
Robotica Antropomorfa

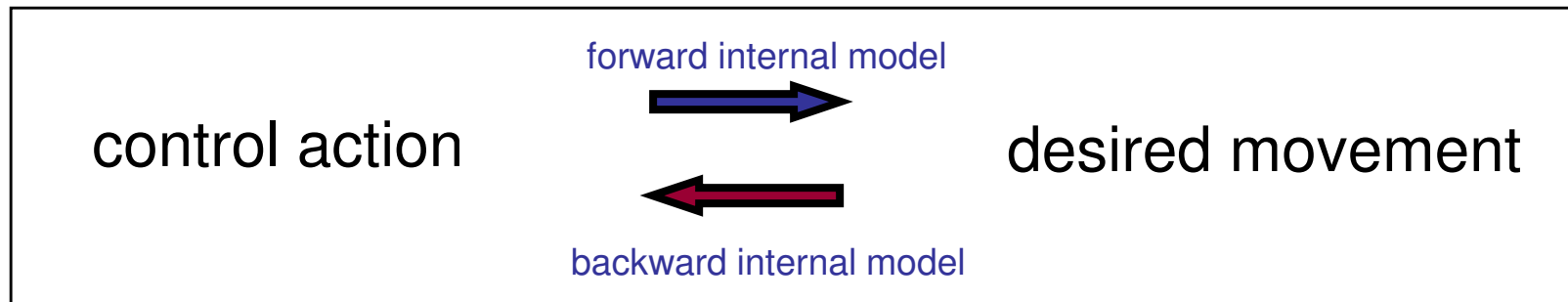
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Internal Model and its Complexity (1/2)

Experimental Evidence: the central nervous system (CNS) uses and updates an **internal model** (Miall and Wolpert, 1996)



Human arm:

- Number of muscles ≥ 21 ,
- Number of degrees of freedom = 7

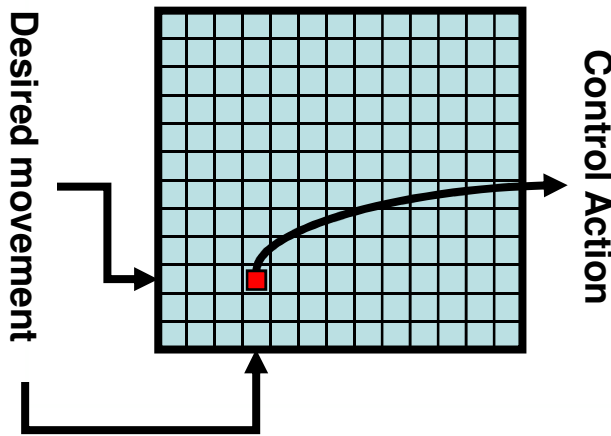
Human hand:

- Number of muscles ≈ 40 ,
- Number of degrees of freedom ≈ 25

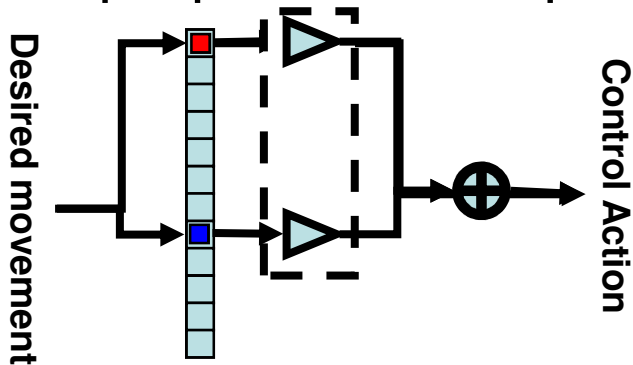
Note: Very high complexity!

Internal Model and its Complexity (2/2)

- Raibert proposed the “look-up table” idea:

