Trading off Feedforward and Feedback, Remote and Local in the Control of Complex Systems

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Control Systems: The State of our Field

- Outstanding results:
  - in the understanding of feedback systems
  - in the design of effective solutions for applications
  - in the improvement of the quality of life of citizens.
- What are the new challenges to progress further?
  - Ability to cope with complexity
  - Domains of life and social sciences
  - Understanding, regulating, and even replicating natural systems and social organizations

Control Systems and the Neurosciences: A New(?) Convergence

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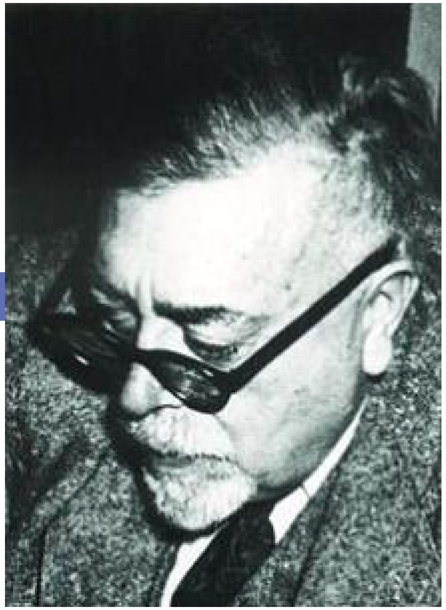
What Cyber-physical systems have to do with Cybernetics?



- Cybernetics, "the scientific study of control and communication in the animal and the machine,“ Norbert Wiener
- "Science concerned with the study of **systems of any nature** which are **capable of receiving, storing and processing information** so as to use it for control,“ A. N. Kolmogorov
- "The art of steersmanship': deals with all forms of behavior: stands to the real machine – electronic, mechanical, neural, or economic – much as geometry stands to real object in our terrestrial space; offers a method for the scientific treatment of the system in which **complexity** is outstanding and too important to be ignored.“ – W. Ross Ashby
- "A branch of mathematics dealing with problems of **control, recursiveness, and information**, focuses on forms and the patterns that connect." – G. Bateson
- "The art of **interaction in dynamic networks**." - Roy Ascott
- Robotics**,** “the intelligent link between perception and action.” – Michael Brady
- Cyberphysical systems are physical, biological, and engineered systems whose operations are monitored, coordinated and controlled by a communication and computation core – P. Antsaklis

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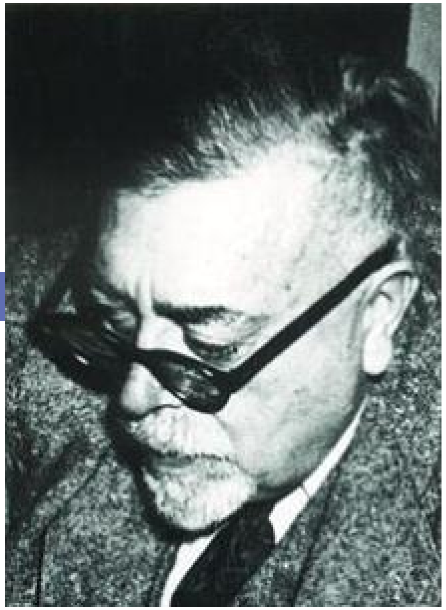

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Outline

- An enormous potential in the combination of powerful analytical tools and ideas and inspiration that comes from neurosciences

- Will show some examples of how this process can work, reporting on few case-studies where a fruitful multidisciplinary collaboration has led to interesting insight and technological solutions

- Open problems and discussion points

Embodied Intelligence

- “**Cognition depends on the kind of experiences that come from having a body**”
  Esther Thelen
- That the body may determine and anticipate cognition is not “the innocuous and obvious claim that we need a body to reason;… **The very structure of reason itself comes from the details of our embodiment.**“
  Philosophy in the flesh: The embodied mind and its challenge to western thought, G. Lackoff, M. Johnson, 1999
- “In cyberphysical systems you can’t tell what behaviour belongs to the physical, and what to the cyber parts”, A Speaker, this morning
- CPS and EI

A Classic: Optimal Control

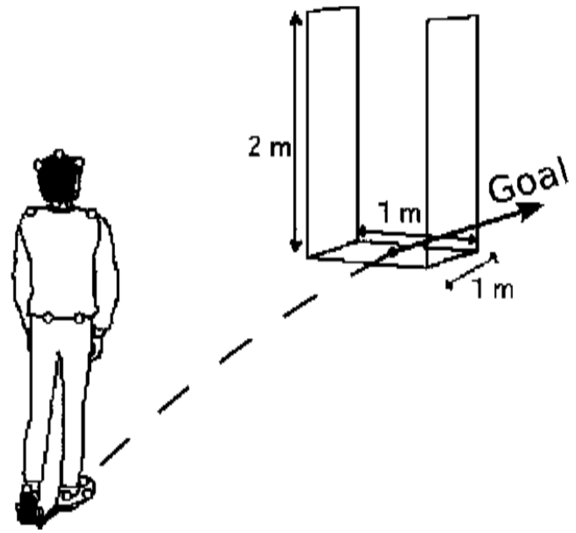
- One of the central tools **to translate theoretical intuitions in precise concepts and usable tools**
- OC is also fundamental under other regards – as it provides **a principled basis to compare** the performance of different embodiments and system designs

OC for Abstraction

- In the embodied intelligence philosophy, a large part of the functional capabilities of an organ reside in its physical characteristic
- This raises a fundamental question: ***what can we learn by observing how "body A" works that is relevant to controlling "body B"?***
- We need *abstractions* at a sufficiently high level, but still transparently operational, at which natural and artificial movement science and technology can meet and share ideas

