

## *Learning and Remapping in the Sensory Motor System*

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## **Movement and the brain.**

- The anecdote of the sea-squirt (Lilas).



## **Prologue – A practical Context**



"...movements are possible under conditions of the most accurate and uninterrupted agreement- unforeseen in advance- between the central impulses and the events occurring at the periphery, and are frequently quantitatively less dependent on these central impulses that on the external force field."

N. Bernstein 1935

## The Brain is expert in Dynamics

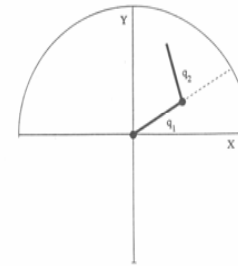


$$F = m a$$

$$x(t) = \iint \frac{F}{m} dt dt'$$

$$F(t) = m\ddot{x}(t)$$

## Simplified limb dynamics



$$D(q, \dot{q}, \ddot{q}) = C(q, \dot{q}, t)$$

$$D_1 = \left( I_1 + I_2 + m_2 l_1 l_2 \cos(q_2) + \frac{m_1 l_1^2 + m_2 l_2^2}{4} + m_2 l_1^2 \right) \ddot{q}_1$$

$$+ \left( I_2 + \frac{m_2 l_2^2}{4} + \frac{m_2 l_1 l_2}{2} \cos(q_2) \right) \ddot{q}_2$$

$$- \left( \frac{m_2 l_1 l_2}{2} \sin(q_2) \right) \dot{q}_2^2 - (m_2 l_1 l_2 \sin(q_2)) \dot{q}_1 \dot{q}_2$$

$$+ B_1(q_1, q_2, \dot{q}_1, \dot{q}_2) + K_1(q_1, q_2)$$

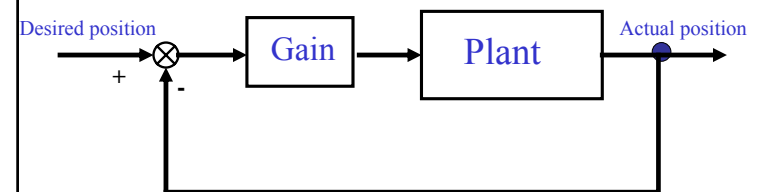
$$D_2 = \left( I_2 + \frac{m_2 l_1 l_2}{2} \cos(q_2) + \frac{m_2 l_2^2}{4} \right) \ddot{q}_1 + \left( I_2 + \frac{m_2 l_2^2}{4} \right) \ddot{q}_2$$

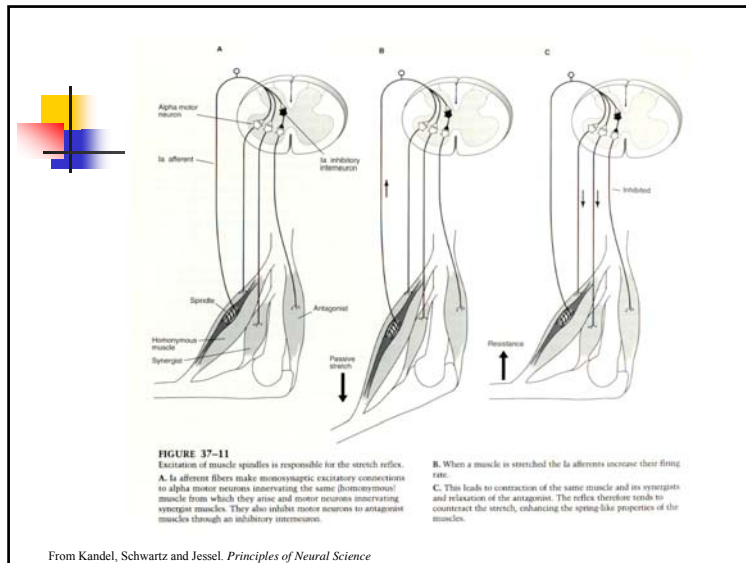
$$+ \left( \frac{m_2 l_1 l_2}{2} \sin(q_2) \right) \dot{q}_1^2$$