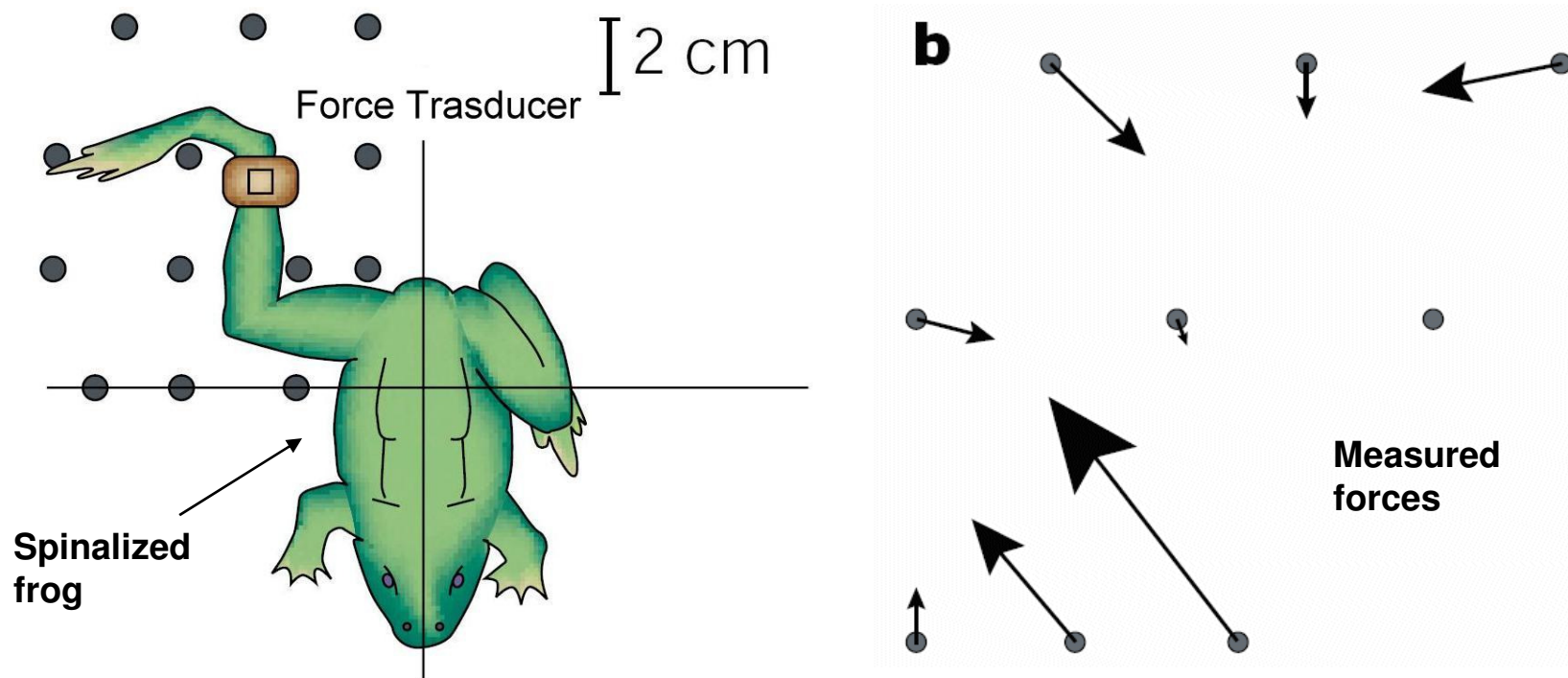


- Mussa-Ivaldi and Bizzi proposed the “spinal fields” idea:

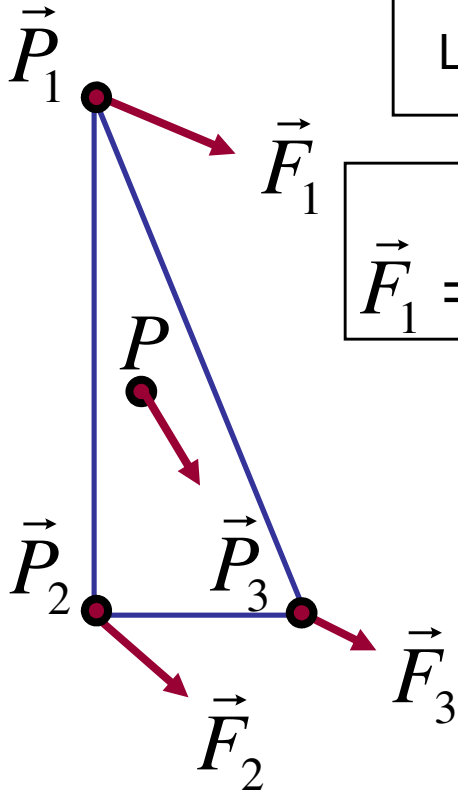


Spinal Fields: E. Bizzi, F.A. Mussa-Ivaldi, S. Giszter

Motor commands are organized in primitives at the spinal cord level



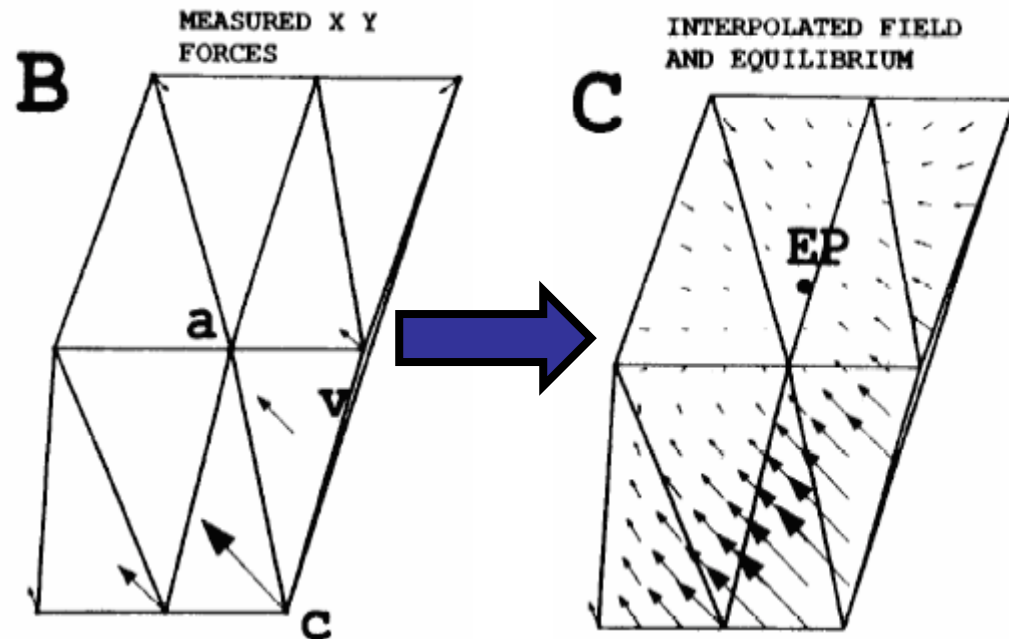
Interpolation of measured data



Linear interpolation on measured data $\vec{F} = A\vec{P} + b$

A and b are computed so as to satisfy:

$$\vec{F}_1 = A\vec{P}_1 + b \quad \vec{F}_2 = A\vec{P}_2 + b \quad \vec{F}_3 = A\vec{P}_3 + b$$



Similarity between force fields

In order to compare two fields, we need to introduce a similarity between force fields.

