Motor control learning and modular control architectures

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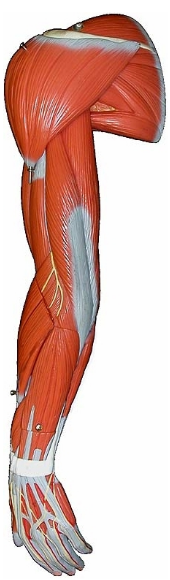
Internal Model and its Complexity (1/2)

1. **Experimental Evidence:** the central nervous system (CNS) uses and updates **internal models**. E.g. the dynamic internal model approximates limb *dynamics*:

$$\boxed{\text{desired movement} \xrightarrow{\text{internal model}} \text{motor command}}$$

2. **Experimental Evidence:** the internal model develops (on the basis of past experience), learns new movements and adapts (to new contingencies).

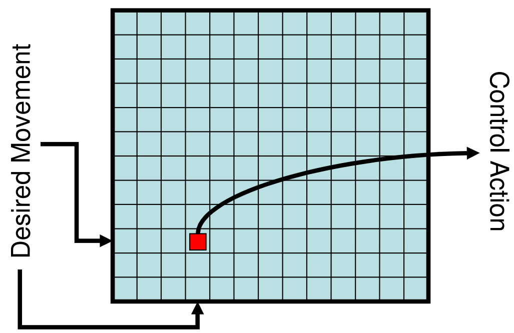


Human arm:	Human hand:
• Number of muscles ≥ 21, • Number of degrees of freedom $= 7$,	• Number of muscles ~ 40, • Number of degrees of freedom ~ 25,

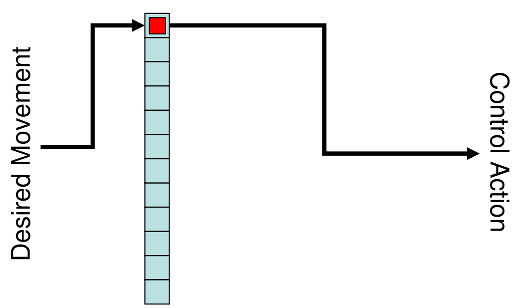
Note: Very high complexity!

Internal Model and its Complexity (2/2)

Which are the 'building blocks' of the internal model?



"Look-up-table" (Raibert): Although simplified the table grows exponentially with the number of DOF!



(Mussa-Ivaldi and Bizzi, 2000): A limited number of motor commands that can be generalized to more complex ones.

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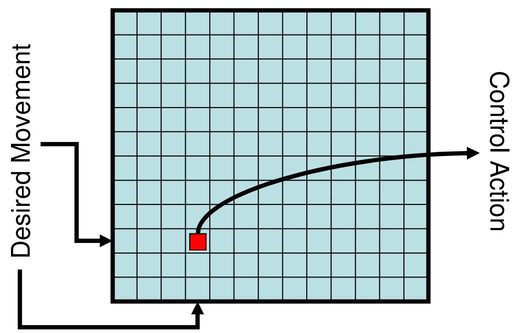

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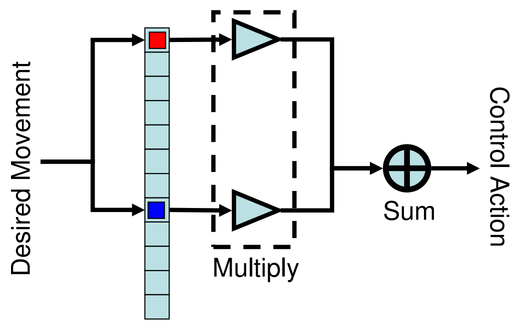

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Outline of the Talk

- Experimental evidence:
  - adaptive **kinematic internal model** (Flanagan& Rao, 1995).
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  - **synthesis** of motion primitives.
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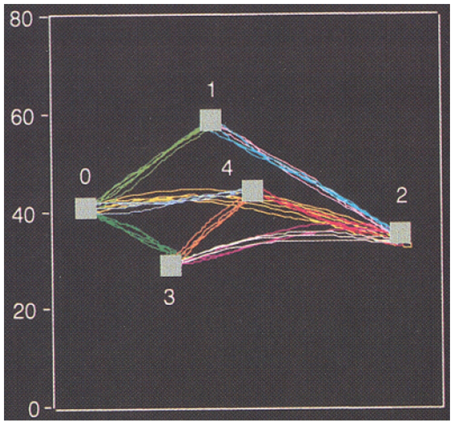
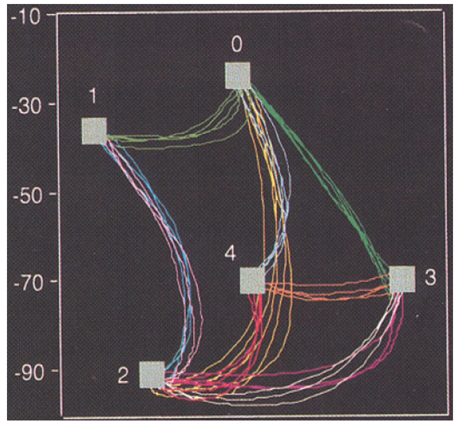
Kinematic internal model (Flanagan& Rao, 1995)

Unperturbed space (cartesian)

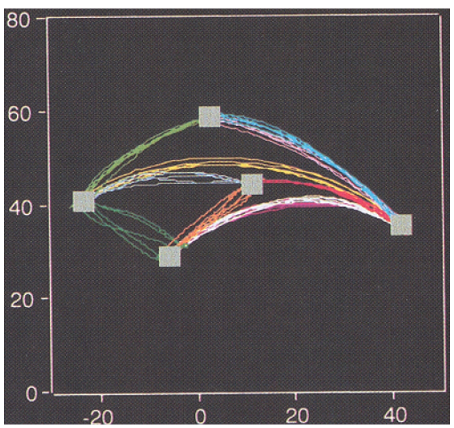
Perturbed space (perceived)



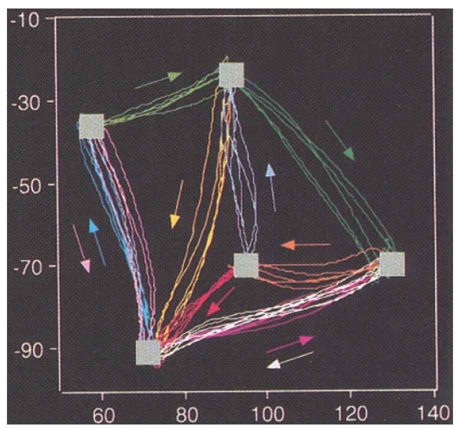
before learning



before learning



after 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 pertubation appears in the cartesian (non-perceived) space.

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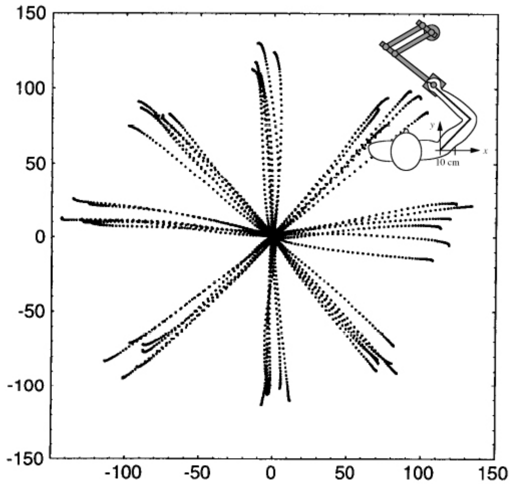
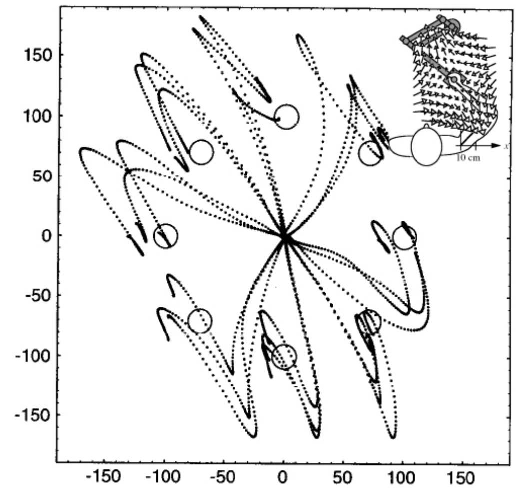
Dynamic internal model (Shadmehr & al., 1994)