$$+ B_2(q_1, q_2, \dot{q}_1, \dot{q}_2) + K_2(q_1, q_2)$$

## SHORTCUTS

## FEEDBACK



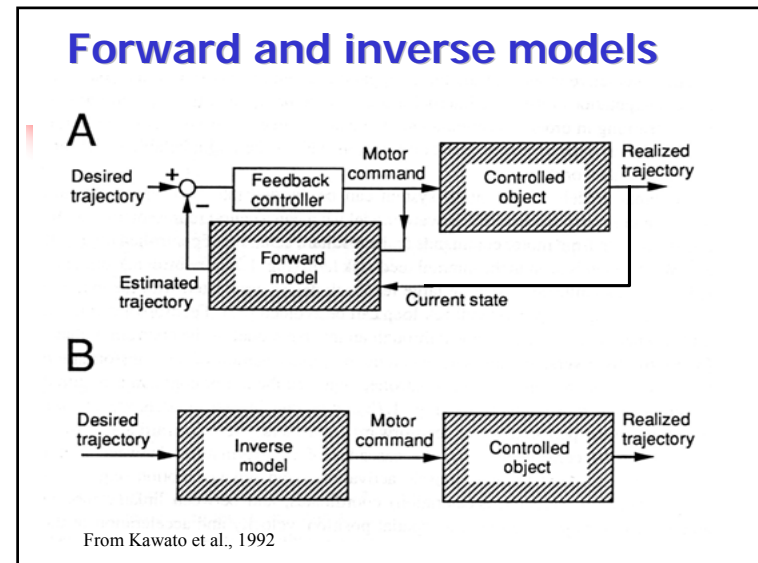


## •The look-up table approach

- Can motor patterns just be stored and then used later on when necessary?

2014-11-06 00:00 am  
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# A MORE PLAUSIBLE APPROACH

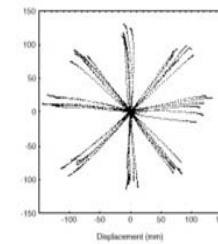


# SOME EXPERIMENTAL EVIDENCE

## Adaptation of hand movements to perturbing fields



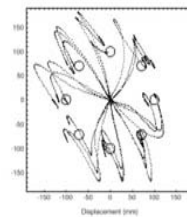
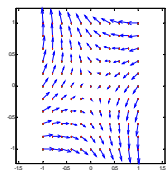
Unperturbed movements



Shadmehr & Mussa-Ivaldi,  
1994

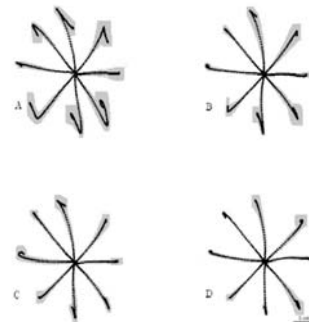
## Perturbing field

$$\mathbf{F} = \begin{bmatrix} -10.1 & -11.2 \\ -11.2 & 11.1 \end{bmatrix} \mathbf{r}$$

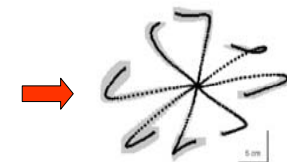


Note: there is no force at rest ( $\mathbf{r} = \mathbf{0}$ )

## Adaptation

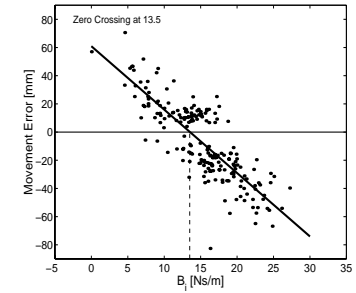
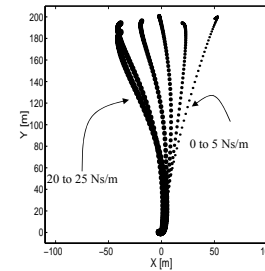


After-effects

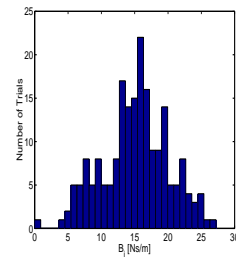
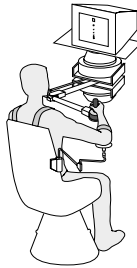
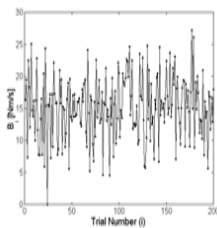


# TIME COURSE OF ADAPTATION

## Subjects Adapt to the Mean Field

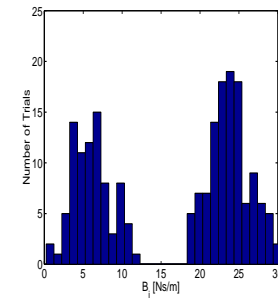
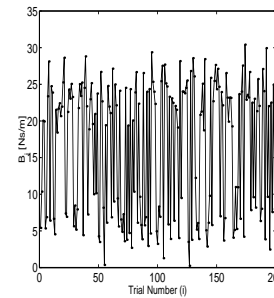


