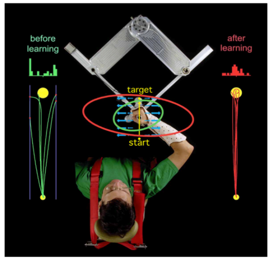
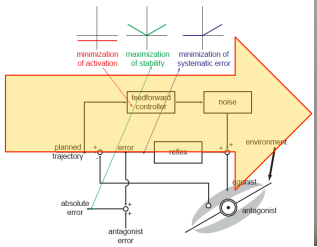
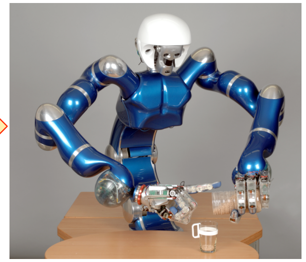
Robots can learn to control haptic interactions as humans do







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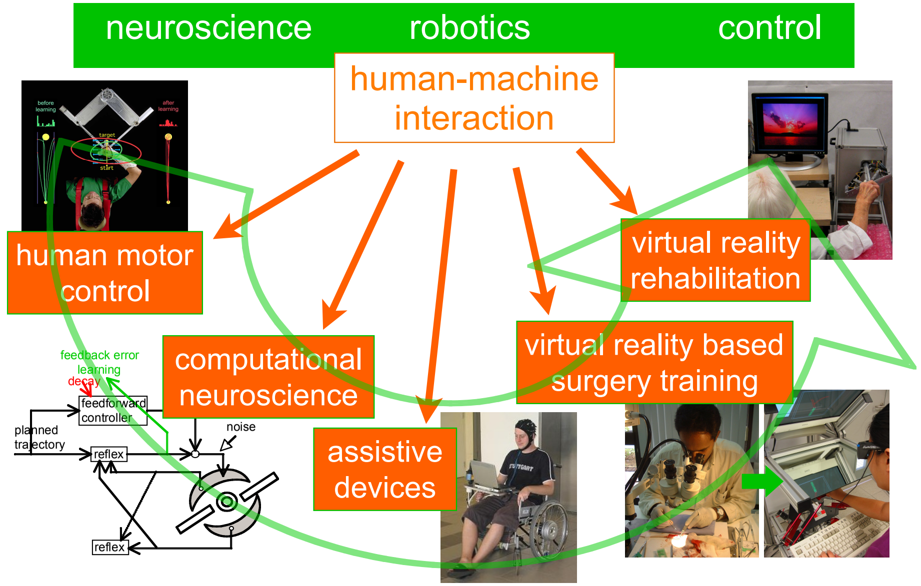

Human Robotics @ Imperial: www.bg.ic.ac.uk/staff/burdet

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THE PROBLEM OF ROBOT

- I fulfil about a body that i have to move with my actuators
- i have limited knowledge about my body and the environment
- i constantly have to perform new tasks and in changing conditions
  - i can get information about my movements and their effects on the environment through my sensors
  - motor learning to improve task performance in interaction with the environment and humans

THE PROBLEM OF ROBOT/HUMAN

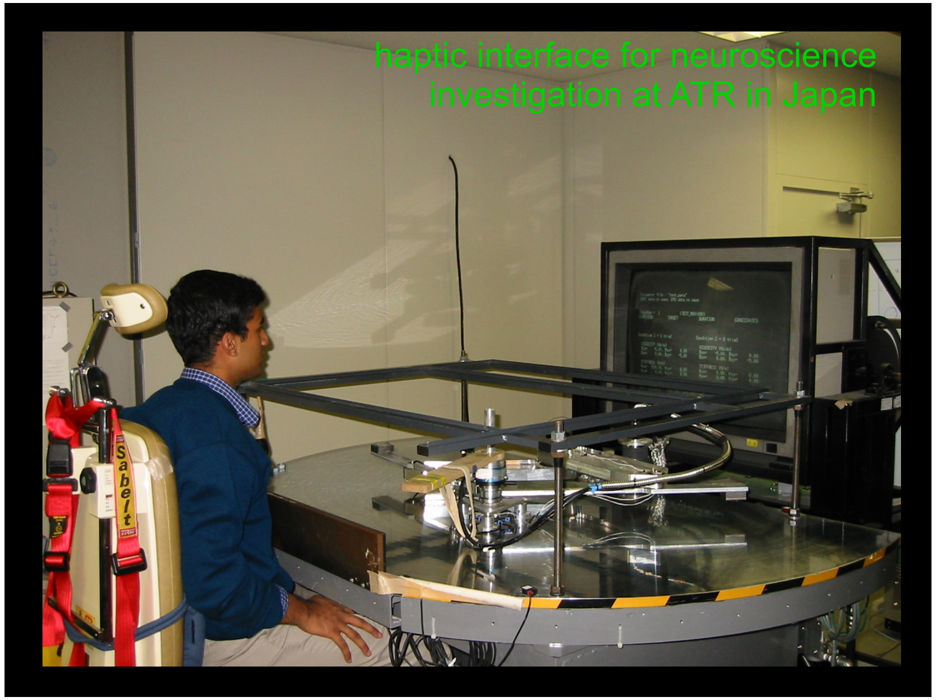
- I fulfil about a body that i have to move with my actuators
- i have limited knowledge about my body and the environment
- i constantly have to perform new tasks and in changing conditions, e.g. during infancy or with ageing
- i can get information about my movements and their effects on the environment through my sensors
- motor learning to improve task performance in interaction with the environment and humans

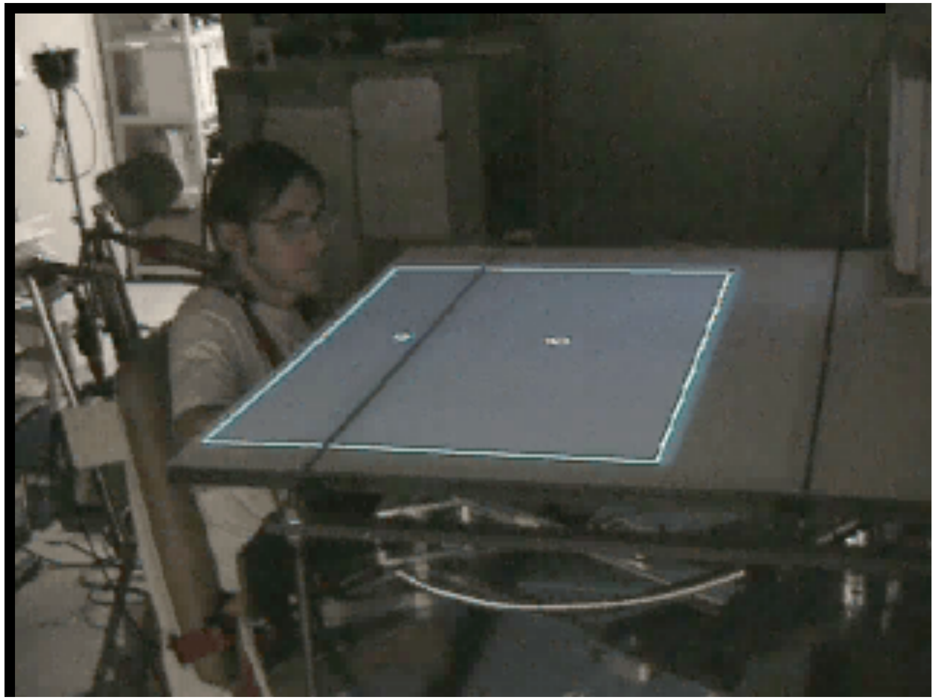
WHY DO HUMANS ADAPT MOTION?