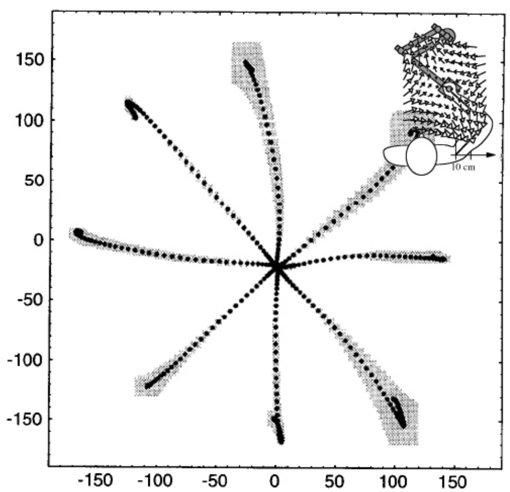


Normal conditions

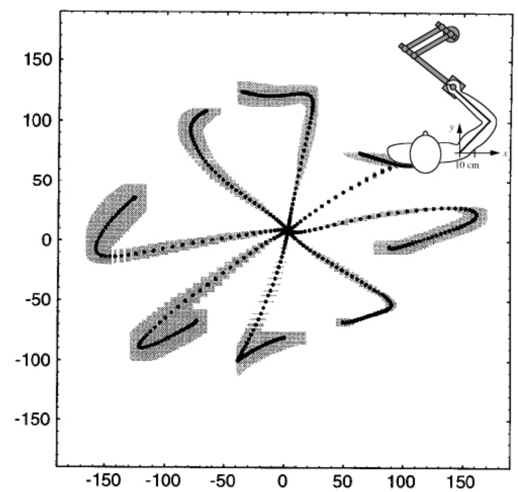


Perturbed conditions

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



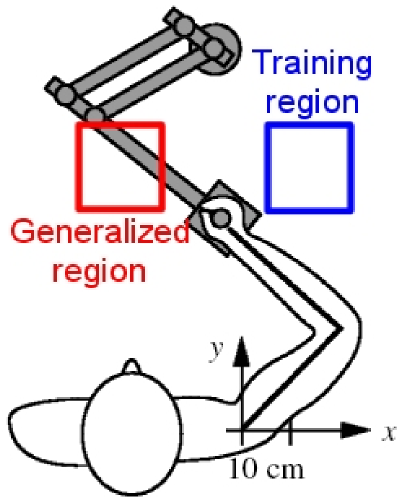
Learned perturbation



After effect

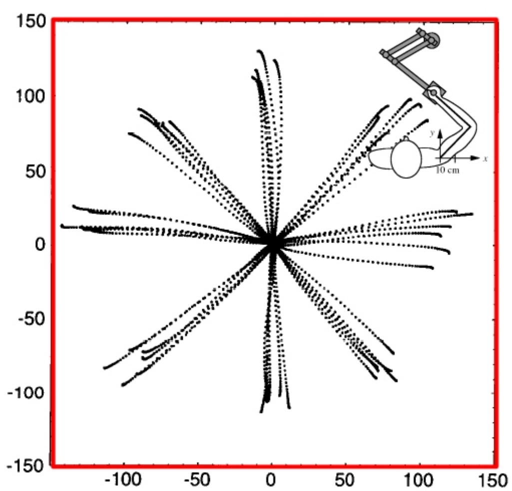
After learning perturbation is compensated. The presence of an evident after effect support the idea that a new internal model has been learnt (see also Milner & Cloutier, 1994).

Generalization and adaptability (Shadmehr & al., 1994)

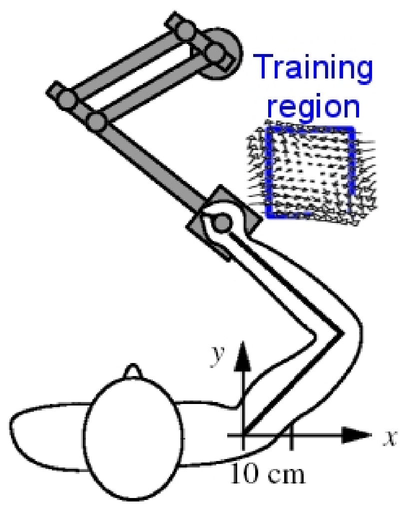


Training VS generalization

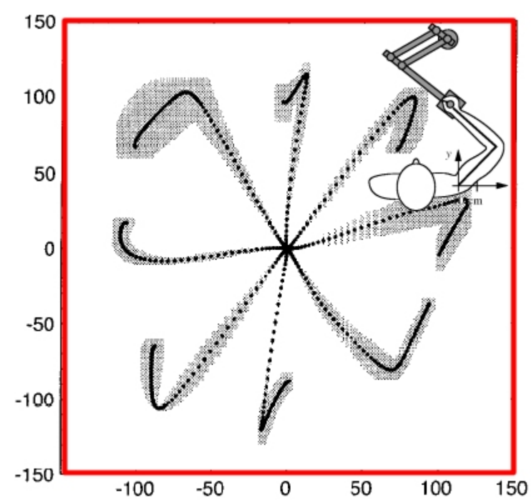
The after effect has been observed even outside the training region. Therefore, adaptation of the internal model is (to a certain extent) **generalized outside the explored workspace**. **The internal model is non-local!**



Normal conditions



Training



Transferred after effect

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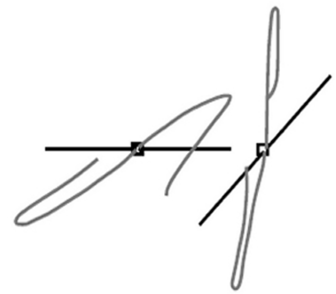
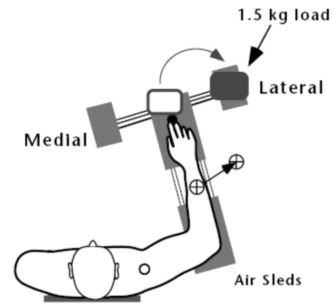
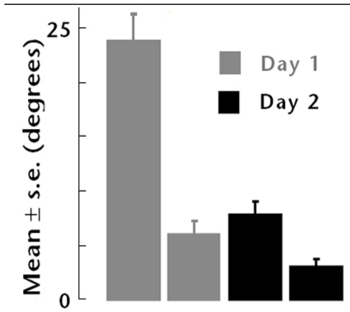
Independent learning of kinematic and dynamic internal models (Krakauer & al., 1999)

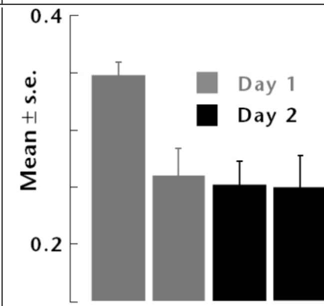


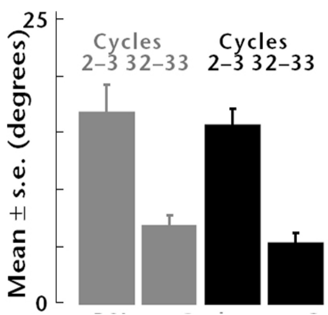
Kinematic perturbation: 30^o field of view CCW rotation

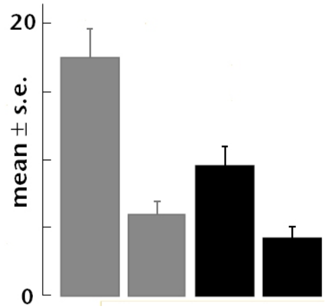


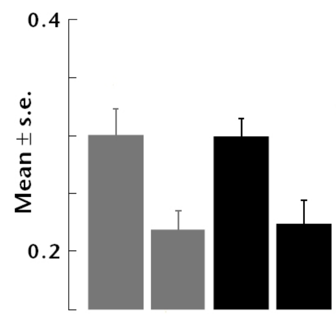
Dynamic perturbation: 1.5 kg mass added to the forearm