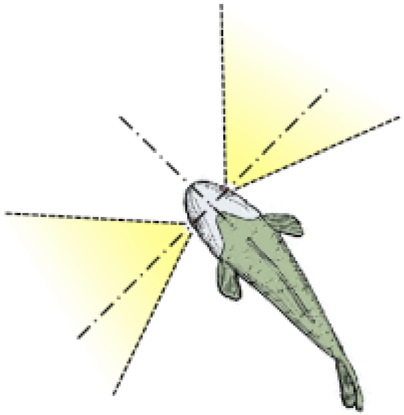
Inverse Optimal Control

- A stereotype of locomotor trajectories could be interpreted as the result of application of an optimization index
- Weights found by numerical fitting of experimental data
- Humans tend to adopt a nonholonomic behaviour, minimizing the bearing angle
- A spiralling path results

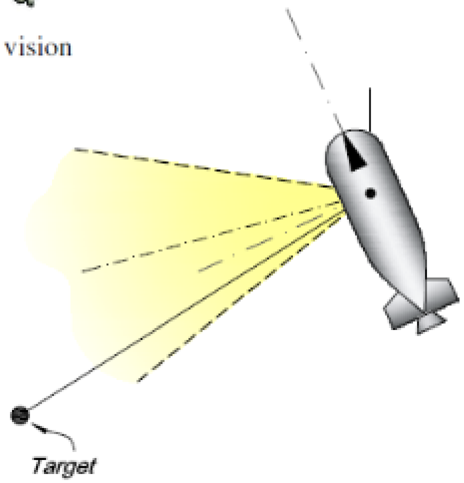


Laumond, Berthoz et al., 2008
Mombaur, Laumond et al., 2010,

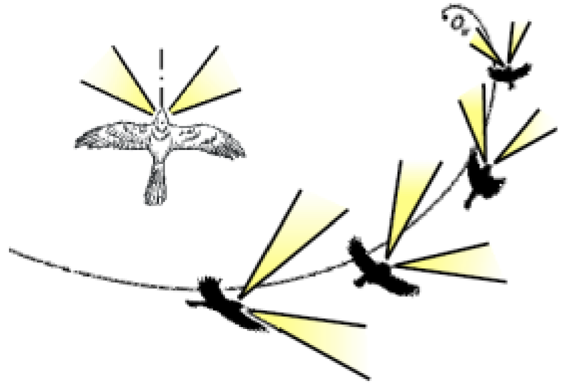
Direct Optimal Control and Finned, Winged, Legged Creatures



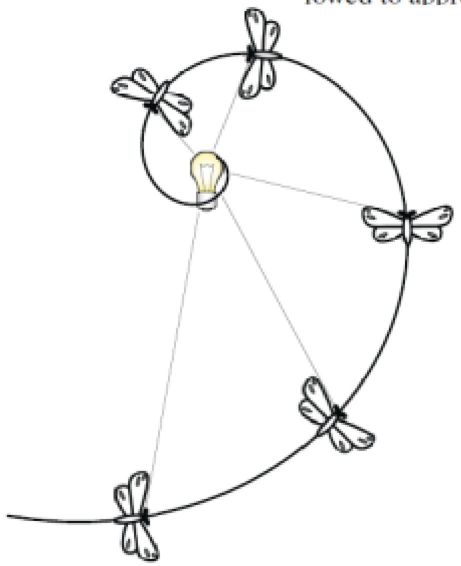
(a) Nurse shark and goldfish vision system.



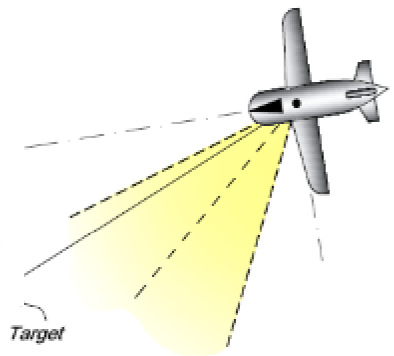
(b) Underwater (Finned) vehicle with lateral-looking sensors.



(a) Raptor vision system and trajectories followed to approach a prey.

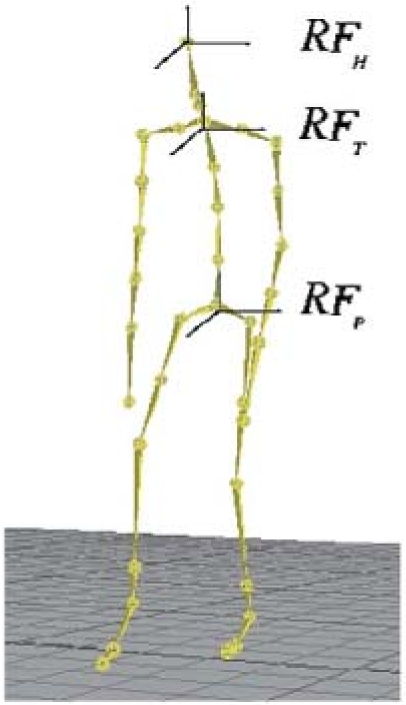


(b) Trajectories followed by moths to approach an electric light.

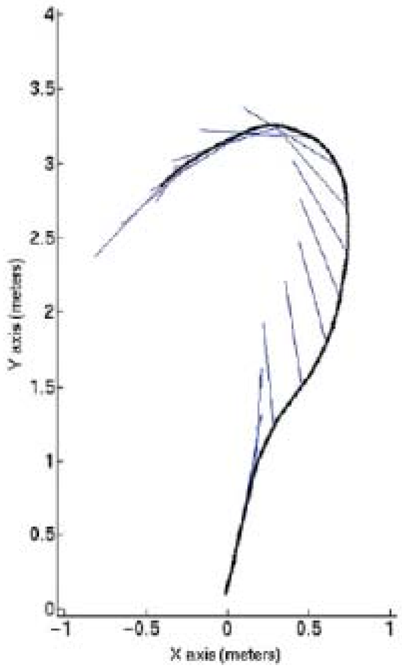


(c) Winged vehicle with side-looking sensors.