- to manipulate objects we have to interact with the environment
- reaching, grasping: 150-600*ms*, delay of visual feedback: 100-250*ms*, stretch reflex delay > 30*ms*
- skilled actions require that humans learn to compensate for the environmental forces and instability in a feedforward way

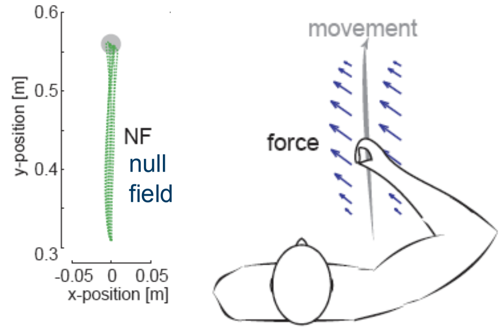
OUTLINE

- motor learning in humans and robots
- learning in unstable dynamics and noise
- interaction control: from human to robot to humans
- learning and generalization





LEARNING STABLE DYNAMICS

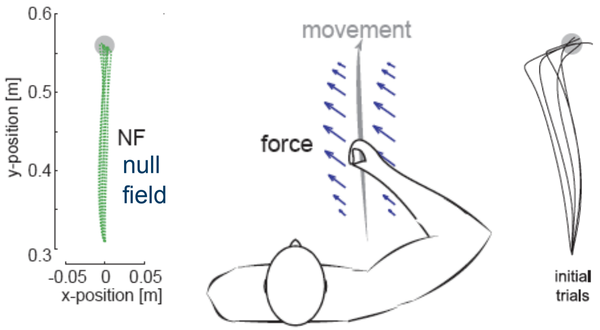


$$\begin{bmatrix} F_x \\ F_y \end{bmatrix}_E = -\begin{bmatrix} 13 & 18 \\ -18 & 13 \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix}$$

reaching movements in a velocity dependent force field (VF)

[Franklin et al. Experimental Brain Research 2003]

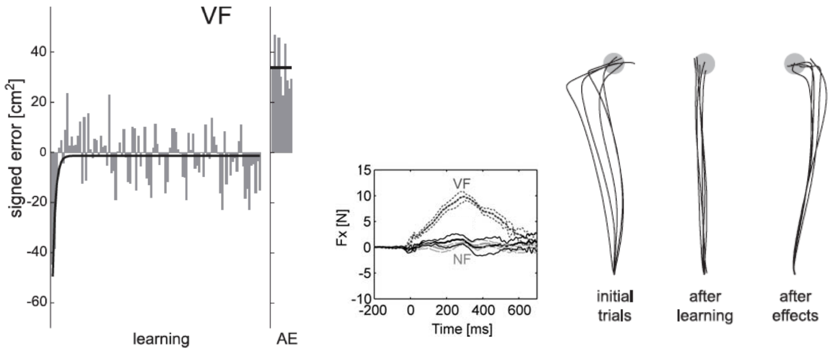
LEARNING STABLE DYNAMICS



after effects: catch trials without force field after learning

[Franklin et al. Experimental Brain Research 2003]

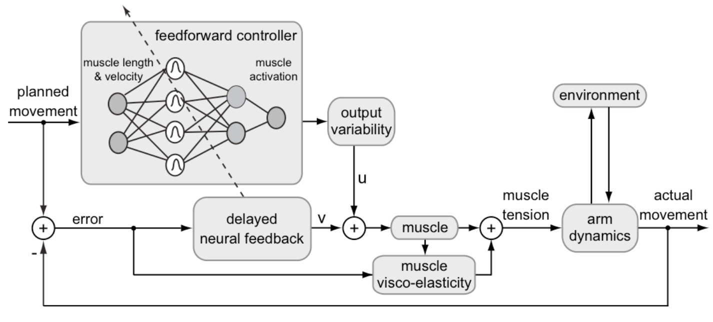
LEARNING STABLE DYNAMICS



- error decreases during learning
- while feedforward motor command is adapted to counteract the external force

[Franklin et al. Experimental Brain Research 2003]

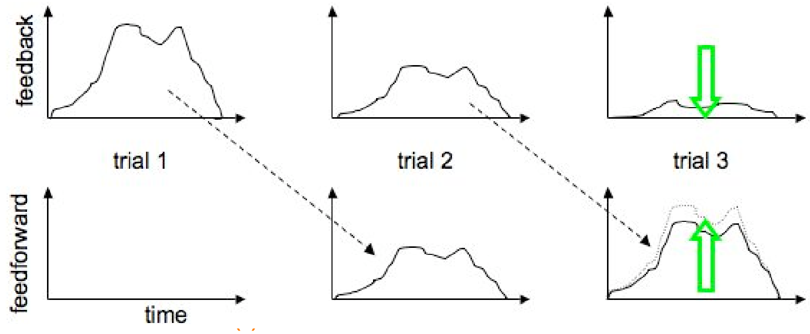
LEARNING CONTROL MODEL



- to adapt the feedforward motor command
- by minimising the feedback error

[Kawato et al. Biological Cybernetics 1987]

ITERATIVE CONTROL IN ROBOTS (1)



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

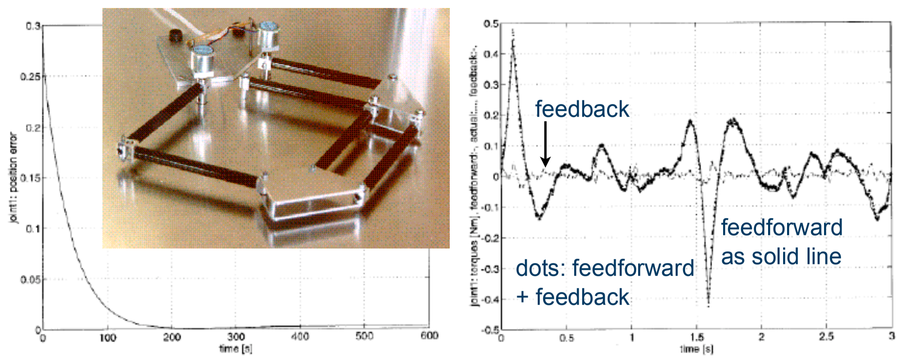
[Burdet et al. IEEE Control System Magazine 1998]

ITERATIVE CONTROL IN ROBOTS (2)

- for tasks such as welding or milling, robots have to follow a trajectory
- nonlinear control to perform good trajectory tracking
- compensating for the task dynamics by using a feedforward term: $\tau = \tau_{FF} + \tau_{FB}$
- learning: start with $\tau_{FF}(t) = 0$
- $\tau_{FF}^{k+1}(t) = \tau_{FF}^{k}(t) + \alpha\, \tau_{FB}^{k}(t)$, $0<\alpha<1$

[Burdet et al. IEEE Control System Magazine 1998]

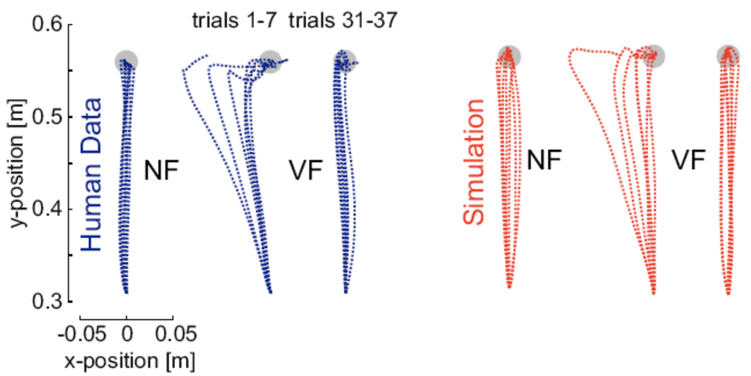
ITERATIVE CONTROL IN ROBOTS (3)