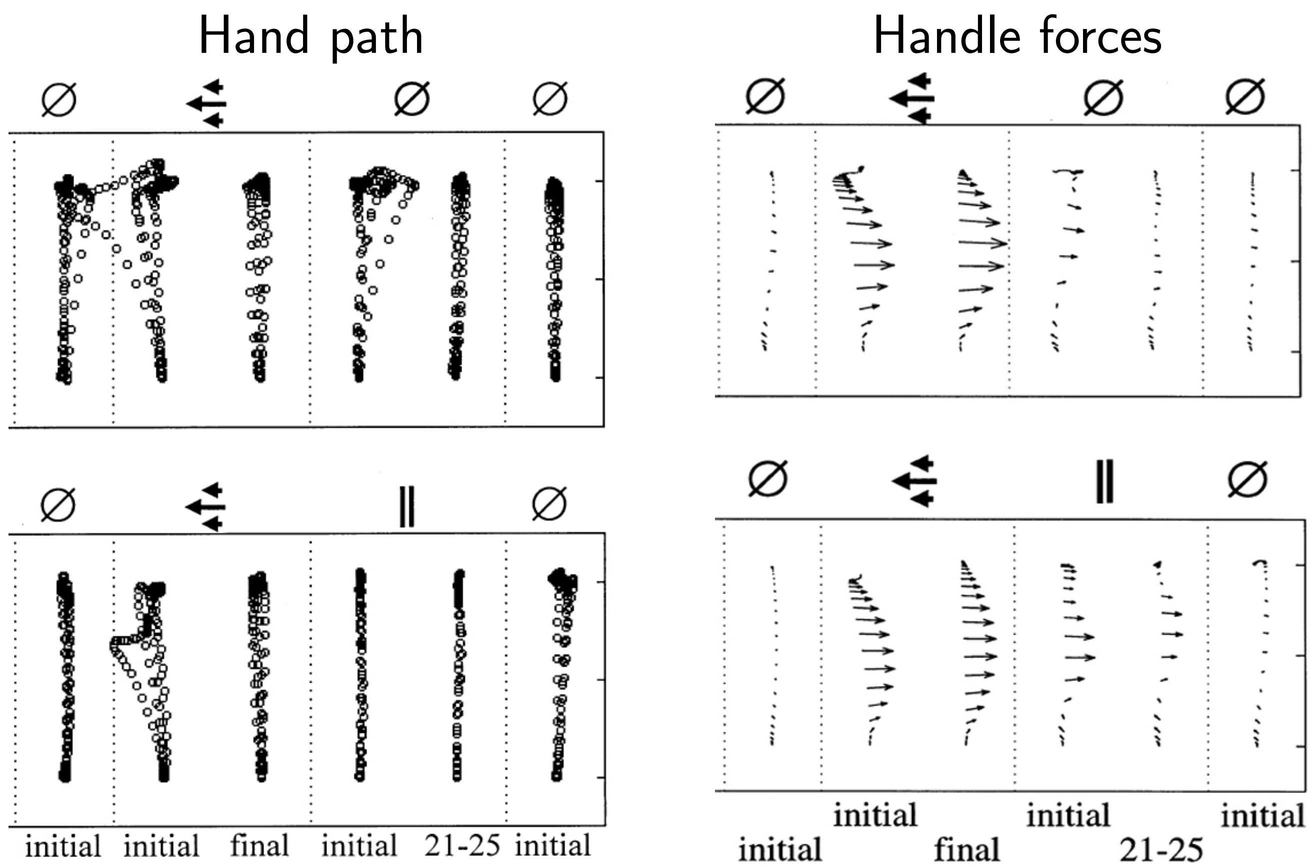






Kinematic learning is influenced by a different kinematic learning but it is not influenced by dynamic learning.

Independent learning of kinematic and dynamic internal models (Scheidt & al., 2000)



Subjects were asked to perform an horizontal movement in presence of an orthogonal force field. After-effects were kinematically prevented by a mechanical guide.

Observation: The dynamical model after effects disappear even if kinematic errors are prevented from occuring.

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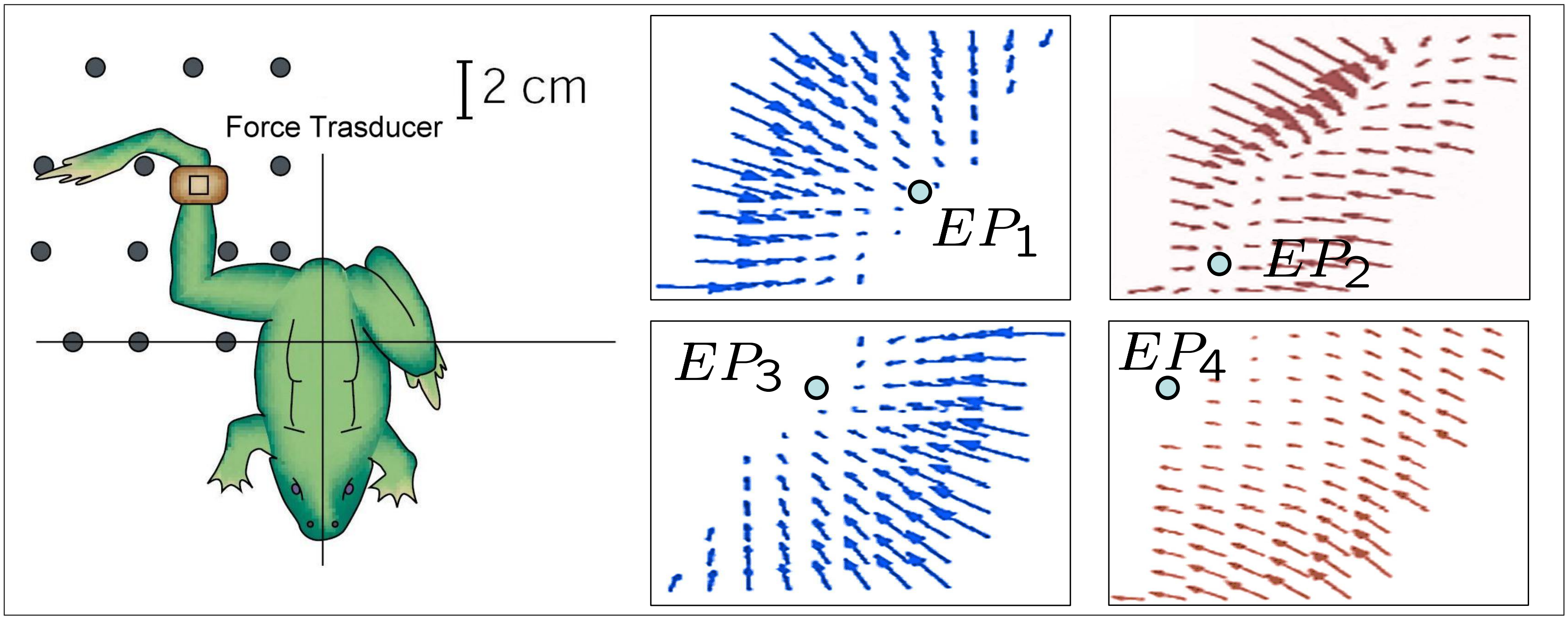
Spinal Fields: E. Bizzi, F.A. Mussa-Ivaldi, S. Giszter

Control actions are organized in (linearly combinable) primitives.

Set of primitives $\leftrightarrow$ Vocabulary Primitives $\leftrightarrow$ Words Movements $\leftrightarrow$ Sentences

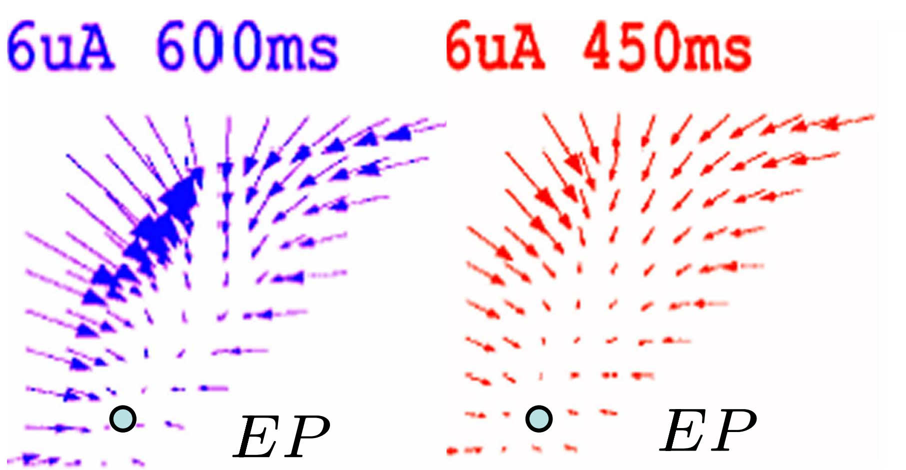


1. generates only a finite number of different force fields (called **spinal fields**);
2. each spinal field **has a unique equilibrium point** in the workspace.