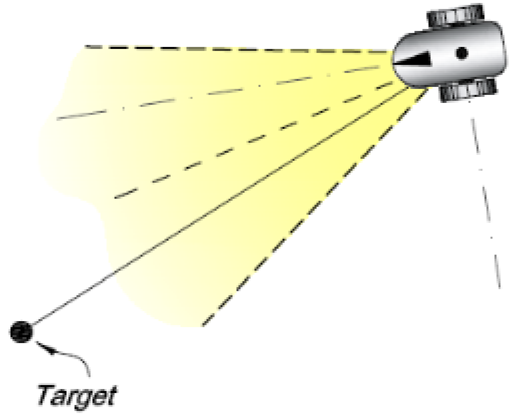
DOC and Finned, Winged, Legged Creatures



(a) Human reference frames (see [Arechavaleta et al., 2008a]).



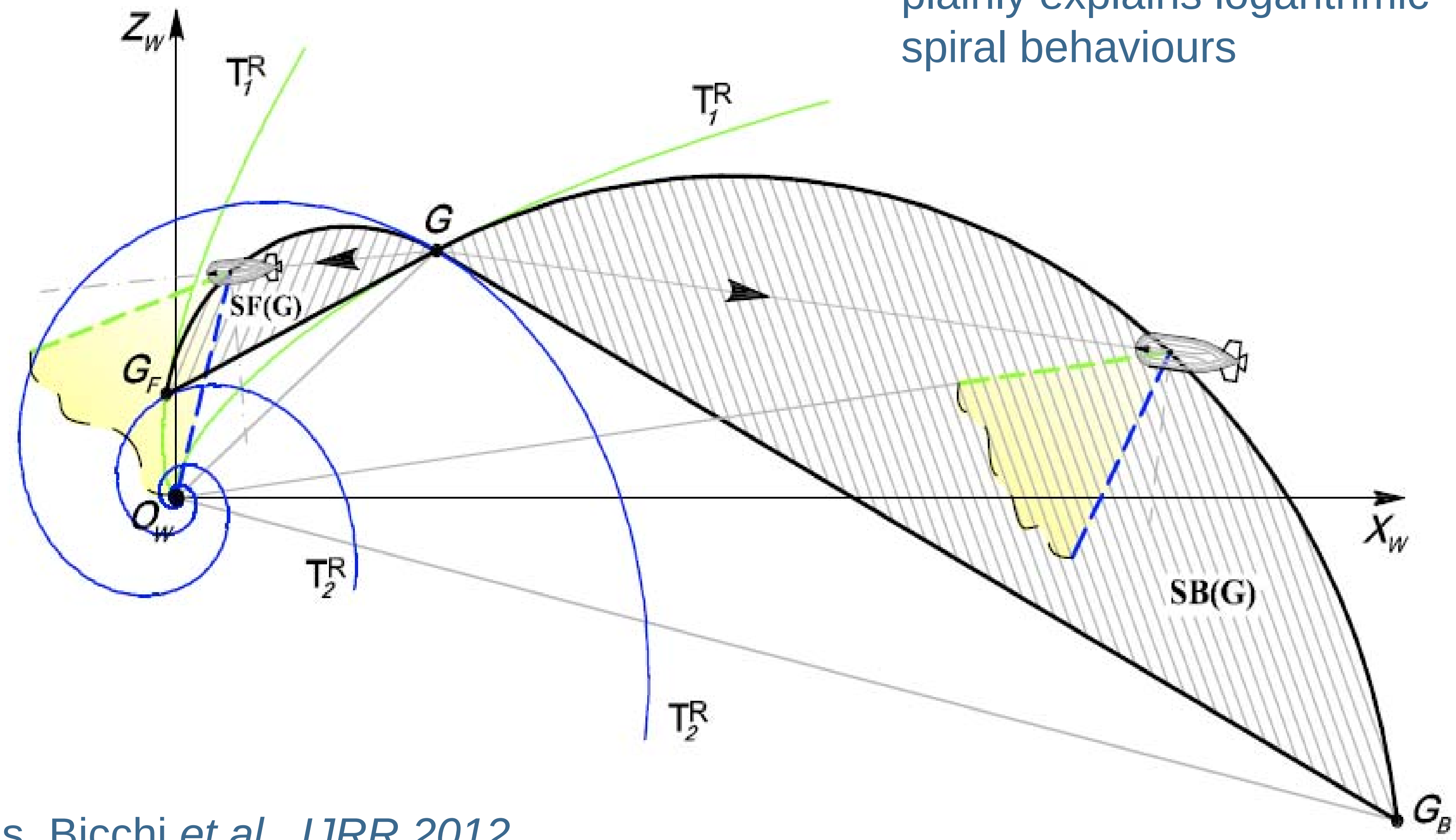
(b) Human trajectories and head direction (see [Arechavaleta et al., 2008a]).



(c) Wheeled (or Legged) robot with Asymmetric Frontal sensors.