## Adaptation to Random Fields

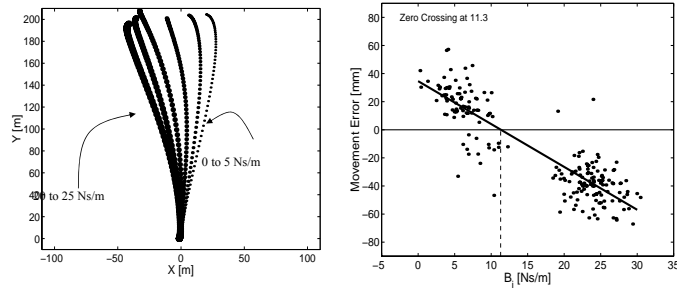


Scheidt, Dingwell & Mussa-Ivaldi

## When the Field is Bi-Modal...



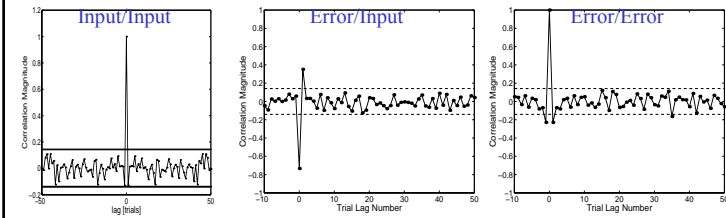
## ...They Still Adapt to the Mean



## Only Recent Memories Contribute to Adaptation

ARX Model: 
$$\varepsilon_i = \sum_{j=1}^{i-L} a_j \varepsilon_{i-j} + \sum_{k=0}^{i-M} b_k B_{i-k}$$

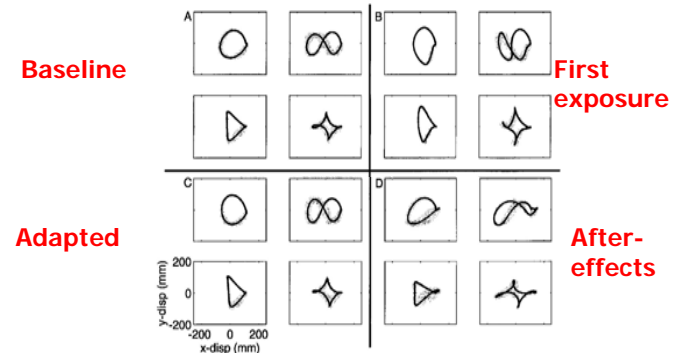
↖ Error      ↖ Input (field strength)



$$\varepsilon_i = a_1 \varepsilon_{i-1} + b_0 B_i + b_1 B_{i-1}$$

# MODEL OR MEMORY?

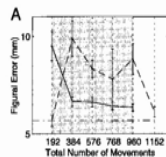
## Not only reaching movements....



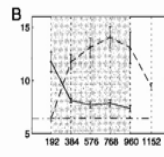
Condit, Gandolfo and Mussa-Ivaldi, (1999).

## Learning curves for shapes

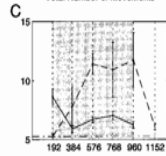
Circle



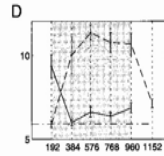
Infinity



Triangle



Diamond



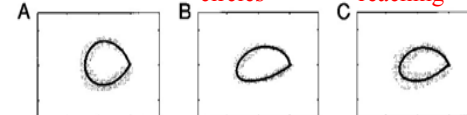
## Not by simple playback of forces

Null field

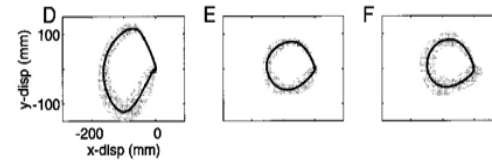
Control

Trained w. circles

Trained w. reaching

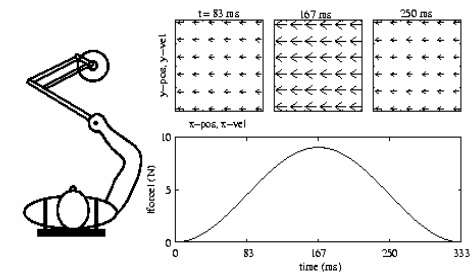


Viscous field



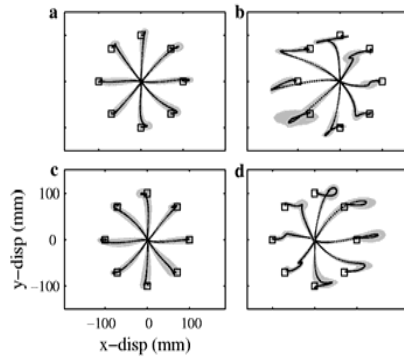
## TIME OR STATE?

## Time-varying Field

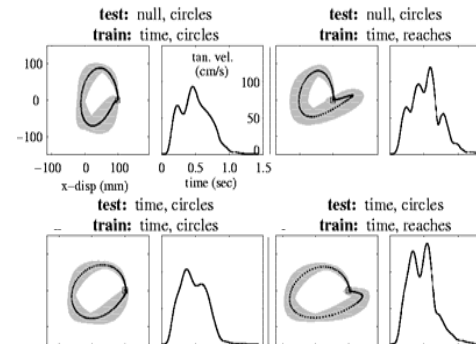


Conditt and Mussa-Ivaldi, (1999).