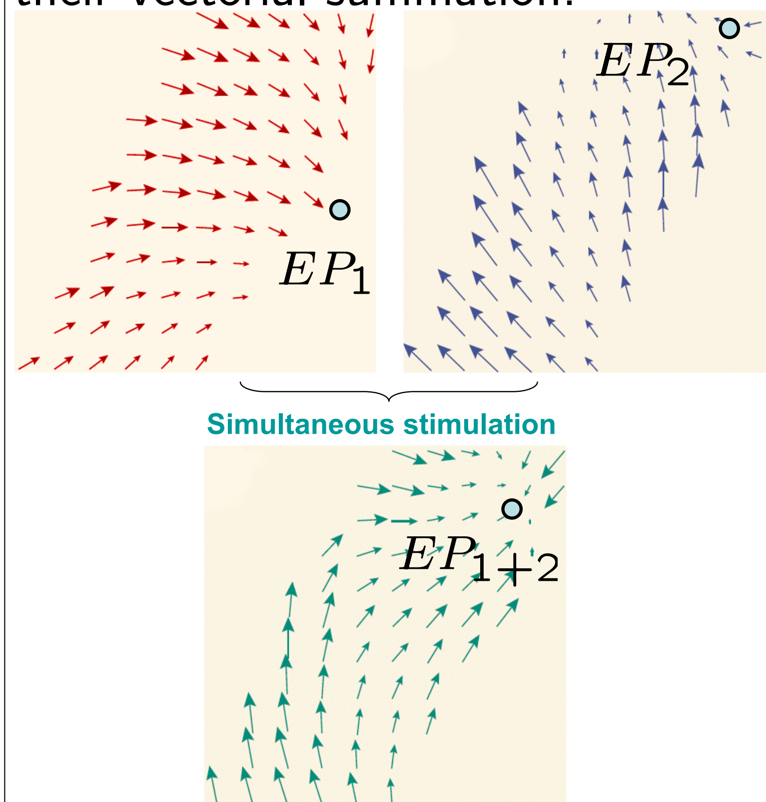
Modulating the same field and composing two fields

How can a finite number of force fields generate a wide range of movements?

(1) Stimulating the same field with different intensities modifies the amplitude of the elicited field.



(2) Stimulation of two fields lead to their vectorial summation.



A very simple syntax: fields can be literally added!

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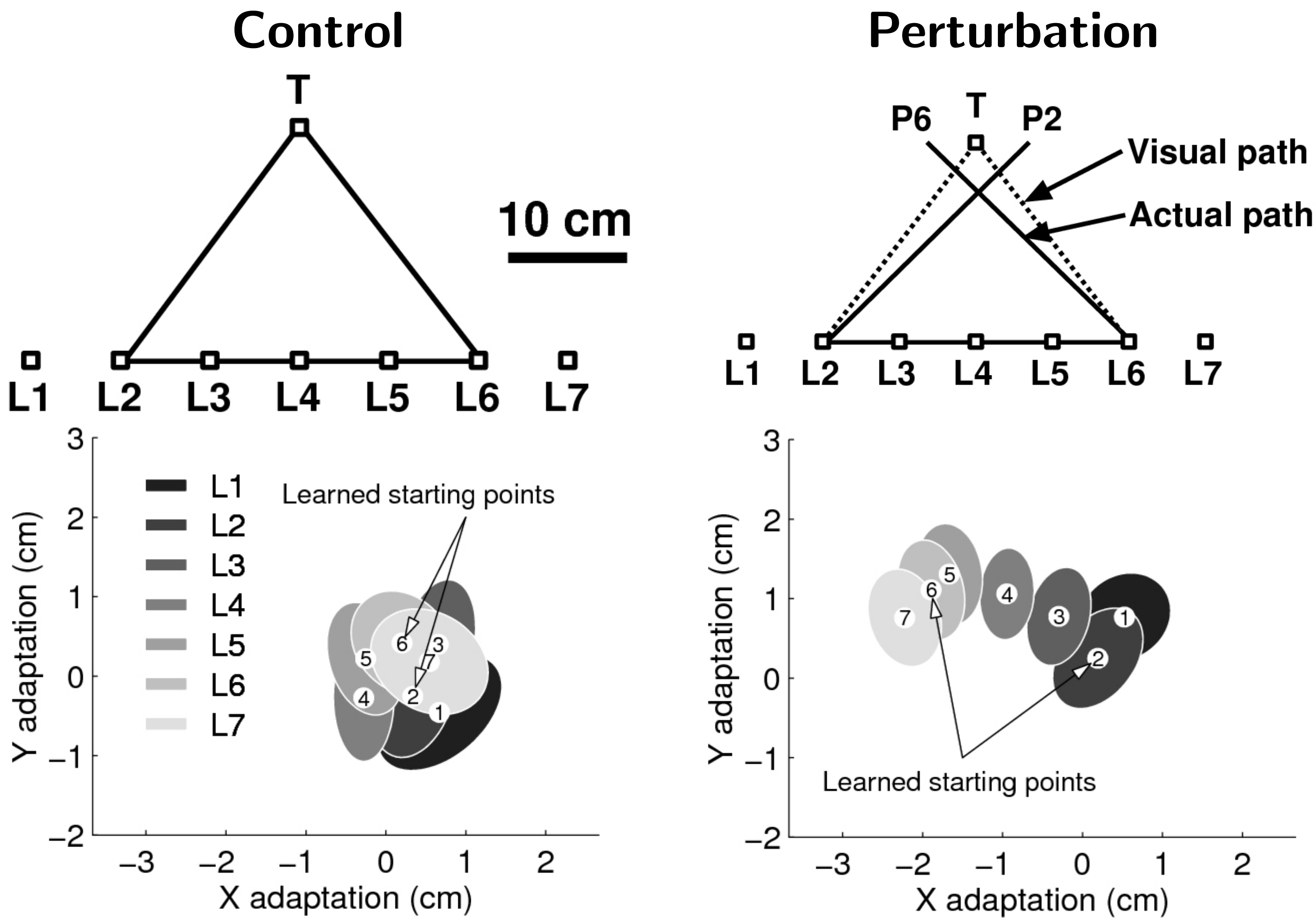
Composability of kinematic internal models (Gaharmani & Wolpert, 1997)



Two different kinematic models have to be visually learnt.

After visual learning perturbation is (blindly) generalized gradually shifting between the learnt models.

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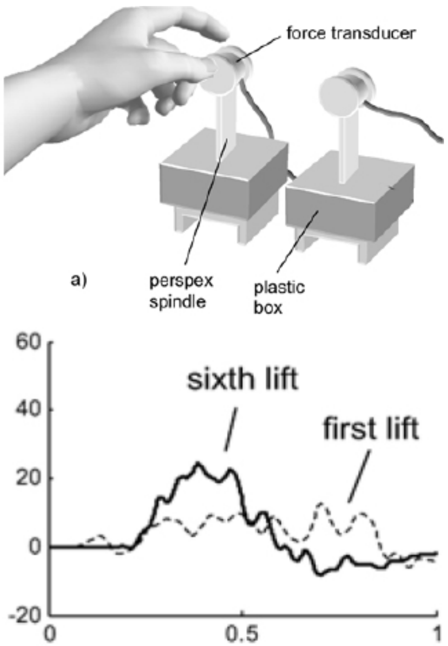
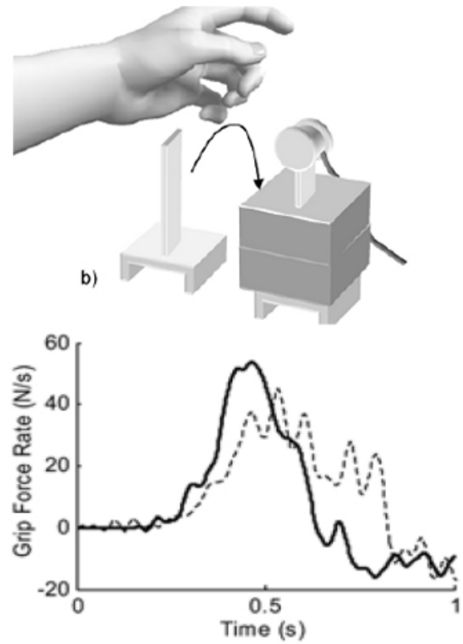
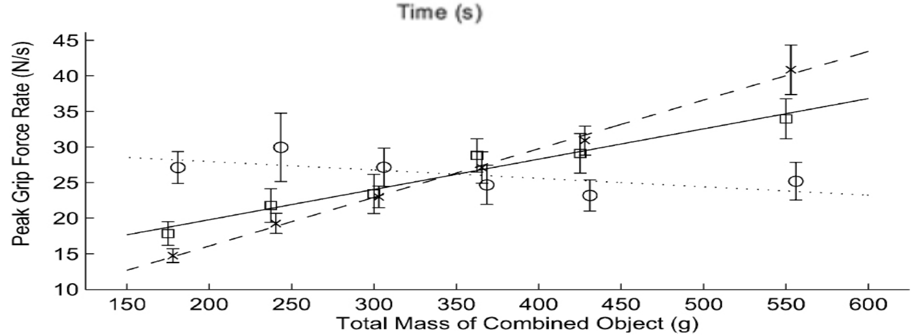
Composability dynamic internal models (Davidson & Wolpert, 2004)

New objects



Composition of known obj.