Given two fields F_1 and F_2 their similarity is computed as follows:

(1) Sample the fields at N locations:

$$\vec{F}_1(\vec{P}_1), \dots, \vec{F}_1(\vec{P}_N) \qquad \vec{F}_2(\vec{P}_1), \dots, \vec{F}_2(\vec{P}_N)$$

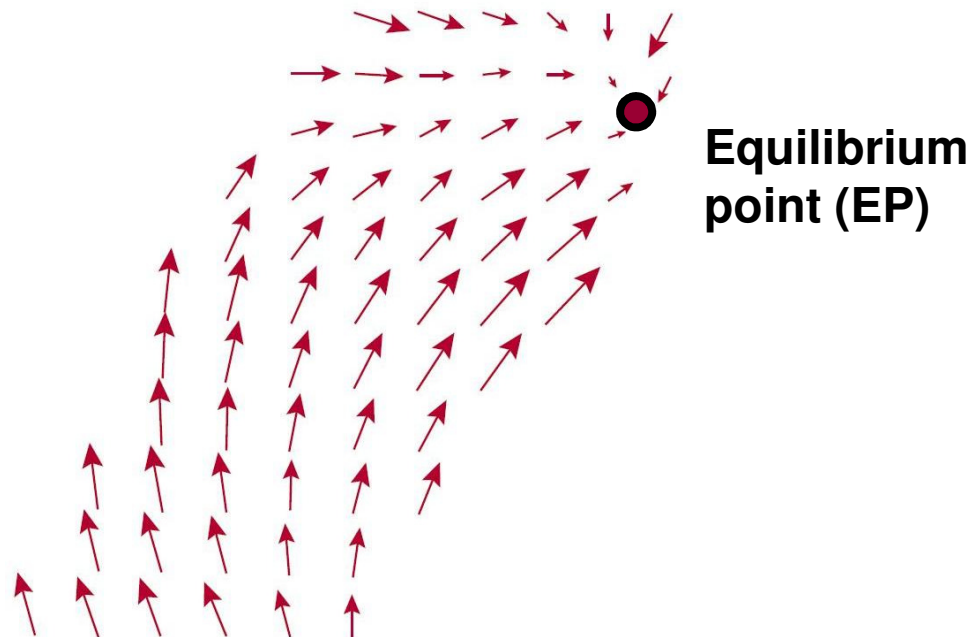
(2) Compute the similarity as follows:

$$d(\vec{F}_1, \vec{F}_2) = \frac{\langle \vec{F}_1, \vec{F}_2 \rangle}{\|\vec{F}_1\| \cdot \|\vec{F}_2\|} \qquad \langle \vec{F}_1, \vec{F}_2 \rangle = \sum_{i=1}^N \vec{F}_1(\vec{P}_i) \cdot \vec{F}_2(\vec{P}_i)$$
$$\|\vec{F}_1\| = \langle \vec{F}_1, \vec{F}_1 \rangle^{1/2}$$

Prop.	$d(\vec{F}_1, \vec{F}_2) = +1$	if and only if	$\exists c > 0$ s.t. $\vec{F}_1 = c\vec{F}_2$
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Observed field features (1)

- Measured fields:
 1. Have a **unique equilibrium point**
 2. Are **convergent** toward the equilibrium (i.e. the equilibrium is stable)

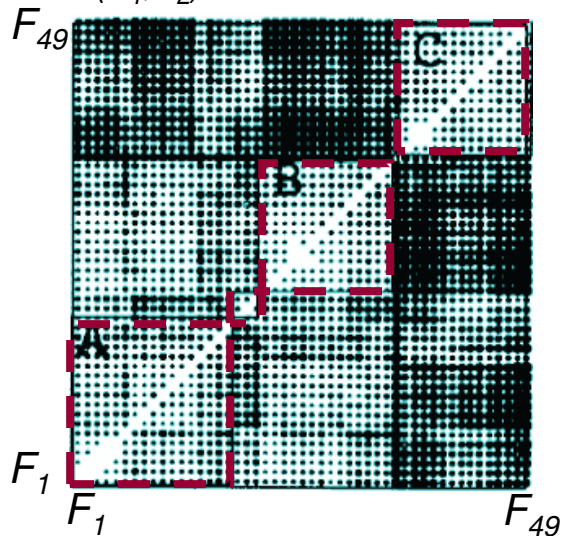


As a consequence, the final position of the leg does not depend on the initial condition.

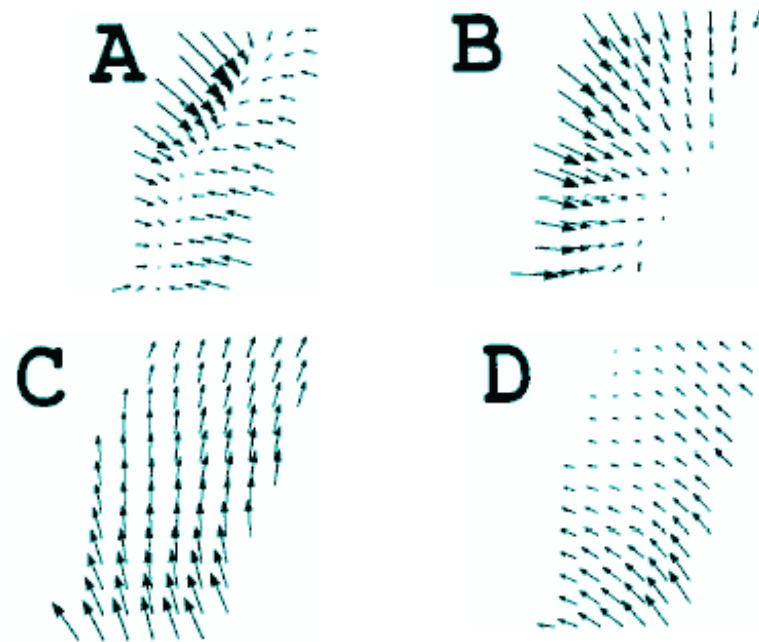
Observed field features (2)

- Systematic stimulation of different regions of the spinal cord produced only a **few types force fields (at least four)**.

