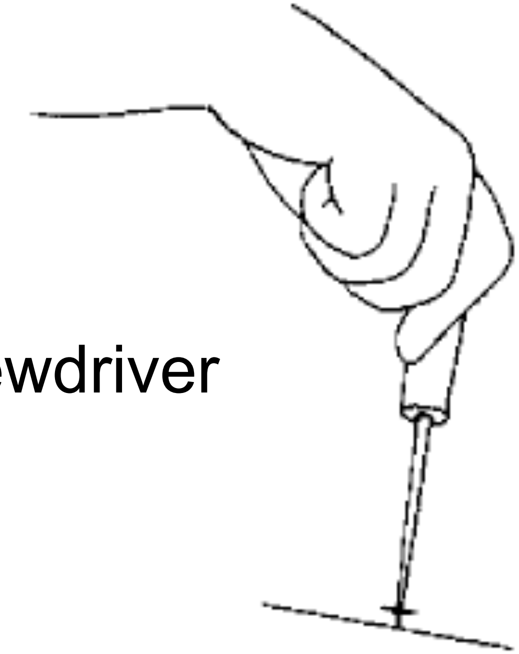
HUMAN ROBOTICS

- 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

LEARNING AND STABILITY

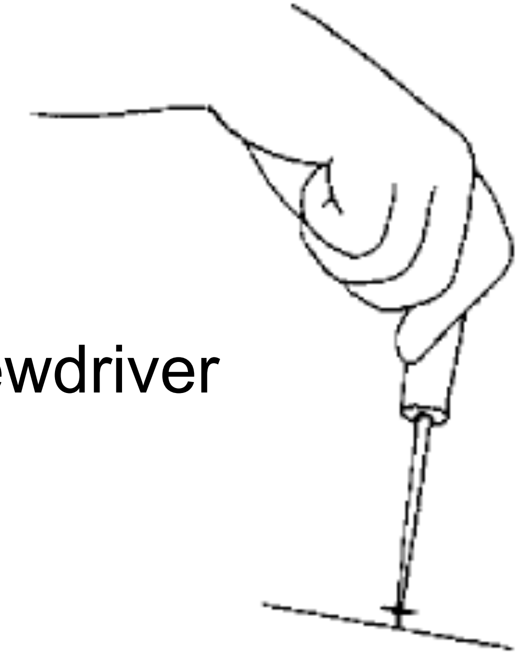


screwdriver

chiseling, carving

- we constantly need to learn new tasks and adapt to changing conditions, e.g. during infancy or with ageing
- many tasks using tools are unstable
- instability: motor variability or environmental disturbances can lead to large error and unpredictability

LEARNING AND STABILITY



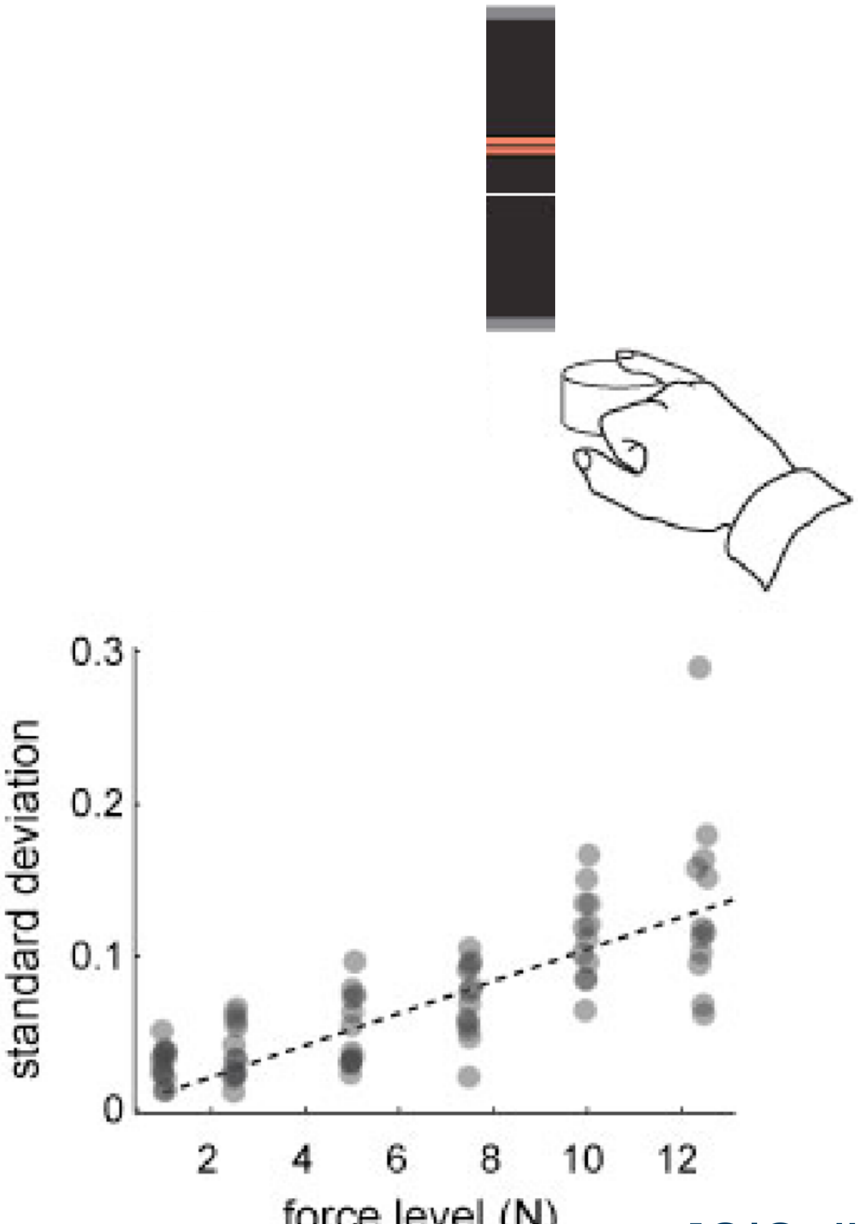
screwdriver

chiseling, carving

- stability means repeatability and reliability
- this is required by the brain to plan actions
- the CNS has to compensate for the environment forces and instability

[Burdet et al. Biological Cybernetics 2006]

NOISE INCREASES WITH FORCE

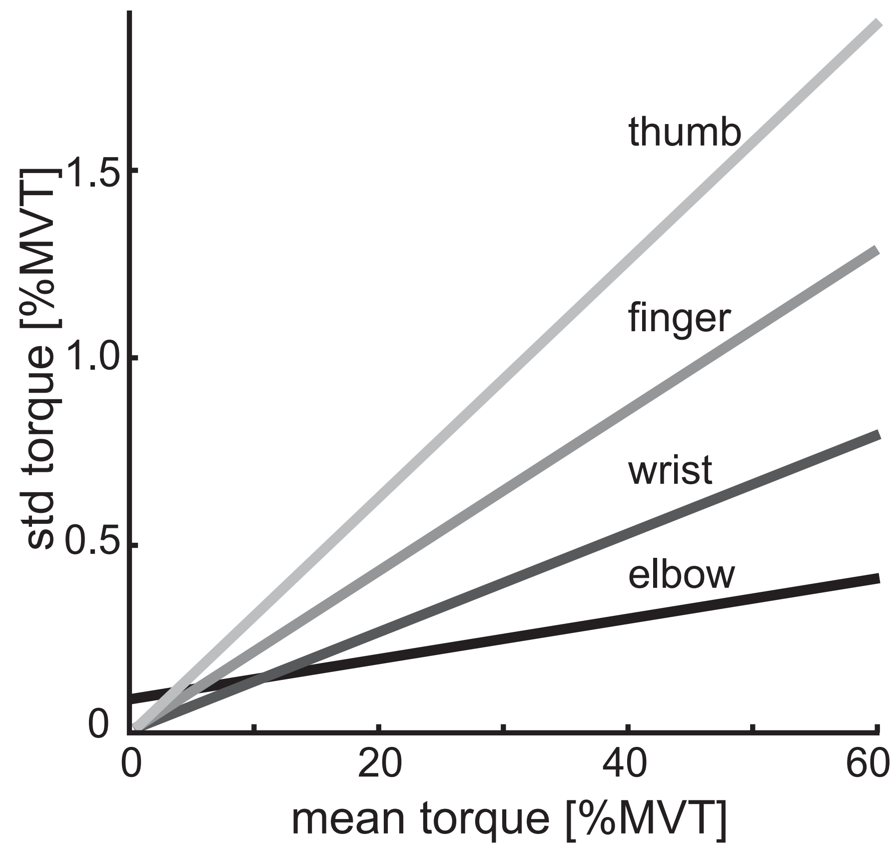


- finger presses on force sensor
- force controlled over visual feedback
- noise standard deviation increases linearly with the applied force

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

NOISE INCREASES WITH FORCE

- noise standard deviation increases linearly with the applied torque
- torque deviation magnitude is higher for smaller muscles



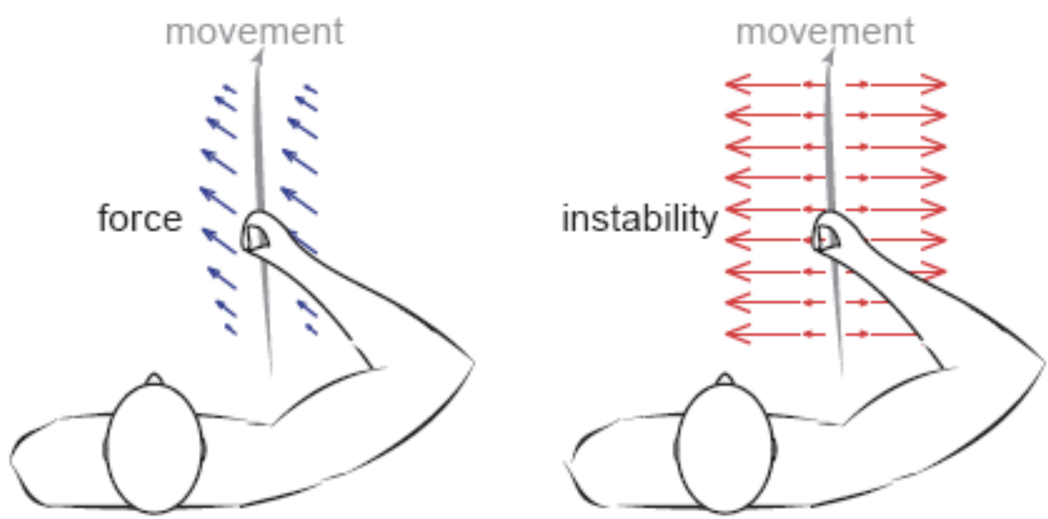
[Hamilton et al. J Neurophysiology 2004]

NOISE AND STABILITY

- velocity dependent force field (VF):

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

- divergent position dependent force field (DF): $\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} 450\,x \\ 0 \end{bmatrix}$



- BE in DF are unpredictable -> unstable?
- how to define (un)stable? is VF unstable?

[Burdet et al. Biological Cybernetics 2006]

NOISE AND STABILITY

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

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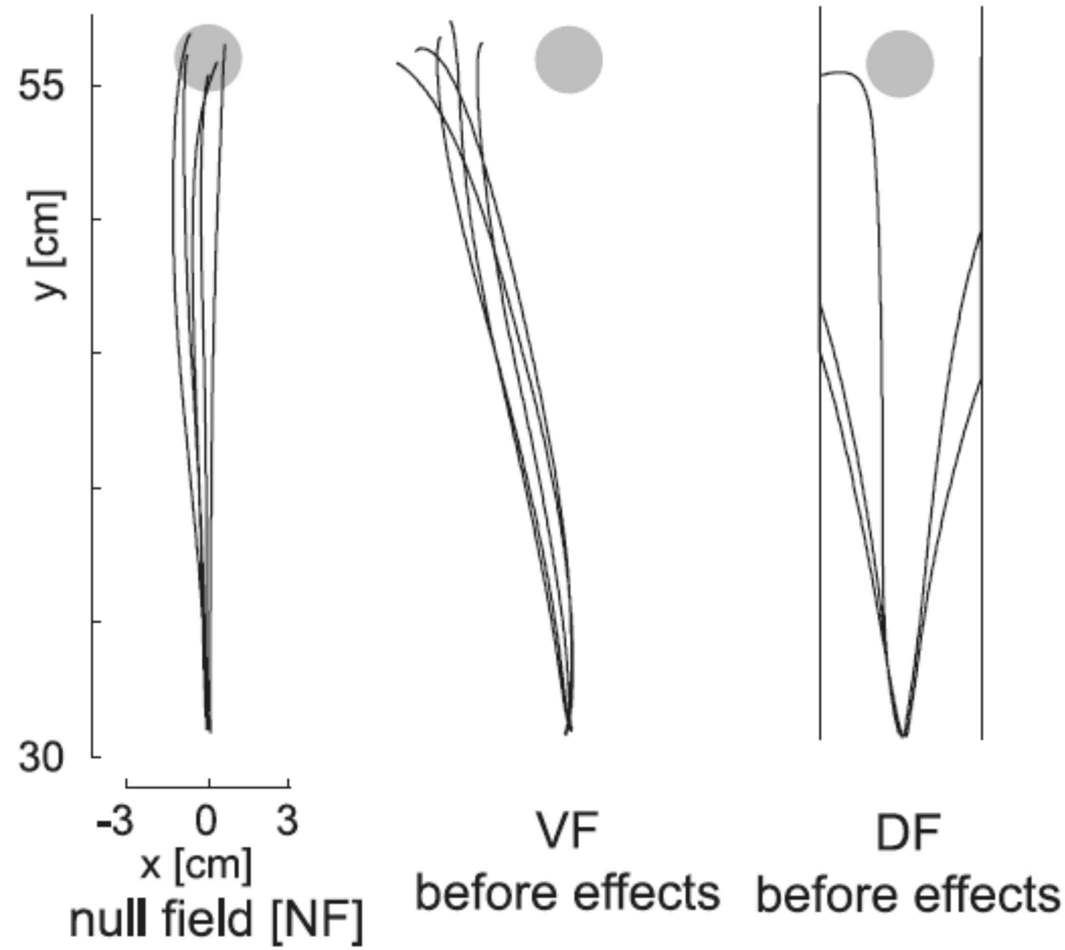
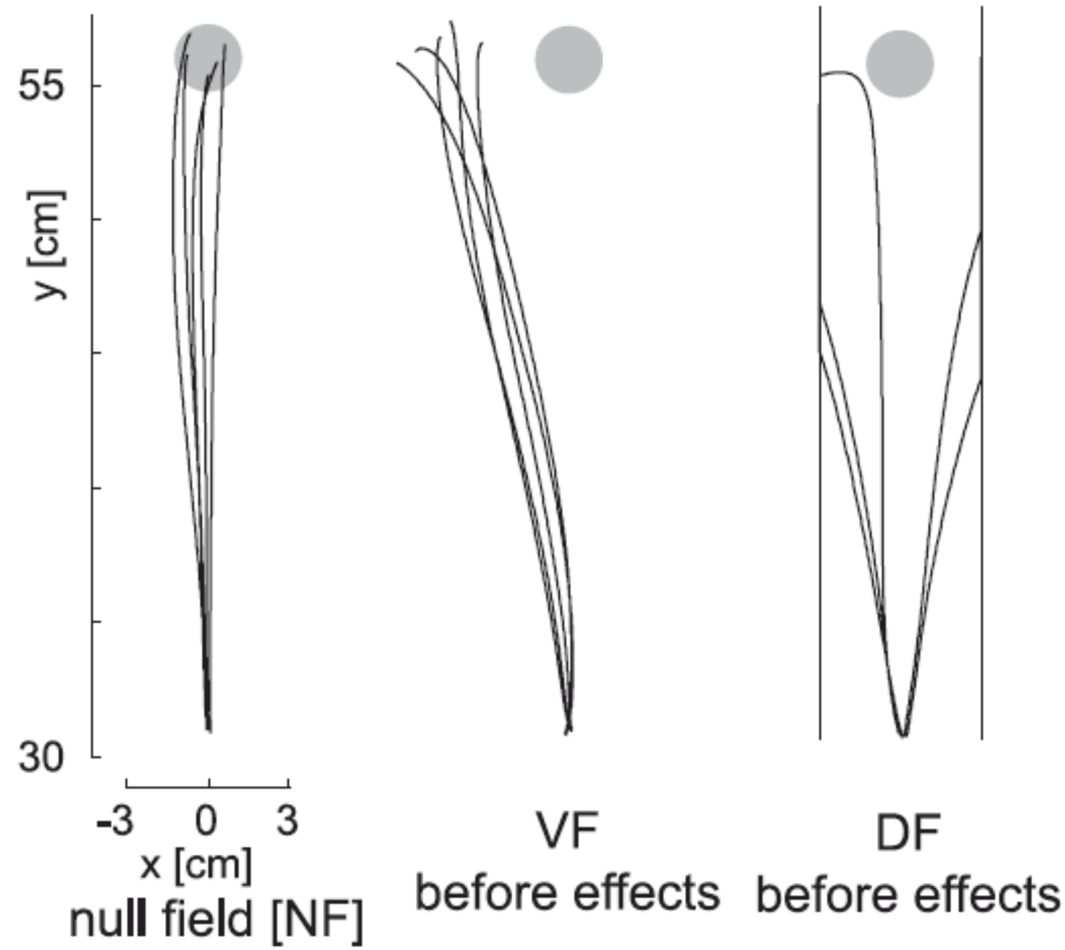


- BE in DF are unpredictable -> unstable?
- how to define (un)stable? is VF unstable?

[Burdet et al. Biological Cybernetics 2006]

NOISE AND STABILITY

- in NF, movements have large variability but remain close to the straight line, even after a perturbation
- stability: similar mean deviation as in NF
- DF trials are unstable

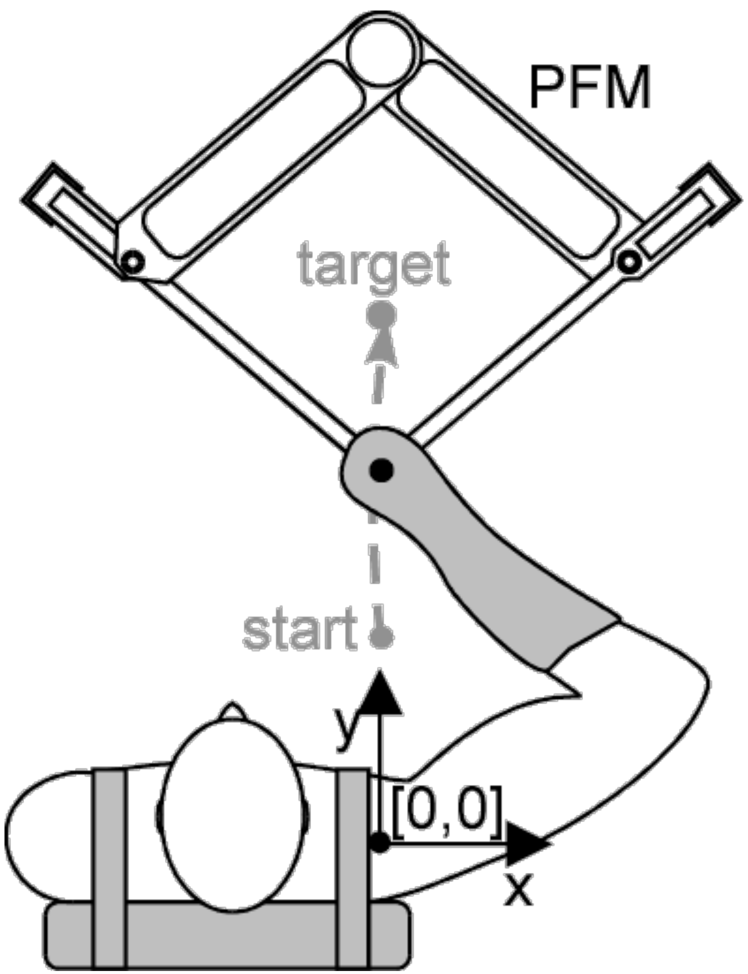


- VF trials are stable and predictable, though not joining the target straight

[Burdet et al. Biological Cybernetics 2006]