When lifting unknown objects a dynamical model is learnt.

When lifting (for the first time) compositions of known objects, the internal model is already there.

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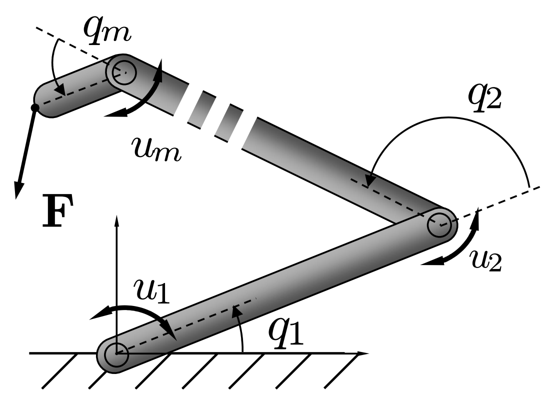
Modelling the Spinal Fields as Motion Primitives

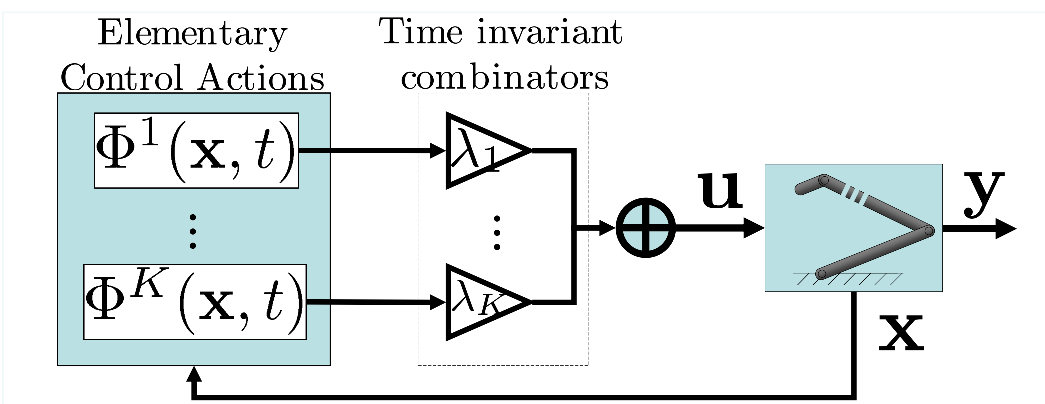
- **Model of a limb**:

$$\boxed{M\ddot{\mathbf{q}} + C\dot{\mathbf{q}} + N = \mathbf{u},}$$

$$\mathbf{x} = \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix}, \quad \mathbf{y} = h(\mathbf{q})$$



- **Model of the spinal field paradigm**:



$$\mathbf{u} = \sum_{k=1}^{K} \underbrace{\lambda_k}_{\text{mixing coeff}} \cdot \underbrace{\Phi^k(\mathbf{x}, t)}_{\text{Motion Primitives}}$$

Φ^k makes the system converge to $\mathbf{x}_f^k$

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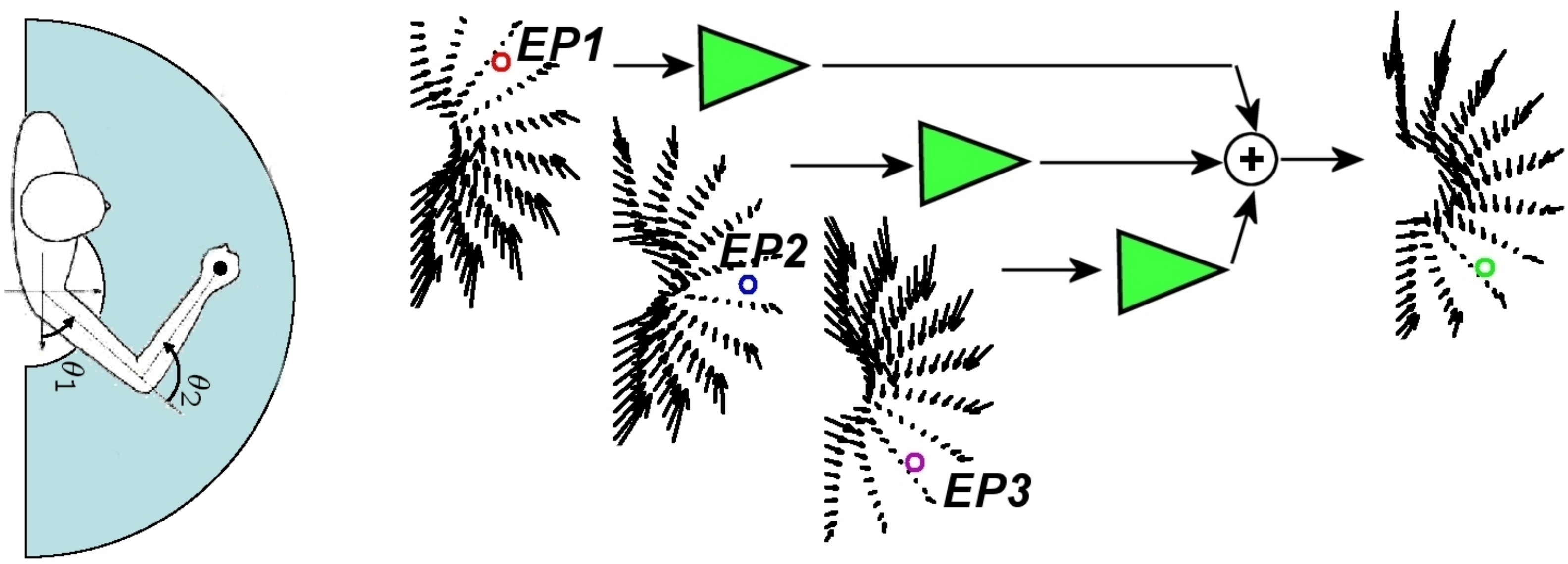
Reformulation in a Control Theoretical framework

$$\underbrace{\text{Admissible } \mathbf{u}}_{\text{Controls}} = \sum_k \underbrace{\lambda_k}_{\text{New Inputs}} \cdot \underbrace{\Phi^k(\mathbf{x}, t)}_{\text{Motion Primitives}} \Longrightarrow$$

Controllability may be lost!

Find a vocabulary for preserving output controllability.

Find $\{\Phi^1, \ldots, \Phi^K\}$ such that, given any reachable output configuration $\mathbf{y}_f$, there exists a time invariant $\lambda(\mathbf{y}_f) = \{\lambda_1, \ldots, \lambda_K\}$ that drives the system to $\mathbf{y}_f$.



Solution of the synthesis problem

We proposed (Nori at al., Biol. Cyb. 2005) a solution to the synthesis problem for **input to output feedback linearizable** systems. Interestingly, 'fully actuated' systems are within this class.

- Feedback linearize the given system:

$$\mathbf{u} = \alpha(\mathbf{x})\mathbf{v} + \beta(\mathbf{x}).$$

- Using the superposition principle solve the synthesis problem for the linearized system:

$$\phi^1(\mathbf{x}, t) \ldots \phi^K(\mathbf{x}, t) \qquad \lambda(\cdot).$$

- Transform the linearized solution into a solution for the nonlinear system:

$$\Phi^1(\mathbf{x}, t) \ldots \Phi^K(\mathbf{x}, t) \qquad \lambda(\cdot),$$

  where:

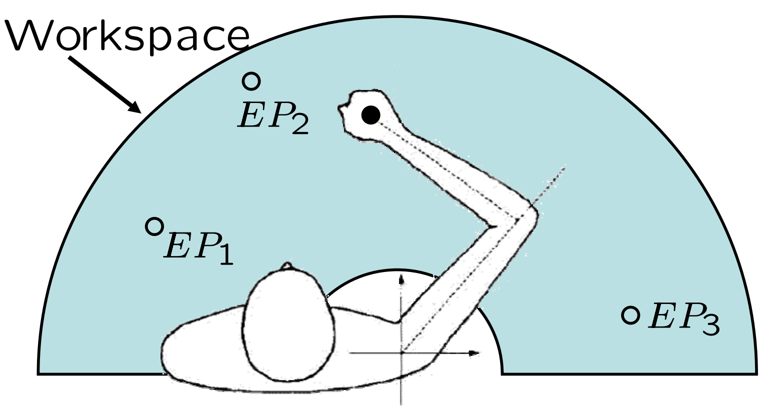
$$\Phi^k(\mathbf{x}, t) = \alpha(\mathbf{x})\phi^k(\mathbf{x}, t) + \beta(\mathbf{x}).$$

Minimum number of Motion Primitives

The number of motion primitives is related to the complexity of the system. **The more motion primitives we have, the more complex the system will be**.