- (integrated) tracking error decreases
- feedback torque is reduced to almost 0

[Burdet et al. IEEE Control System Magazine 1998]

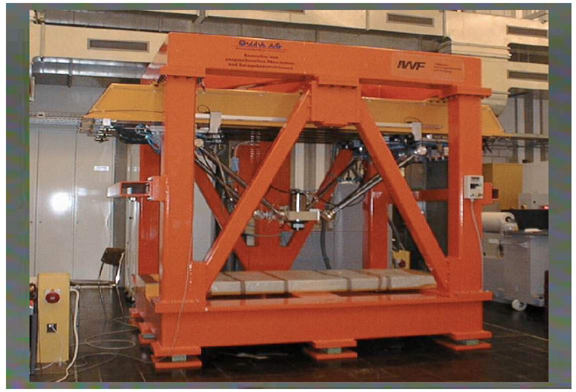
ITERATIVE CONTROL IN HUMANS



- an efficient computational model of motor learning with good prediction of force and trajectory

[Burdet et al. Biological Cybernetics 2006]

ADAPTIVE CONTROL IN ROBOTS



- robots can learn their dynamics in a similar way: (adaptive control: Craig, Slotine, Wen, Horowitz)

SUMMARY

- humans/robots have to learn as they cannot rely on a model
- when repeating movements in a novel (stable) environment, humans gradually compensate for the interaction force
- this is well modelled by iterative learning control
- ... which is an efficient learning strategy to let robots learn the dynamics of a repeated task

OUTLINE

- motor learning in humans and robots
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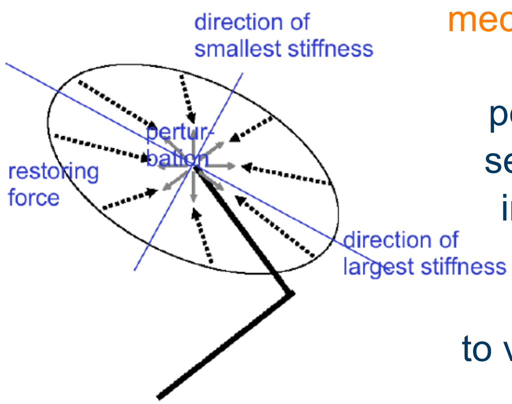
STIFFNESS ELLIPSE



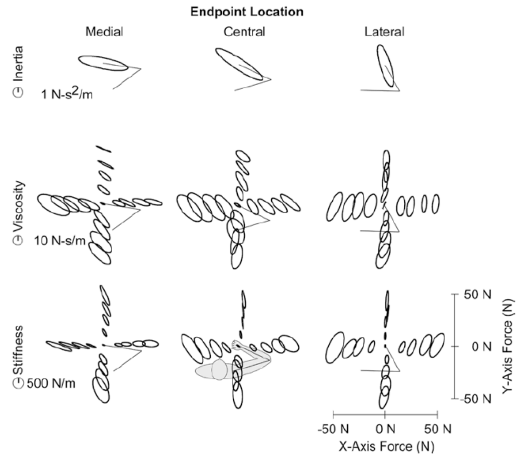
mechanical impedance, the resistance to perturbations, can be seen as composed of inertia, damping and stiffness

to visualize impedance using ellipses

stiffness ellipse $\mathbf{K}_x \frac{\mathbf{x}}{||\mathbf{x}||}$, i.e. force corresponding to a unit displacement, can be plotted to visualize stiffness geometry

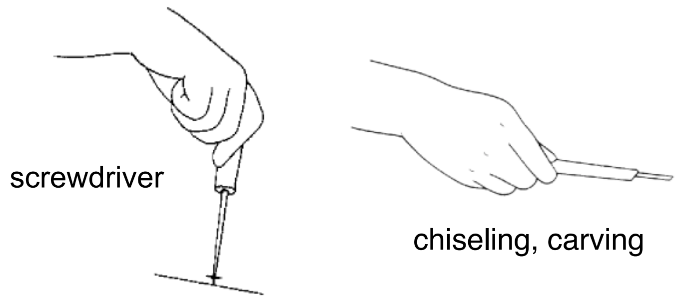
IMPEDANCE & MOTION STABILITY

- stiffness and viscosity increase with muscle activation / force
- in free movements, stability is provided by muscle visco-elasticity and reflexes



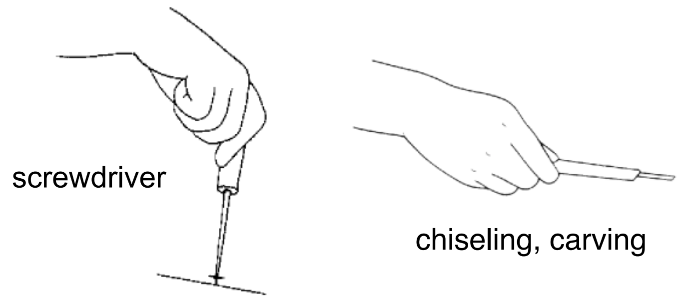
[Perreault et al. Experimental Brain Research 2004]

MOST TASKS WITH TOOLS ARE UNSTABLE



- instability: motor variability or disturbances can lead to large errors and unpredictability
- this requires adaptation of force and elasticity

IMPORTANCE OF STABILITY

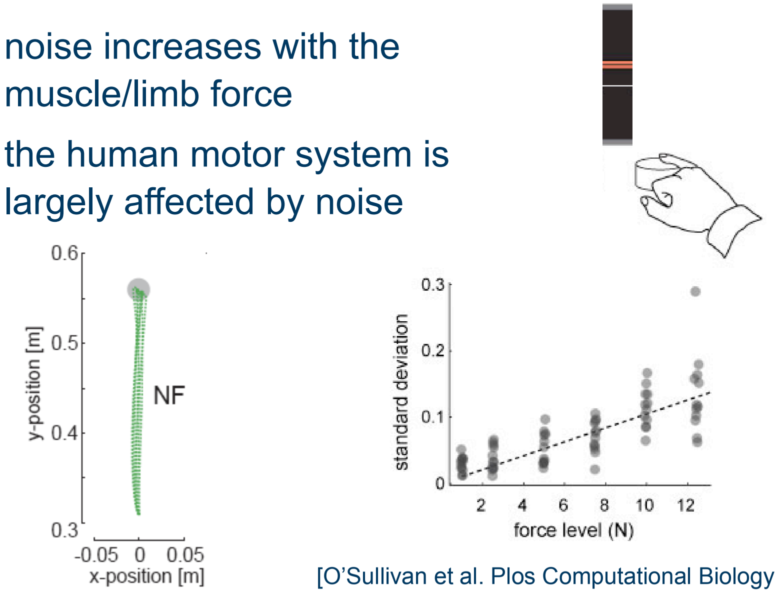


- stability means repeatability and reliability
- this is required by the brain to plan actions

[Burdet et al. Biological Cybernetics 2006]

MOTOR NOISE

- noise increases with the muscle/limb force
- the human motor system is largely affected by noise

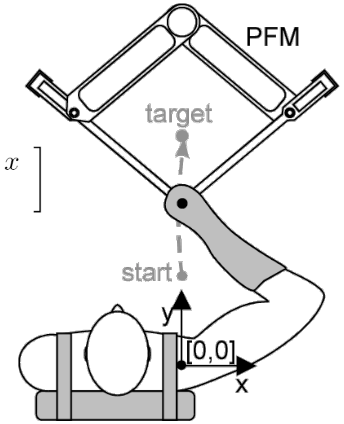


[O'Sullivan et al. Plos Computational Biology 2009]