Dissimilarity matrix of 49 force fields. Darker circles represent $d(F_1, F_2) \ll 1$



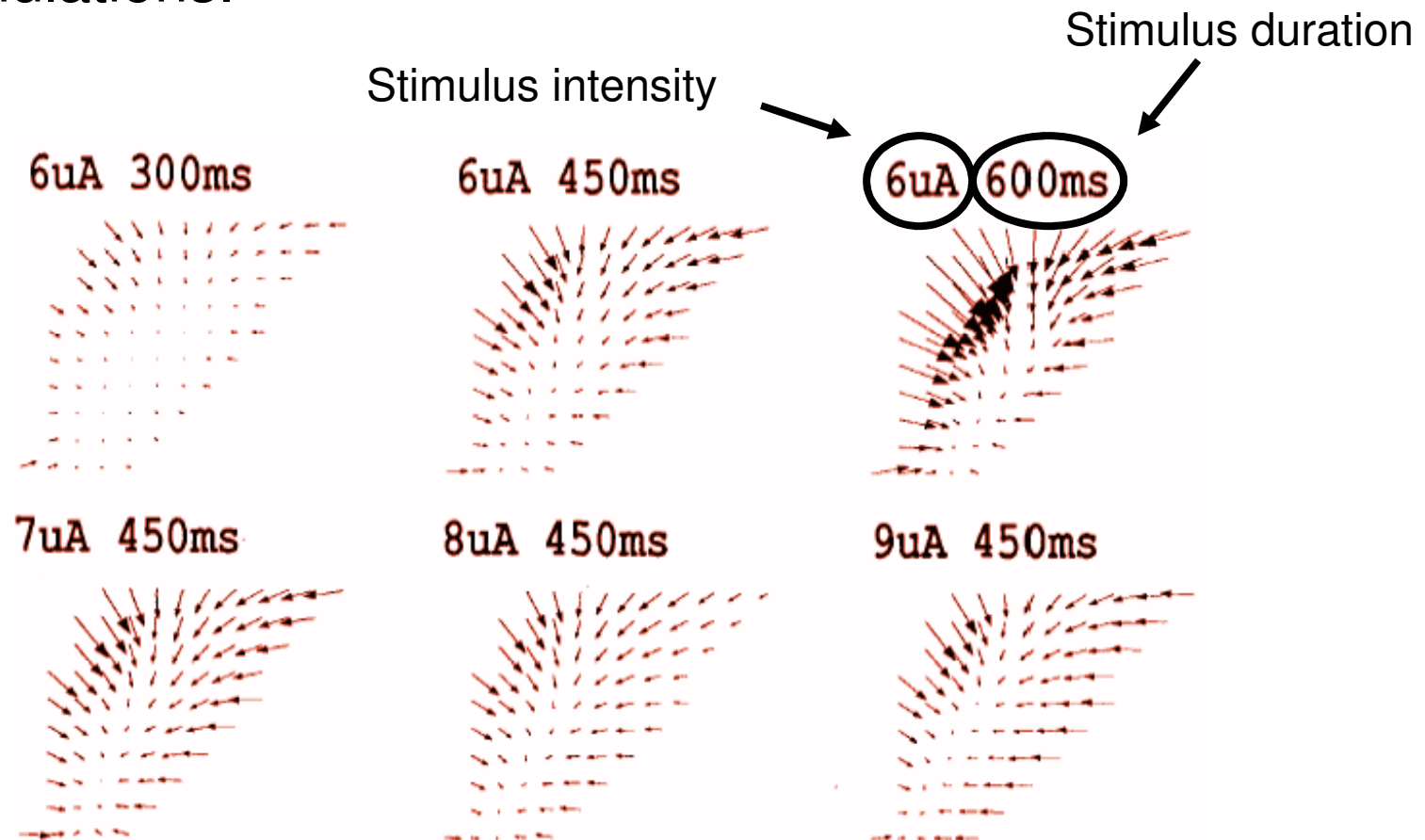
4 clusters can be identified



The presence of only few units of motor output within the spinal cord is difficult to reconcile with the obvious ability of the nervous system to produce a wide range of movements.

