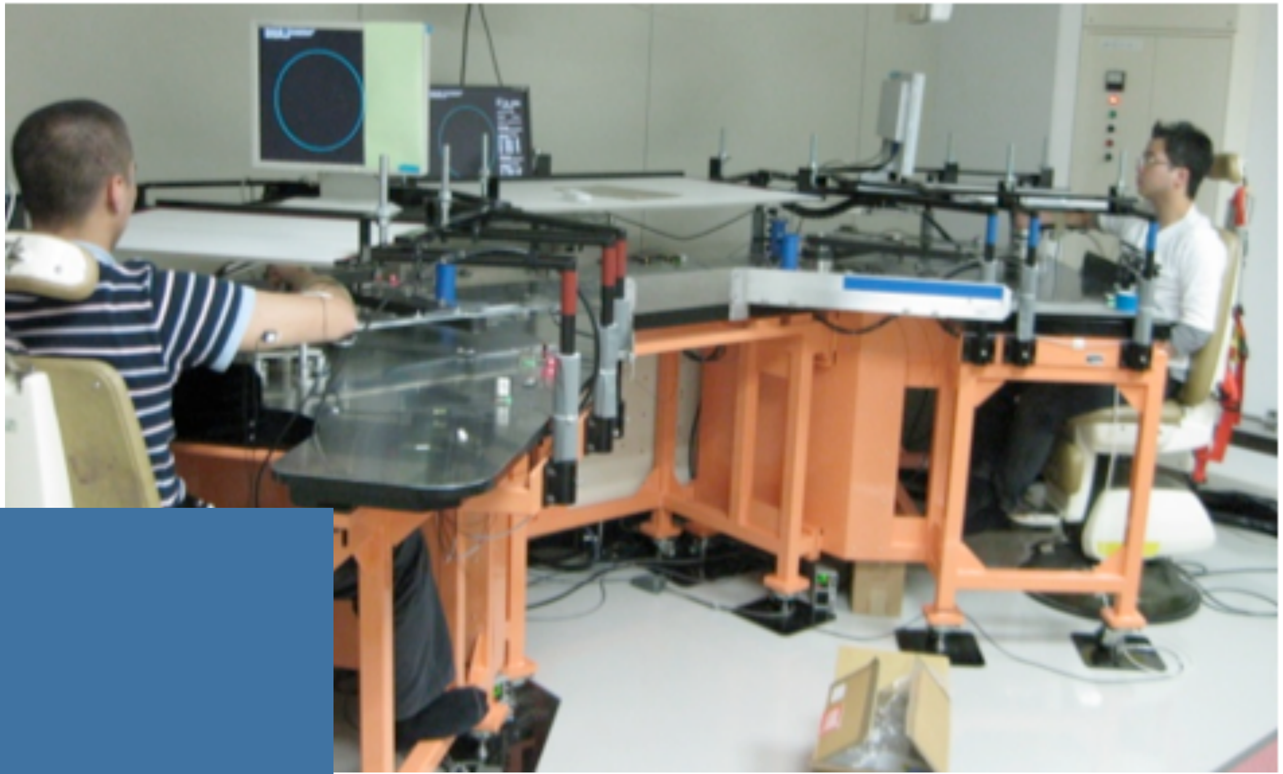


- design simplified by considering motor control factors
- experiments with healthy subjects learning a novel task to develop strategies for rehabilitation
- computational neurorehabilitation: models of motor recovery after stroke
- to investigate neural structures and processes involved in rehabilitation



born @ 27weeks, scanned 2 weeks later

SENSORIMOTOR EXCHANGES



[Ganesh et al. 2014, Scientific Reports]