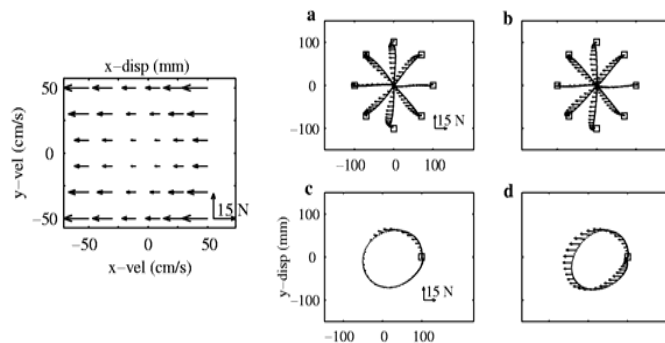
## Compensation of Time-varying Forces...



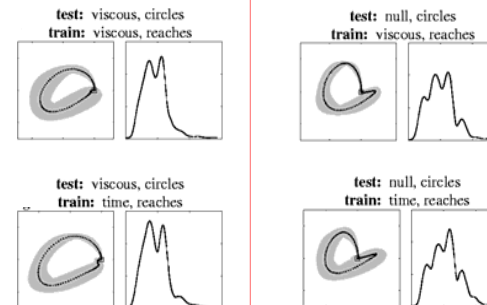
## ...But No Learning



## Equivalent State-dependent Field



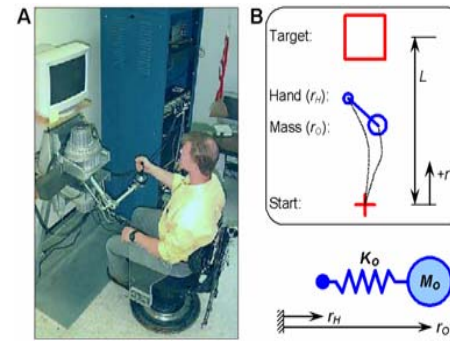
## A "Wrong" Generalization?





# CONTROLLING OBJECTS WITH INTERNAL DEGREES OF FREEDOM

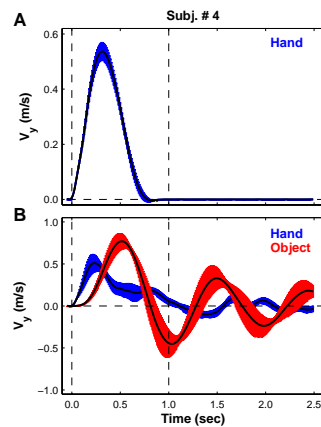
## Smooth motion: a general principle for trajectory formation



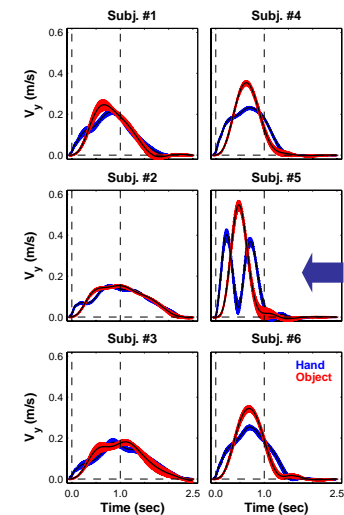
J Dingwell, Mah, C., F.A. Mussa-Ivaldi, 2003

Baseline

Initial response



Post-adaptation kinematics



## Minimum-Jerk (Hogan and Flash)

**Goal: Generate the smoothest motion which brings a limb from equilibrium at the starting position to equilibrium at the target position in a given time.**

Approach: quantify smoothness by high temporal derivative of motion

$$C = \int \sum_{n=1}^{\infty} a_n \left\| \frac{d^n x}{dt^n} \right\|^2 dt$$

Simpler (but sufficient) form

$$C = \int_0^T \frac{1}{2} \left( \frac{d^3 x}{dt^3} \right)^2 dt \quad \text{"Jerk"}$$

## Euler-Poisson-Lagrange

Find the trajectory  $x(t)$  that minimizes the functional

$$C[x(t)] = \int_0^T L(t, x(t), \dot{x}, \ddot{x}, \dots, x^{(n)}) dt$$

This reduces to solving the Euler-Poisson equation:


$$\frac{\partial L}{\partial x} - \frac{d}{dt} \frac{\partial L}{\partial \dot{x}} + \dots + (-1)^n \frac{d^n}{dt^n} \frac{\partial L}{\partial x^{(n)}} = 0$$