TO INVESTIGATE UNSTABLE INTERACTIONS

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

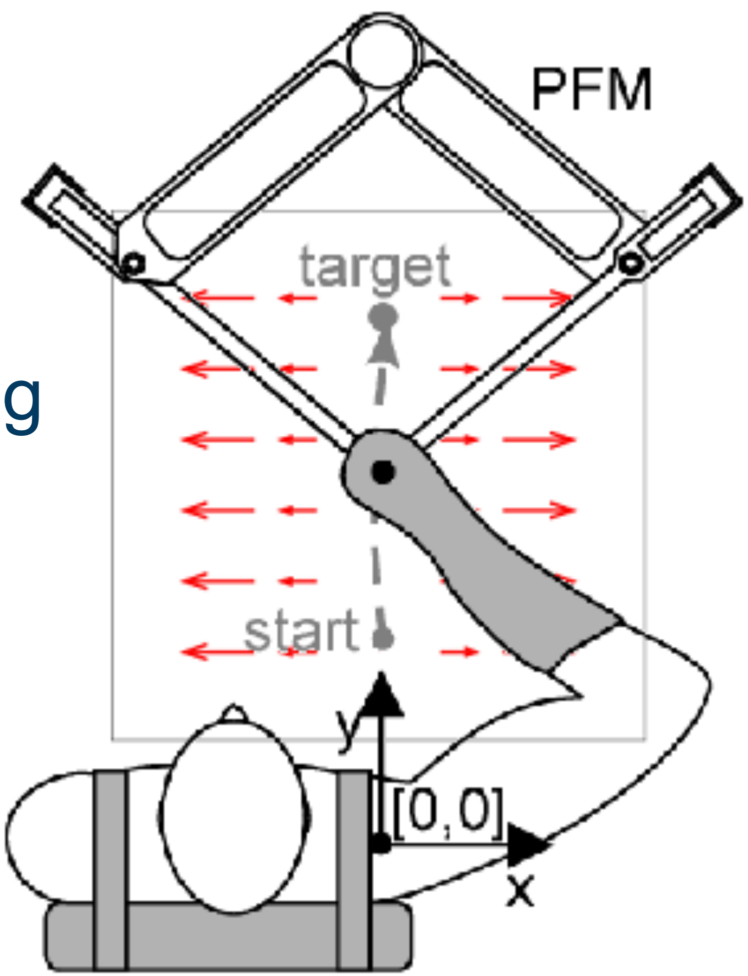


TO INVESTIGATE UNSTABLE INTERACTIONS

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

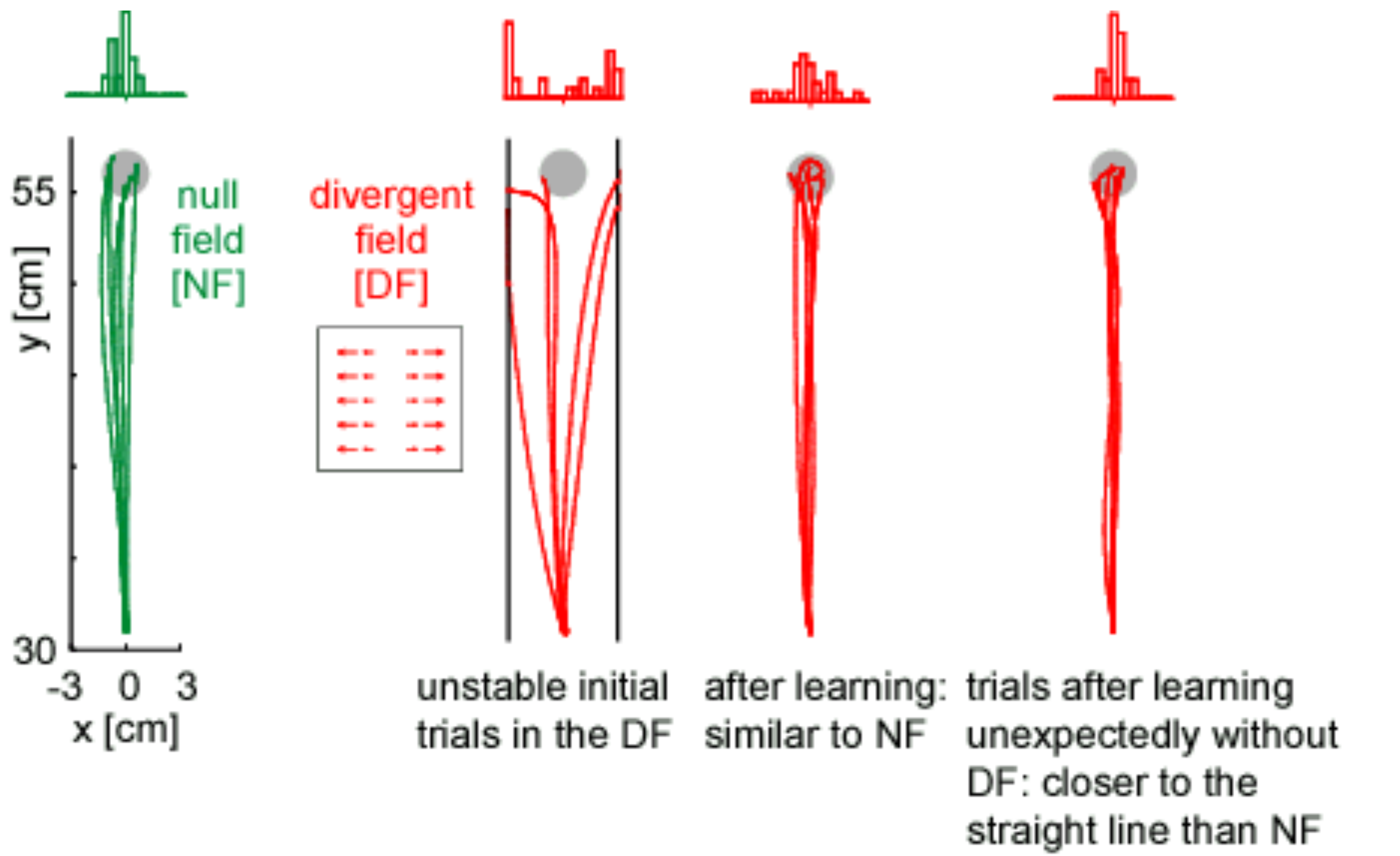
• forces diverting

to left



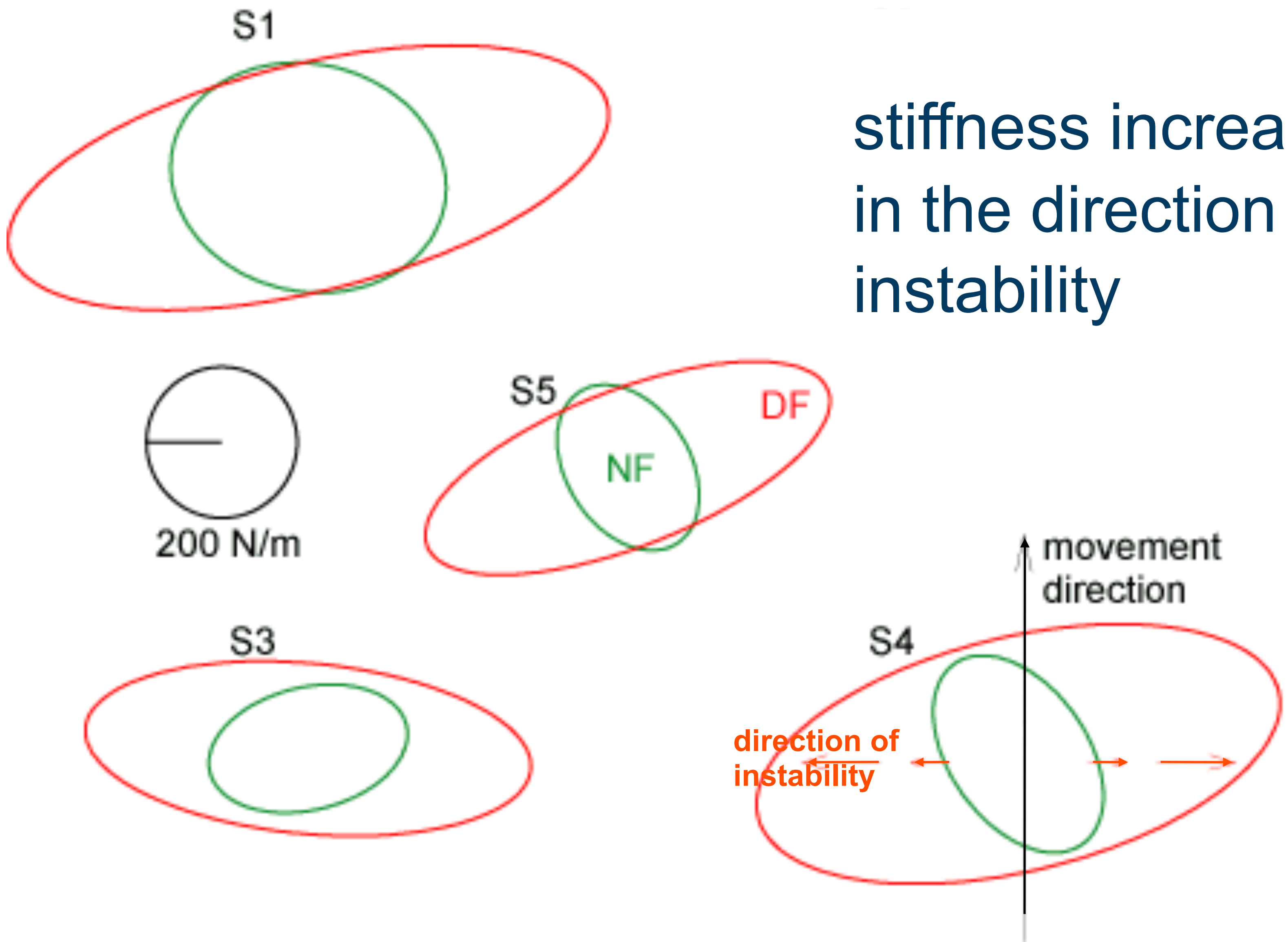
or to right

LEARNING PATTERNS



[Burdet et al., Nature 2001]

STIFFNESS BEFORE AND AFTER LEARNING THE INSTABILITY



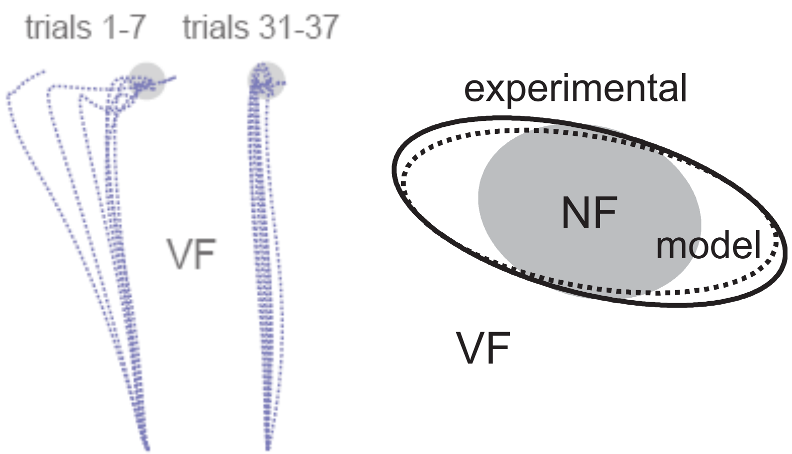
stiffness increases in the direction of instability

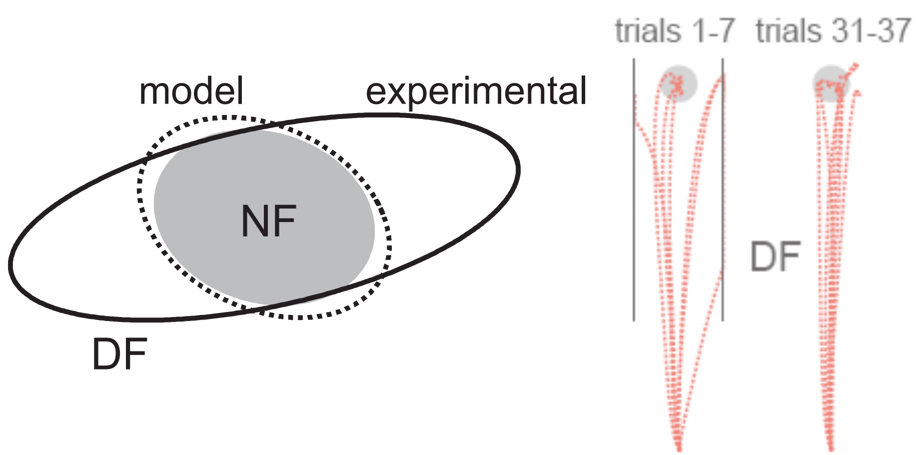
[Burdet et al., Nature 2001]

DF ADAPTATION IS NOT DUE TO FORCE

stable interaction

unstable interaction



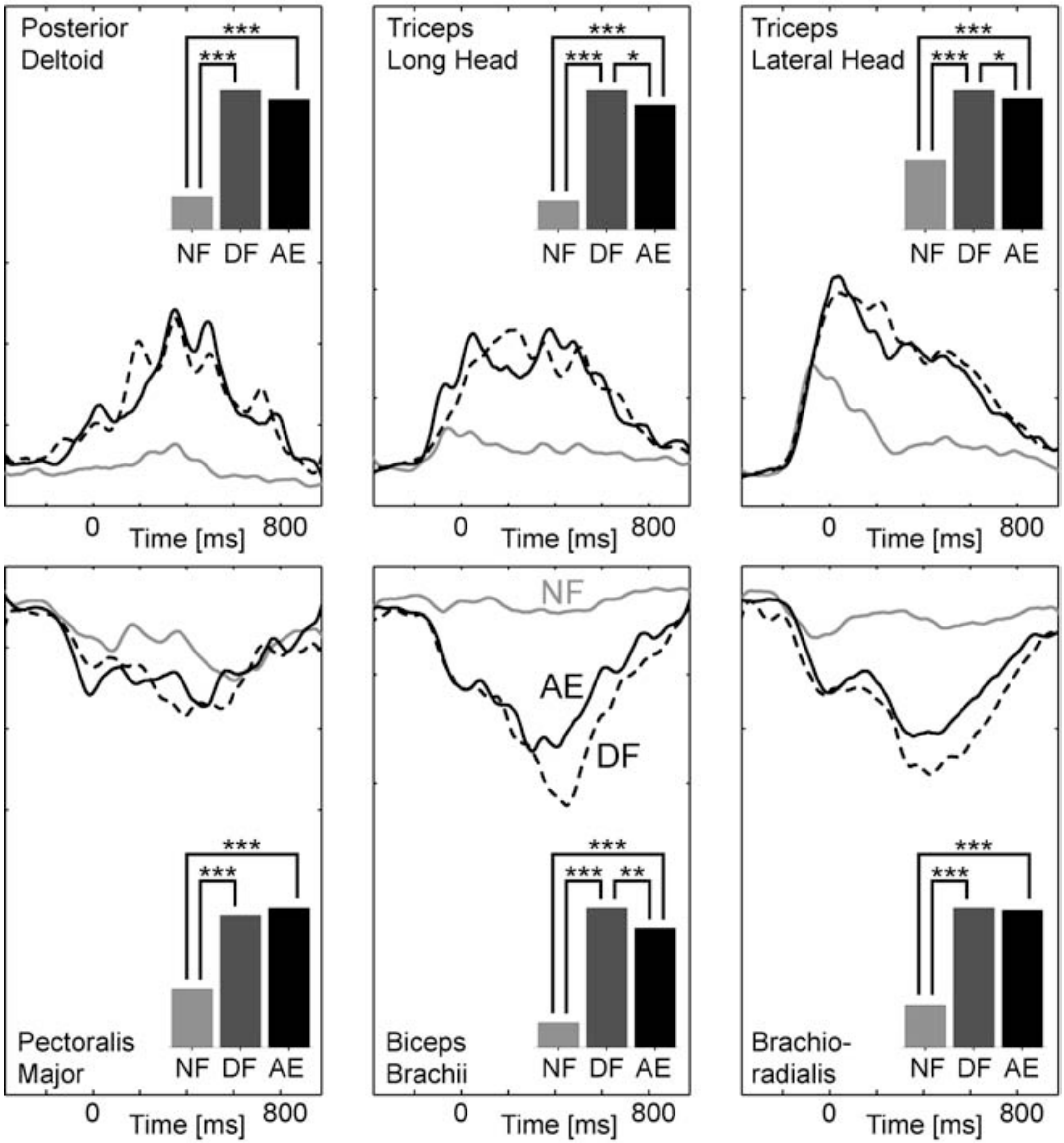


$$\mathbf{K} = \begin{pmatrix} 10.8 + 3.18|\tau_s| & 2.83 + 2.15|\tau_e| \\ 2.51 + 2.34|\tau_e| & 8.67 + 6.18|\tau_e| \end{pmatrix} \frac{Nm}{rad}$$

- in a stable interaction, stiffness scale linearly with the torque magnitude
- this does not explain the adaptation to unstable dynamics

[Franklin et al., Experimental Brain Research 2003]

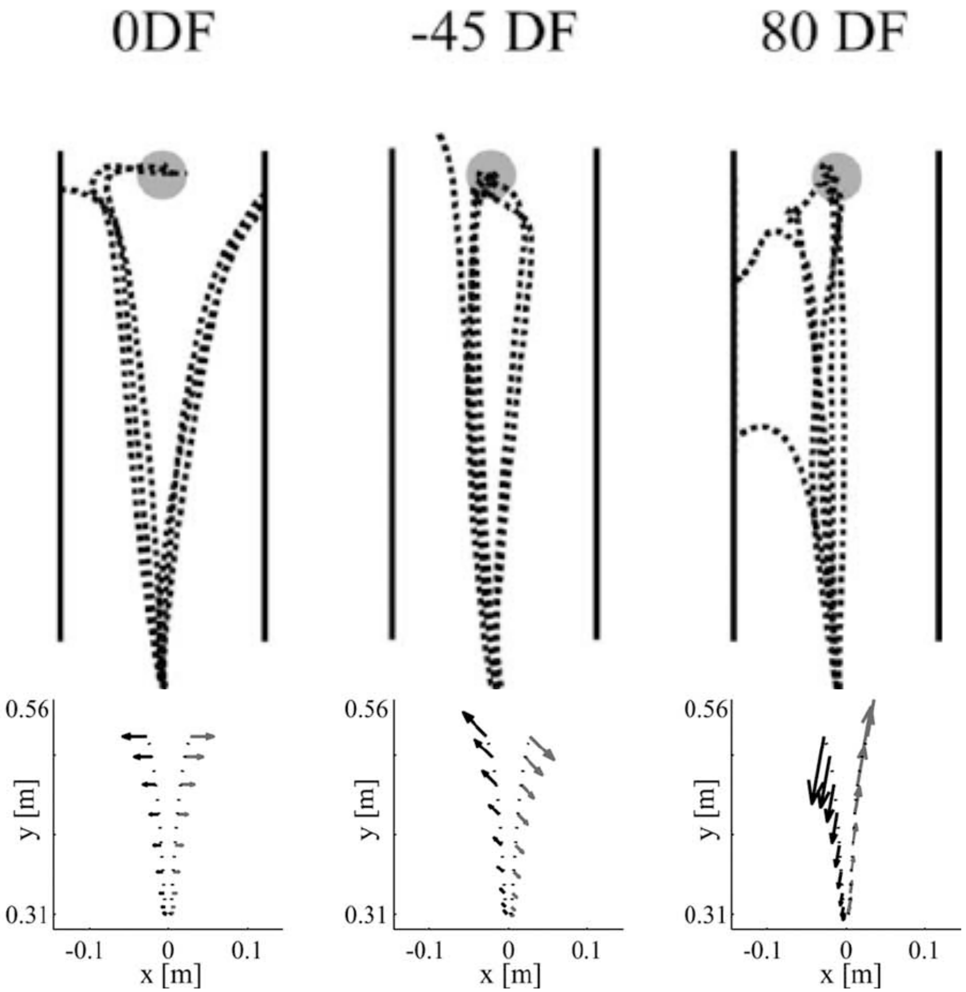
IMPEDANCE FEEDFORWARD



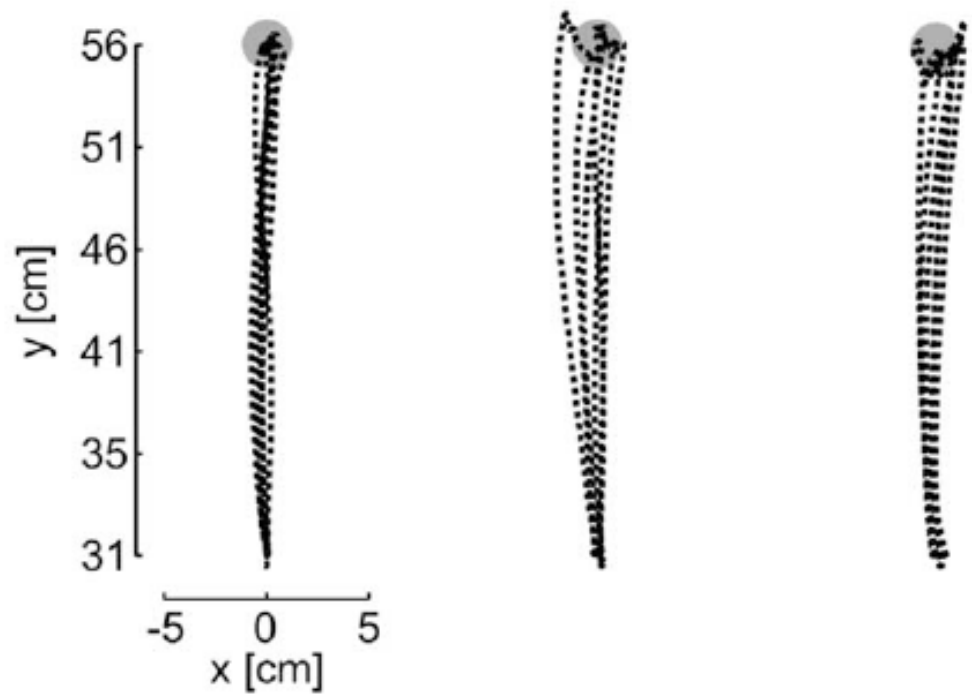
- co-contraction in after-effects trials is similar as at the end of the learning
- this indicates that a feedforward has been formed to compensate for the environment instability

[Franklin et al., Experimental Brain Research 2003]

DIRECTION SELECTIVE STIFFNESS?