TO STUDY UNSTABLE INTERACTIONS

- unstable divergent position dependent force field (DF) to amplify deviation

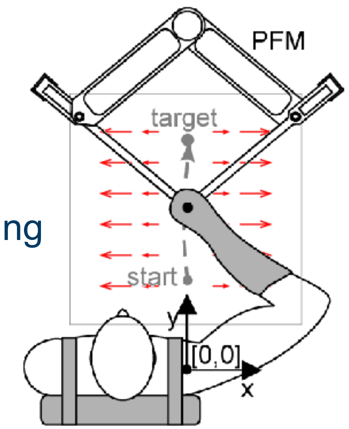
$$\begin{bmatrix} F_x \\ F_y \end{bmatrix}_E = \begin{bmatrix} -450\,x \\ 0 \end{bmatrix}$$



TO STUDY UNSTABLE INTERACTIONS

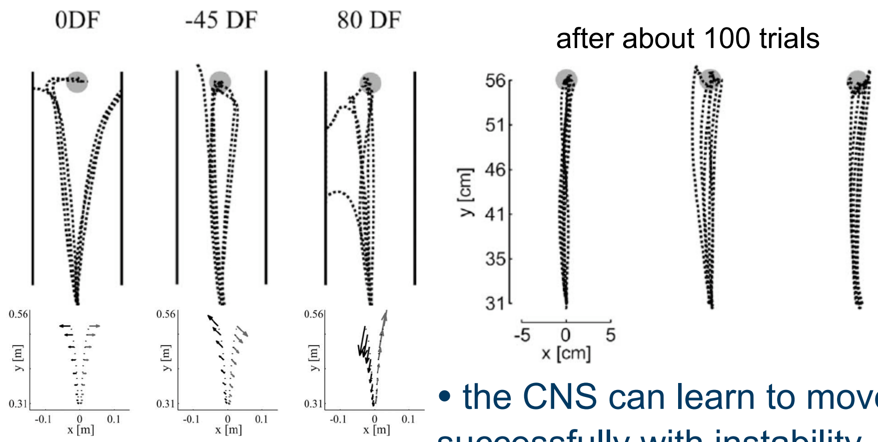
- unstable divergent position dependent force field (DF) to amplify deviation

- forces diverting to left



or to right

LEARNING PATTERNS



$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \zeta \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix} x$$

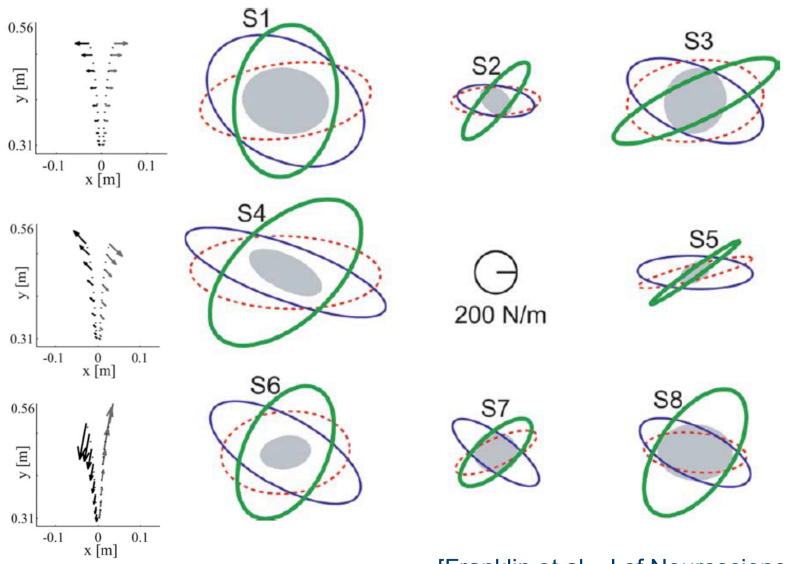
$$\theta = \{-45^o, 0^o, 80^o\}$$

$$\zeta = \{360, 450, 225\} N/m$$

- the CNS can learn to move successfully with instability
- without changing force

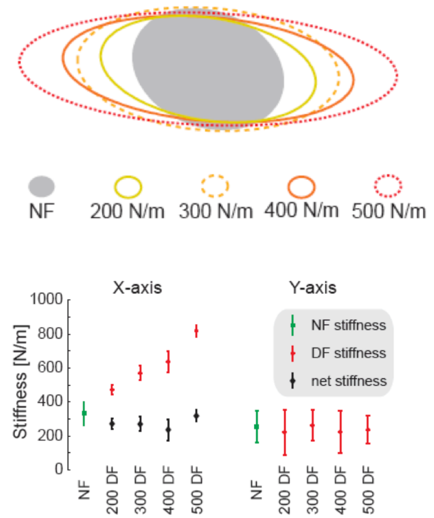
[Franklin et al., J of Neuroscience 2007]

DIRECTION SELECTIVE IMPEDANCE



[Franklin et al., J of Neuroscience 2007]

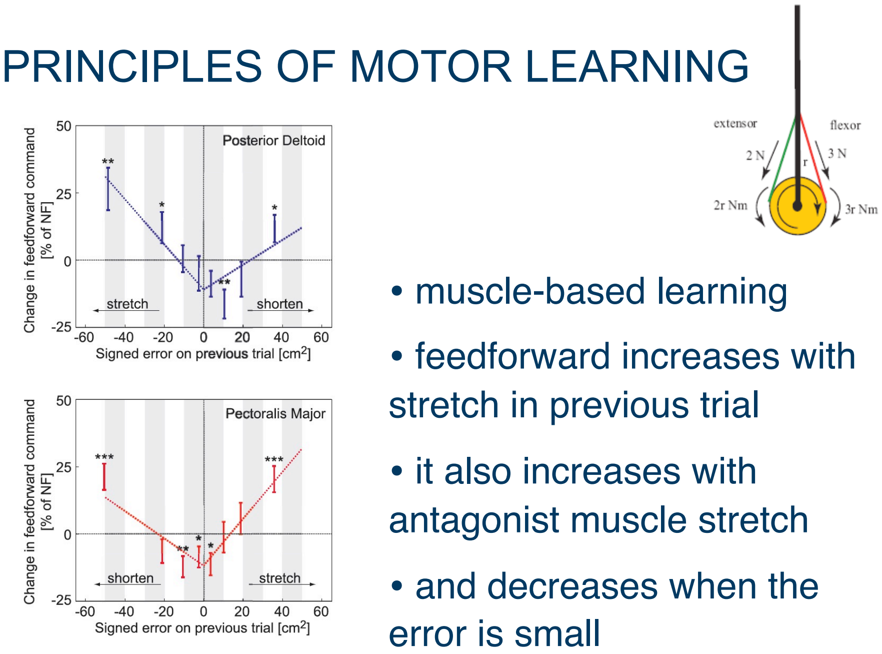
STABILITY MARGIN



- learning leads to the same stability margin ~300*N/m* in all environments
- movements are stable and always have similar deviation
- the brain can plan actions independently of the environment interaction

[Tee et al., Biological Cybernetics 2010]