## For reaching movements

$$L = \frac{1}{2} (\ddot{x})^2$$

Euler equation becomes simply

$$-\frac{d^3}{dt^3} \frac{\partial L}{\partial \ddot{x}} = -\frac{d^3}{dt^3} \ddot{x} = -\frac{d^6 x}{dt^6} = 0$$



$$\frac{d^6 x}{dt^6} = 0$$


The most general solution is the 5th degree polynomial

$$x(t) = c_0 + c_1 t + c_2 t^2 + c_3 t^3 + c_4 t^4 + c_5 t^5$$

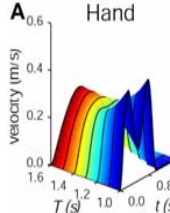
The six coefficients are determined by the boundary conditions:

- Initial/final position
- Initial/final velocity (0)
- Initial/final acceleration (0)

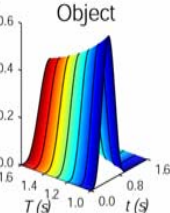
## Optimally Smooth Transport (OST)



**A** Hand



**B** Object



Both hand and object must start and end at rest this gives  $6 \times 2 = 12$  Boundary conditions.

$$M_o \ddot{r}_o = K_o (r_H - r_o)$$


Hand and object movements are not independent (two BC on the object acceleration BC on object and hand position)

↓

10 Boundary Conditions (12-2)


↓

Minimum "crackle"

$$C = \int_0^T \frac{1}{2} \left( \frac{d^2 r_o}{dt^2} \right)^2 dt$$



## Summing up

- The motor system adapts to novel dynamical conditions by forming internal representations of the functional relationship between forces and motions
- Internal models of limb dynamics are constructed based on recent memories
- Internal models of limb dynamics are based on representations of states of motion but (probably) not of time.
- Adaptation of reaching movements aims at preserving the smoothness and linearity of the endpoint motion
- Planning and control of movements are separate processes




## Glove Talk

Sidney Fels and Geoffrey Hinton



Vocabulary



Sam-I-am

# The representation of space.

## What is space ?

### Intuitive Concept

Geometry, from a physical standpoint is the totality of the laws according to which rigid bodies mutually at rest can be placed with respect to each other... "Space" in this interpretation is in principle an infinite rigid body – or skeleton - to which the position of all other bodies is related."

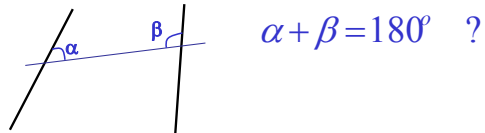


1949  
**Less Intuitive Concepts**  
 Signal spaces, configuration spaces, state spaces, feature spaces, etc...

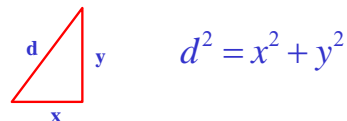
## Ordinary Space

Two equivalent statements

### Euclid



### Pythagoras



## Euclidean Symmetry

Among all possible norm only the  $L_2$  (Euclidean) norm is invariant under rigid transformations (e.g. rotations, translations).

Size does not depend upon position and orientation.

$$\|x\|^2 = x^T \cdot x \quad \text{Euclidean (L}_2\text{) Norm}$$

$$y = Ax \quad \text{Orthogonal transformation}$$

$$A^T = A^{-1}$$

$$\|y\|^2 = y^T y = x^T A^T A x$$

$$= x^T A^{-1} A x = x^T x = \|x\|^2$$

## Signal spaces

- Neither the visual nor the motor signals spaces are Euclidean.

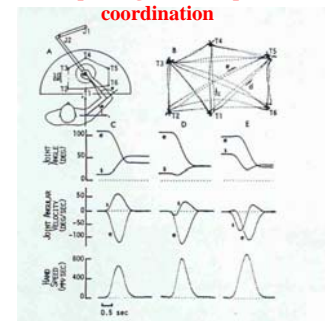
## Yet...

•We perceive Euclidean symmetries



Francesco Borromini. Palazzo Spada. Rome

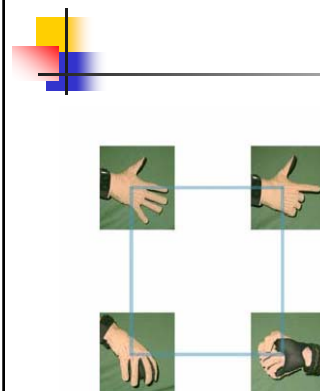
•Euclidean kinematics of the endpoint guides complex coordination



Morasso (1981)

Is the bias toward Euclidean symmetry a guiding principle for the emergence of new motor programs?