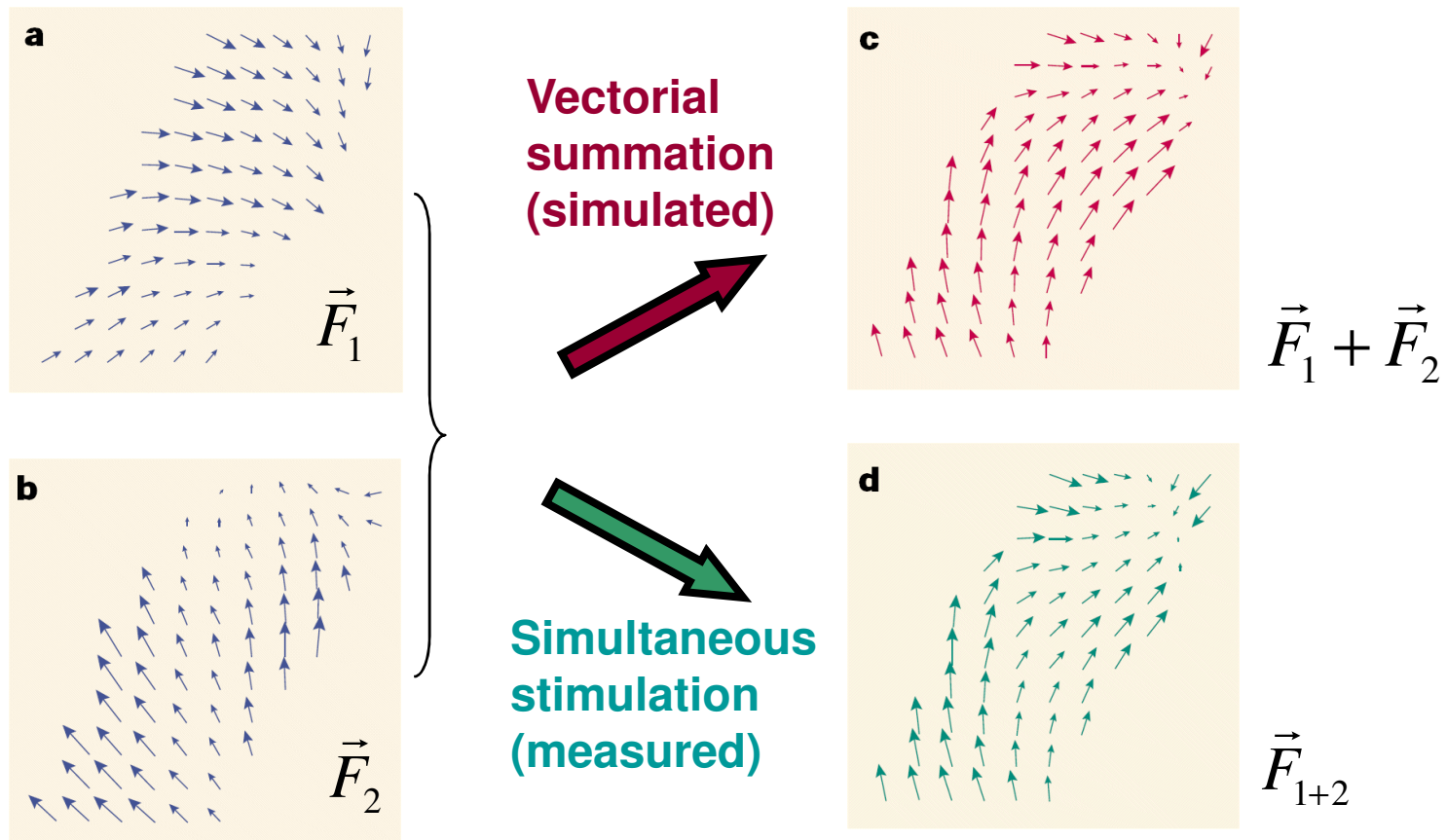
Observed field features (3)

- Each field can be modulated in amplitude (i.e. amplitude changes but orientation does not change) by different stimulations.



Observed field features (4)

- The fields induced by the stimulation of the cord follow a principle of vectorial summation



$$d(\vec{F}_1 + \vec{F}_2, \vec{F}_{1+2}) > 0.9$$

Various tests

Goal: verify that fields in Cartesian space summate

1. Non-redundant manipulator (simulation): 100%, > 0.9
 2. Redundant manipulator (simulation): 83.3%, > 0.9 correlation, 0.947 ± 0.04
 3. Spinal cord level (measured): 87.8% > 0.9 correlation
- I.e. with good approximation fields summate in Cartesian space, I can generate the total field starting from muscle synergies (in joint space for example)

Considerations: Pros

- **Nonlinearity** (that characterizes the interactions both among neurons and between neurons and muscles) **is somehow eliminated**. Linear summation is surprising because a number of nonlinear factors intervene between micro-stimulation and the produced force.
- **Learning is simplified** with this modular structure. If a system learns to generate a set of different outputs, then the same system is also capable of generating the entire linear span of these outputs.
- **Hierarchical structure**. Lower levels take care of realizing a predefined equilibrium. Higher levels decide where the system should be driven.
- These findings fit well in the of **equilibrium point hypothesis**, i.e. movements are the result of shifting an equilibrium point.

Considerations: Cons

- The force field **does not allow to predict the trajectory** followed by the system. The actual trajectory depends on the dynamical parameters (masses, inertias, frictions...) of the system.
- The force field **does not allow to predict the time to reach** the equilibrium point.
- The combination of force fields **does not correspond to the combination of equilibrium points** i.e.

$$EP_{1+2} \neq EP_1 + EP_2$$

e.g.

$$\begin{aligned} \vec{F}_1(\vec{P}) &= K_1(\vec{P} - EP_1) \\ K_1 &= K_1^T > 0 \end{aligned}$$

$$\begin{aligned} \vec{F}_2(\vec{P}) &= K_2(\vec{P} - EP_2) \\ K_2 &= K_2^T > 0 \end{aligned}$$

$$EP_{1+2} = (K_1 + K_2)^{-1}(K_1 EP_1 + K_2 EP_2)$$

Control Model of the spinal field experiment

The above experiment has been modeled in terms of the linear superposition of a finite number of force fields:

$$\vec{F}(P) = \sum_{k=1}^K \lambda_k \vec{F}_k(\vec{P})$$

Basis field should be convergent to an equilibrium

i.e. allowed force fields F belongs to the (linear) space spanned by a finite number of force fields F_k .

NOTE:

- Each force field is the result of a muscle synergy.
- The number of fields is finite. The way of combining them (i.e. the way of choosing combinatorics) is infinite. This explains the wide range of movements displayed by animals.

Movement execution using the spinal field paradigm

- Select a specific type of elementary force fields F_k :

$$\vec{F}_k(\vec{P}) = K_k(\vec{P} - EP_k) \exp\left[-\frac{1}{2}(\vec{P} - EP_k)^T K_k(\vec{P} - EP_k)\right]$$

- Given a desired movement (i.e. trajectory):
 1. Find a force field F corresponding to the desired movement (knowledge of dynamics is necessary),
 2. Approximate the given field as a combination of the basis force fields F_k .
 3. Choose the combinators.