Given a kinematic chain with n degrees of freedom, the minimum number of motion primitives (necessary to preserve the system controllability) is $n + 1$.

Given a set of tasks described by a p dimensional space (manifold), the minimum number of motion primitives (necessary to perform all the tasks in the set) is $p + 1$.

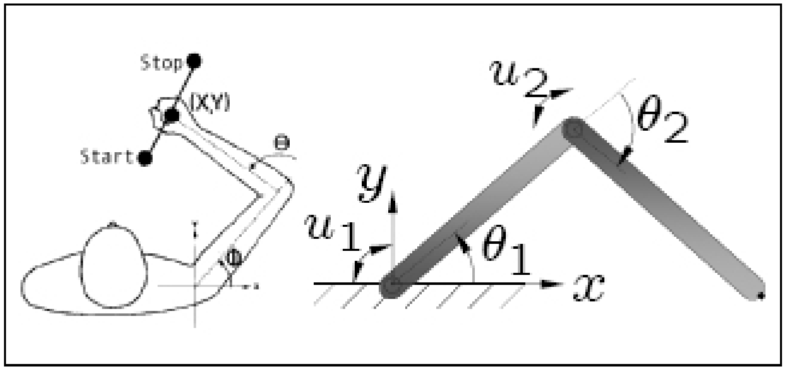


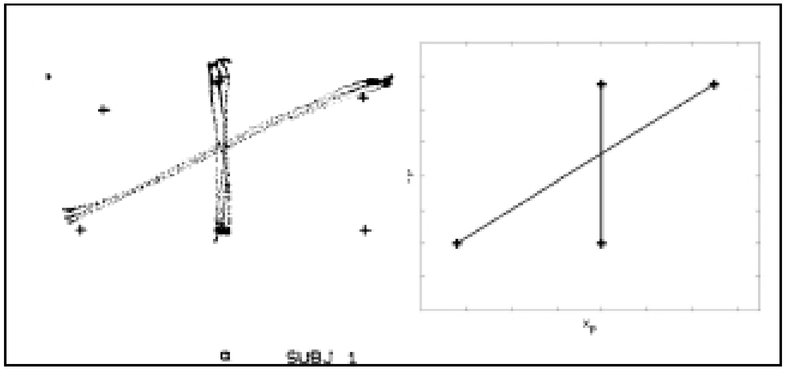
$p = 2$: two-dimensional workspace

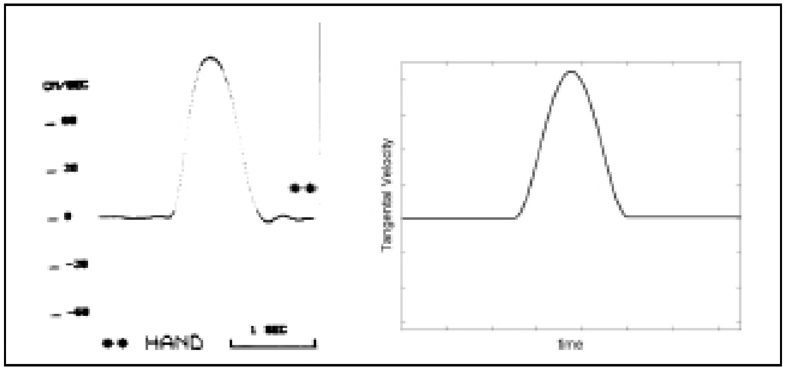
$p + 1 = 3$: minimum number of primitives (EP's should not be collinear)

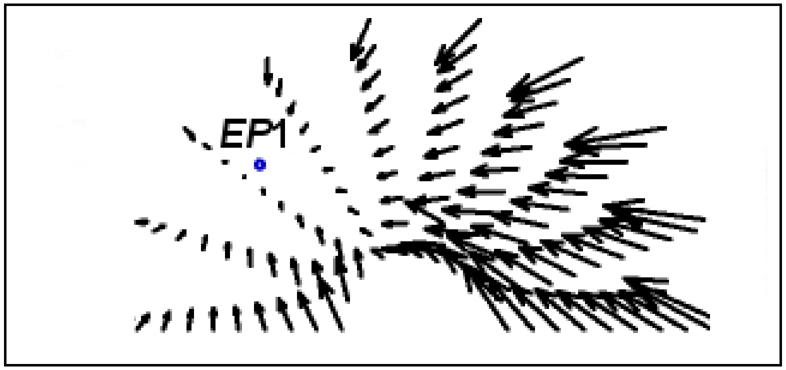
Qualitative Comparison with Experimental Data

Using the proposed paradigm we can subdivide the **"minimum jerk"** paradigm into a finite number of motion primitives.









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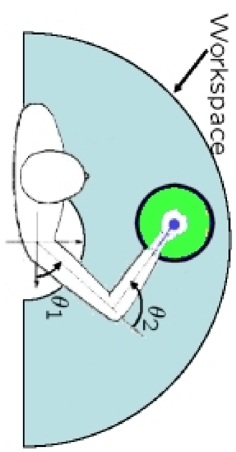
Adaptation to dynamical changes (1/3)

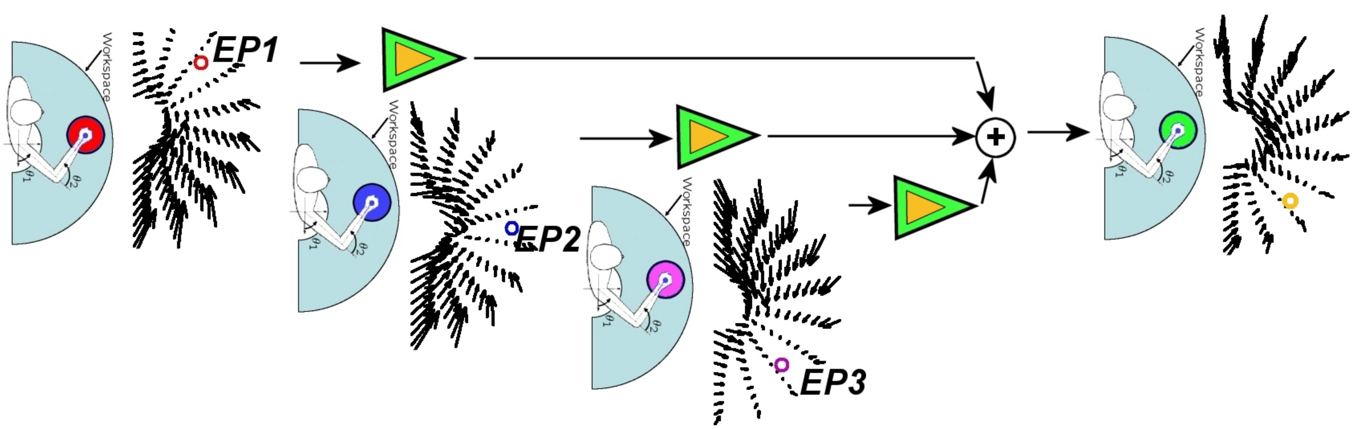
During everyday life dynamics we experience different dynamical contexts:

$$\mathbf{p} \triangleq \left[\underbrace{m_1}_{\text{mass}} \ \underbrace{I_1}_{\text{inertia}} \ \underbrace{\mathbf{c}_1}_{\text{c.o.m. position}} \ \ldots \ m_n \ I_n \ \mathbf{l}_n \ \mathbf{c}_n \right]^\top$$

Find a vocabulary for adapting to different dynamics.

Find $\{\Phi^1, \ldots, \Phi^K\}$ such that, given any reachable output configuration $\mathbf{y}_f$, there exists a time invariant $\lambda(\mathbf{y}_f, \mathbf{p}) = \{\lambda_1, \ldots, \lambda_K\}$ that drives the system with dynamical parameters $\mathbf{p}$ to $\mathbf{y}_f$.