Motor Program: Open loop rapid movement  
 – Not under visual guidance



19 SIGNALS  
 (Hand Configuration)  
 ↓  
 2 Screen Coordinates

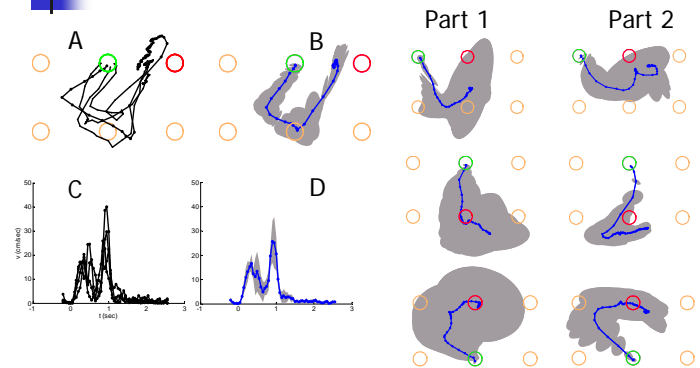
F.A. Mussa-Ivaldi, S. Acosta, R. Scheidt, K.M. Mosier

## The task

- The subject must place the cursor corresponding to the hand inside a circular target
- Experiment begins with the cursor inside a target.
- New target is presented – Cursor is suppressed.
- The subject must try to make a single rapid movement of the fingers so as to place the (invisible) cursor inside the new target and stop.
- As the hand is at rest after this initial movement, the cursor reappears
- The subject corrects by moving the cursor under visual guidance inside the target
- Only the initial open loop movement is



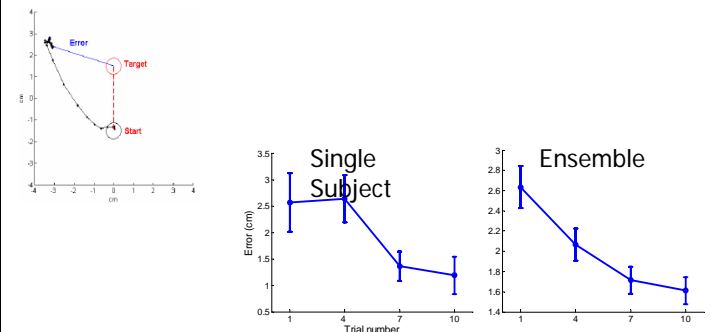
## Some examples

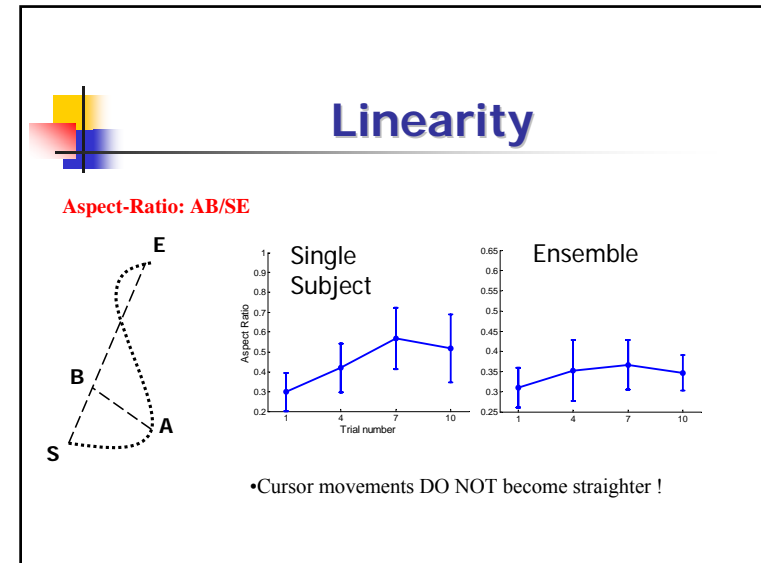
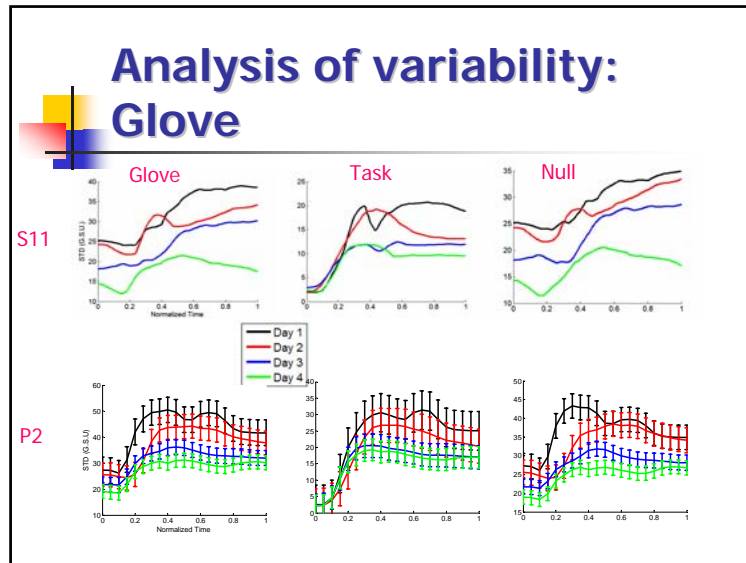