DOC and
Finned, Winged, Legged Creatures

Classical Pontryagin synthesis plainly explains logarithmic spiral behaviours



Salaris, Bicchi *et al.*, *IJRR 2012*

Body and Mind
The philosophy behind

[…] man is the most intelligent of animals because he has hands…

Anaxagoras, cited by Aristotle, De partibus animalium

Embodied Intelligence

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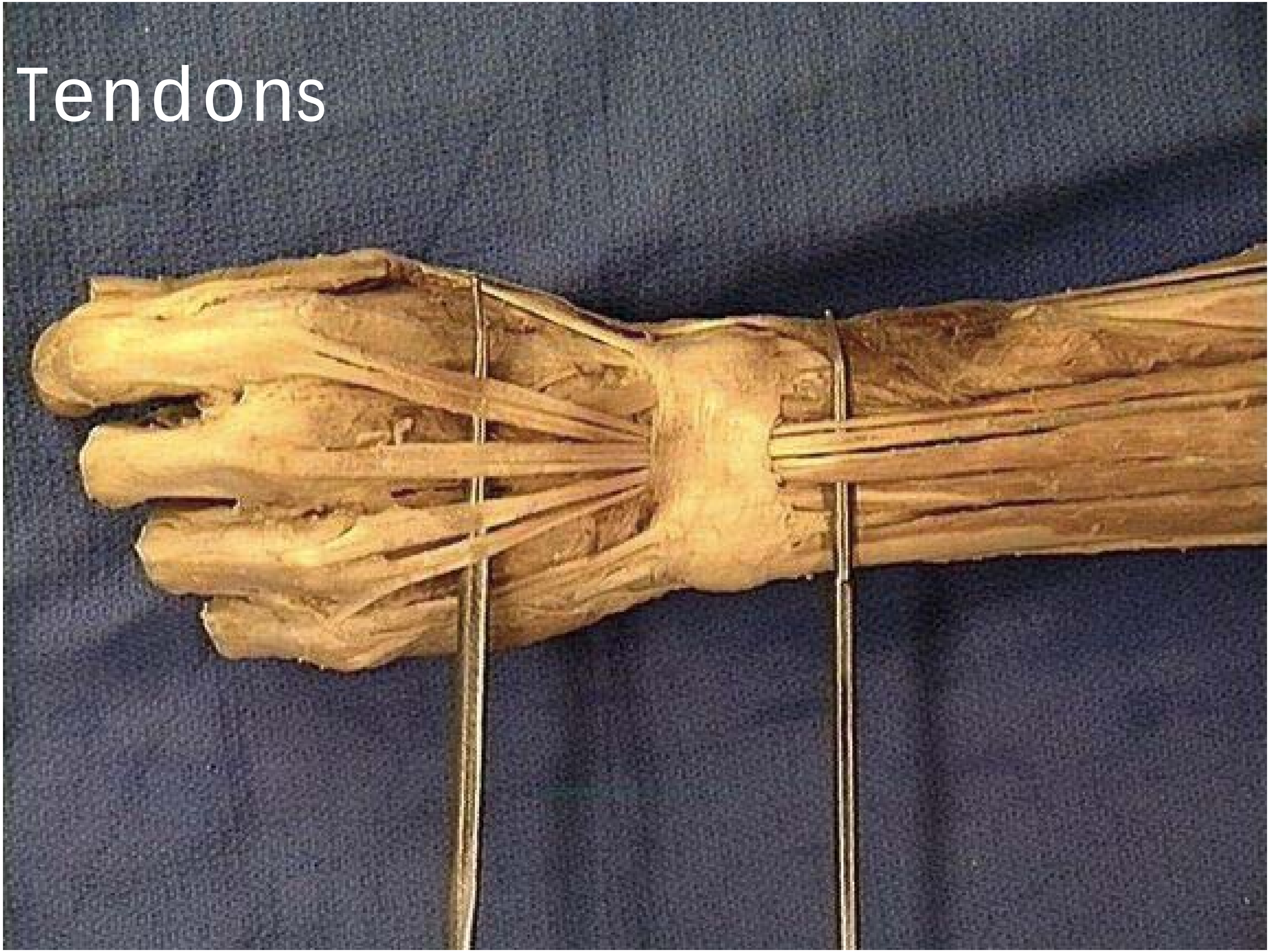
Mens et Manus

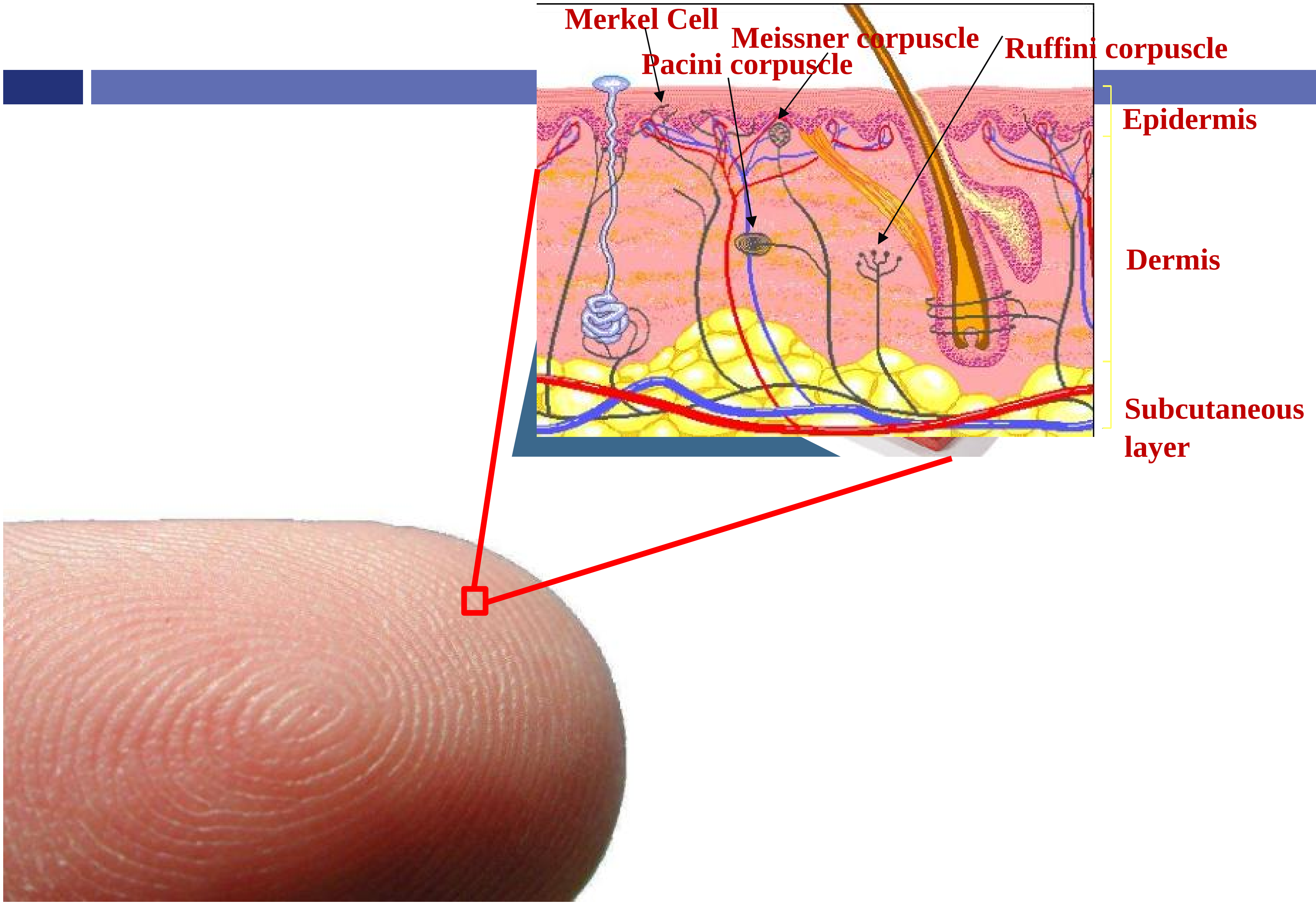
- *"The modern human brain came after the hominide hand"*
  Sherwood Washburn, Scientific American, 1960