after learning



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

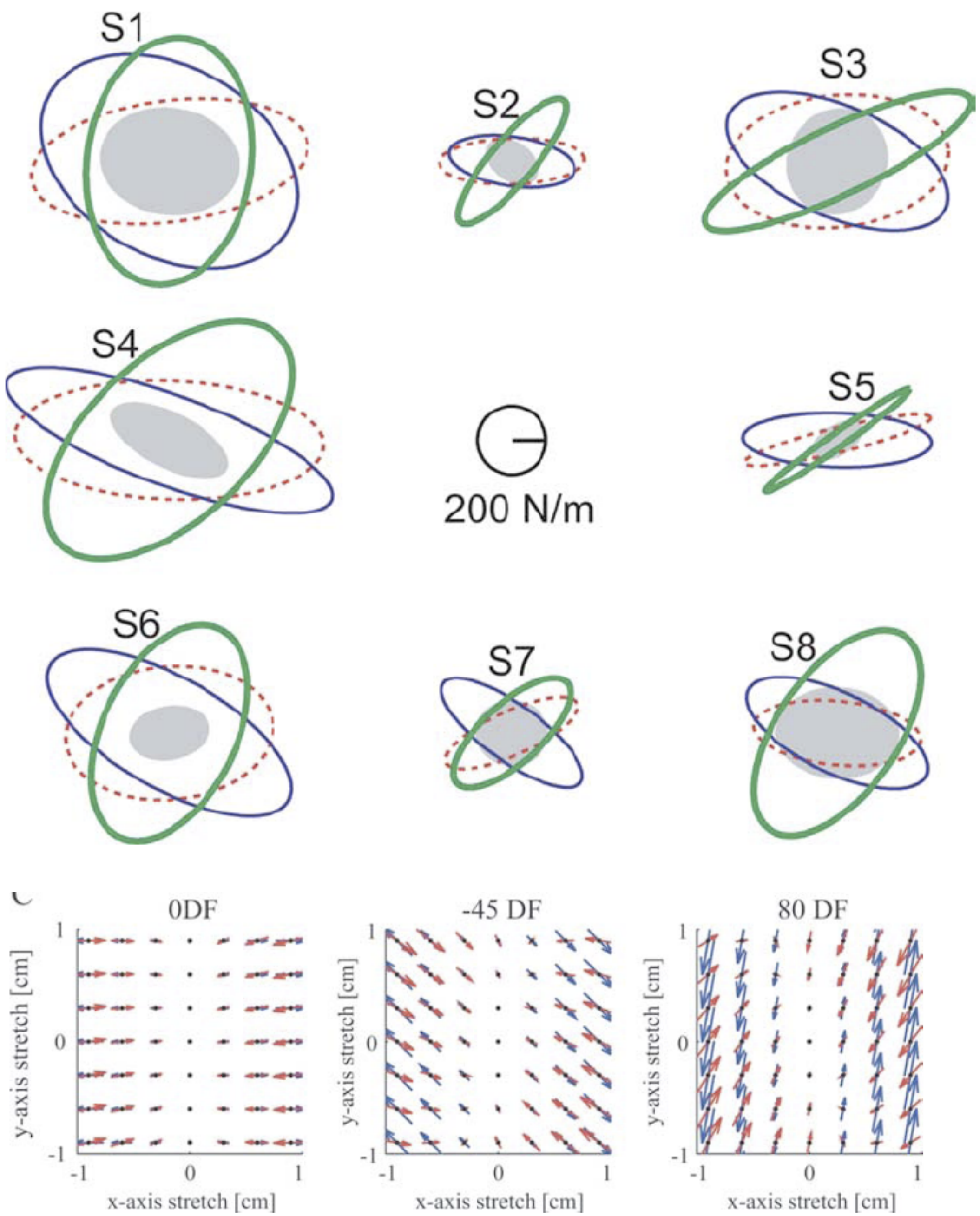
$$\theta = \{-45^o, 0^o, 80^o\}$$

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

the CNS can learn to move successfully with instability in various directions

[Franklin et al., J of Neuroscience 2007]

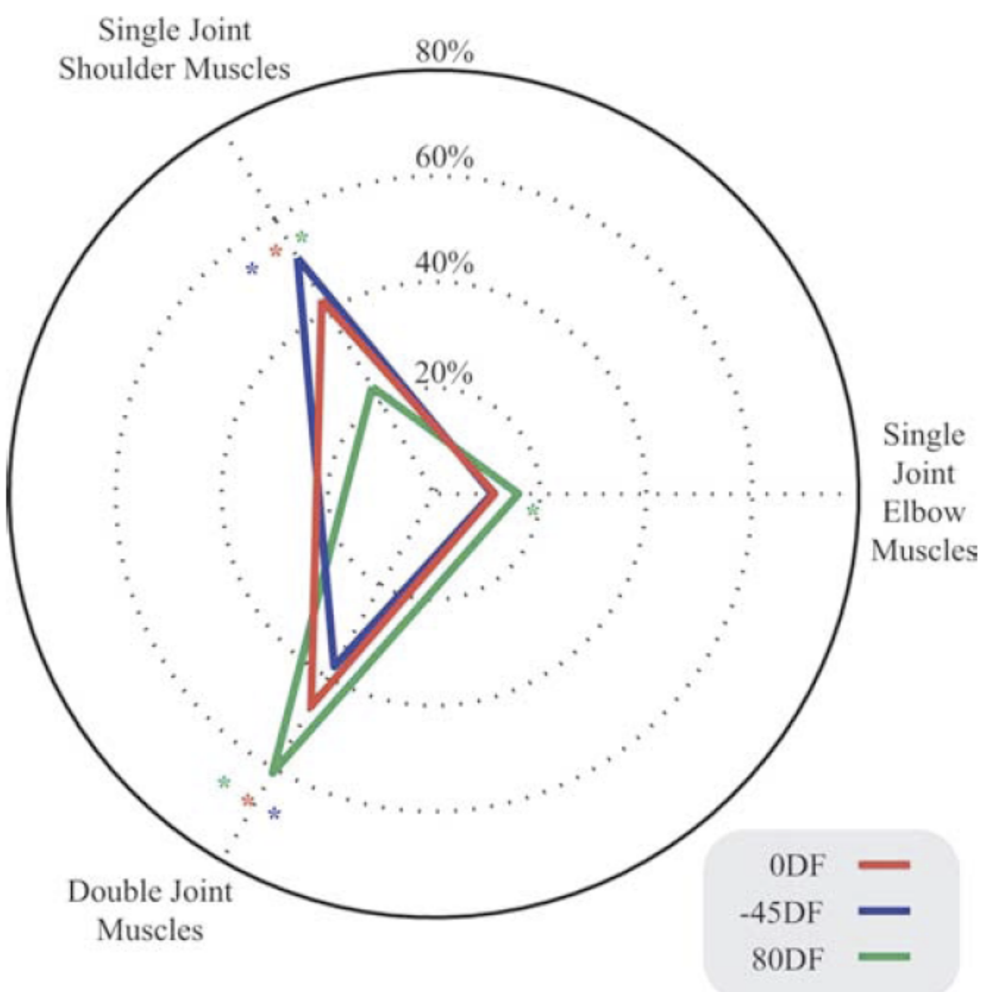
DIRECTION SELECTIVE STIFFNESS



- the CNS can move successfully in environments with instability in various directions
- by learning to compensate for the instability

[Franklin et al., J of Neuroscience 2007]

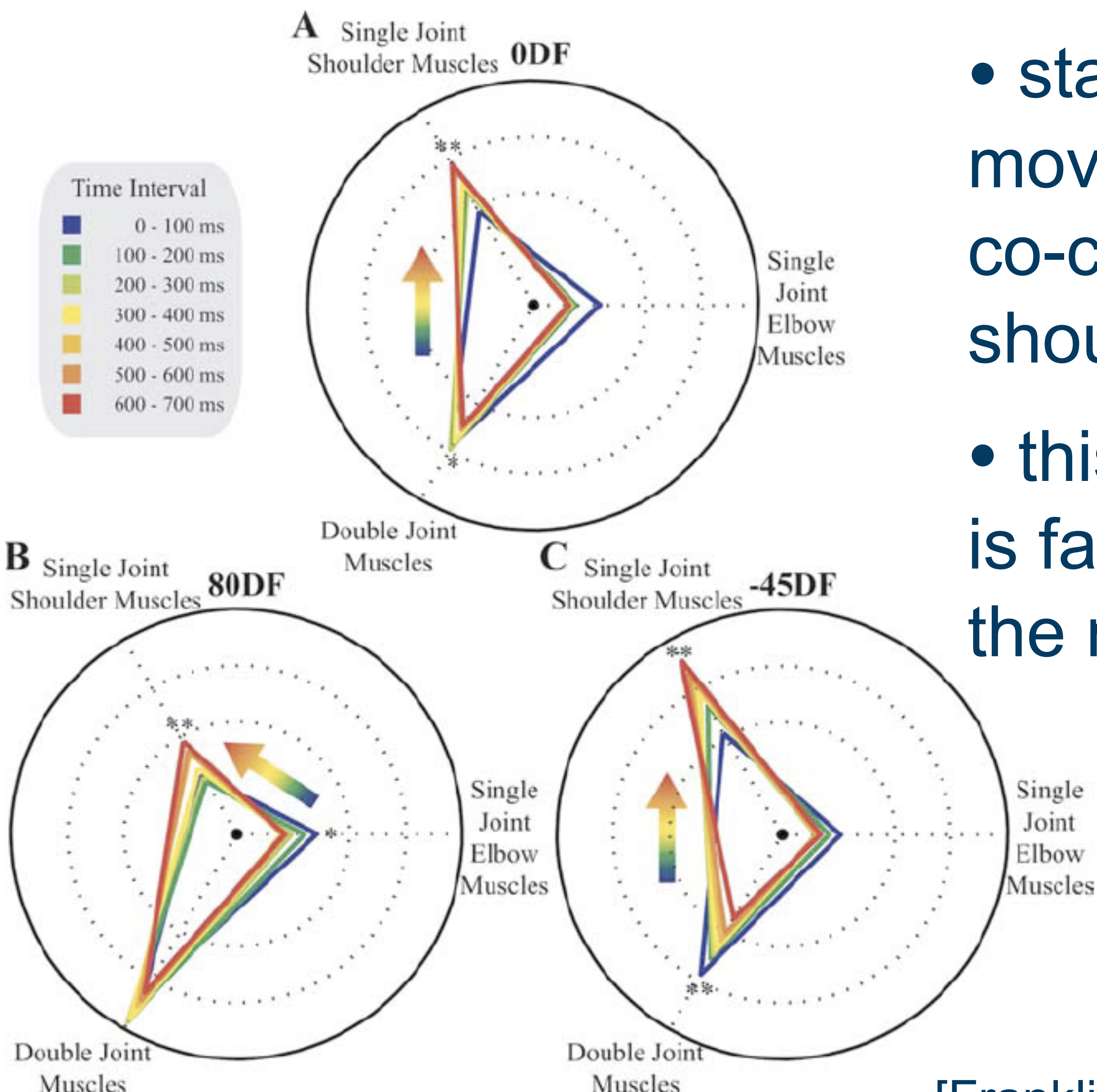
MUSCLES ARE COORDINATED TO COMPENSATE FOR INSTABILITY (1)



- stabilisation normal to the -45° and 0° directions requires co-contracting the shoulder muscles
- stabilisation normal to the 80° is provided by the biarticular and elbow muscles
- this is consistent with the arm geometry

[Franklin et al., J of Neuroscience 2007]

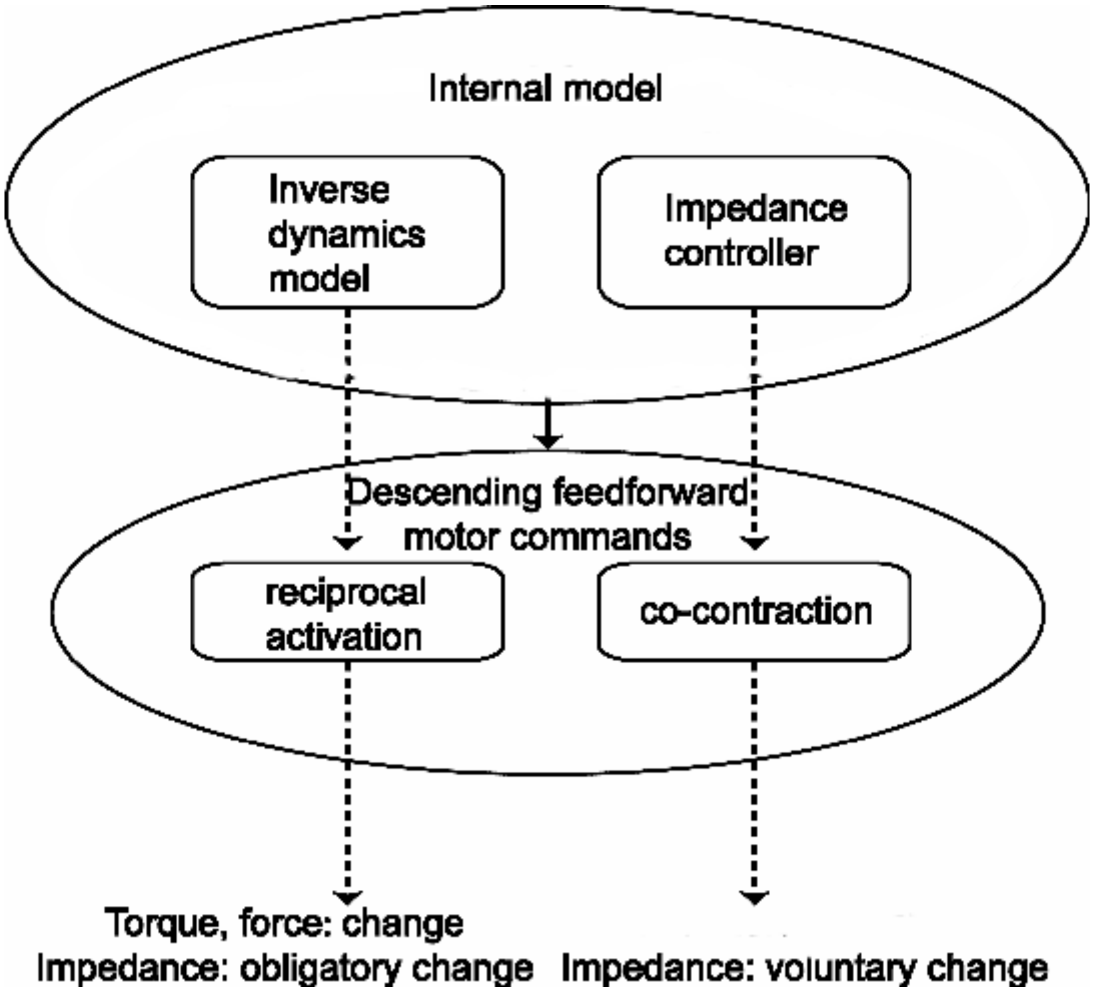
MUSCLES ARE COORDINATED TO COMPENSATE FOR INSTABILITY (2)



- stabilization around the movement end requires co-contracting the shoulder muscles
- this is because the hand is far from the shoulder, so the moment arm is longer

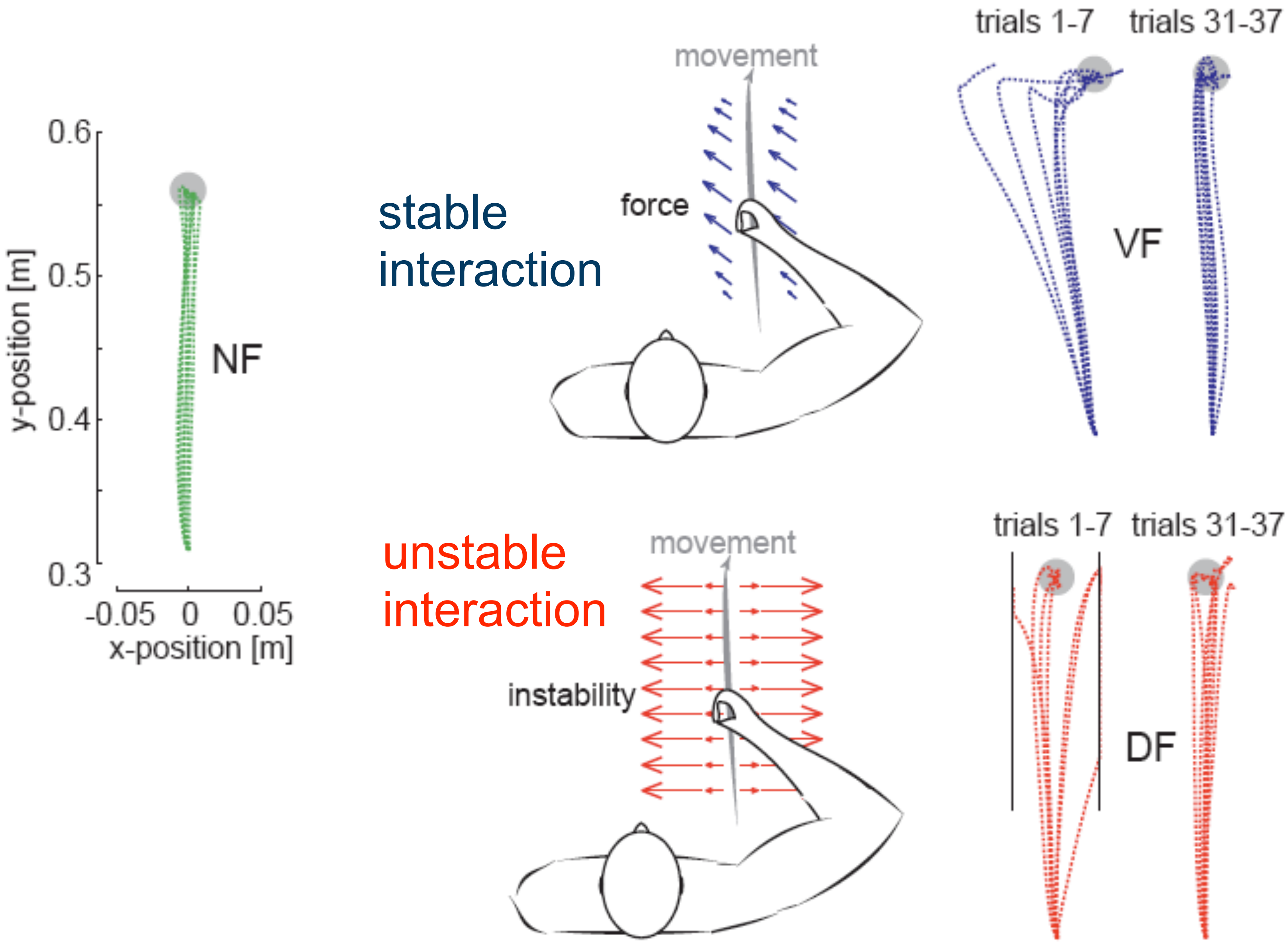
[Franklin et al., J of Neuroscience 2007]

FEEDFORWARD MODEL TO COMPENSATE ENVIRONMENT FORCE AND INSTABILITY?

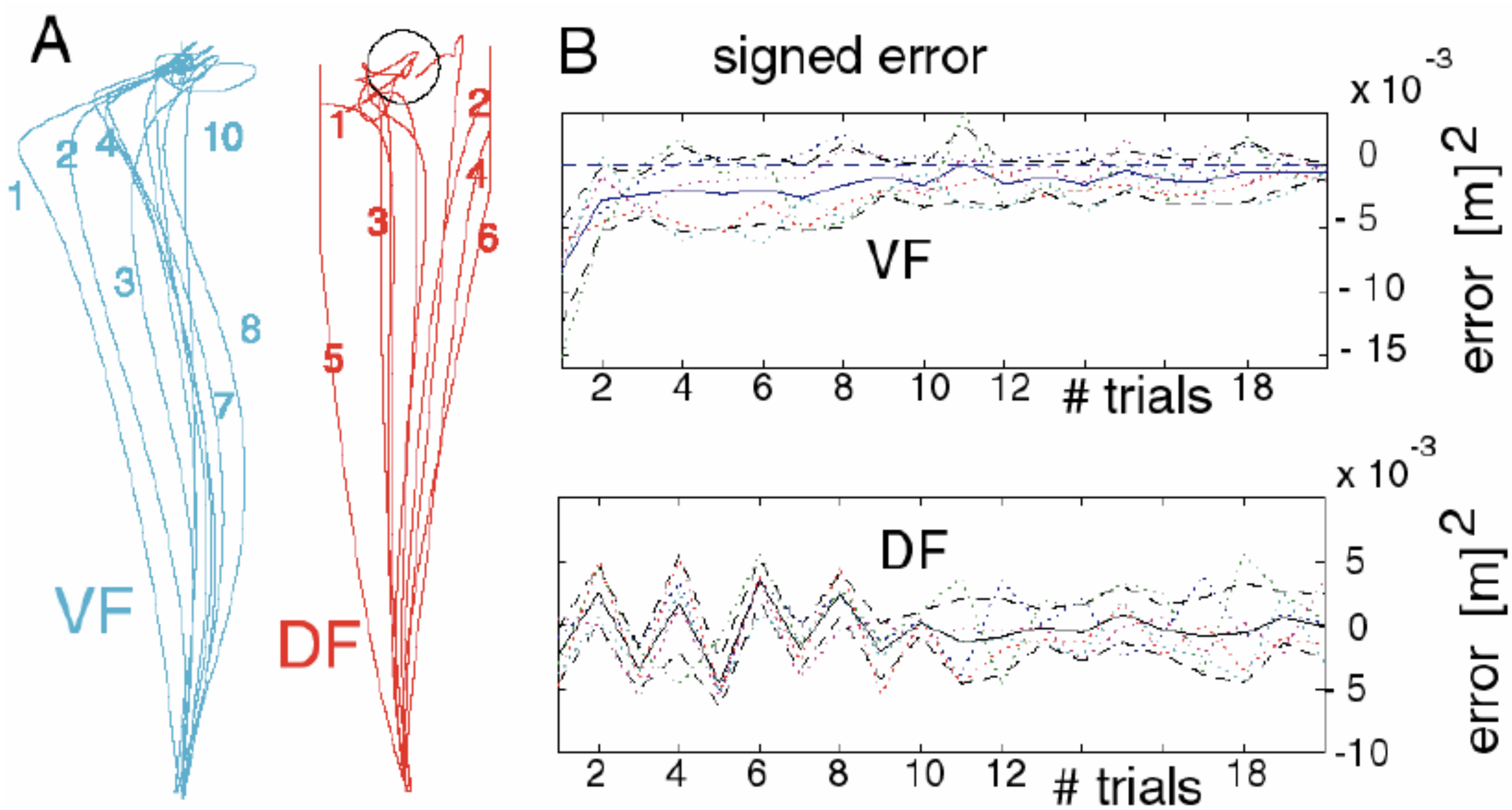


- what are the mechanisms of the adaptation to stable and unstable dynamics?
- develop a computational model consistent with measured data (hand position, force, EMG)