## Some observations

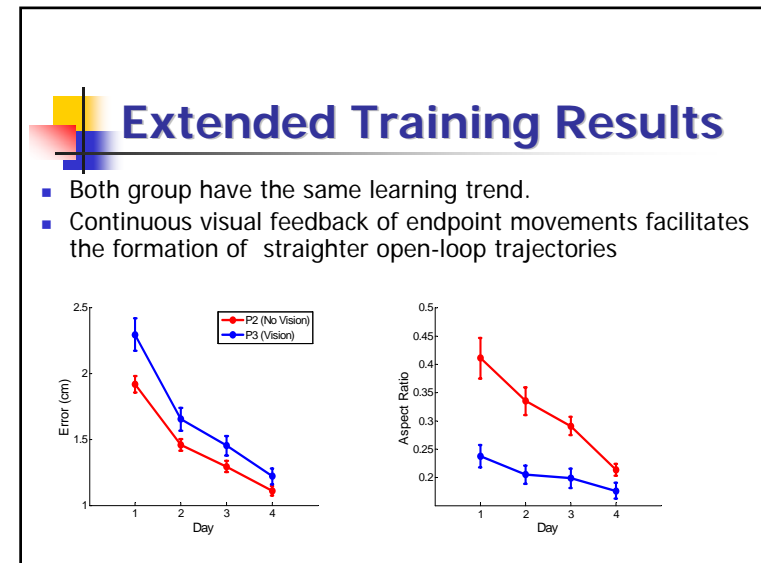
- Weird task. Cannot be represented before the experiment
- Body and task endpoint are physically uncoupled
- Only feedback pathway is vision
- Dimensional imbalance
- Metric imbalance

## Endpoint error

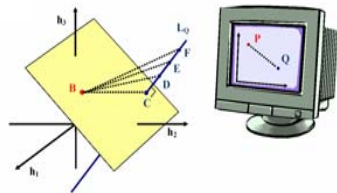




- ## Extended training
- 4 consecutive days
  - 2 groups of subjects
  - No-Vision subjects (P2) just engage in the task for 4 days
  - Vision subjects (P3) train with continuous visual feedback trials. But they are tested in the same no-vision condition as the other group.
  - The two groups receive the same amount of training



## Decomposition of Glove Signals



$$A^+ \equiv A^T (A \cdot A^T)^{-1}$$

$$T(A) \equiv A^+ \cdot A$$

$$N(A) \equiv I_n - T(A)$$

$$\begin{cases} h_N = N(A) \cdot h & \text{"Null-Space Component"} \\ h_T = T(A) \cdot h & \text{"Task-Space Component"} \end{cases}$$

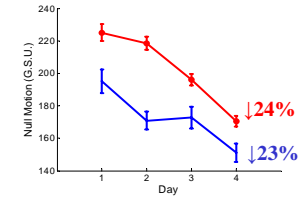
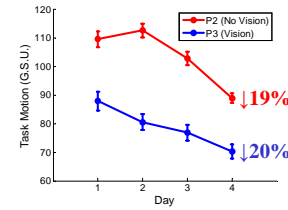
$$h = h_N + h_T$$