Next
slides

Approximate a given field F

- Choose a set of N (key) points in the workspace

$$\vec{P}_1 \quad \vec{P}_2 \quad \dots \quad \vec{P}_N$$

- Choose combinator λ_k so as to satisfy the following:

$$\vec{F}(\vec{P}_1) = \sum_{k=1}^K \lambda_k \vec{F}_k(\vec{P}_1) \quad \dots \quad \vec{F}(\vec{P}_N) = \sum_{k=1}^K \lambda_k \vec{F}_k(\vec{P}_N)$$

i.e. we exactly impose the value of the combined fields to be equal to the desired field F.

In matrix form

$$\begin{array}{c}
 D \cdot N \left\{ \begin{array}{l}
 \overbrace{\left[\begin{array}{cccc}
 \vec{F}_1(\vec{P}_1) & \vec{F}_2(\vec{P}_1) & \cdots & \vec{F}_K(\vec{P}_1) \\
 \vec{F}_1(\vec{P}_2) & \vec{F}_2(\vec{P}_2) & & \\
 \vdots & & \ddots & \vdots \\
 \vec{F}_1(\vec{P}_N) & \vec{F}_2(\vec{P}_N) & & \vec{F}_K(\vec{P}_N)
 \end{array} \right]}^{\Phi}
 \end{array} \right.
 \begin{array}{l}
 \left[\begin{array}{c}
 \lambda_1 \\
 \lambda_2 \\
 \vdots \\
 \lambda_K
 \end{array} \right] \\
 \lambda
 \end{array}
 =
 \begin{array}{l}
 \left[\begin{array}{c}
 \vec{F}(\vec{P}_1) \\
 \vec{F}(\vec{P}_2) \\
 \vdots \\
 \vec{F}(\vec{P}_N)
 \end{array} \right] \\
 \mathfrak{N}
 \end{array}
 \end{array}$$

• Exact solution (for every possible field F) is possible if and only if the matrix Φ is full row rank. In particular a solution exists only if K is greater or equal than DN (i.e. we should have enough basis fields).

• If Φ is full row rank than an **exact solution** (minimum norm solution) is given by:

$$\lambda = \Phi^T (\Phi \Phi^T)^{-1} \mathfrak{N}$$

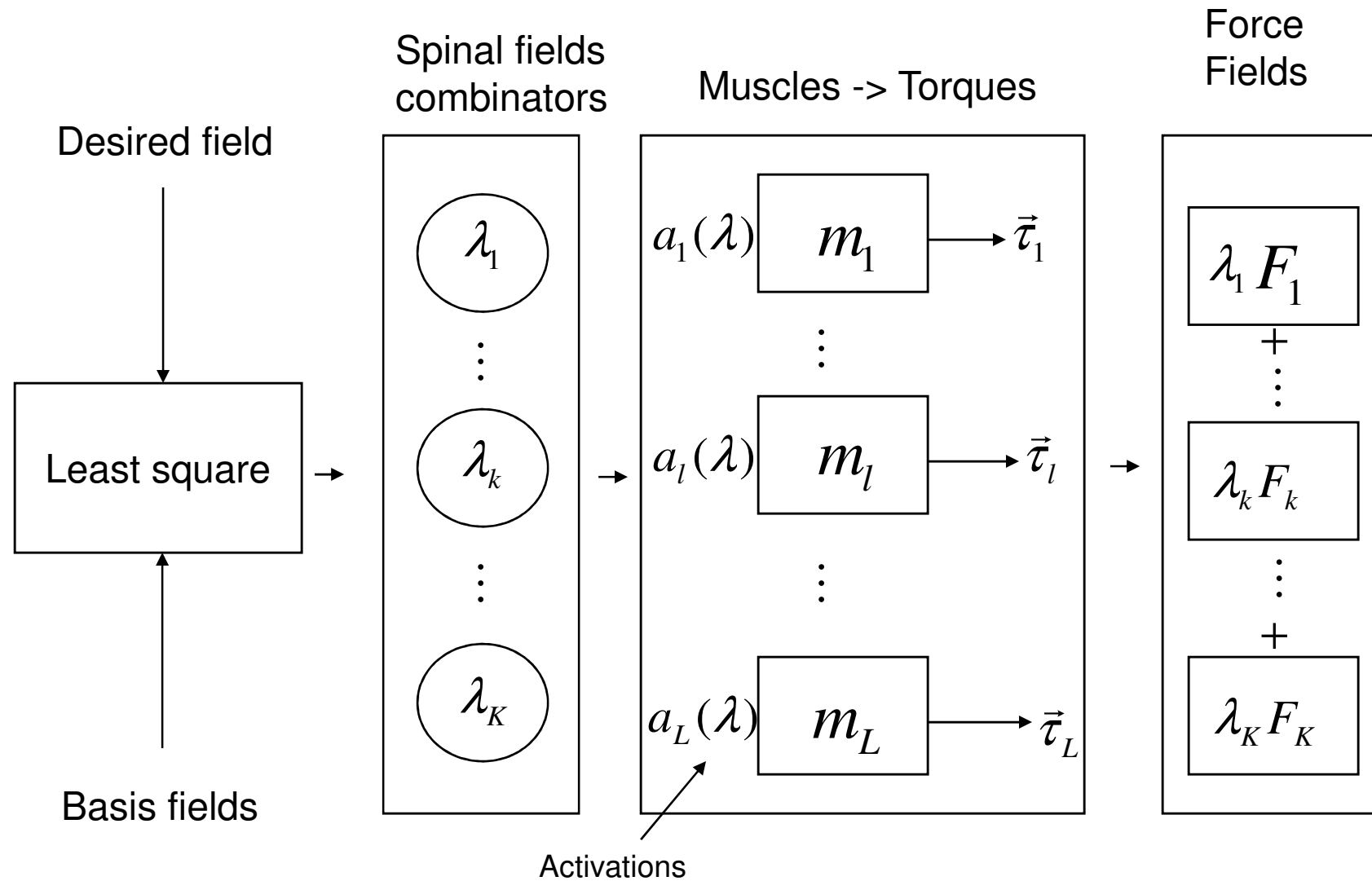
• If Φ is full column rank than an **approximate solution** (least square solution) is given by:

$$\lambda = (\Phi^T \Phi)^{-1} \Phi^T \mathfrak{N}$$

Pros and Cons...