TO UNDERSTANDING LEARNING IN STABLE AND UNSTABLE DYNAMICS



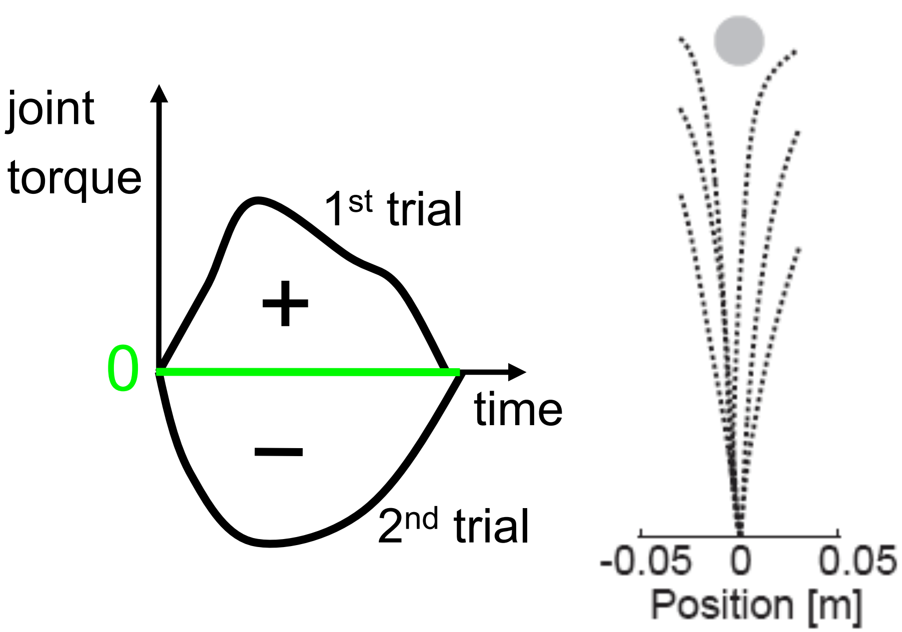
ITERATIVE LEARNING IN STABLE AND UNSTABLE DYNAMICS



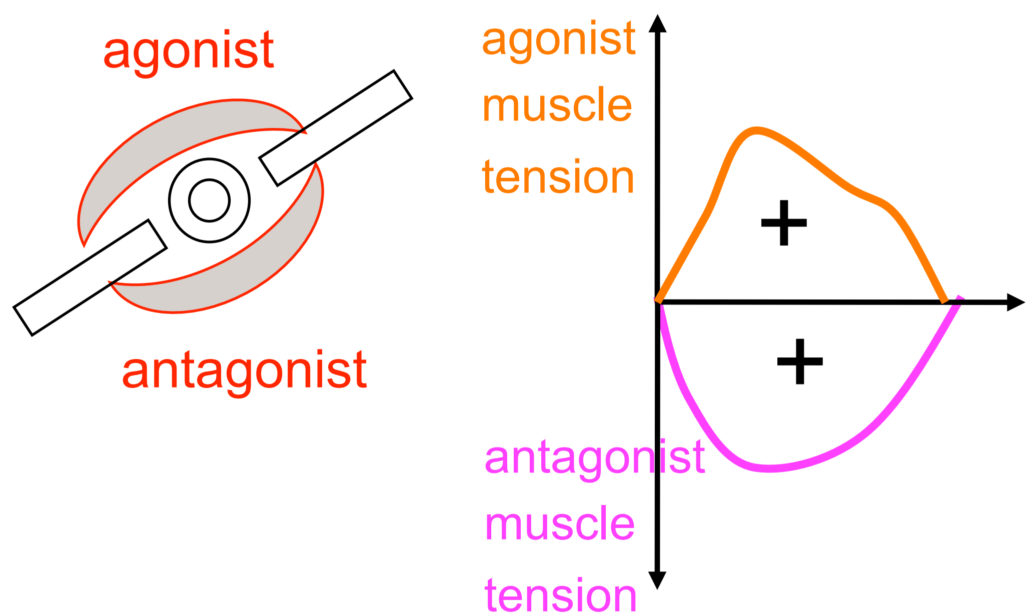
the controller tends to minimize the kinematic error experienced in the previous trial

JOINT VERSUS MUSCLE SPACE ADAPTATION IN UNSTABLE DYNAMICS

adapting feedforward by compensating for the kinematic error in the previous trial

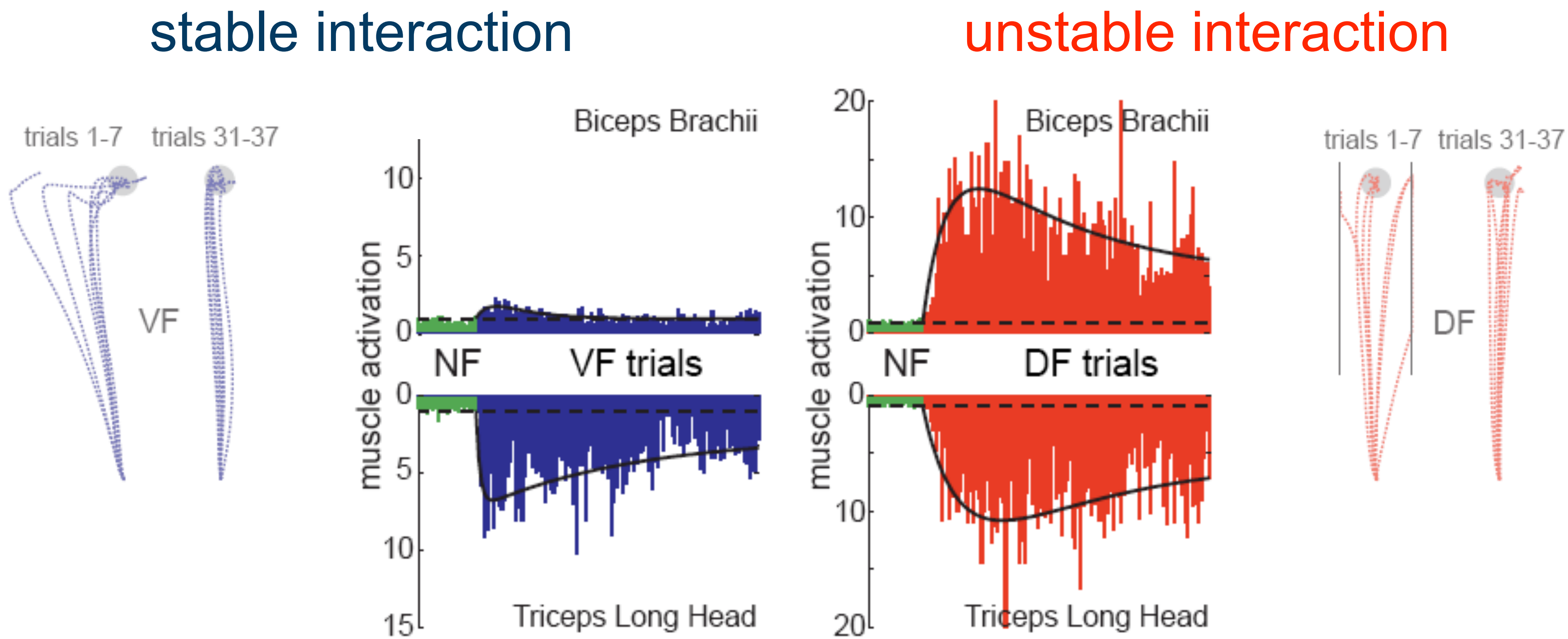


joint space adaptation does not succeed in unstable dynamics



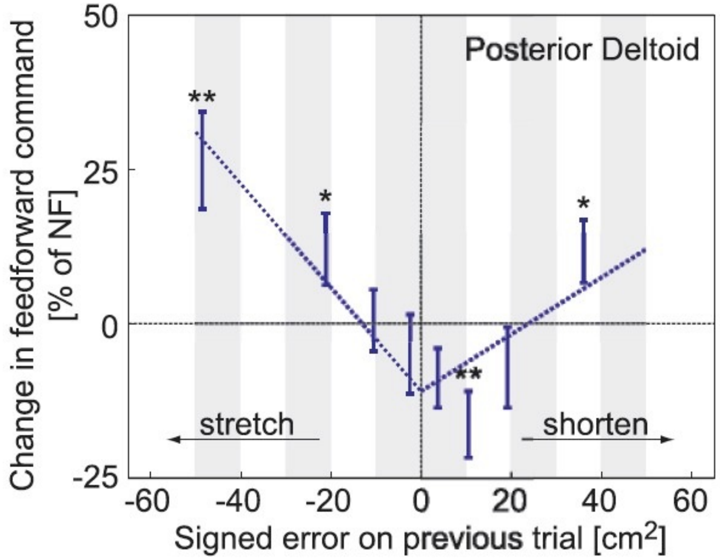
muscle space adaptation can build up co-contraction and so increase stability

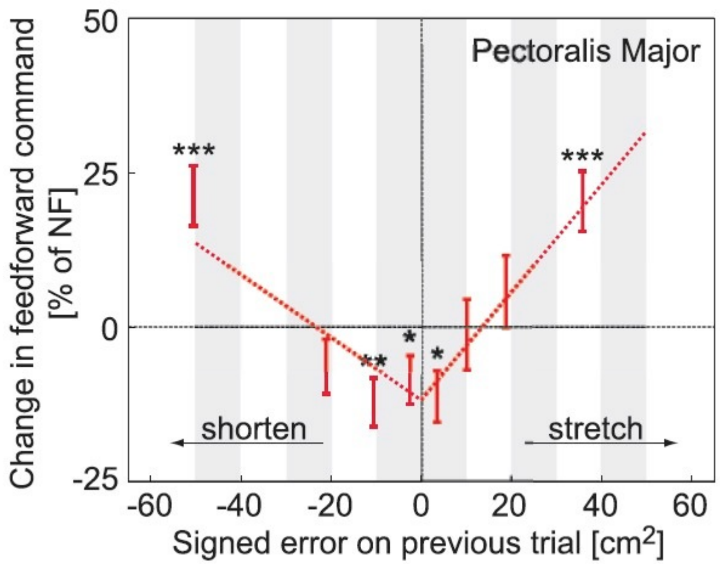
MUSCLE LEVEL ADAPTATION

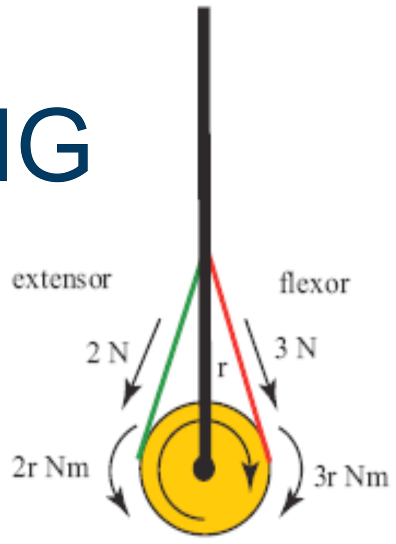


- overall reduction of muscle activation
- increase in the agonist and antagonist in response to stretch in the agonist

PRINCIPLES OF MOTOR LEARNING



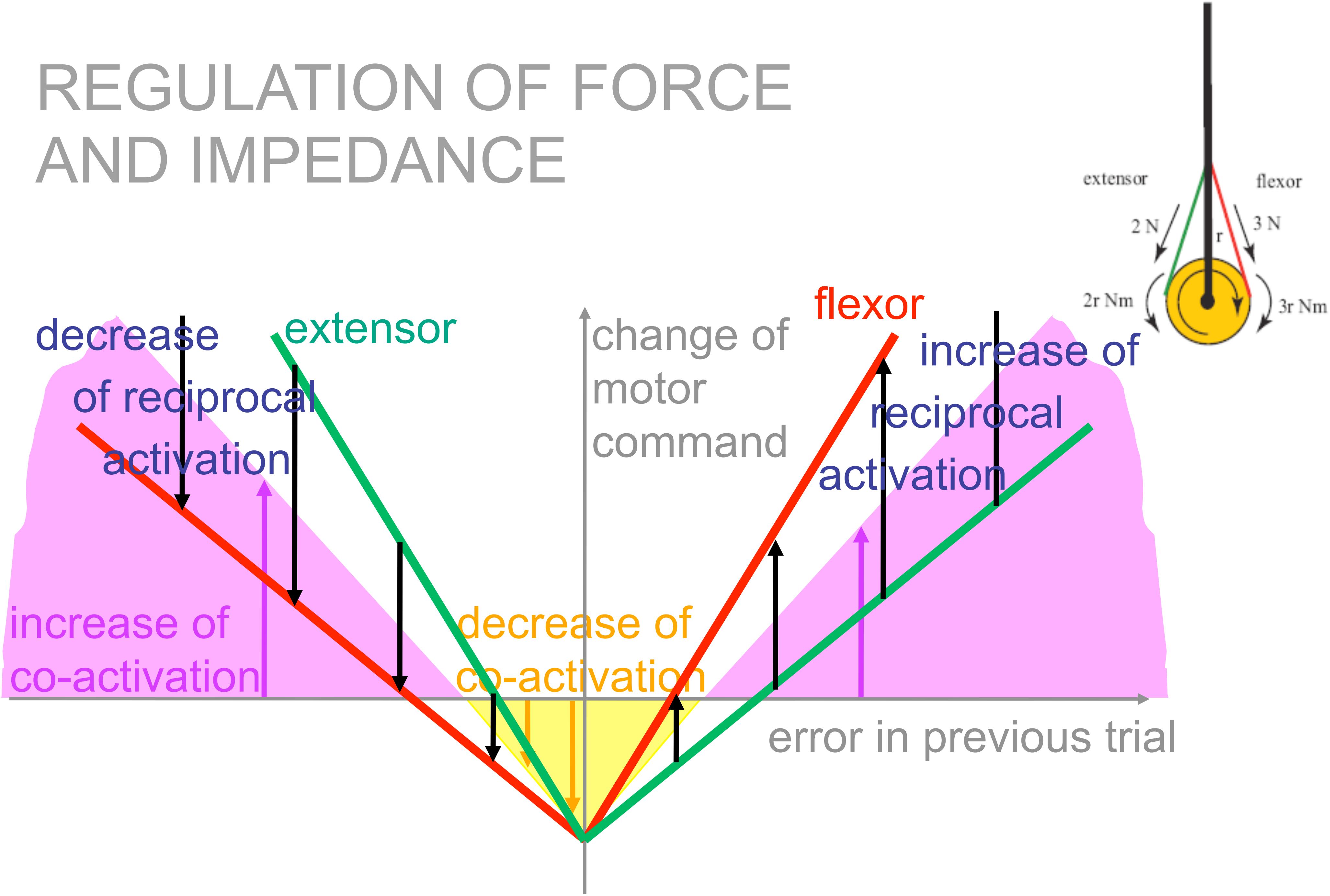




- learning in a muscle space
- feedforward increases with the muscle stretch in previous trial
- it also increases with antagonist muscle stretch
- and decreases when the error is small

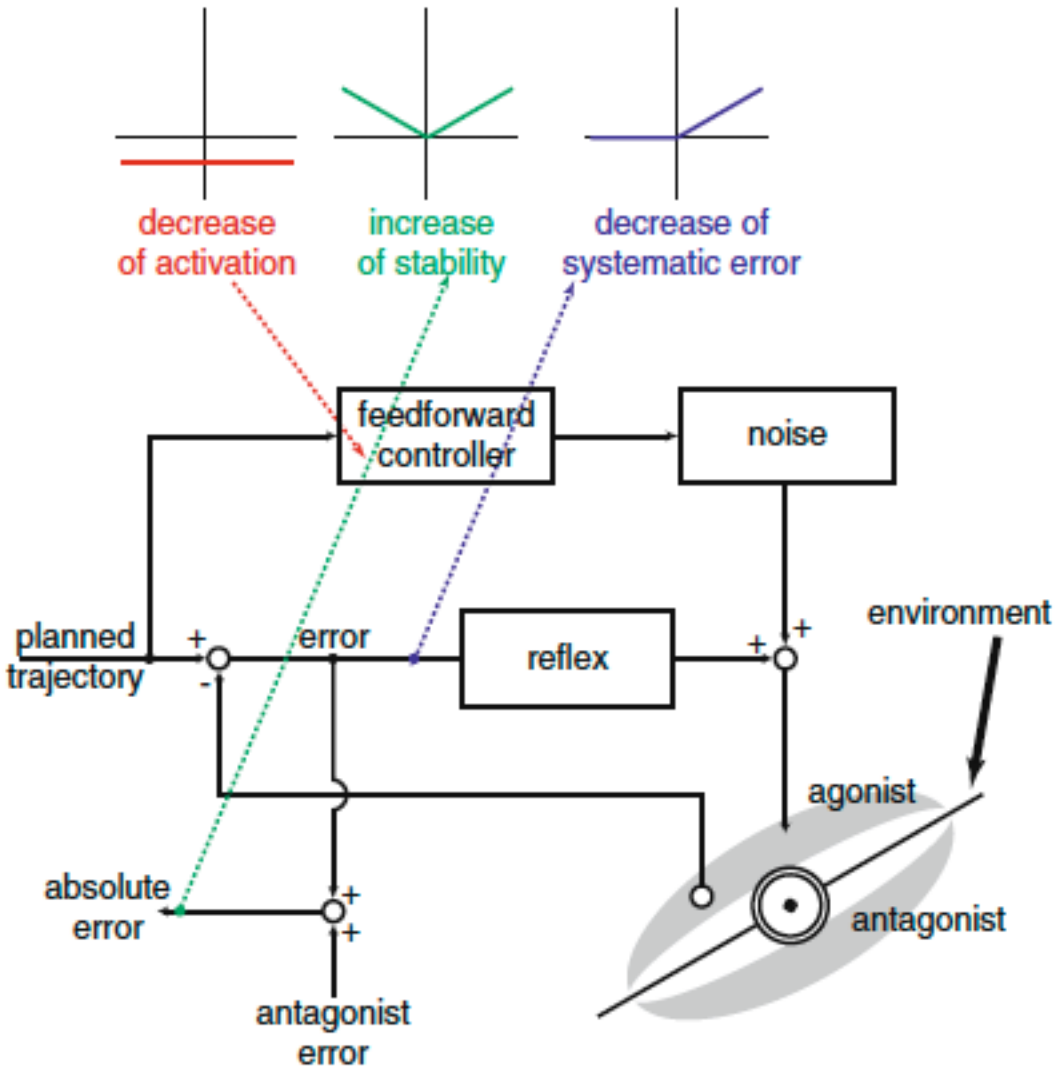
[Franklin et al. J Neuroscience 2008]

REGULATION OF FORCE AND IMPEDANCE



[Franklin et al. J Neuroscience 2008]

CONTROL DIAGRAM

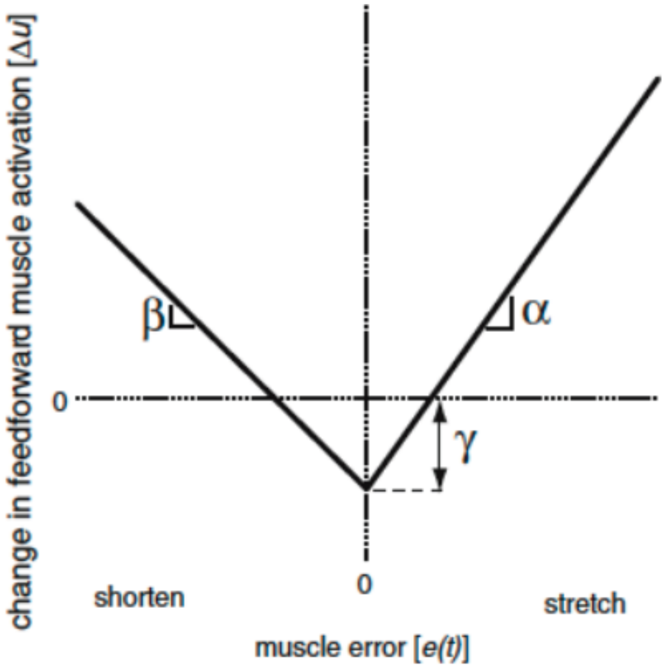


- signal dependent noise
- stiffness and damping increase with activation
- delayed feedback

[Tee et al., Biological Cybernetics 2010]

LEARNING LAW

- motor command $\mathbf{v} = (v_1 \ldots v_M)^T$ is composed of feedforward and feedback: $\mathbf{v} = \mathbf{u} + \mathbf{u}_{\mathrm{FB}}$
- in each muscle i feedforward u^k_i is updated from trial k to $k+1$ by:



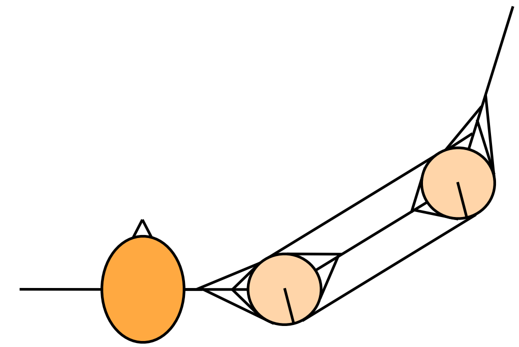
$$
\begin{aligned}
u_i^{k+1}(t) &\equiv \left[u_i^k(t) + \triangle u_i^k(t+\phi)\right]_+ , \quad [\cdot]_+ \equiv \max\{\cdot, 0\} \\
\triangle u_i^k(t) &= \alpha\varepsilon_{i,+}(t) + \beta\varepsilon_{i,-}(t) - \gamma \,, \; [\cdot]_- \equiv [-\cdot]_+ \qquad (2) \\
\varepsilon_i(t) &= e_i(t) + g_d\, \dot{e}_i(t) \,, \; \alpha > \beta > 0, \; \gamma, g_d > 0 \,,
\end{aligned}
$$