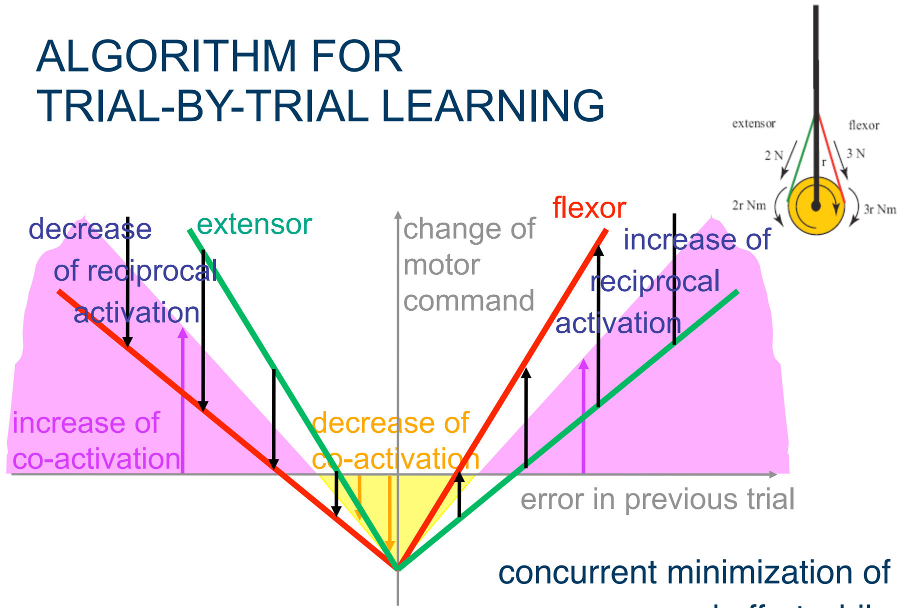
PRINCIPLES OF MOTOR LEARNING



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

[Franklin et al. J Neuroscience 2008]

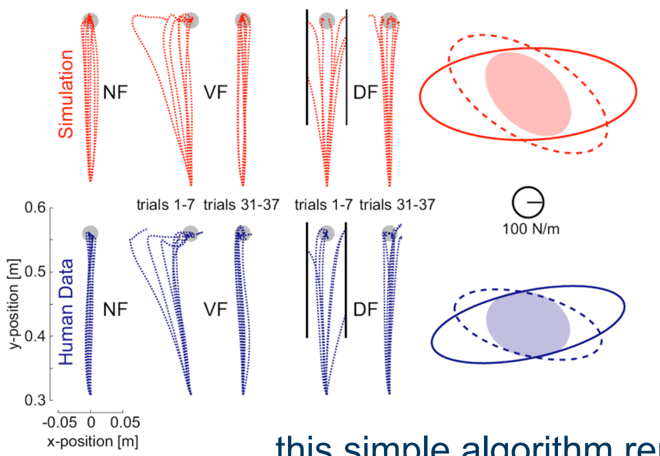
ALGORITHM FOR TRIAL-BY-TRIAL LEARNING

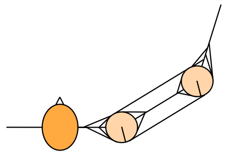


concurrent minimization of error and effort while maintaining a stability margin

[Franklin et al. J Neuroscience 2008]

COMPUTATIONAL MODEL





simulation with a 2-joint 6-muscles model

this simple algorithm reproduces the adaptation observed in experiments

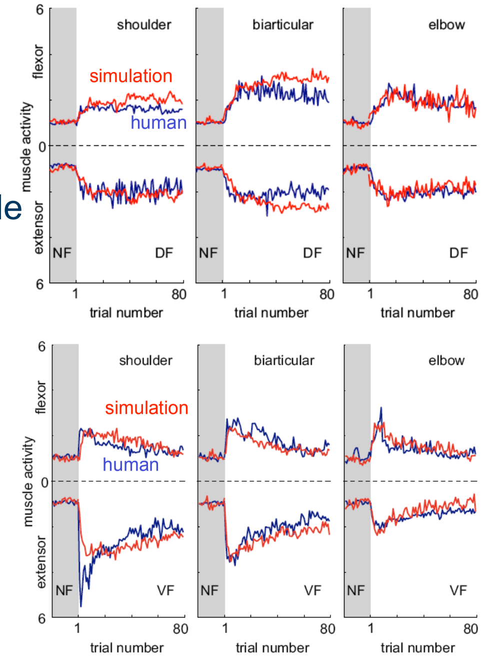
[Franklin et al. J Neuroscience 2008]

EVOLUTION OF ACTIVATION

DF: unstable interaction

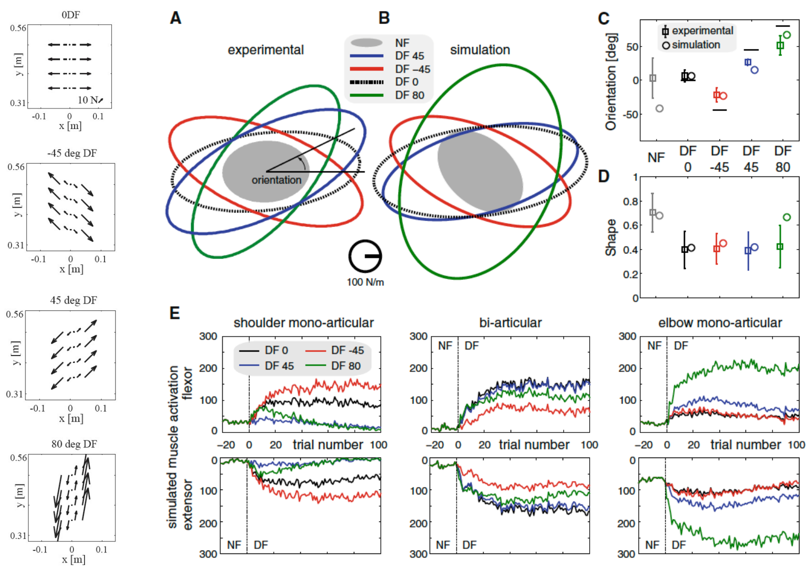
The model can predict the trial-by-trial changes of muscle activation

VF: stable interaction



[Franklin et al. J Neuroscience 2008]

DIRECTION SELECTIVE IMPEDANCE



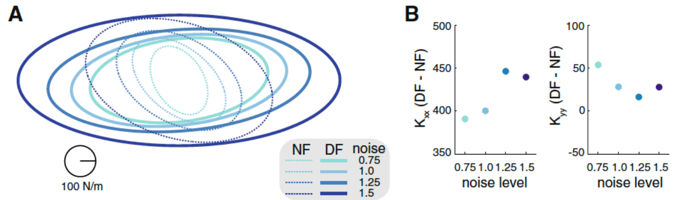
[Tee et al., Biological Cybernetics 2010]

COMPENSATION FOR NOISE (1)

- the amount of motor noise with which the CNS must contend varies among healthy, increases with age and in pathological states such as cerebellar disorders
- how does neural control adapt to such differences?
- use our model to compare adaptation under conditions of different levels of motor noise

[Tee et al., Biological Cybernetics 2010]

COMPENSATION FOR NOISE (2)



- endpoint stiffness grows with the noise level, through an increase in the activation of all muscles
- increase of K_{xx} term is larger in DF than in NF

[Tee et al., Biological Cybernetics 2010]