- PROS:
 - Easy to be implemented (it only requires a matrix inverse plus trivial computations)
- CONS:
 - It's just a local approximation of the desired field
 - Cannot predict the resulting trajectory
 - Does not say anything about how to choose muscles activation that lead to a given elementary field F_k .

What does the controller look like?



In case we'd like to simulate the force fields

- DC motors can generate a torque proportional to the current!
- Programming currents so to simulate the force fields

This considerations open a set of interesting question if we want to implement the spinal fields idea on a real robot!

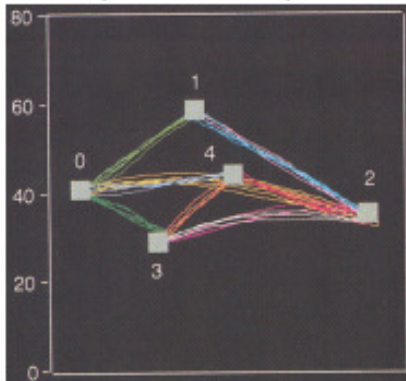
Open Questions

- How should we choose joint torques so as to obtain a given basis force field F_k ?
- How do we choose muscle activations so as to obtain a given joint torque?
- How can we predict the trajectory followed by the system when it is driven by a given force field F ?
- Is there an optimal way of choosing the elementary force fields F_k ?
- Which is the minimum number of elementary force fields that we need to perform a 'complete' set of movements?
- Is there a way of choosing the primitives to accommodate different kinematic structures?

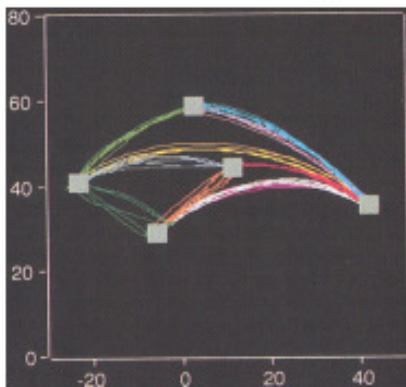
Kinematic model

Flanagan & Rao, 1995

Unperturbed space
(cartesian)

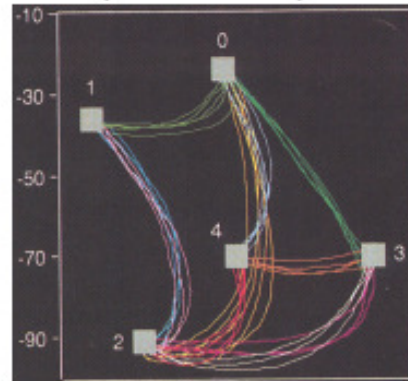


before learning

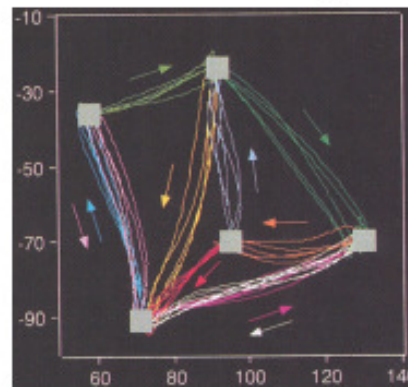


after learning

Perturbed space
(perceived)



before learning



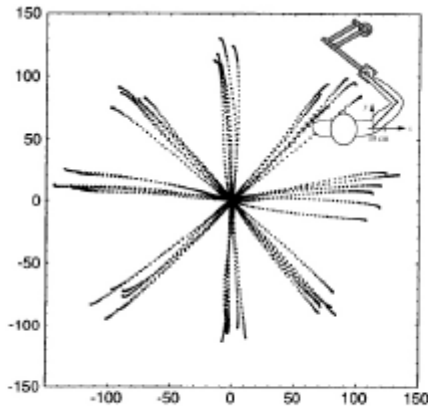
after learning

Before learning **perturbation causes a distortion in the perceived space**. The old internal kinematic model produces a wrong prediction.

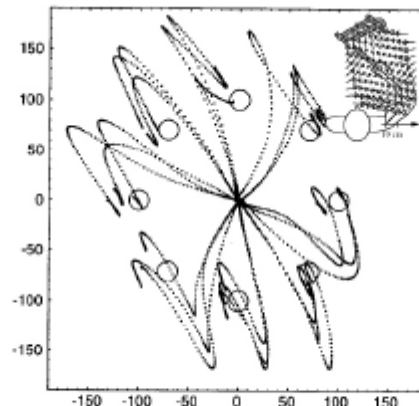
After learning **perturbation is compensated in the perceived space**. An evident perturbation appears in the cartesian (non-perceived) space.