$e_i(t)$: stretch/shortening in muscle i at time t

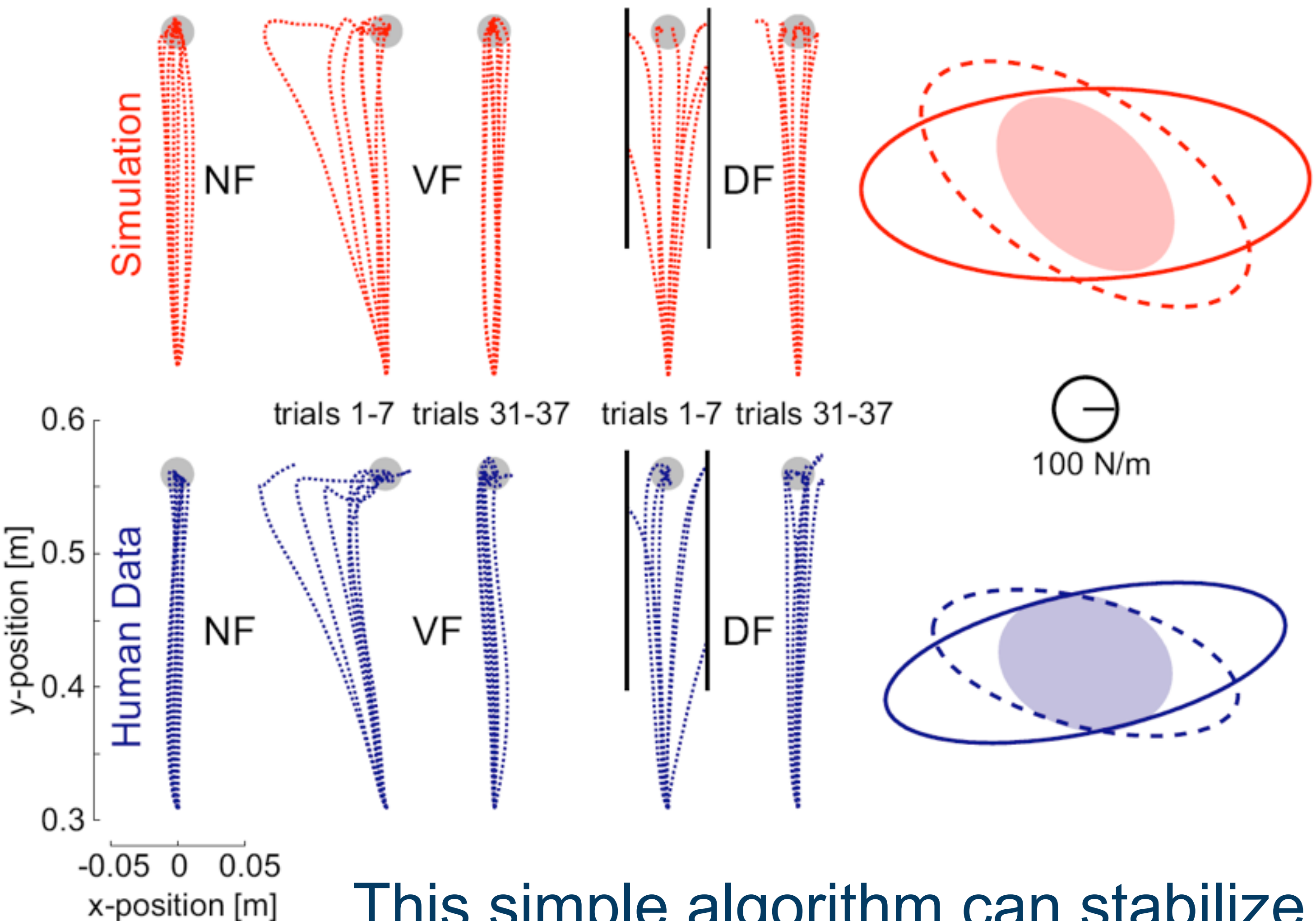
Δu is phase advanced by ϕ= feedback delay

[Tee et al., Biological Cybernetics 2010]

COMPUTATIONAL MODEL



simulation with a 2-joint 6-muscles model

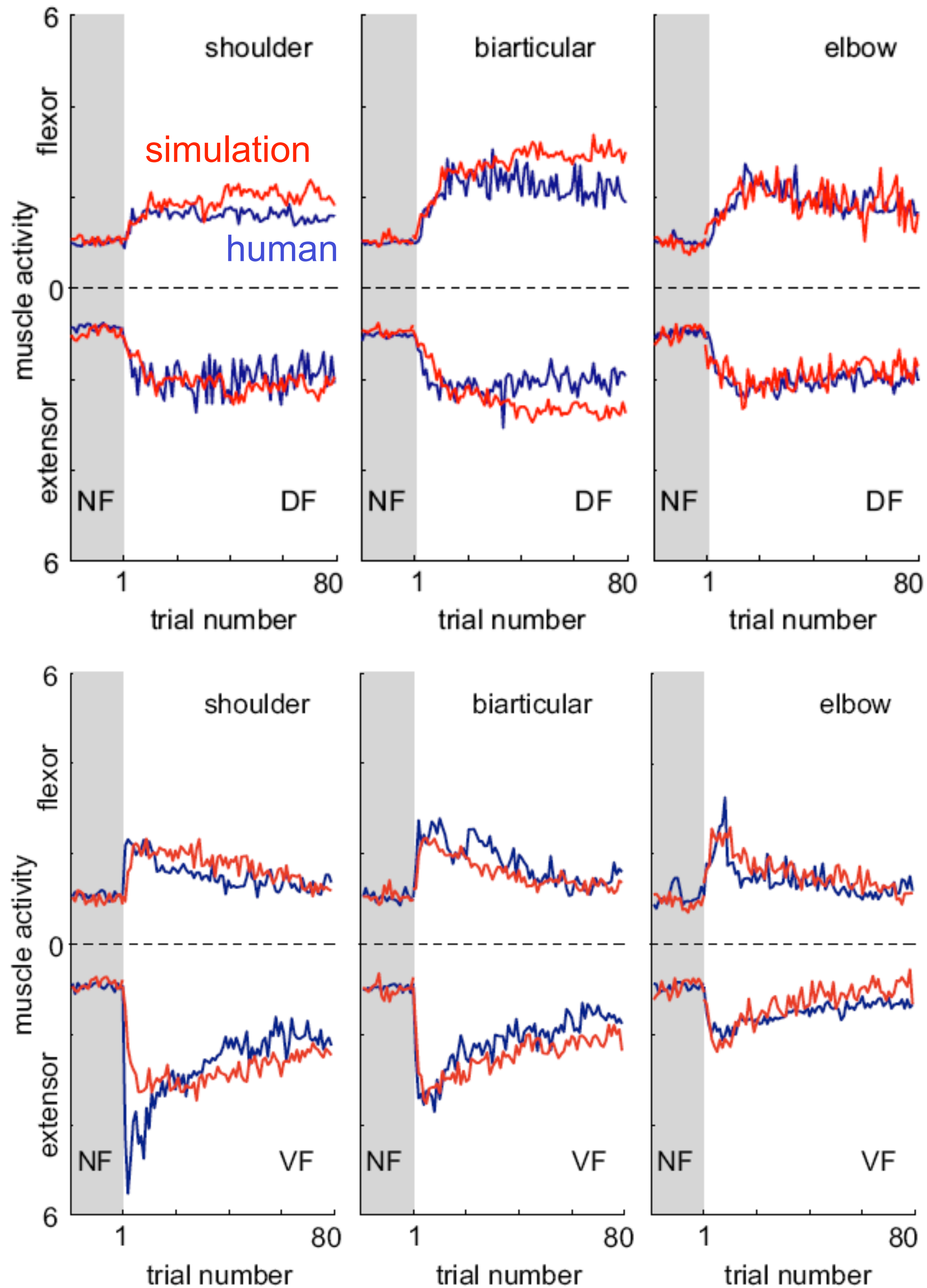


This simple algorithm can stabilize unstable dynamics and learn suitable force and impedance

[Franklin et al. J Neuroscience 2008]

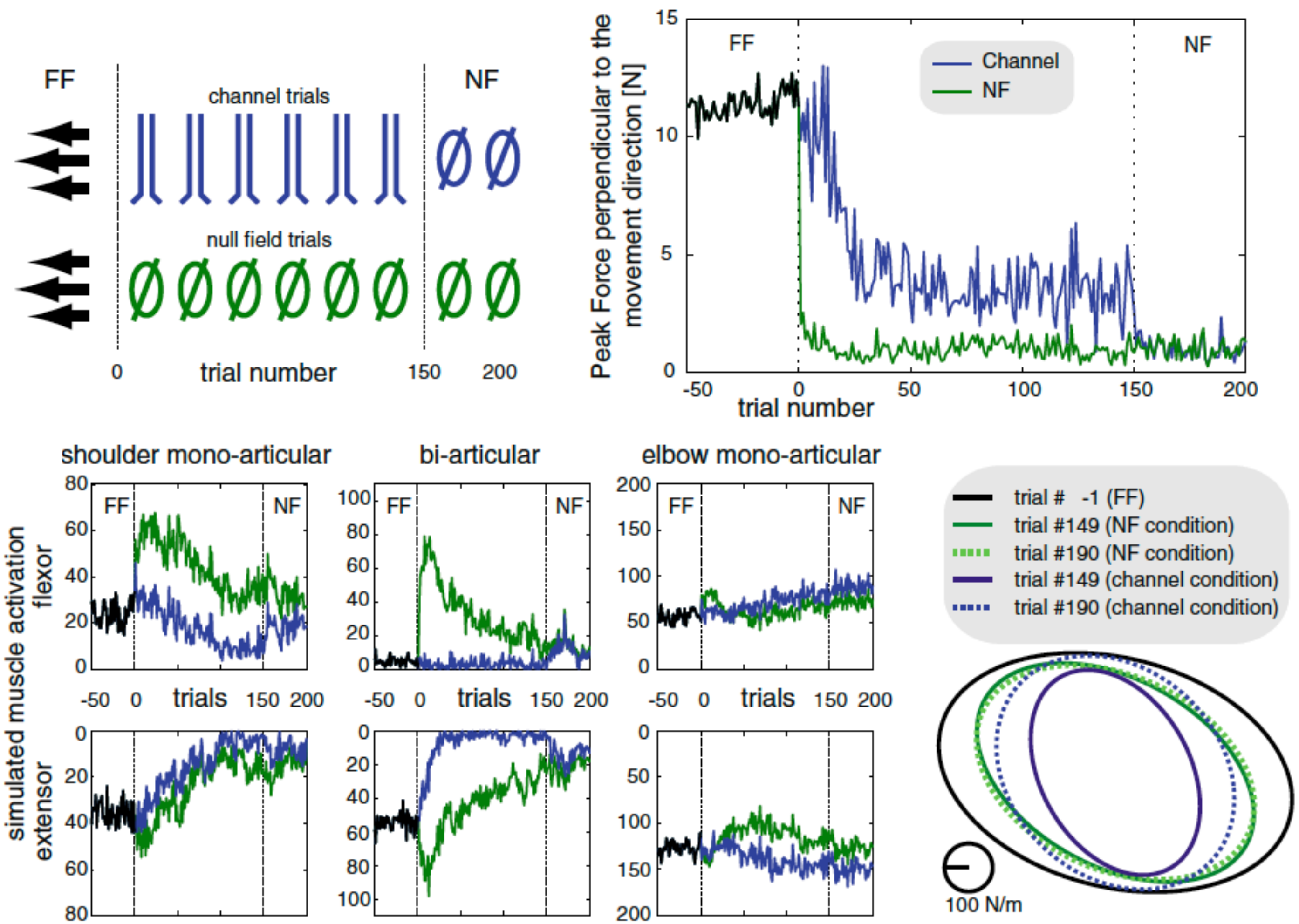
MUSCLE ACTIVATION TRANSIENTS

The model does predict the trial by trial changes of muscle activation in stable and unstable dynamics



[Franklin et al. J Neuroscience 2008]

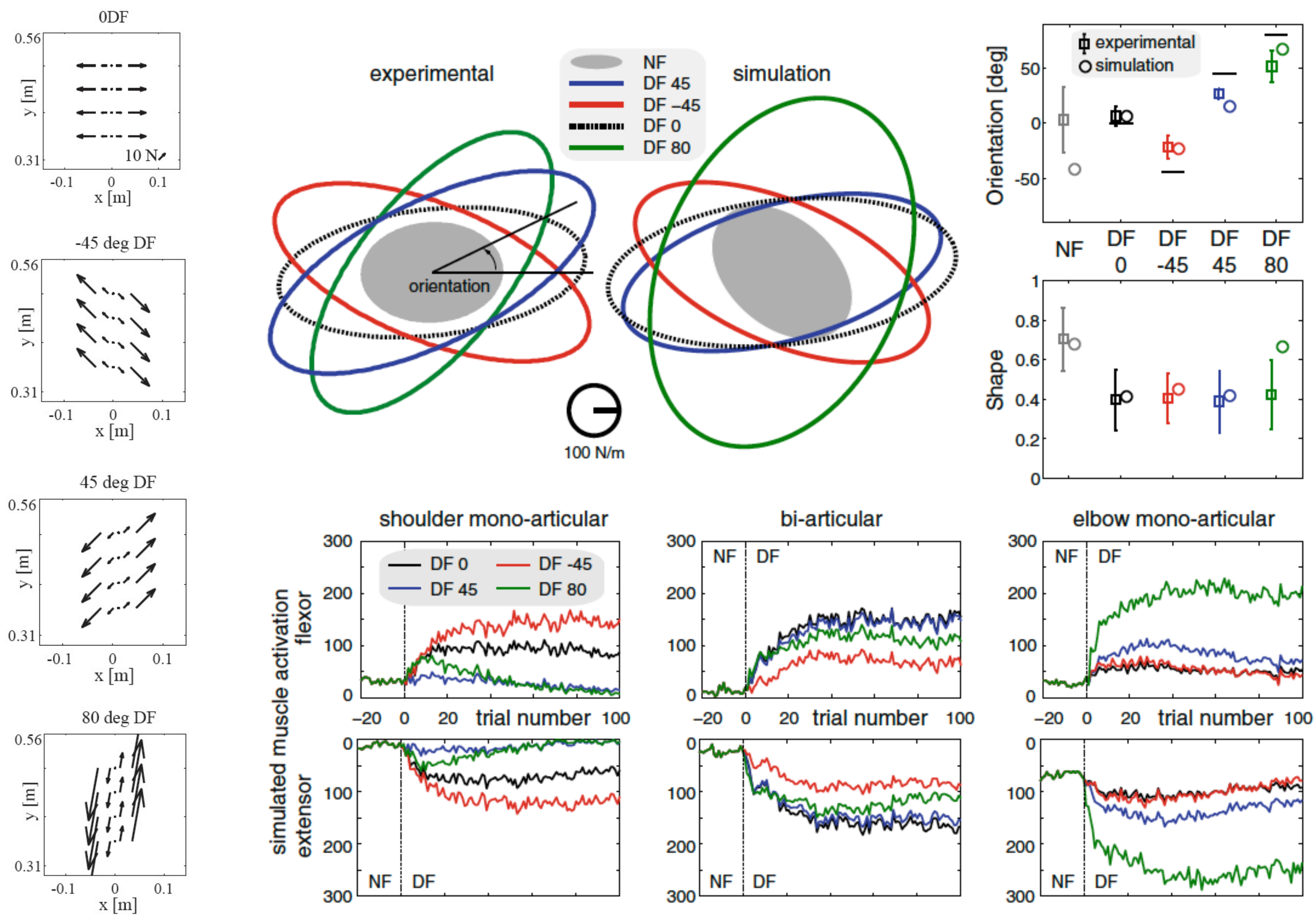
OPTIMISATION IN THE REDUNDANT MUSCLE SYSTEM



- learning is dominated by kinematic error
- the algorithm solves the redundancy in the muscles without any inverse transformation from hand to muscle space

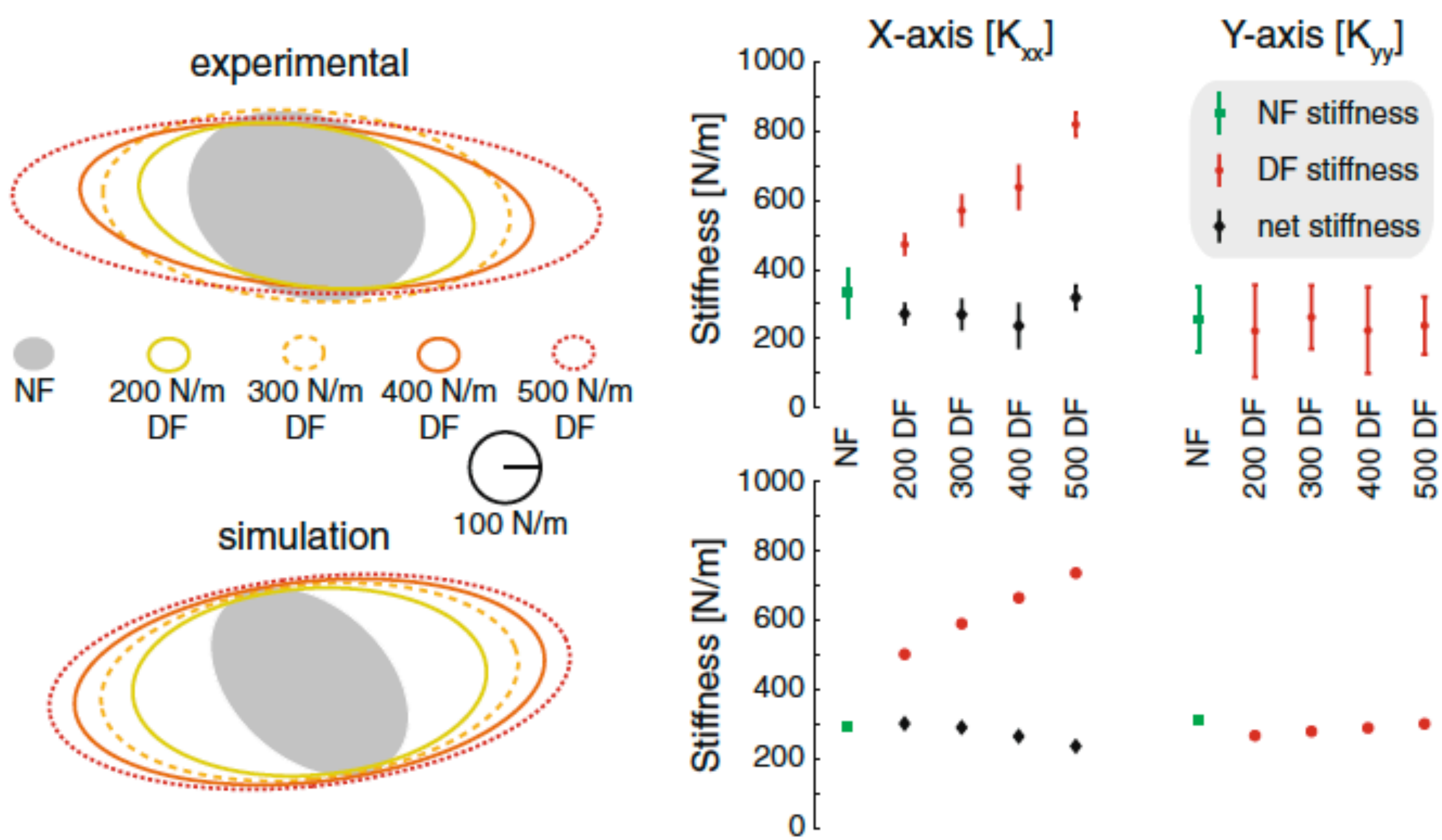
[Tee et al., Biological Cybernetics 2010]

DIRECTION SELECTIVE IMPEDANCE



[Tee et al., Biological Cybernetics 2010]

STABILITY MARGIN



- learning leads to the same stability margin ~300*N/m* in all environments
- therefore movements are stable thus reproducible, helping the brain to plan actions

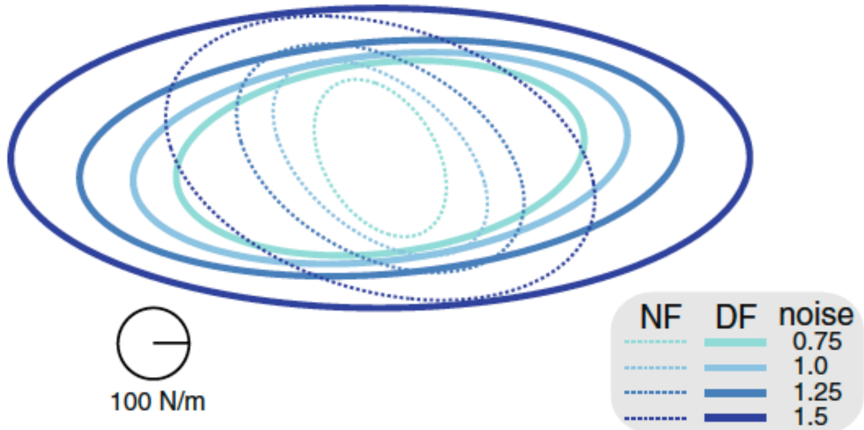
[Tee et al., Biological Cybernetics 2010]

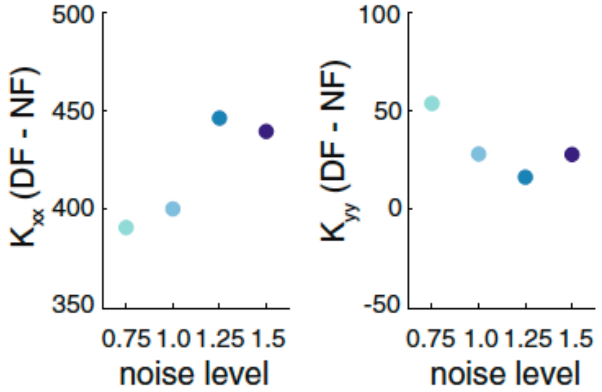
COMPENSATION FOR NOISE (1)

- 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)