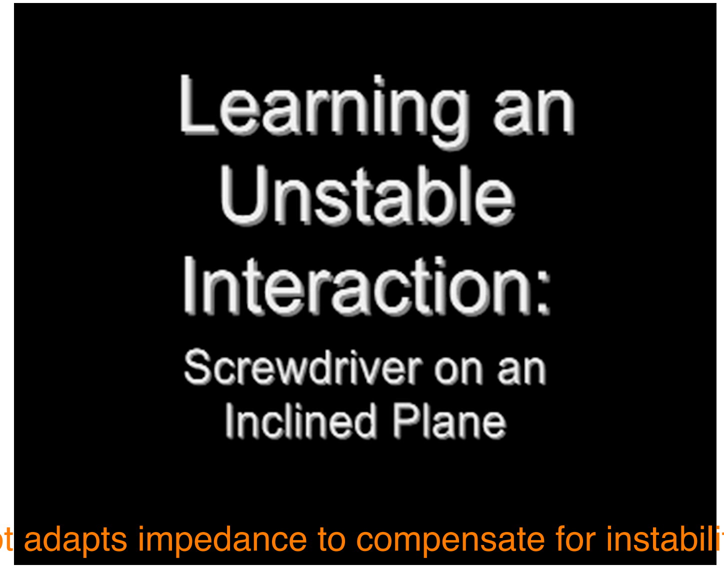
OUTLINE

- motor learning in humans and robots
- learning in unstable dynamics and noise
- interaction control: from human to robot to humans
- learning and generalization

SUMMARY

- interaction with the environment can create instability, i.e. when using tools; this amplifies the motor variability and leads to unpredictability
- the CNS automatically learns to coordinate muscles in order to stabilize unstable dynamics
- the CNS so produces the same stability margin independent of the environment
- this learning can be described with a simple algorithm, that correctly predicts the whole evolution of motor commands, as well as joint/endpoint force and impedance

AUTOMATIC IMPEDANCE ADAPTATION



robot adapts impedance to compensate for instability arising from the interaction of tools with the environment

FORCE&IMPEDANCE ADAPTATION

feedforward and feedback provided by muscles

$$\tau_u(t) = -L(t)\varepsilon(t) \underbrace{- \tau(t) - K(t)e(t) - D(t)\dot{e}(t)}_{\text{learned feedforward force and impedance}}$$

stability margin $-L(t)\varepsilon(t)$

$$\varepsilon \equiv \dot{e}(t) + \Gamma e(t), \quad \Gamma = \Gamma^T > 0,$$

$$e(t) \equiv q(t) - q_r(t), \quad \dot{e}(t) \equiv \dot{q}(t) - \dot{q}_r(t)$$

reference trajectory $q_r(t)$, $t \in [0, T]$

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

FORCE&IMPEDANCE ADAPTATION

$$\tau_u(t) = -L(t)\varepsilon(t) - \tau(t) - K(t)e(t) - D(t)\dot{e}(t)$$

adaptation of impedance and torque: *i*-> *i*+1

$$K^{i+1}(t) = K^i(t) + Q_K\left(\varepsilon^i(t)e^{iT}(t) - \gamma^i(t)K^i(t)\right)$$

$$D^{i+1}(t) = D^i(t) + Q_D\left(\varepsilon^i(t)\dot{e}^{iT}(t) - \gamma^i(t)D^i(t)\right)$$

$$\tau^{i+1}(t) = \tau^i(t) + Q_\tau\left(\varepsilon^i(t) - \gamma^i(t)\tau^i(t)\right)$$

Lyapunov-like analysis to minimize effort and error

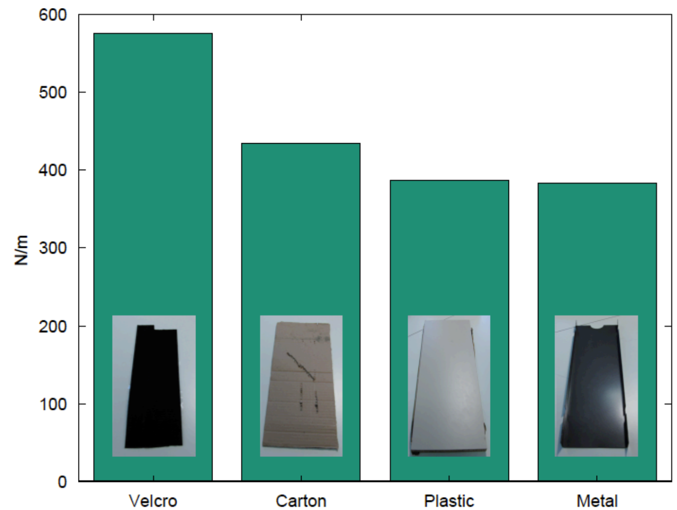
-> stability acquired, convergence to a small set

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

LEARNING: FROM HUMAN TO ROBOT

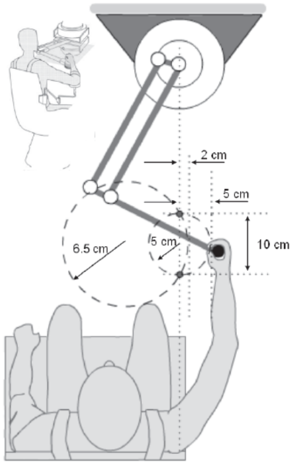
[Yang et al. IEEE Trans on Robotics 2011]

IDENTIFICATION OF SURFACE IMPEDANCE



TRAJECTORY ADAPTATION: EXPERIMENT

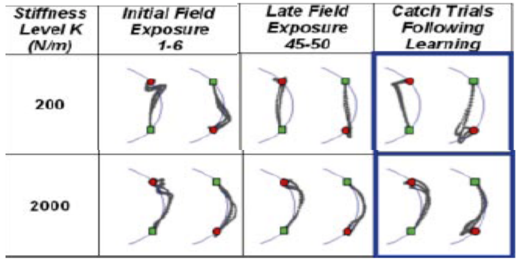
- when there is an obstacle on the way, there is adaptation of trajectory
- our and other groups are currently performing psychophysical experiments to understand the mechanisms of this adaptation



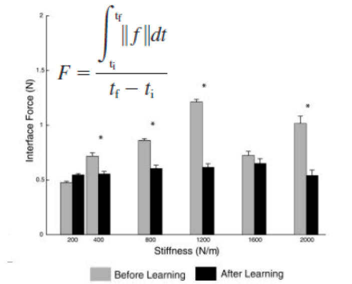
Chib et al, J Neurophysiology 2005

TRAJECTORY ADAPTATION: EXPERIMENT

Chib et al, J Neurophysiology 2005



average interaction force



the subjects seemingly modify the trajectory to apply the same level of force in various conditions

TRAJECTORY ADAPTATION: MODELING

To learn: *sensor reference trajectory* $q_r(t)$ to minimize interaction force and motion error:

$$J = \int_0^T \|F_q(\sigma)\|_Q^2 + \|q(\sigma) - q^*(\sigma)\|_R^2 \, d\sigma$$

planned trajectory $q^*(t)$, $t \in [0, T]$

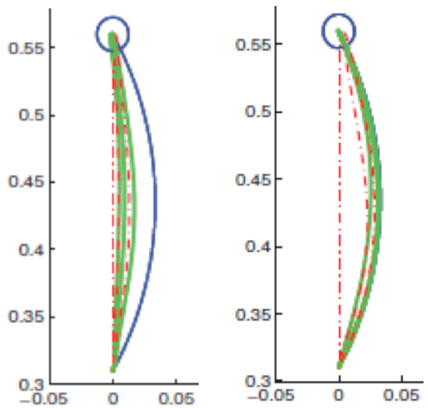
yields the adaptation law

$$q_r^0 = q^*, \qquad z = (\dot{q} - \dot{q}^*) + \Lambda(q - q^*) - f_q$$

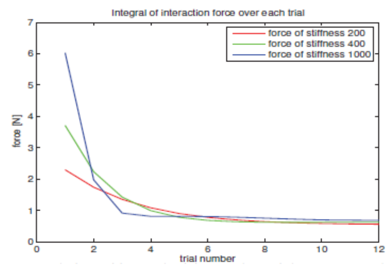
$$q_r^{i+1} = q_r^i - Lz^i, \quad i = 0, 1, 2, \ldots$$

[Yang and Burdet, IEEE IROS 2011]