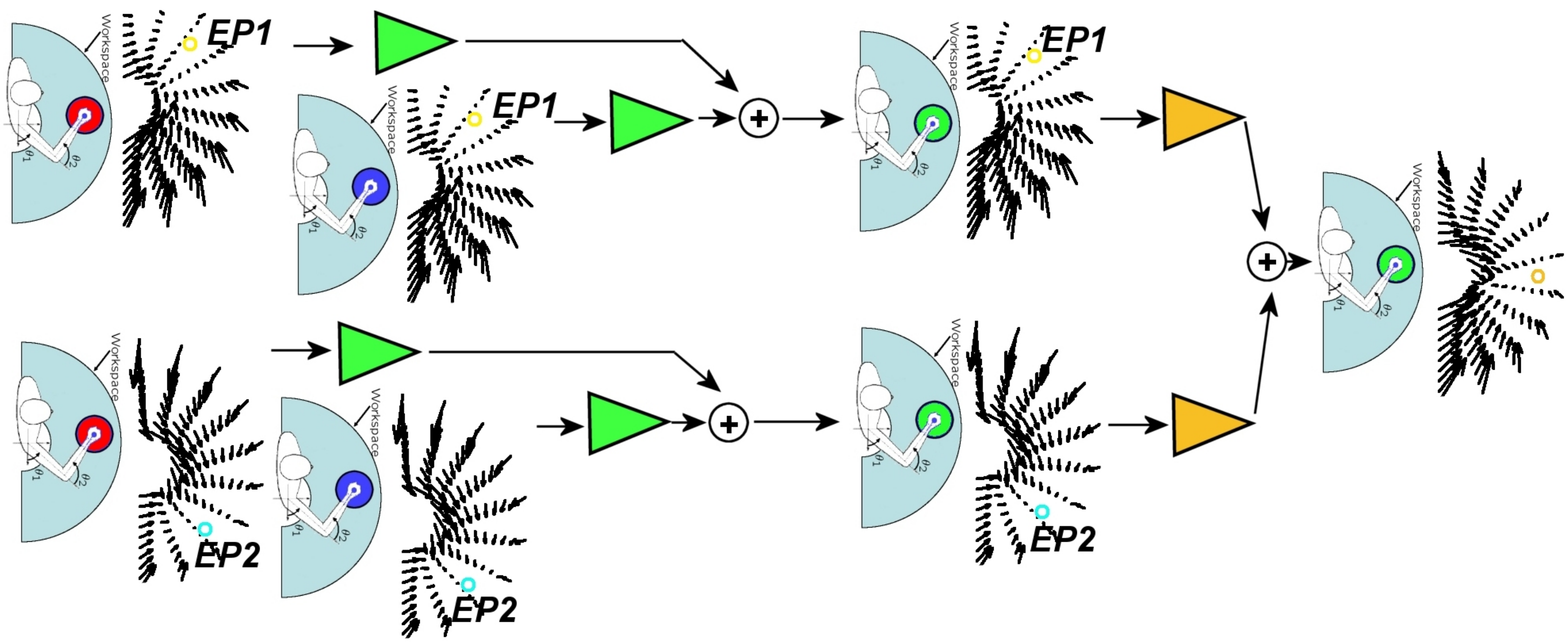


Adaptation to dynamical changes (2/3)

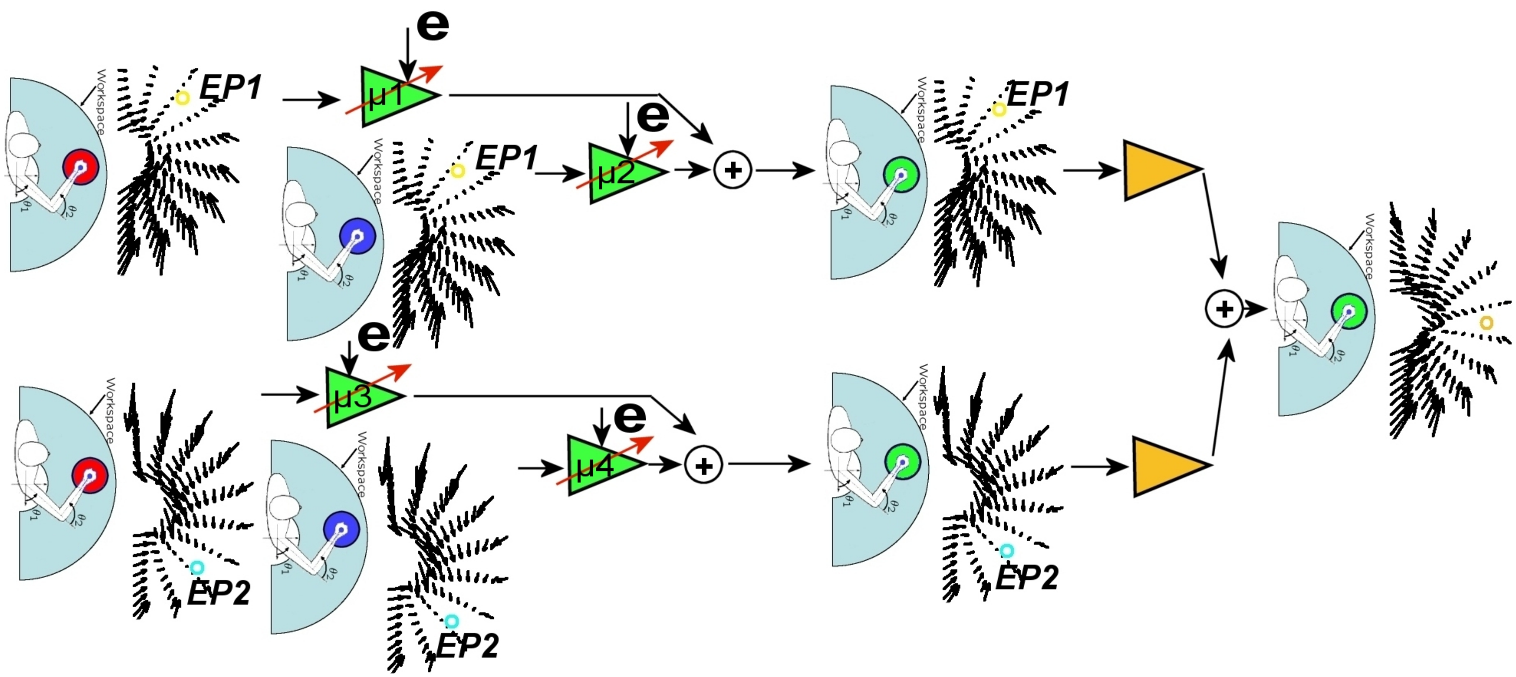
$$\mathbf{u} = \sum_{k,j} \lambda_k(\mathbf{y}_f)\mu_j(\mathbf{p})\Phi^{k,j}(\mathbf{x}, t).$$

where $\Phi^{1,j}(\mathbf{x}, t)$, ..., $\Phi^{K,j}(\mathbf{x}, t)$ is a solution for a dynamic context $\mathbf{p}^j$.

Dynamic and kinematic have been separated:



Adaptation to dynamical changes (3/3)



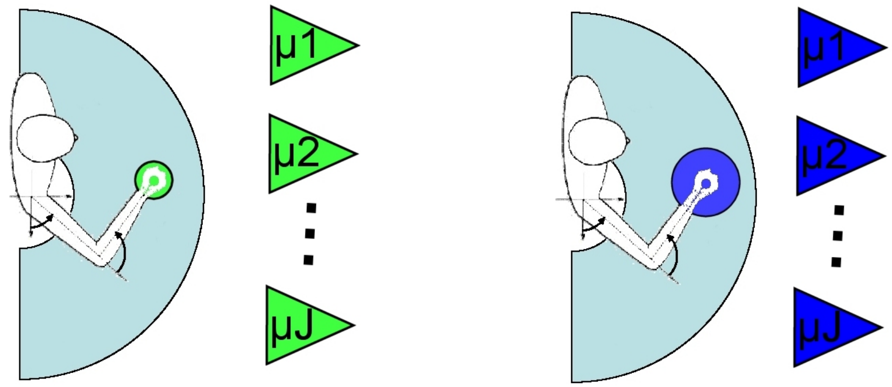
The on-line adaptation rule is given by:

$$\frac{d\mu_j}{dt} = -\mathbf{e}^\top(t) \left[\sum_k \lambda_k(\mathbf{y}_f) \Phi^{k,j}(\mathbf{x}, t) \right].$$