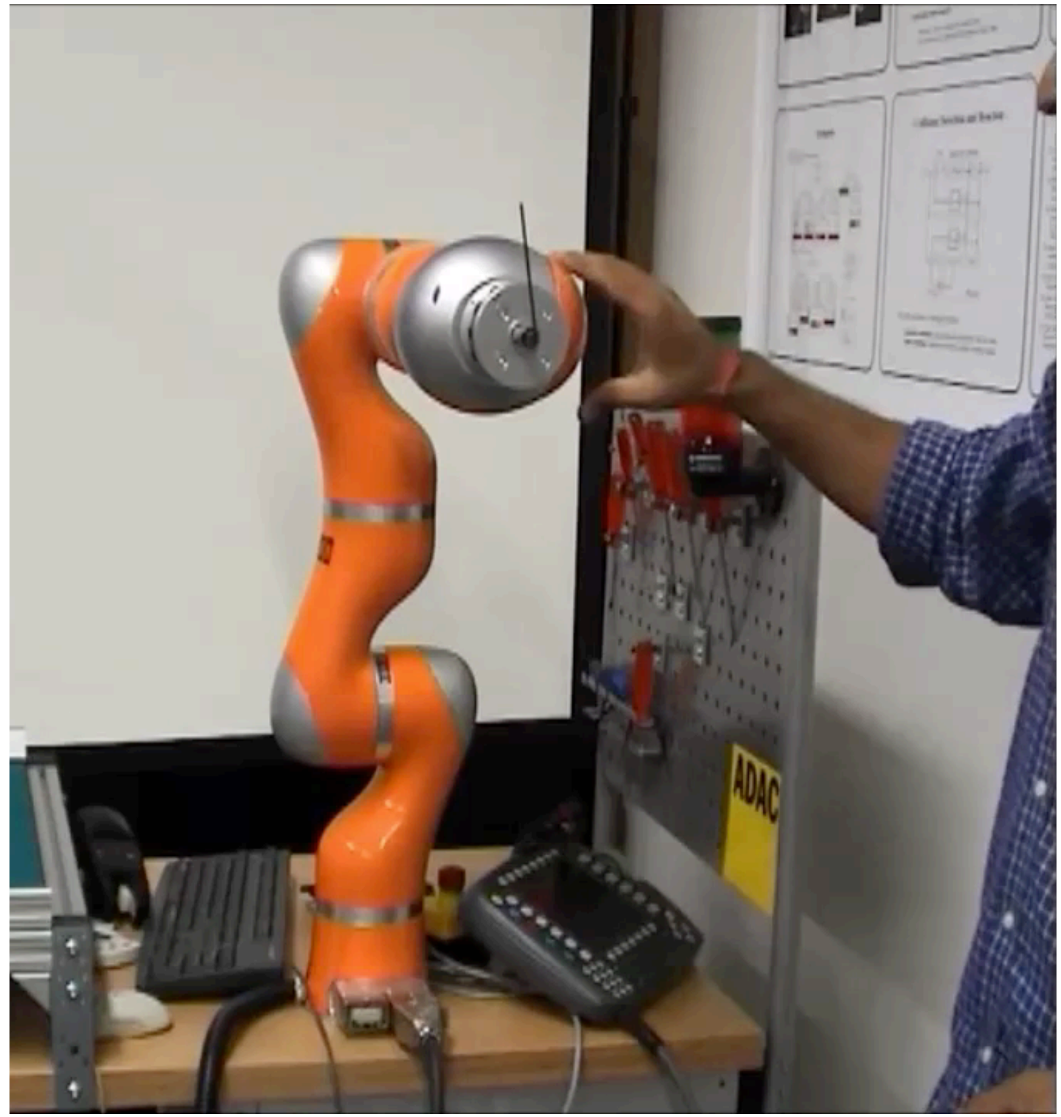




- endpoint stiffness grows with the noise level, through an increase in the activation of all muscles
- increase of K_{xx} term is larger in DF than in NF

[Tee et al., Biological Cybernetics 2010]

LEARNING: FROM HUMAN TO ROBOT



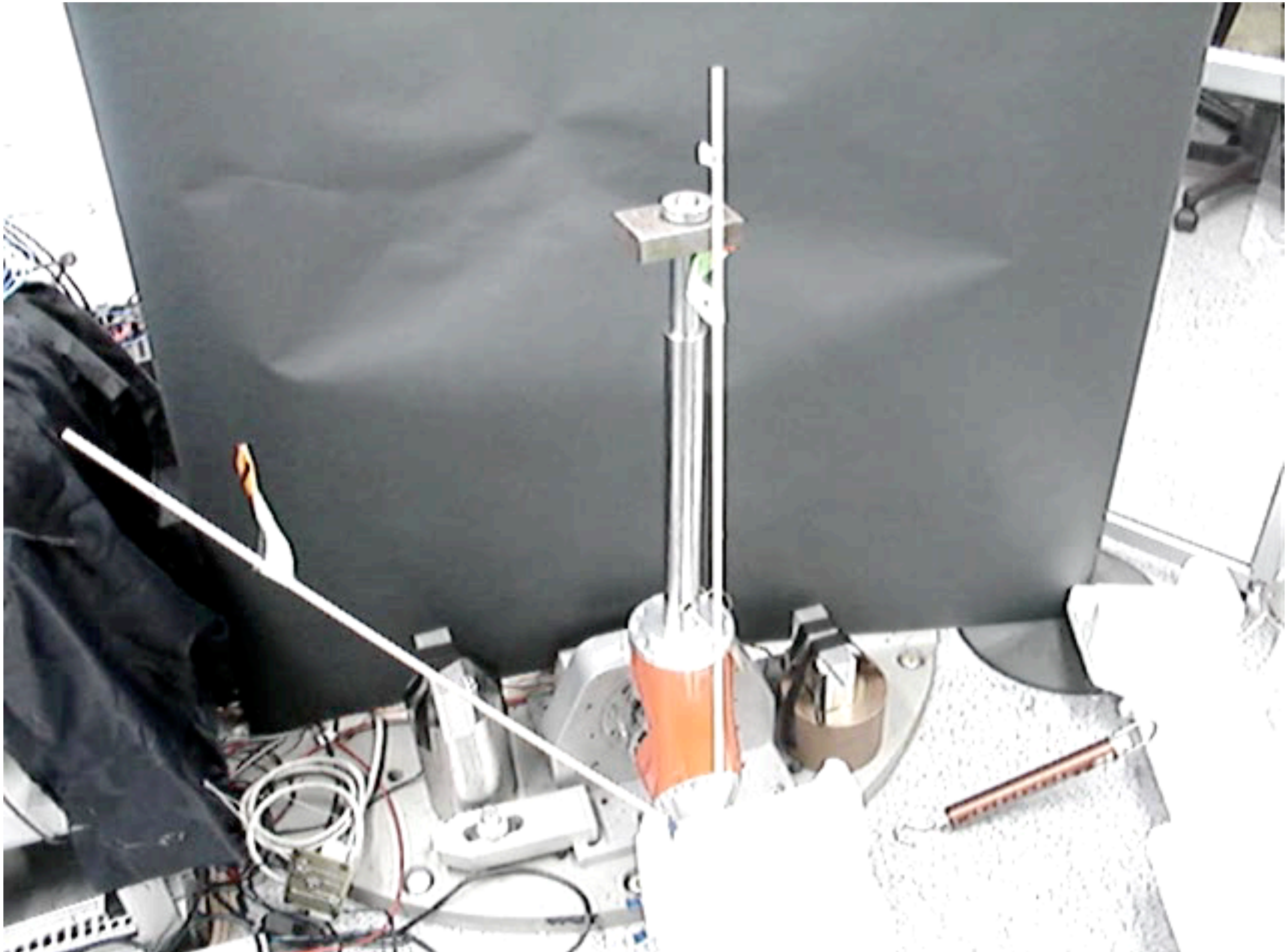
Ganesh Gowrishankar

Imperial College London

DLR

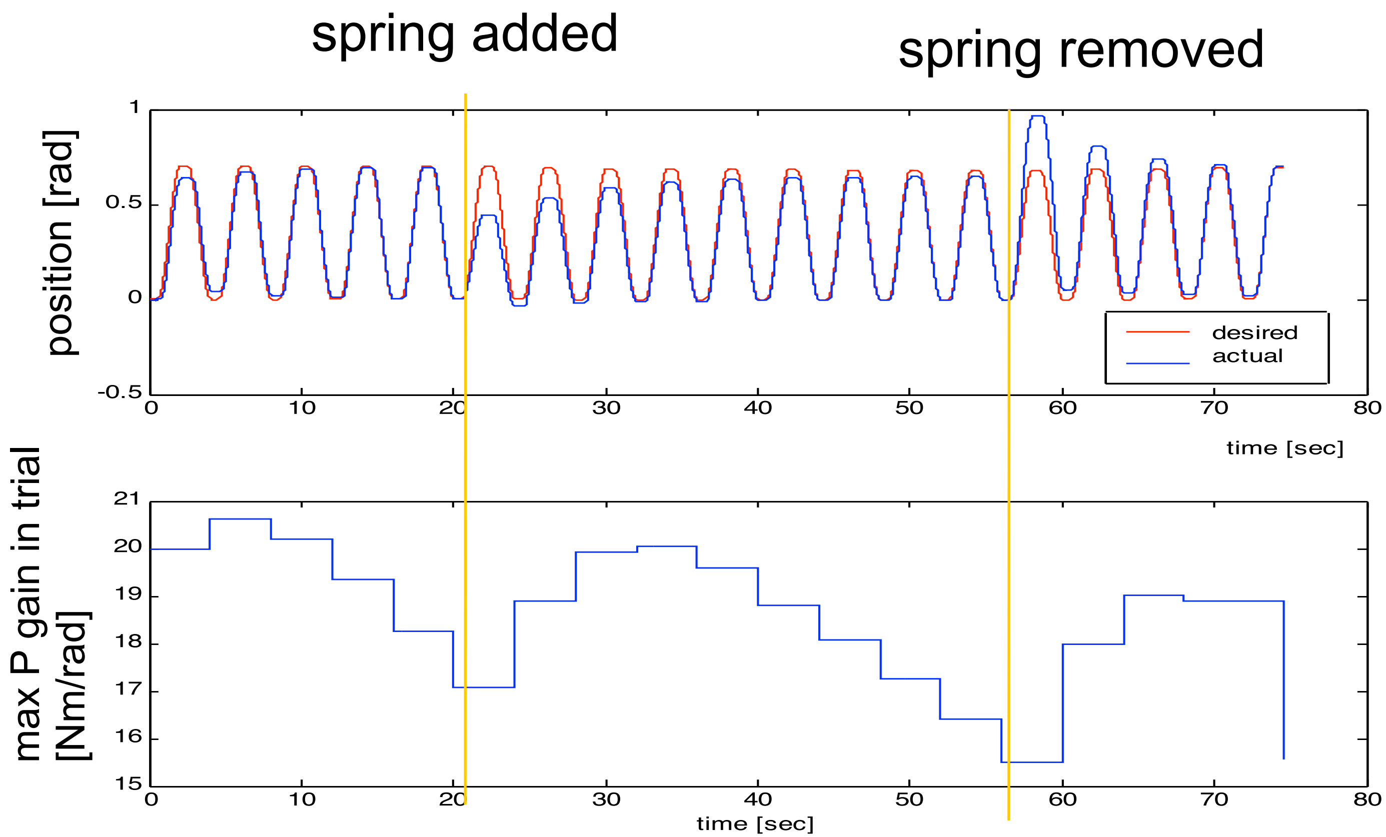
[Yang, Ganesh et al. IEEE T Robotics 2011]

LEARNING: FROM HUMAN TO ROBOT



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

BIOMIMETIC STIFFNESS EVOLUTION

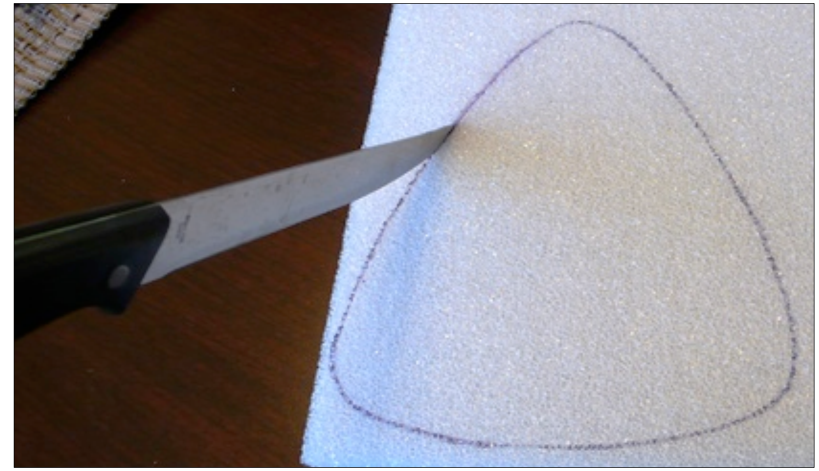


in the presence of external disturbance the robot increases its impedance, learns and then reduces the impedance again

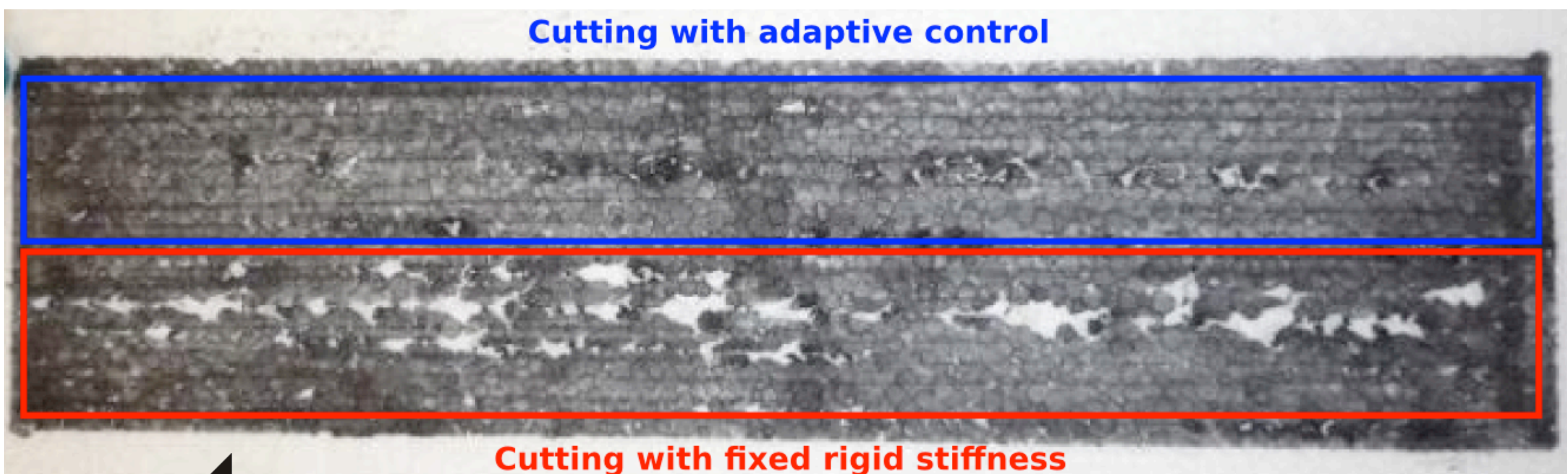
[Yang, Ganesh et al. IEEE T Robotics 2011]

TO BRING ROBOT HUMAN DEXTERITY !

humans adapt
force & impedance



robot: human-like adaptation
improves performance



Imperial College London

DLR

[Li et al. 2017 IEEE Transactions on Robotics]

TO BRING ROBOT HUMAN DEXTERITY !

humans adapt
force & impedance

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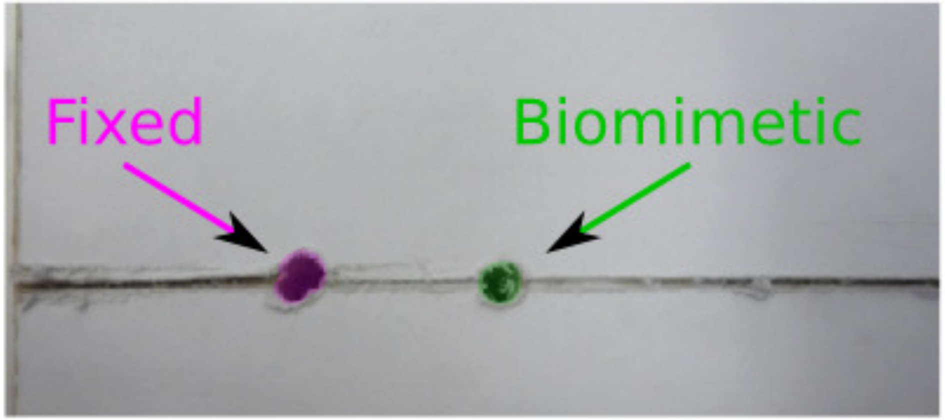

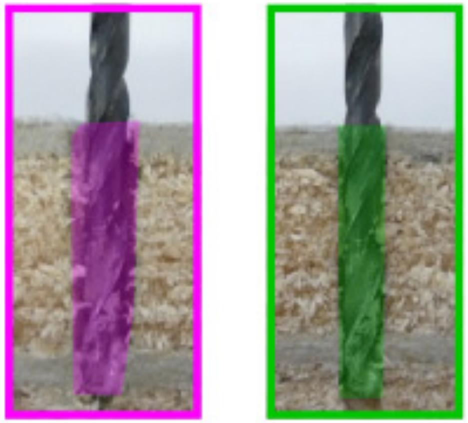

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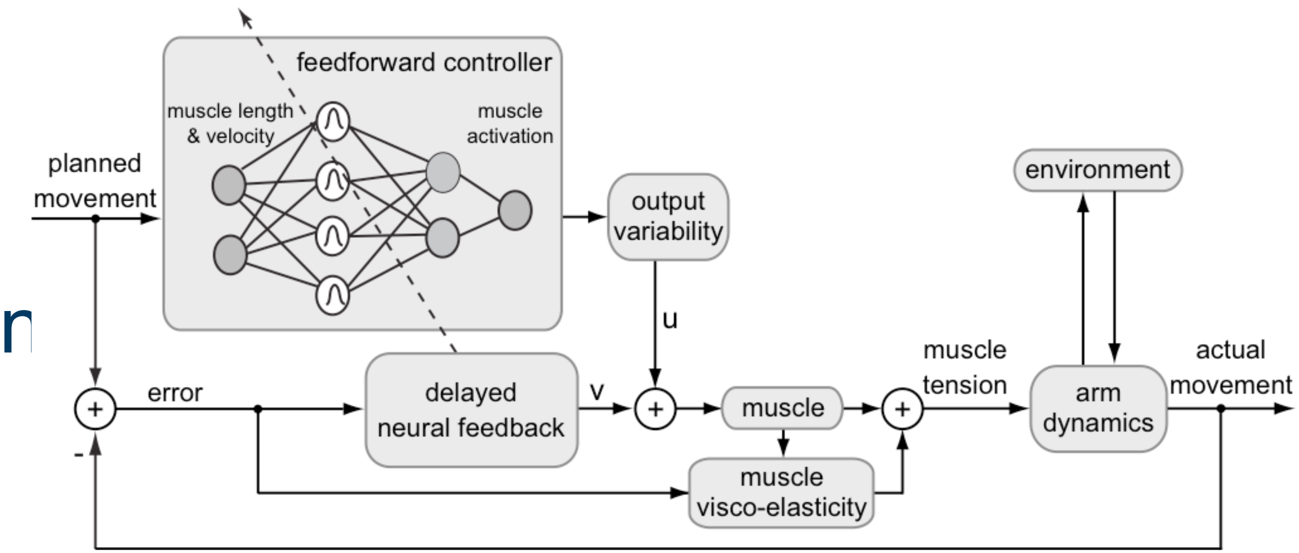
[Li et al. 2018 IEEE Transactions on Robotics]

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. 2012 PLoS ONE]

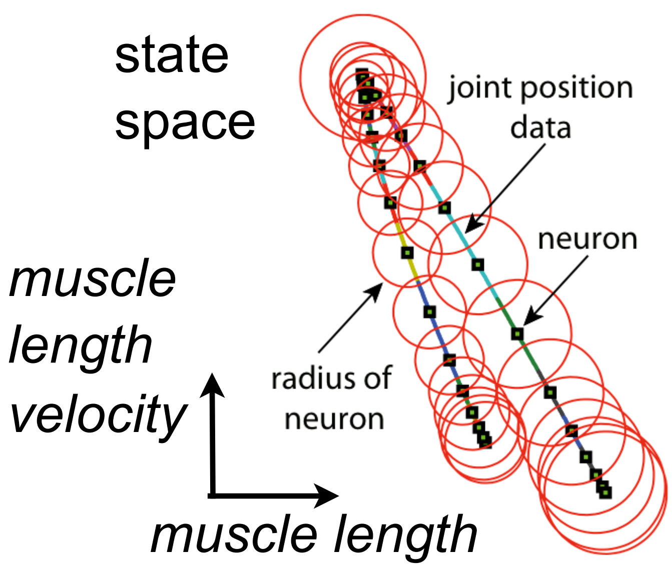
GENERALISATION

$$\mathbf{u} = \mathbf{W}\psi$$ feedforward motor command

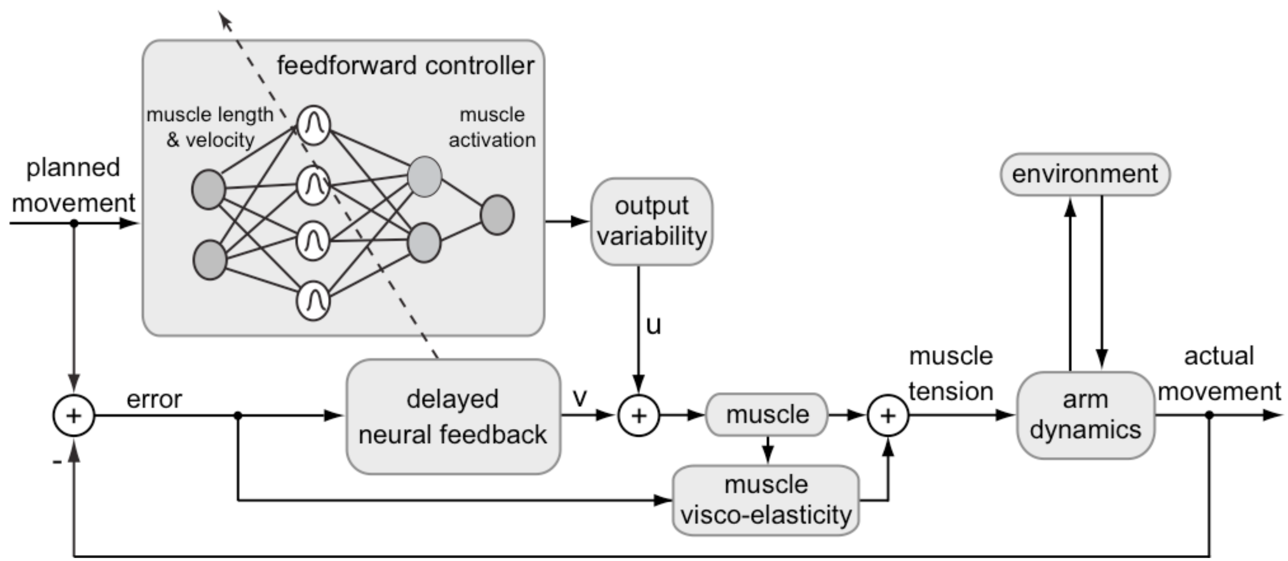
$$\boldsymbol{\psi} = (\psi_1, \psi_2, \ldots, \psi_N)^T \quad \psi_j(\mathbf{s})$$ *s*: state