TRAJECTORY ADAPTATION: SIMULATION



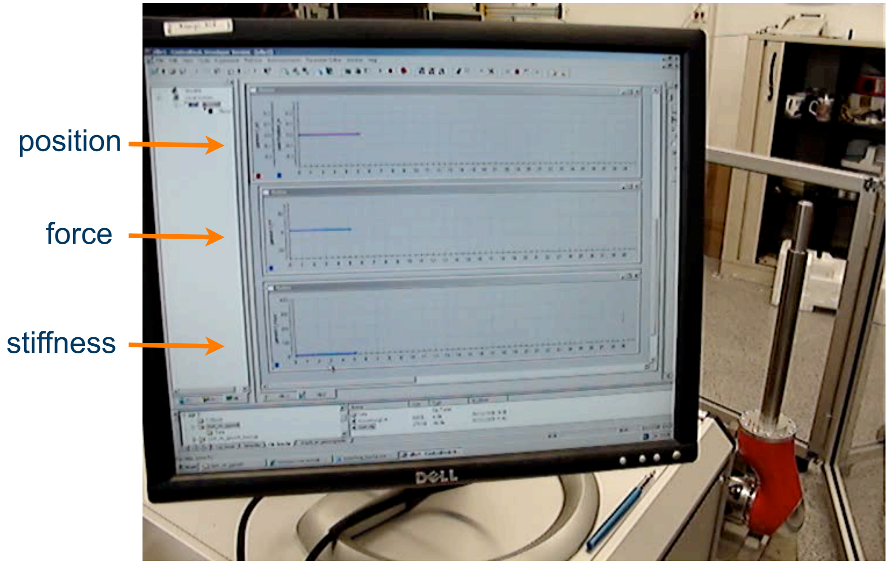
stiffness: 200N/m 1000N/m



force against the surface

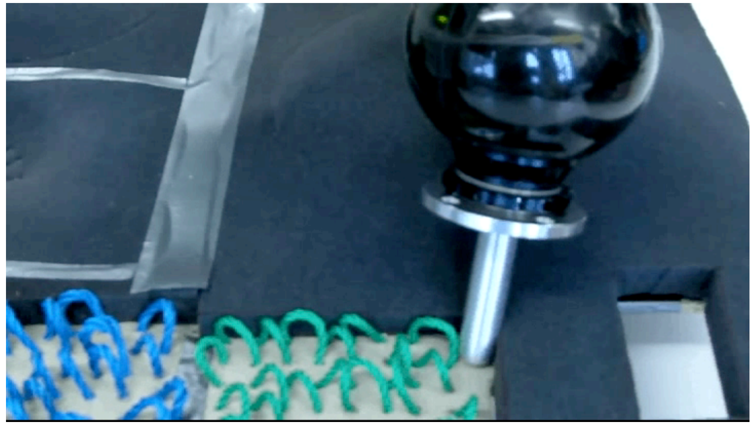
[Yang and Burdet, IEEE IROS 2011]

ADAPTABLE HUMAN-ROBOT CONTROL



[Yang et al. IEEE Trans on Robotics 2011]

HAPTIC EXPLORATION
straight scanning trajectory @ 4cm depth

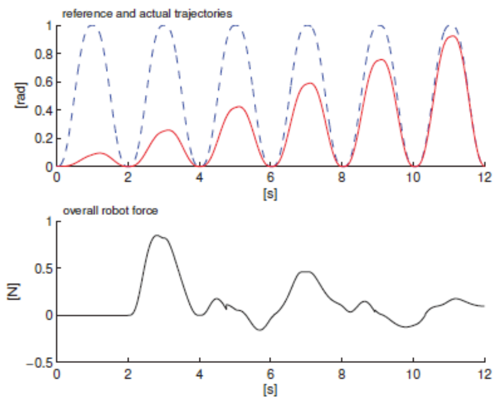


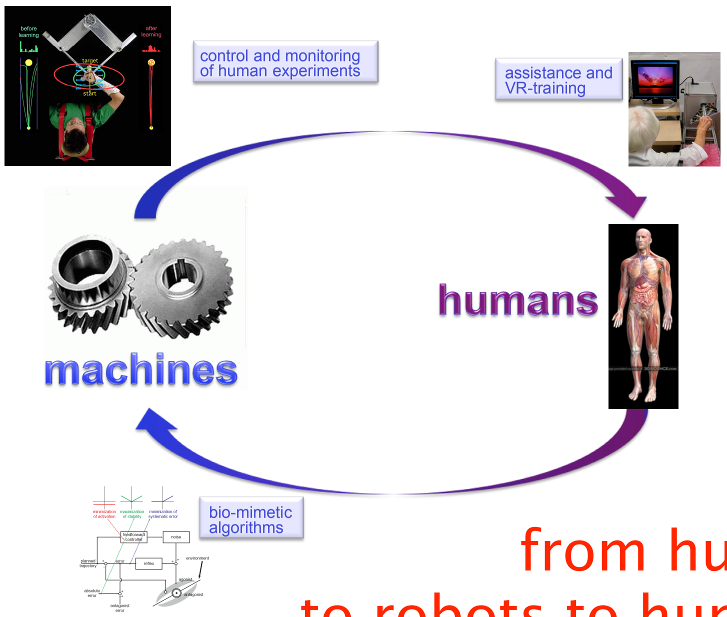
robot adapts geometry *and impedance* to interact with unknown surface characteristics

MOTOR LEARNING:
in human, for robots, for humans

- using our model as controller, the rehabilitation robot will tend to increase the range, provide force and guidance...
- ... and gradually relax this assistance as the subject improves
- ongoing implementation on the BiManuTrack in Berlin (collaboration with H Schmid, Frauenhofer Institut)

MOTOR LEARNING:
in human, for robots, for humans





from human to robots to humans

OUTLINE

- motor learning in humans and robots
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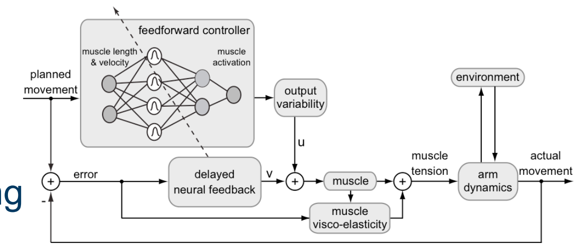
- interaction control: from human to robot to humans
- learning and generalisation

GENERALISATION



- iterative control can learn only along a single trajectory
- to learn performing several distinct movements, it is necessary to adopt as inverse model a mapping of the state
- artificial neural network to map the state to the required muscle activations

[Kadiallah et al., submitted]

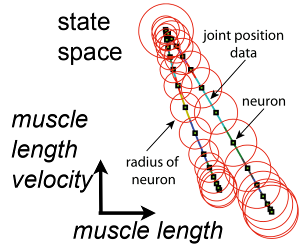
GENERALISATION

$$\mathbf{u} \;=\; \mathbf{W}\boldsymbol{\psi} \qquad \text{feedforward motor command}$$

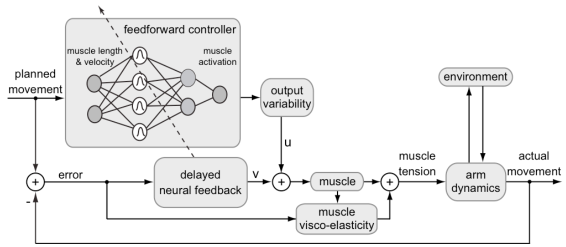
$$\boldsymbol{\psi} \;=\; (\psi_1, \psi_2, \ldots, \psi_N)^T \qquad \psi_j(\mathbf{s}) \quad s\text{: state}$$

physical model, (muscle) synergies, differential equations, central pattern generators, radial basis functions neural networks:

$$\psi_j(\mathbf{s}) = \exp\left[\frac{||\mathbf{s}-\mathbf{s}_j||^2}{2\,\sigma_j^2}\right]$$