Tendons

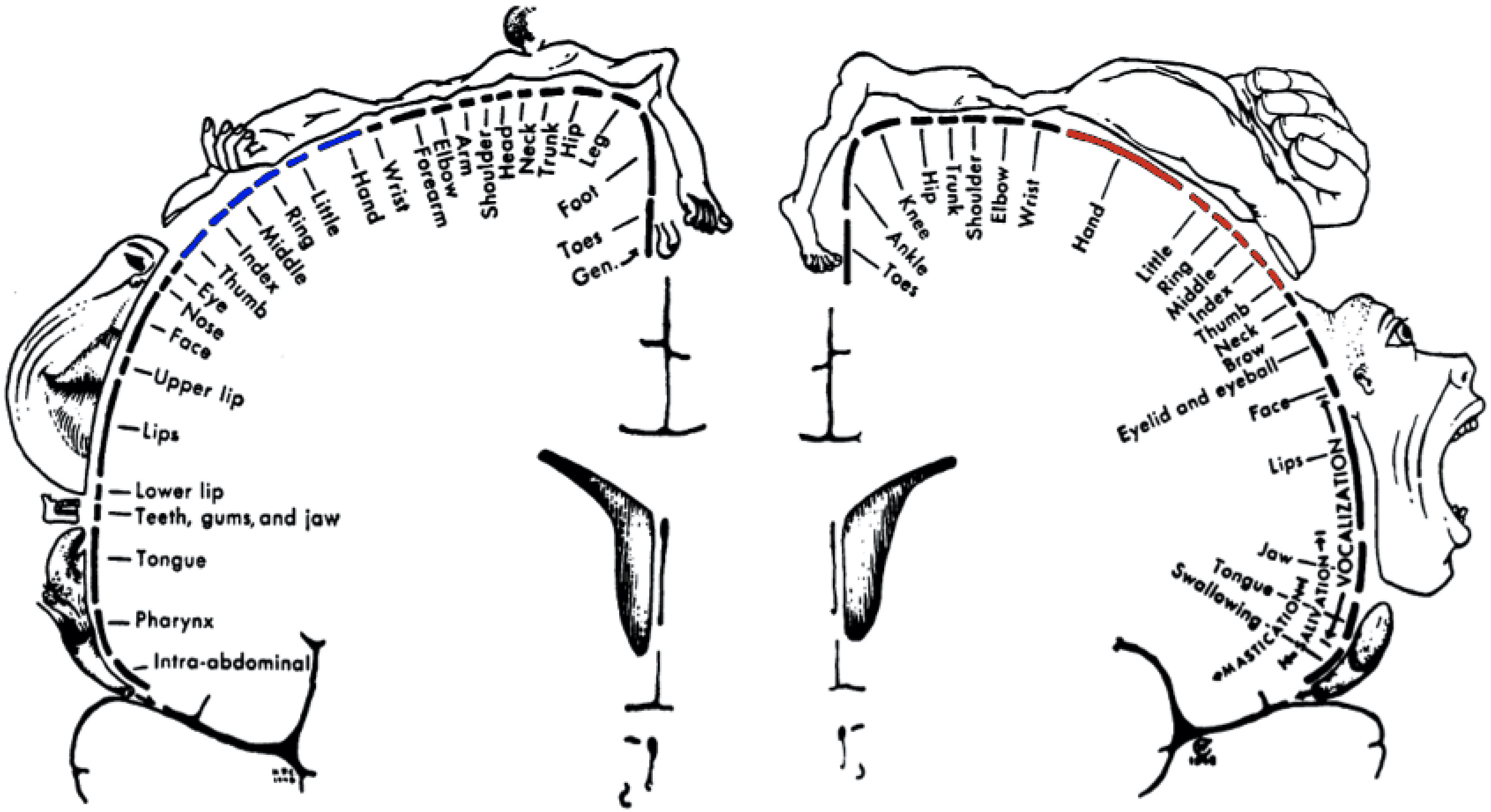


Nerves

Under a pin's head



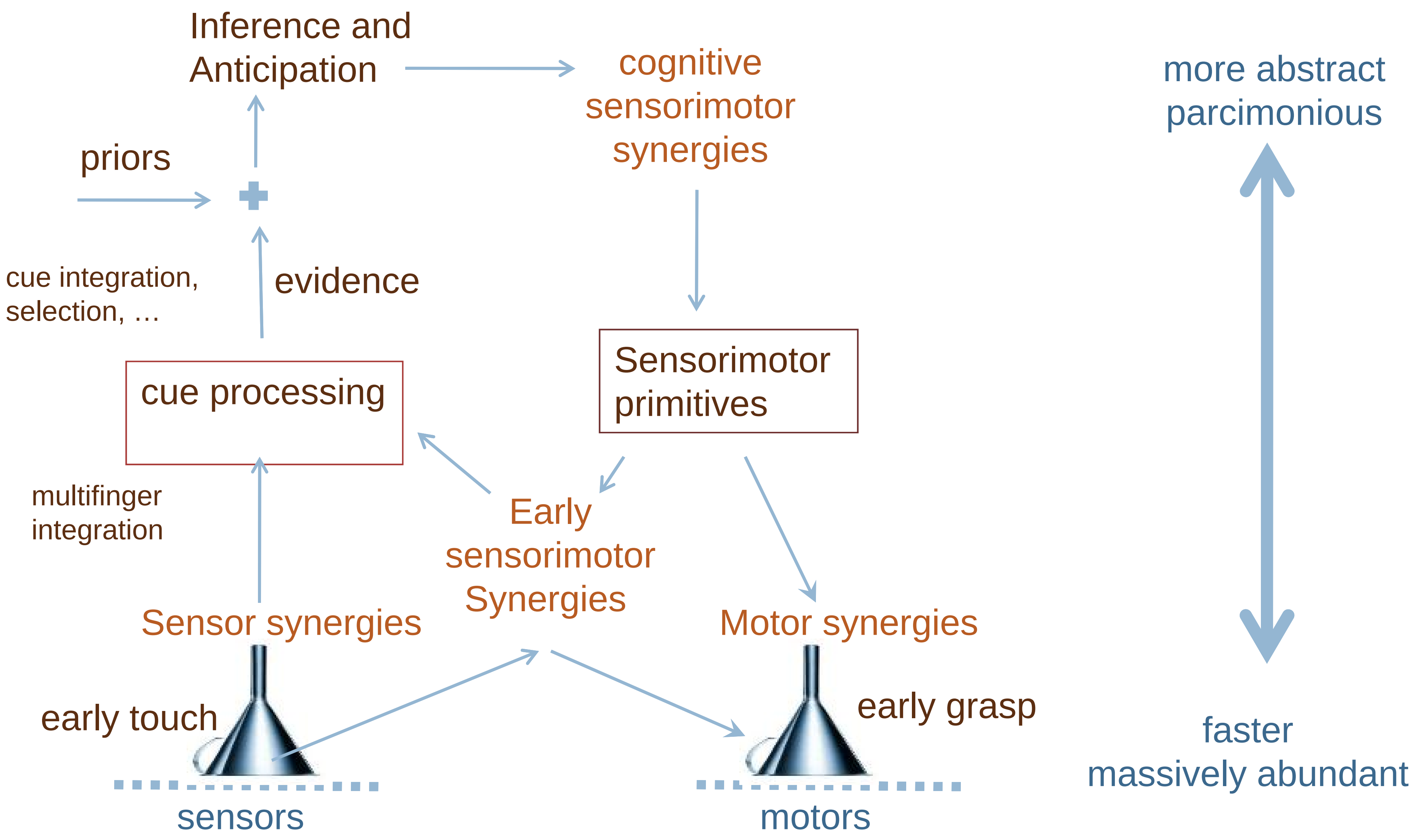