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

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



MINIMISATION OF FEEDBACK AND FEEDFORWARD COMMANDS

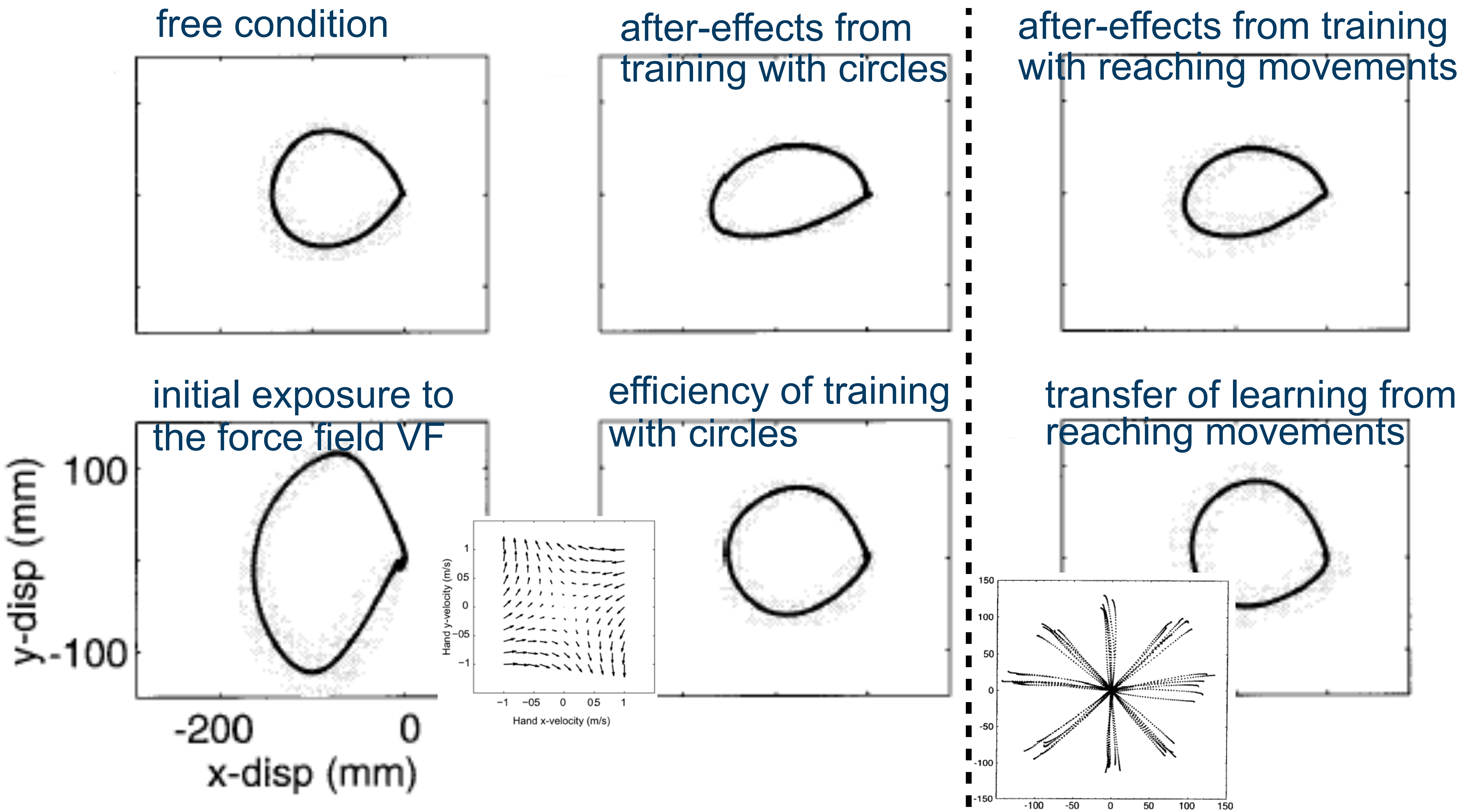


$$V(\mathbf{p}) \equiv \frac{\alpha}{2}\mathbf{v}^T\mathbf{v} + \gamma \sum w_{ij} \qquad \alpha, \gamma > 0$$

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

[Kadiallah et al. 2012 PLoS ONE]

INVERSE MODEL IS STATE DEPENDENT



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

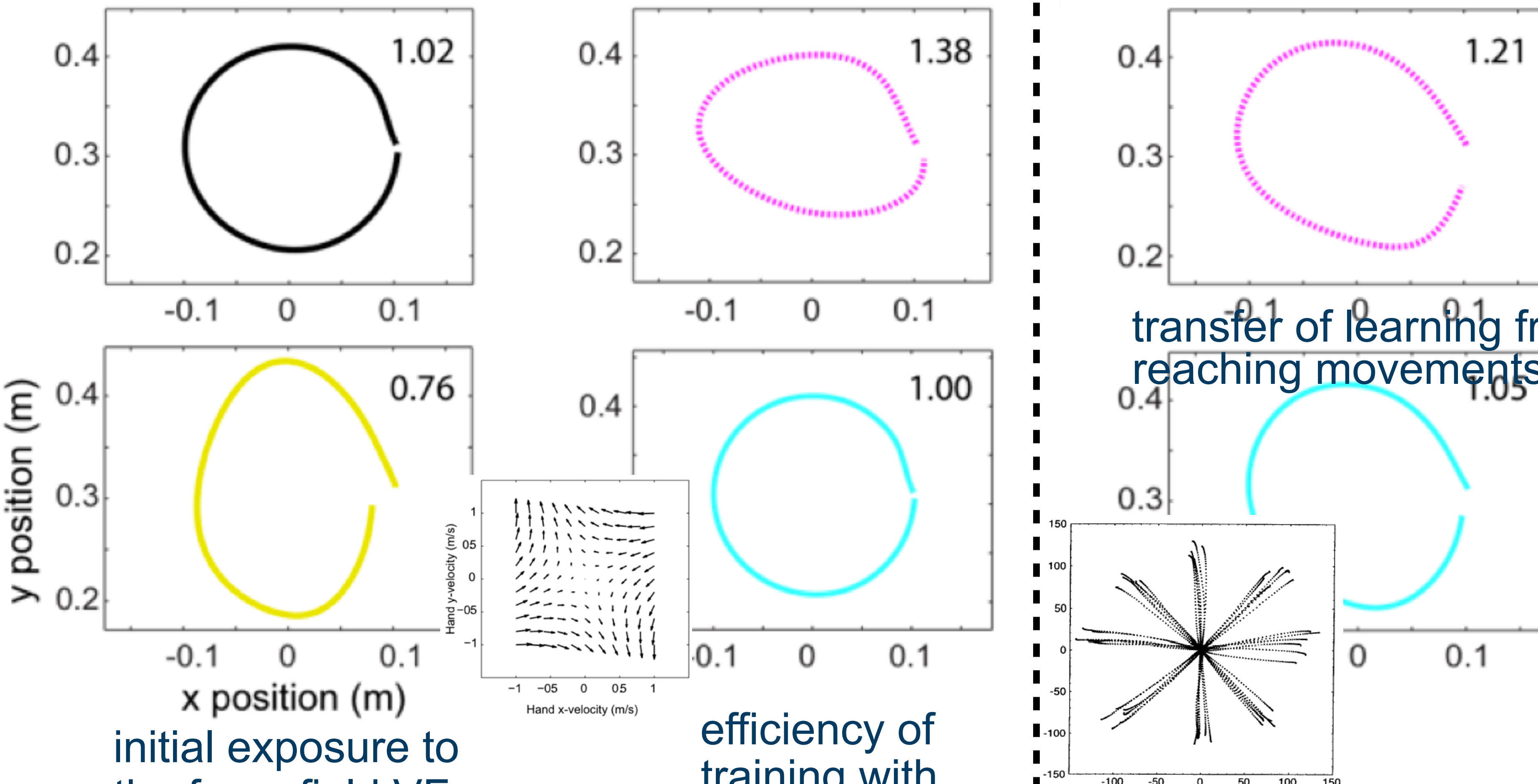
[Conditt et al., J Neurophysiology 1997]

GENERALISATION OVER MOVEMENTS

free condition

after-effects from training with circles

after-effects from training with reaching movements



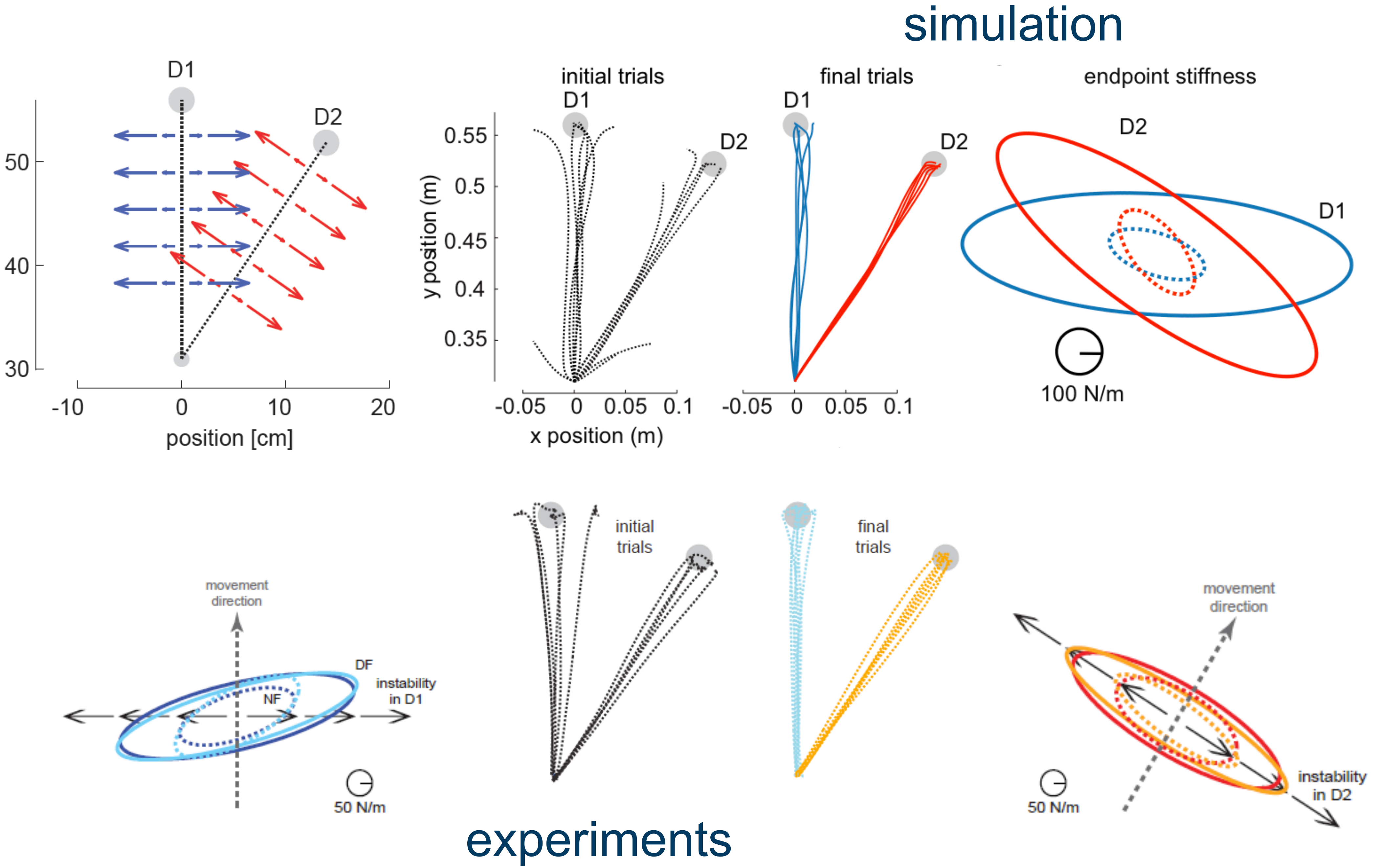
transfer of learning from reaching movements

initial exposure to the force field VF

efficiency of training with circles

[Kadiallah et al. 2012 PLoS ONE]

GENERALISATION OVER MOVEMENTS



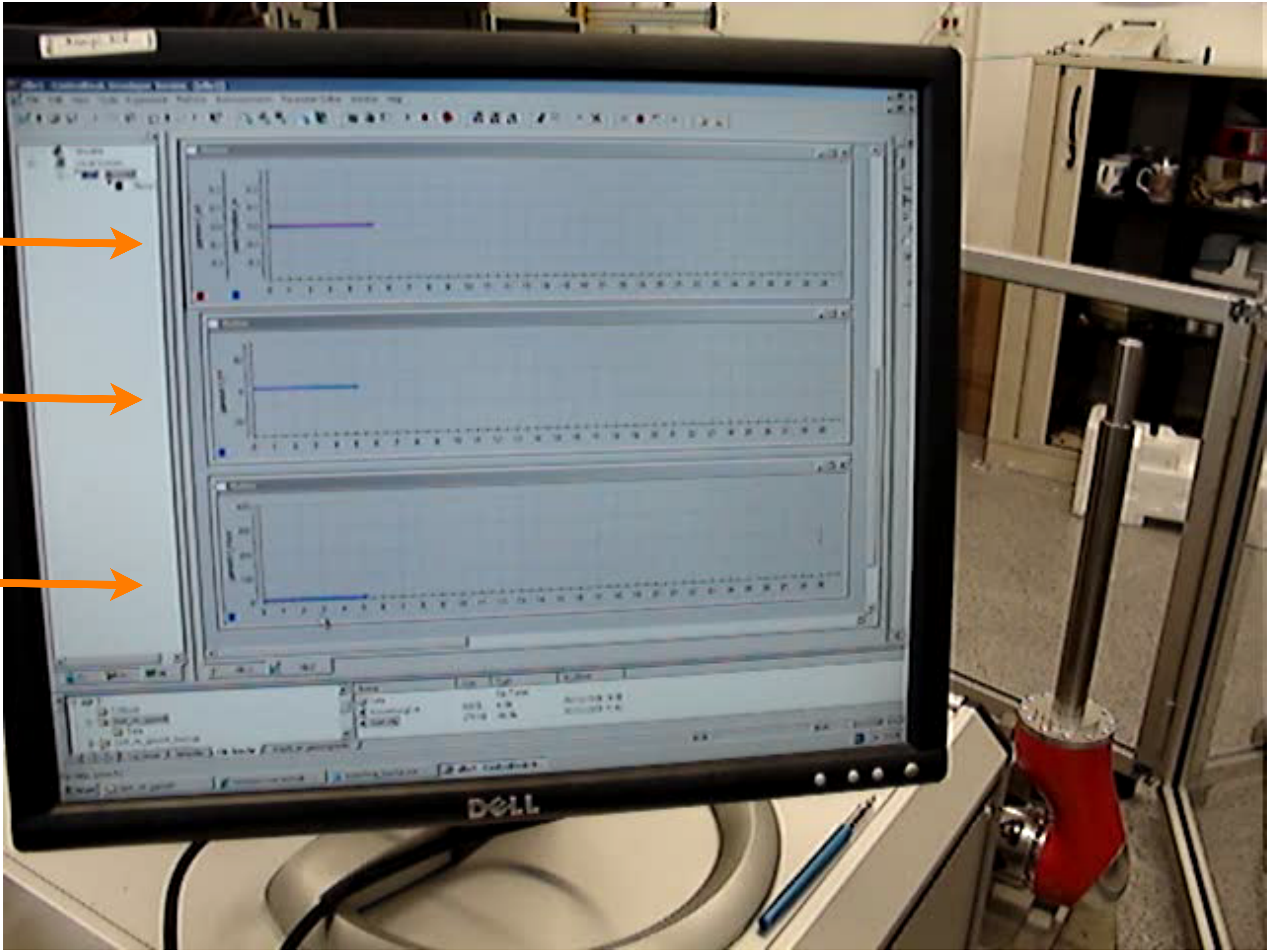
[Kadiallah et al., PLoS ONE 2012]

ADAPTABLE HUMAN-ROBOT CONTROL

position

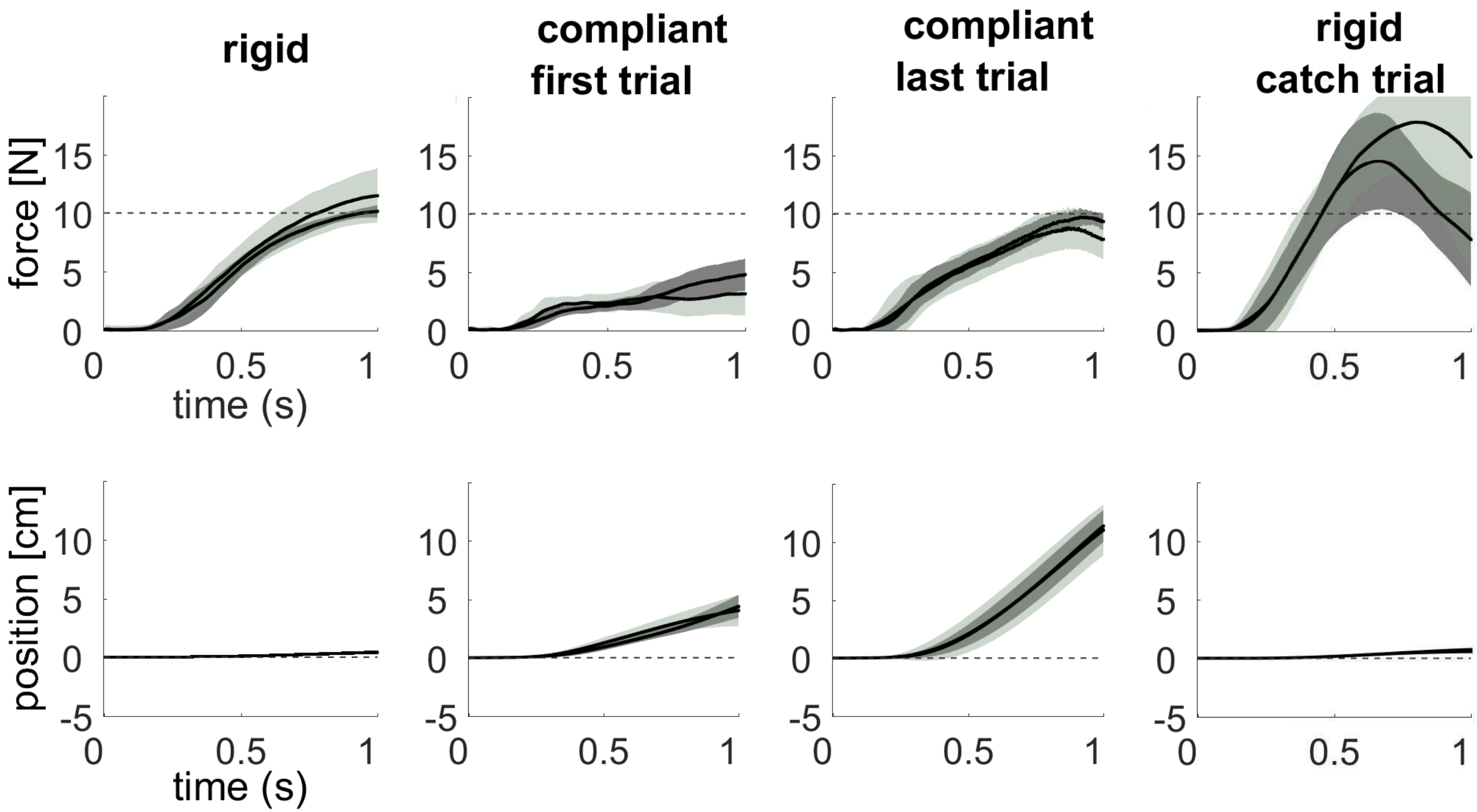
force

stiffness



[Li et al. 2018 IEEE Transactions on Robotics]