MINIMIZATION OF FEEDBACK AND FEEDFORWARD COMMANDS

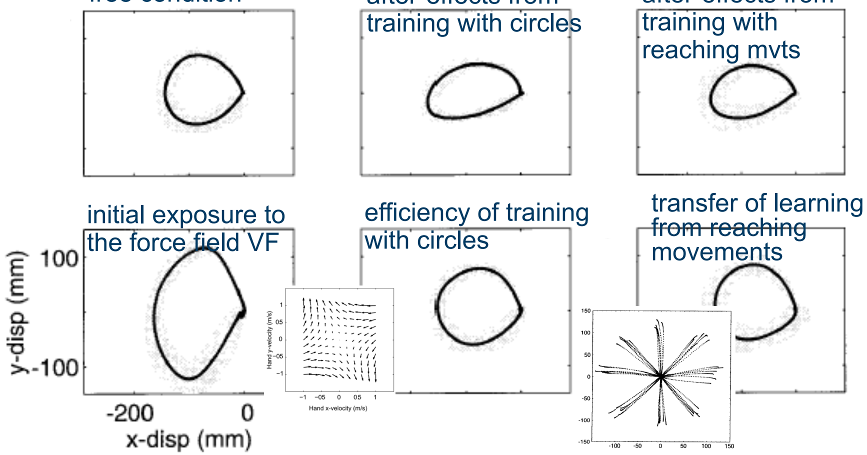


$$V(\mathbf{p}) \equiv \frac{\alpha}{2}\mathbf{v}^T\mathbf{v} + \gamma \sum w_{ij} \quad \alpha, \gamma > 0$$

$$\mathbf{W}^{k+1} = \mathbf{W}^k + \triangle \mathbf{W}^k, \ \triangle w_{ij}^k = \alpha\, v_i\, \psi_j - \gamma$$

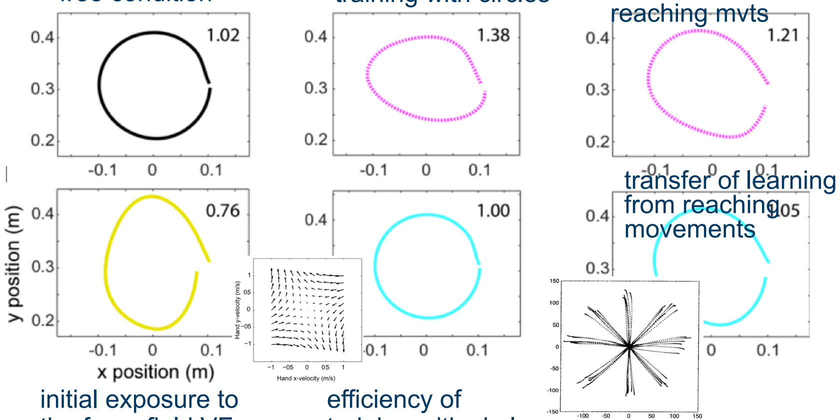
[Kadiallah et al., submitted]

INVERSE MODEL IS STATE DEPENDENT



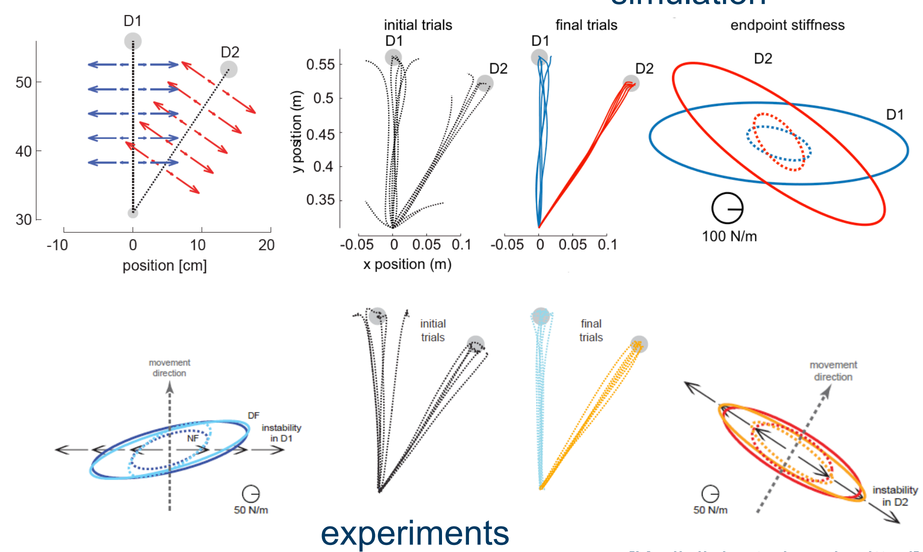
the CNS does not learn by rote memorization, but forms a state dependent internal model

INVERSE MODEL IS STATE DEPENDENT



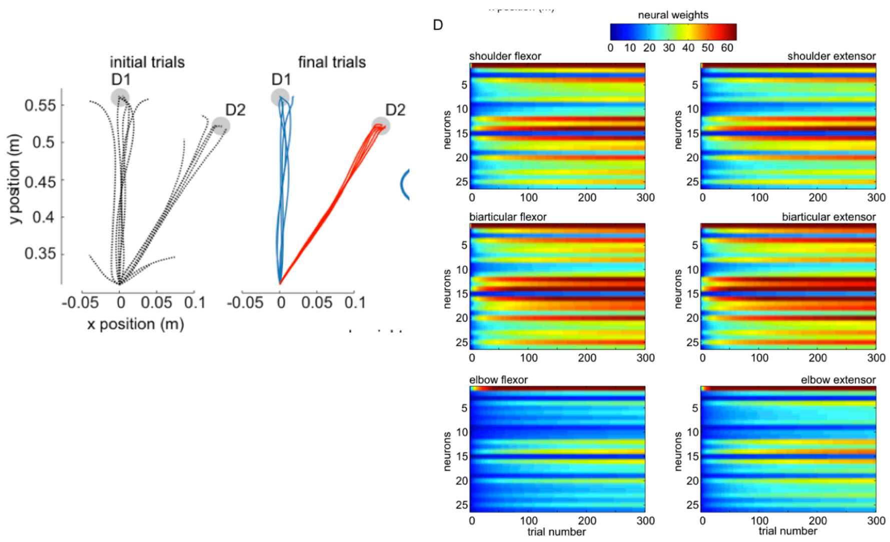
[Kadiallah et al., submitted]

GENERALIZATION



[Kadiallah et al., submitted]

GENERALIZATION



[Kadiallah et al., submitted]

Human learning in unstable environments

- the CNS automatically learns to coordinate muscles in order to compensate for the interaction force and instability
- this produces movements with the same mean trajectory and deviation in all environments
- the CNS may rely on this invariance for higher motor control levels
- this learning was modelled by an adaptive controller able to predict the evolution of muscles activation trial after trial

A novel motor behaviour for robots

- this gave rise to the first model-free controller for simultaneous adaptation of force, impedance and trajectory
- able to deal with unstable situations typical of tool use
- derived from the minimisation of error and energy
- can learn a large range of dynamics and generalise in multiple movements

A novel motor behaviour for robots

- particularly suitable for human-robot interaction, such as in rehabilitation and physical training
- compliant force control-like haptic identification of unknown surfaces
- ideal to fully utilise the new possibilities offered by variable impedance actuators