How can the brain cope?



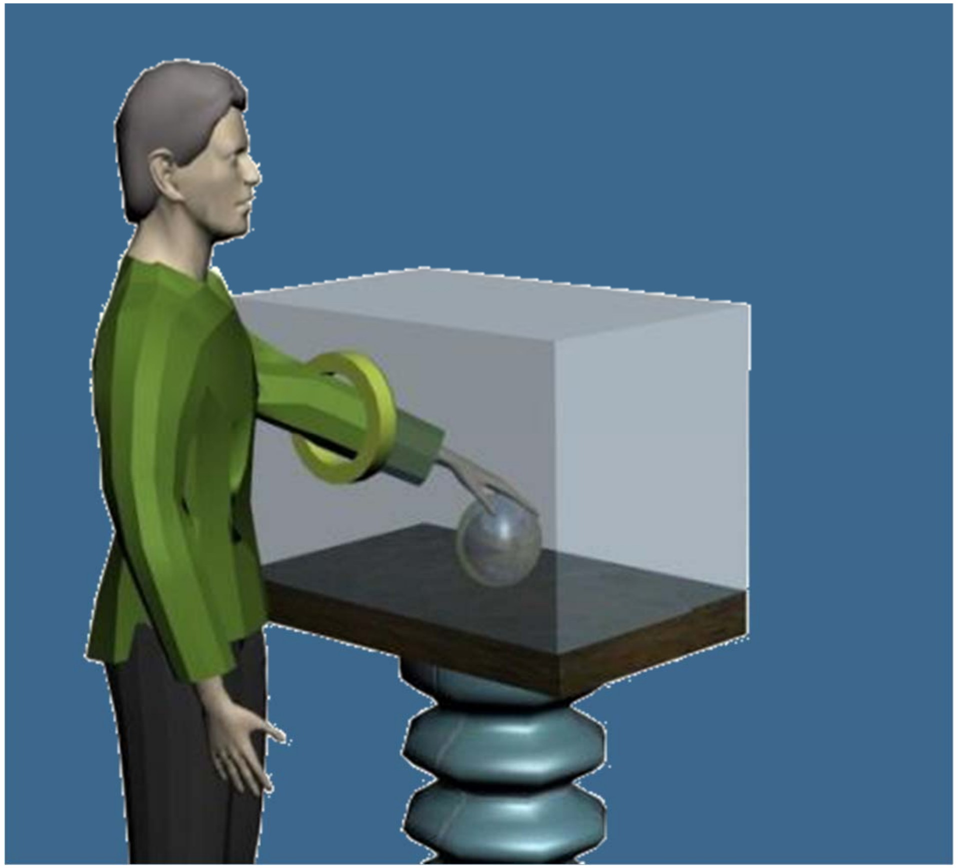
Taming the Complexity: the role of *Synergies*