ADAPTATION IN FORCE PUSHING



v: impedance term

$$w = u + v \qquad v = K e + D \dot{e}, \quad e = x_r - x$$

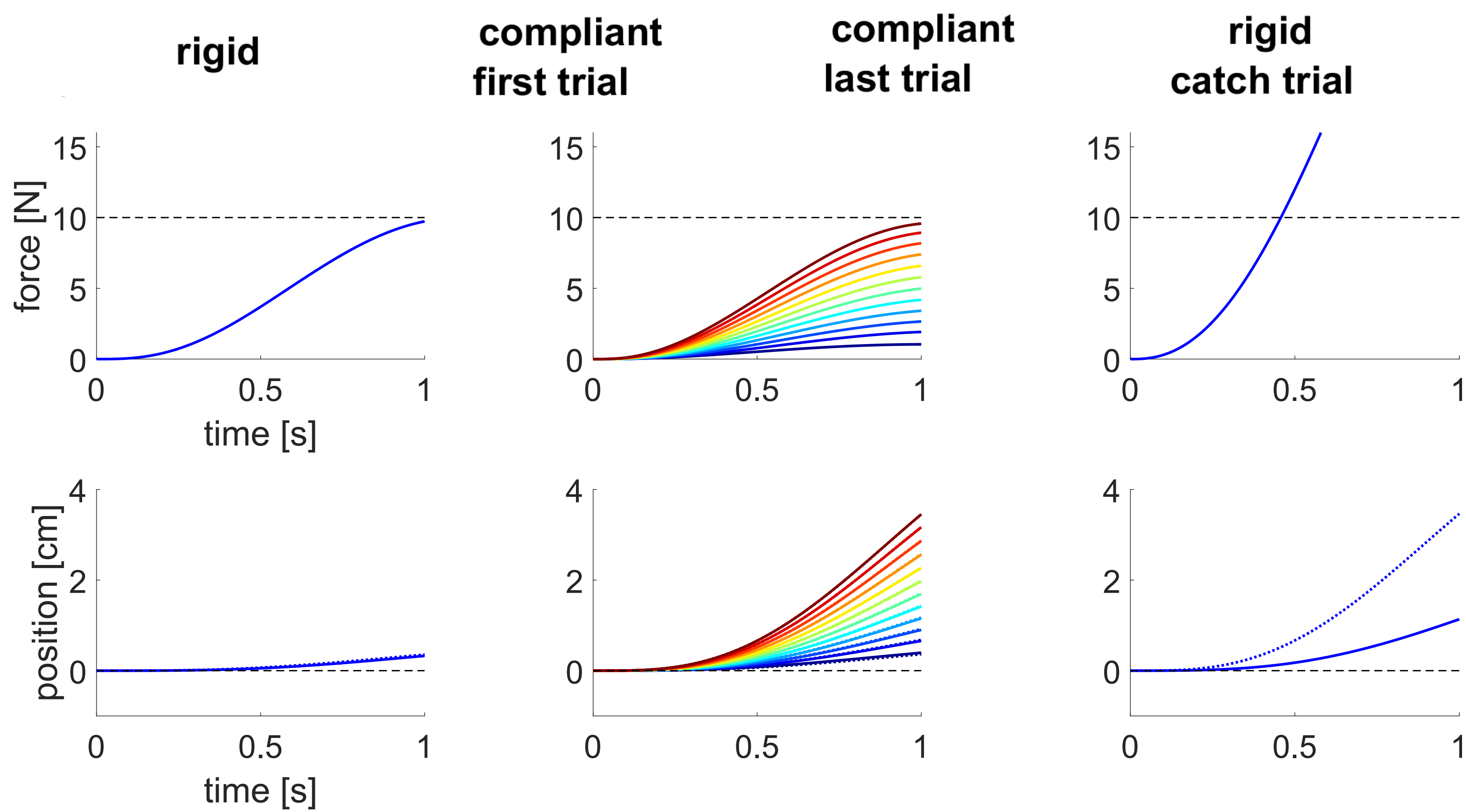
u: force feedforward

error to reference position

to test the existence and adaption of trajectory control

[Casadio&Mussa-Ivaldi, Frontiers in Computational Neuroscience 2015]

ADAPTATION IN FORCE PUSHING



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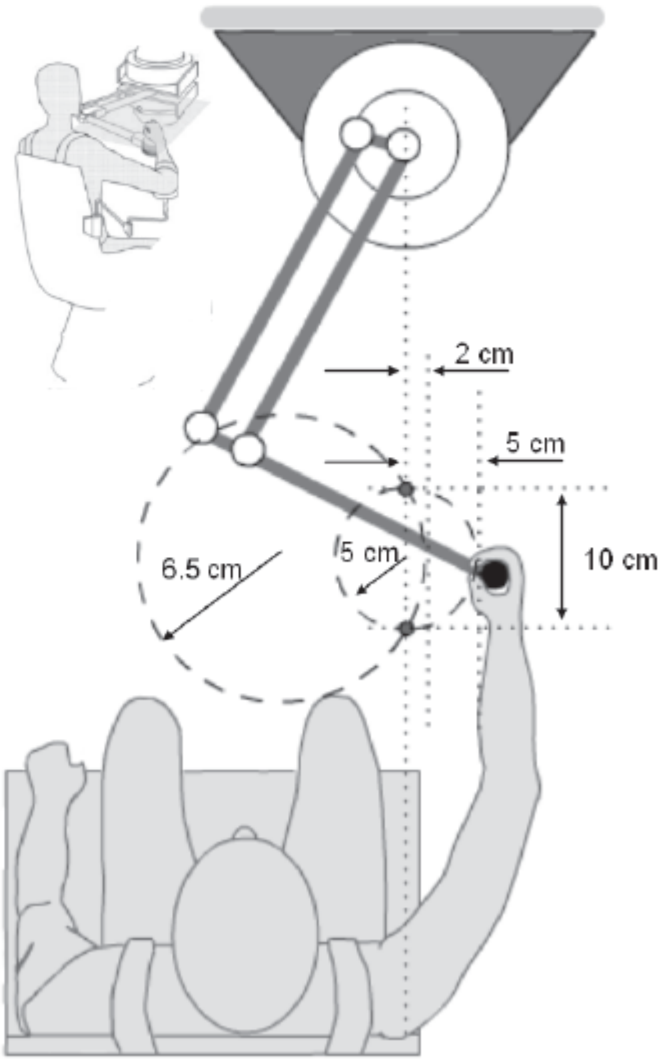
[Li&Burdet, Laumond Ed, Springer 2017]

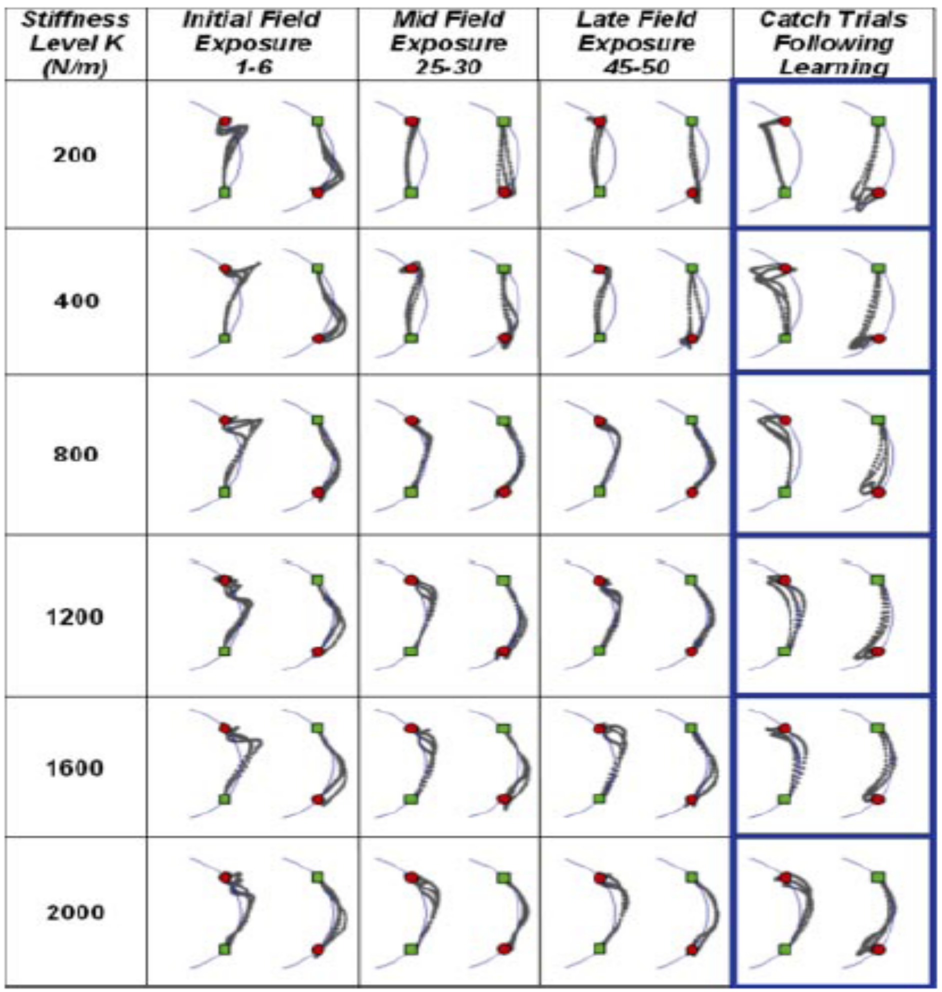
TRAJECTORY ADAPTATION



- repeat point to point arm movements ahead of the body
- stiff or compliant obstacle on the way
- how is the motor control adapted?

[Chib et al. J Neurophysiology 2006]

TRAJECTORY ADAPTATION

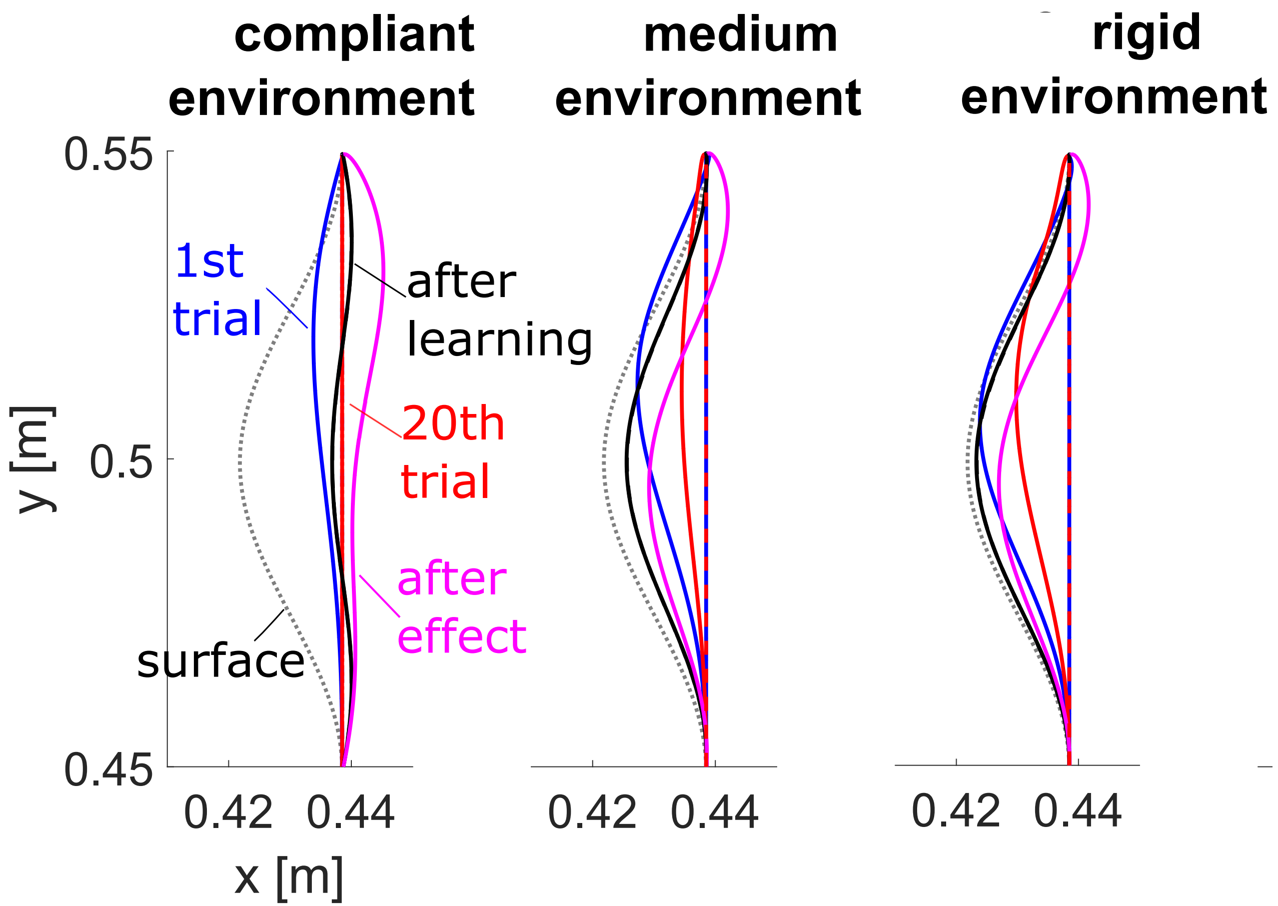


- low stiffness: “pillow”
  -> no change of trajectory after learning, “usual” feedforward force adaptation

- stiff obstacle: “haptic water melon”
  -> trajectory adaptation

[Chib et al. J Neurophysiology 2006]

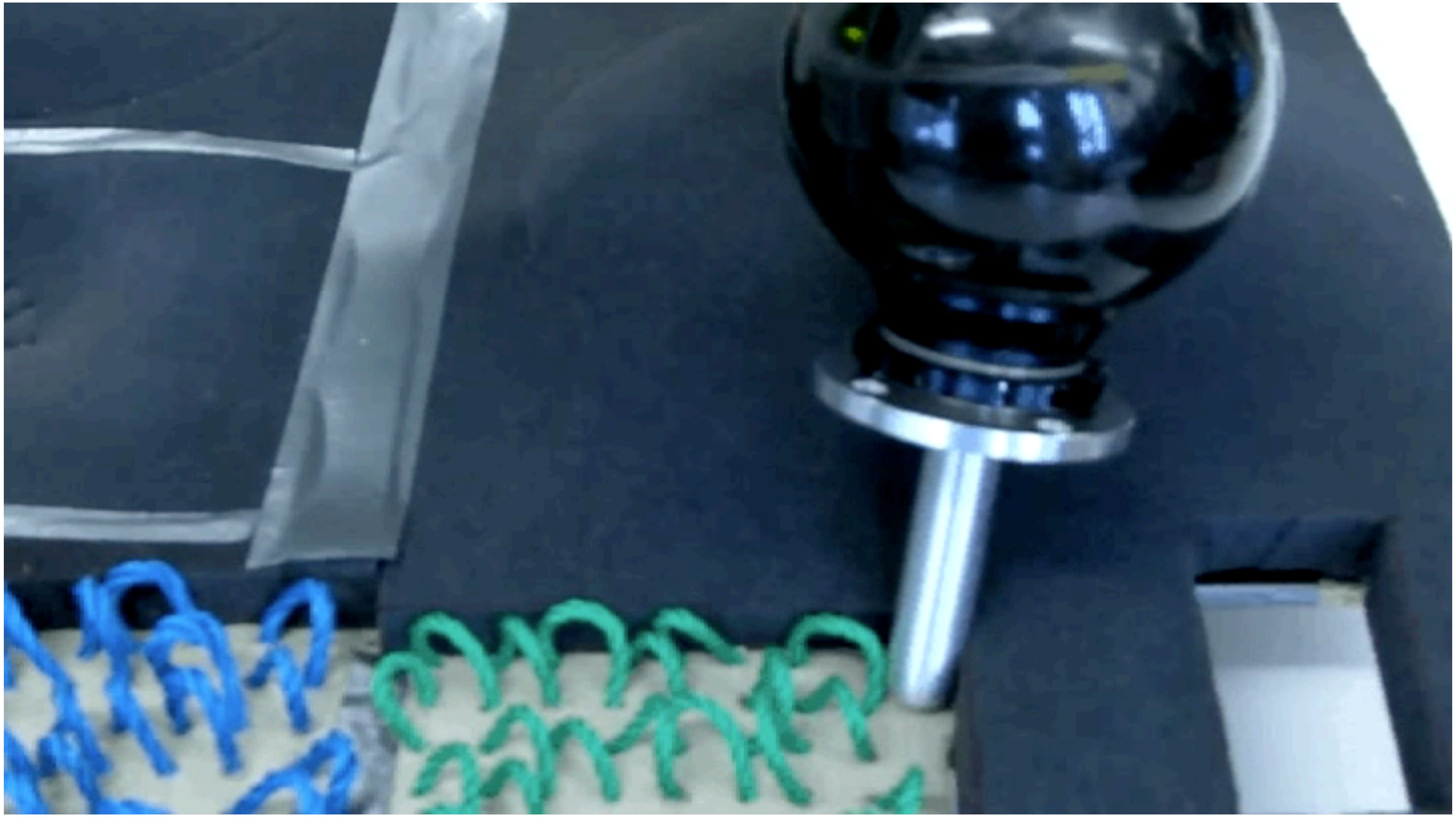
TRAJECTORY ADAPTATION



- in the presence of an obstacle, trajectory drifts trial after trial
- this tends to limit the interaction force
- we have derived the dynamics of this human adaptation strategy and simulated it

[Li&Burdet, Laumond Ed, Springer 2017]

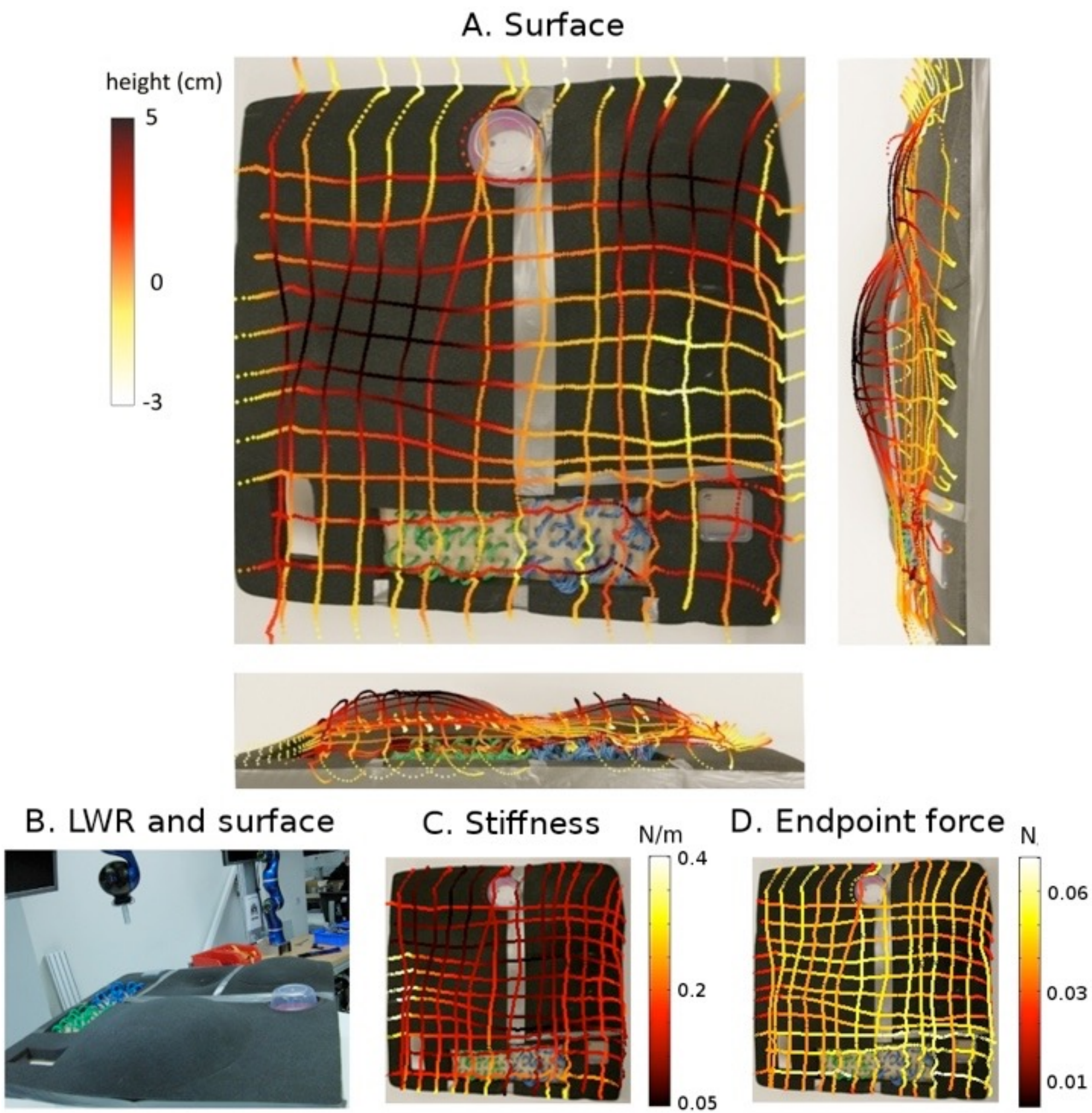
HAPTIC EXPLORATION



robot adapts geometry and impedance to interact with unknown surface characteristics

[Li et al. 2018 IEEE Transactions on Robotics]

HAPTIC EXPLORATION



robot identifies unknown geometry and impedance

[Li et al. 2018 IEEE Transactions on Robotics]

SUMMARY (1)

- inherent motor noise, generally increasing with the motor command, critically affects tasks requiring unstable interactions

- our experiments showed that in unstable situations the CNS adapts force and mechanical impedance by coordinating muscles in a suitable way to compensate for the external dynamics

SUMMARY (2)

- by changing the activation of each muscle independently using a simple function of the kinematic error, our model learns coordinated control of the redundant muscles, in a behaviour that reduces instability, systematic error and metabolic cost

- our model can adapt muscle reciprocal and co-activation to compensate for environment forces and instabilities, with patterns similar to those observed in human learning experiments

SUMMARY (3)

- this predictive tool may be used to investigate the mechanisms of impairments arising from motor disorders and design optimal neurorehabilitation protocols, or to create robots able to interact smoothly while applying large forces