$$h^T_N \cdot h_T = 0$$

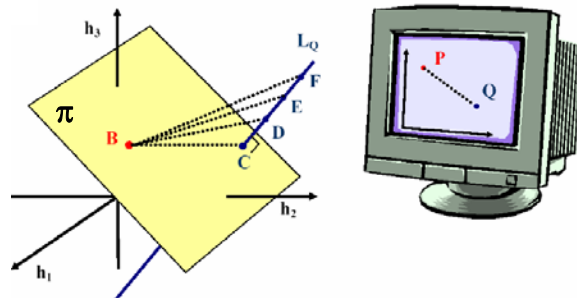
$$BF \xrightarrow{A} PQ$$

$$BF = BC + CF$$

## Task-space and Null-space Motion



## Importing a metric structure

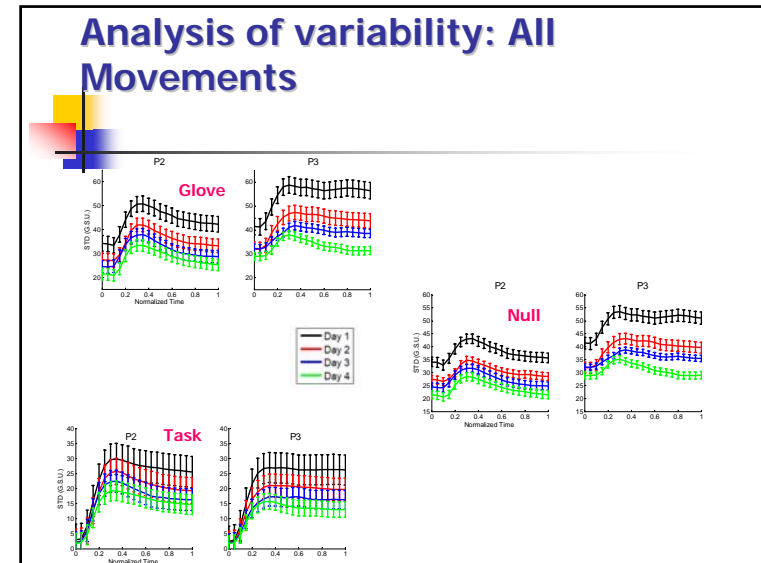
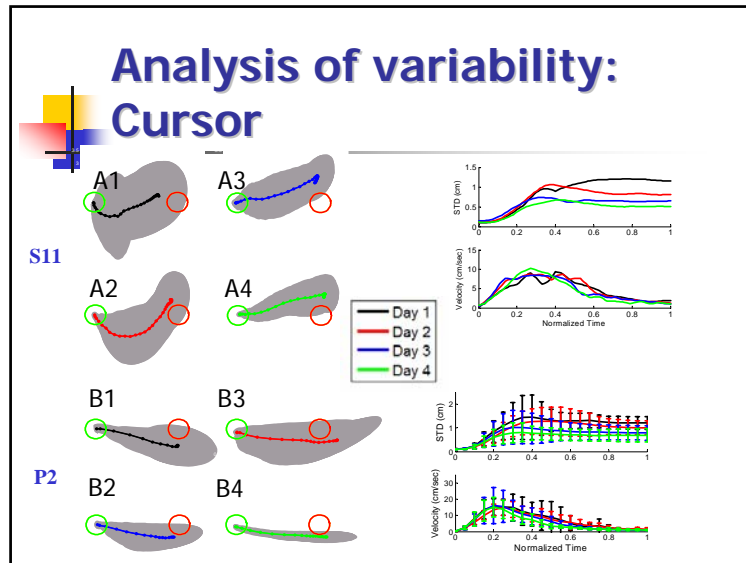


## A Different View

Optimal feedback Control (Todorov, Jordan 2002):

- There is no explicit control of trajectories
- The control system minimizes the variance of the endpoint by allowing variability in redundant dimensions

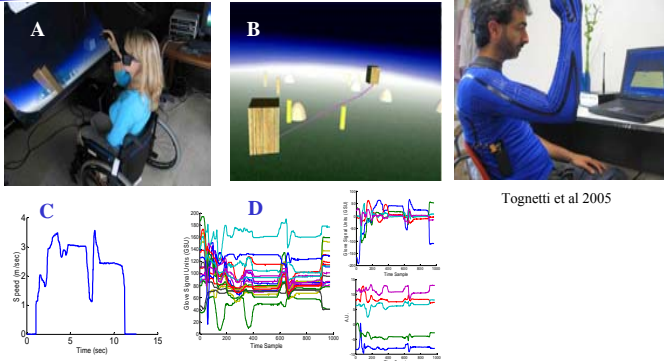




- ## Conclusions
- Practice with and without feedback leads to improved mapping of target positions into finger postures (an ill-posed problem).
  - This is not sufficient for trajectory learning (Euclidean metric)
  - Extended practice of movement facilitates the generation of rectilinear cursor motion. This trend is stronger in the presence of continuous feedback of endpoint motion
  - Final error improvement is independent of trajectory learning
  - Practice of movement leads to a general and uniform decrease of movement variability, including null-space variability, NOT an increase.
  - Whole movement trajectories (not just final positions) appears to be explicitly regulated to conform with the Euclidean metric of the controlled endpoint

## Epilogue 1 – Relearning space

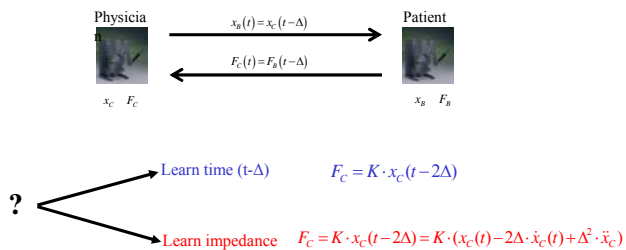
# Human/Machine Learning



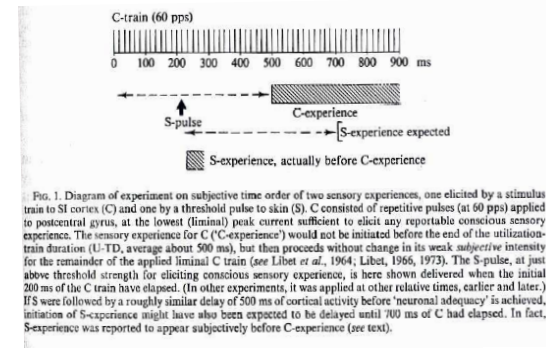
# The representation of time. When is “now” ?

# Open questions

- How do we perceive simultaneous events ? (How “thick” is now?)
- Can we adapt to perceptual delays ?



# Libet's Experiment



## Epilogue 2. Aristotelian science

- A legend about gravity.