- Central Concept: *constraints* that the embodiment imposes are not mere bounds that limit degrees of freedom
  - Rather, make it possible for the brain to deal with the huge redundancy of sensory and motor apparatuses
  - Ultimately, dominating factors in affecting and determining how cognition has evolved into the admirable form we observe on Earth
- Constraints that organize and enable *“THE Hand Embodied”*
- What is the **conceptual structure** and **the geometry** of such ***enabling constraints*** (aka “primitives” or “***synergies***”)?

The idea behind



Images for Hands



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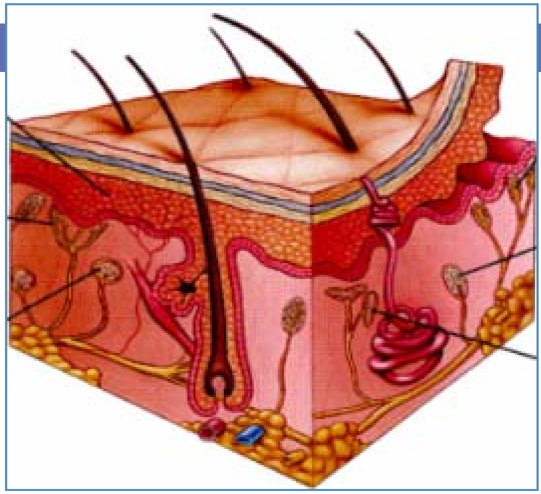
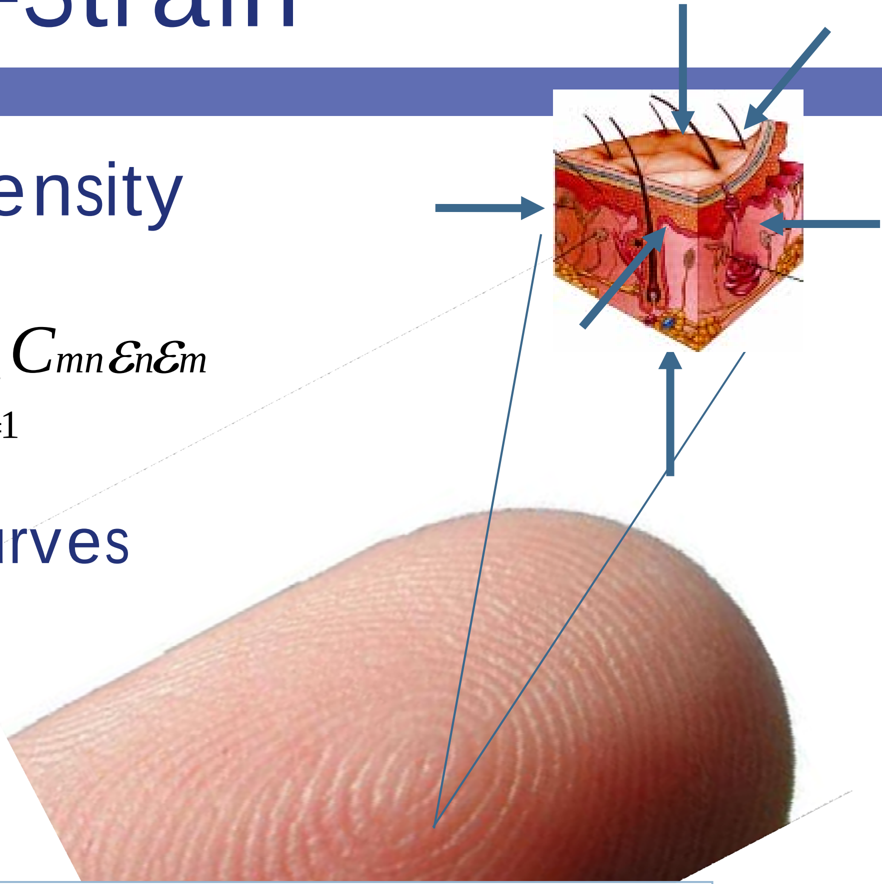


Dynamic Constraints: Surfaces of Iso-Strain

Let υ Strain Energy Density

$$\upsilon = \frac{1}{2}\sum_{m=1}^{6}\sigma_m\varepsilon_m = \frac{1}{2}\sum_{m,n=1}^{6}C_{mn}\varepsilon_n\varepsilon_m$$