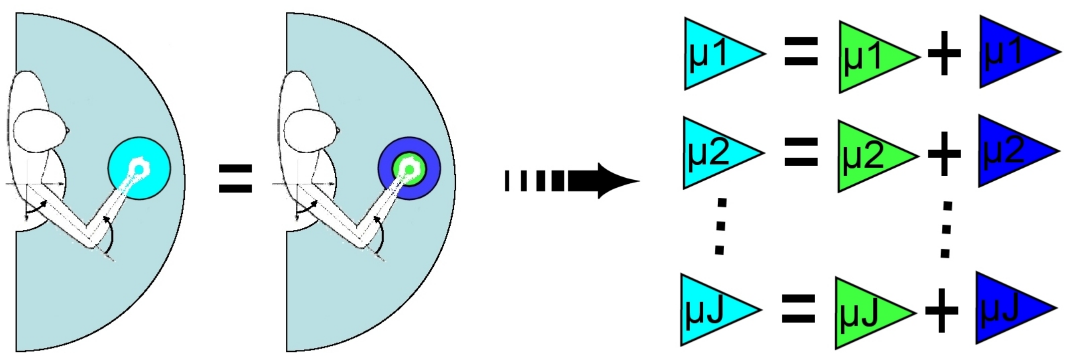
The stability of the above control structure can be proven using standard adaptive control tools.

Recombination of learned experiences

Suppose that a couple of objects is known, i.e. we know the coefficients that describe their dynamics:

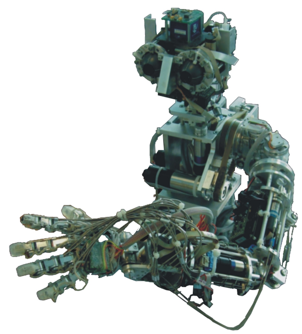


If an unknown third object can be interpreted as the combination of two known objects, then its dynamics can be represented as follows:

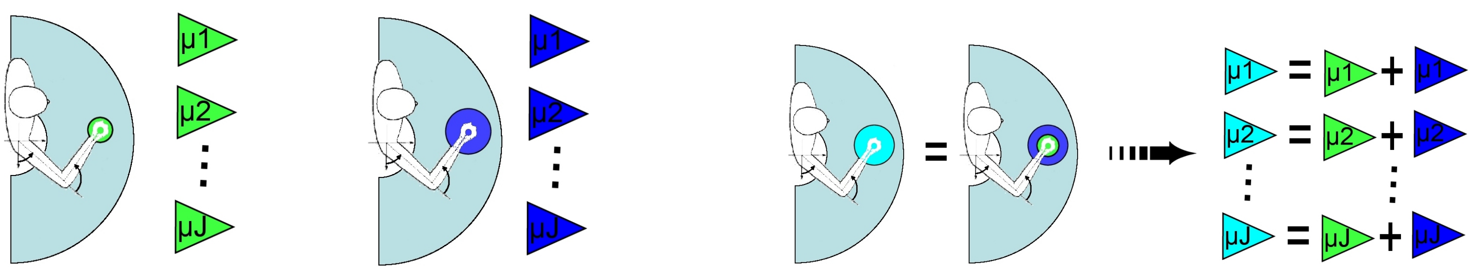


Recombination of learned experiences: experiments

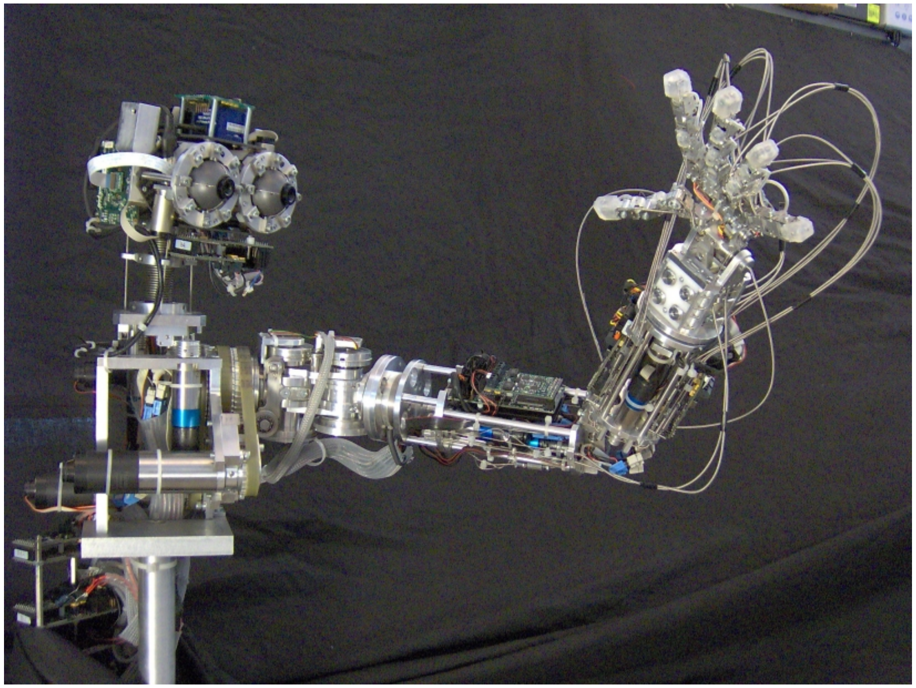
We tested the combination hypothesis on James.

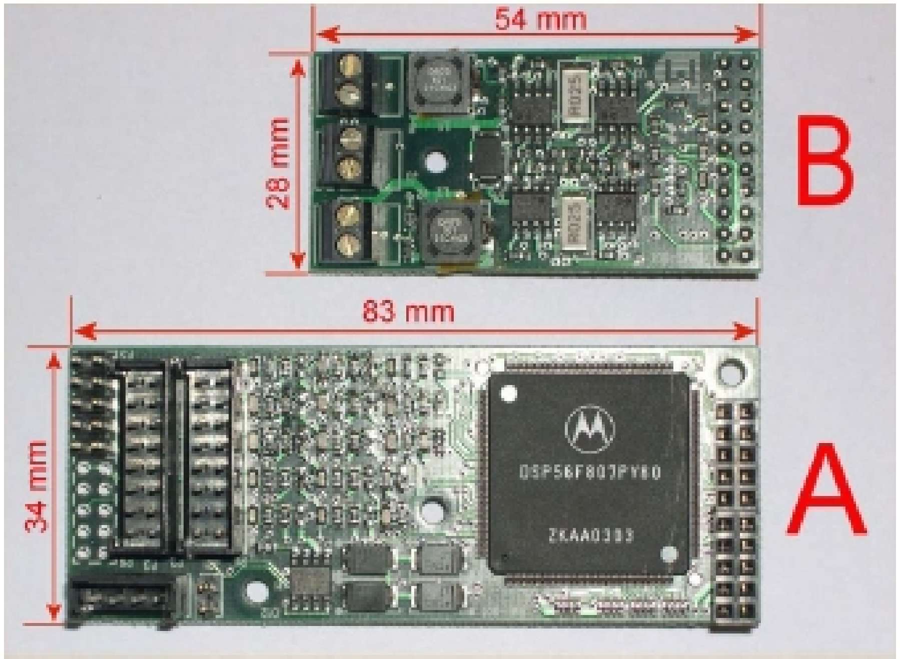


Context	Training set MSE	Testing set MSE	Combnators
$\mathbf{p}_1$	0.5392	0.6086	$\mu_1 \ldots \mu_J$
$\mathbf{p}_2$	0.5082	0.5638	$\mu_1 \ldots \mu_J$
$\mathbf{p}_{1\&2}$	0.6143	0.5770	$\mu_1 \ldots \mu_J$
$\mathbf{p}_1 + \mathbf{p}_2$	-	0.7458	$\mu_1 + \mu_1 \ldots \mu_J + \mu_J$



Future works on James





We will implement the adaptive motion primitives paradigm in the DSP boards of our humanoid robot James. The idea is to give James a representation of its own dynamics (and of held objects) in terms of the spinal field mixing coefficients and not in terms of classical parameters (masses, inertias, link lengths, etc.).

Conclusions

Conclusions:

- Machine learning provides tools for learning from experience thus mimicking human adaptive capabilities.
- Humans do not only learn. They also generalize previous experience in a smart way. Modern robots barely show this capability.
- There is experimental evidence supporting the idea that biological sensory motor systems are organized into modular structures.
- Modularity is potentially a way to generalize previously learnt experience.

Future Works:

- Investigating the potentialities of modular structures.
- Understanding more on human learning.
- Develop mathematical tools to compare human and machine learning.