Dynamic Model

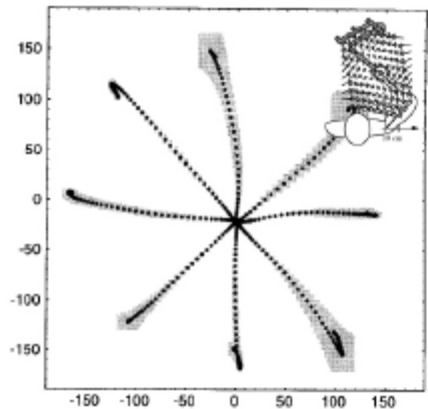
Shadmehr et al. 1994



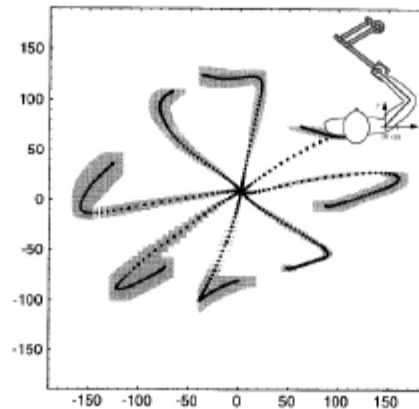
Normal conditions



Perturbed conditions



Learned perturbation



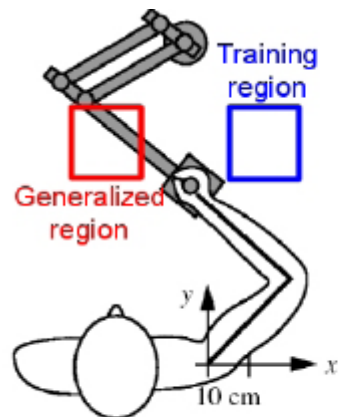
After effect

Hand path is modified if we change the dynamics of the controlled system.

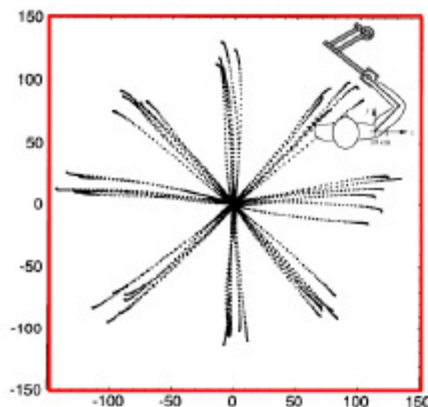
After learning **perturbation is compensated**. The presence of an evident after effect support the idea that **a new internal model has been learnt** (see also Milner & Cloutier, 1994).

Generalization of the dynamic model

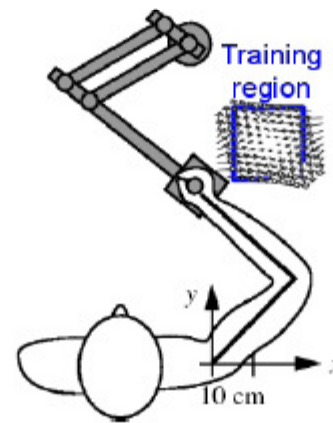
Shadmehr et al. 1994



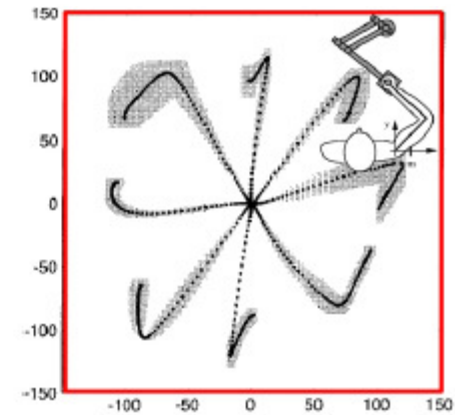
Training VS generalization



Normal conditions



Training

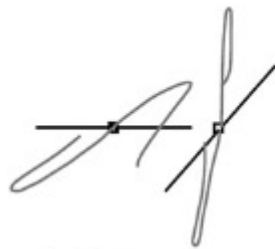


Transferred after effect

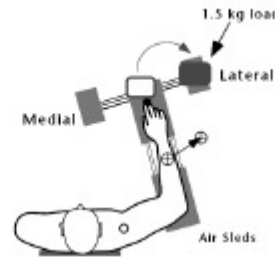
The after effect has been observed even outside the training region. Therefore, adaptation of the internal model is (to a certain extent) **generalized outside the explored workspace**. **The internal model is non-local!**

Independence of Dynamic and Kinematic models

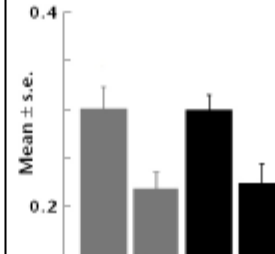
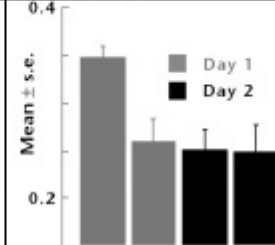
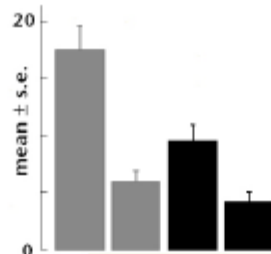
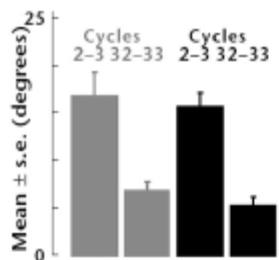
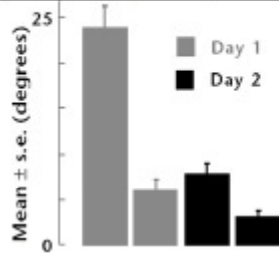
Krakauer & al., 1999



Kinematic perturbation: 30° field of view CCW rotation



Dynamic perturbation: 1.5 kg mass added to the forearm



Kinematic learning is influenced by a different kinematic learning but it is not influenced by dynamic learning.

Interested?

Check out my web page

(<http://www.dei.unipd.it/~iron>)

and have a look at Bizzi Lab web site

(<http://web.mit.edu/bcs/bizzilab/>)