Consider the ISO-SED curves when P varies



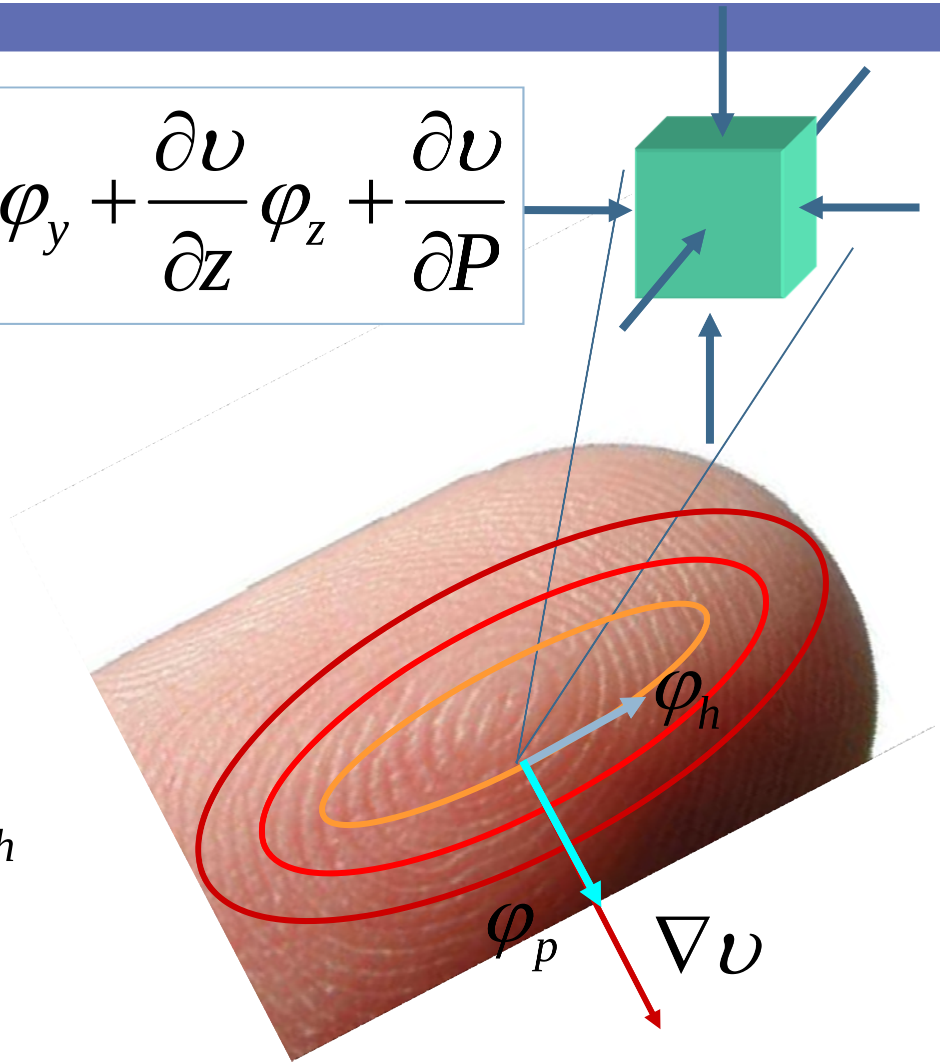
$$\frac{d\upsilon}{dP} = 0 = \frac{\partial\upsilon}{\partial x}\varphi_x + \frac{\partial\upsilon}{\partial y}\varphi_y + \frac{\partial\upsilon}{\partial z}\varphi_z + \frac{\partial\upsilon}{\partial P}$$

Dynamic Touch and Tactile Flow

$$\frac{d\upsilon}{dP} = 0 = \frac{\partial \upsilon}{\partial x}\varphi_x + \frac{\partial \upsilon}{\partial y}\varphi_y + \frac{\partial \upsilon}{\partial z}\varphi_z + \frac{\partial \upsilon}{\partial P}$$

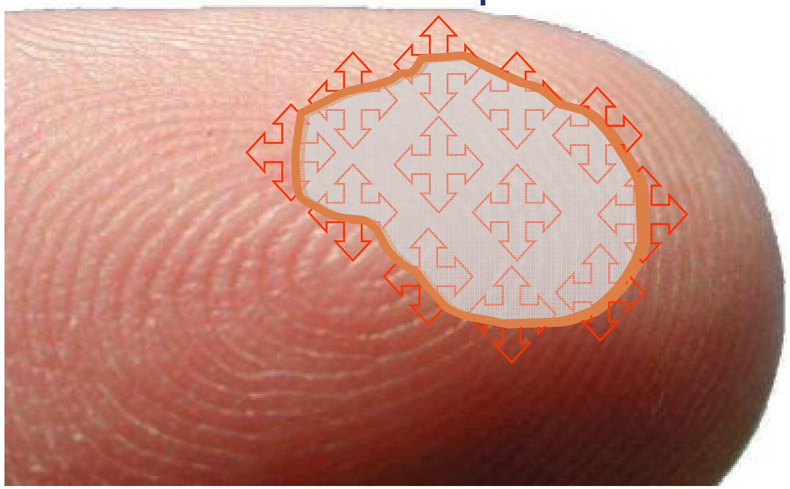
$$\nabla \upsilon \cdot \varphi = -\frac{\partial \upsilon}{\partial P};$$

$$\varphi = \begin{pmatrix} \varphi_x \\ \varphi_y \\ \varphi_z \end{pmatrix} = \varphi_p + \varphi_h$$



Tactile Flow and CASR

Rate at which volumes within iso-SDE surfaces grow under increasing contact force – related to rate at which contact area spreads



$$\frac{dV}{dP} = \int div(\varphi)\, dV$$

$$\frac{dA}{dP} = \int div(\varphi_s)\, dA$$

"Contact Area Spread Rate" represents an integral form of Tactile Flow (analogous to Time-To-Contact)

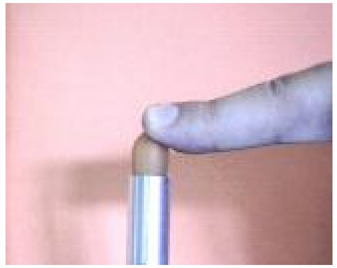
Tactile Cues: Contact Area Spread Rate

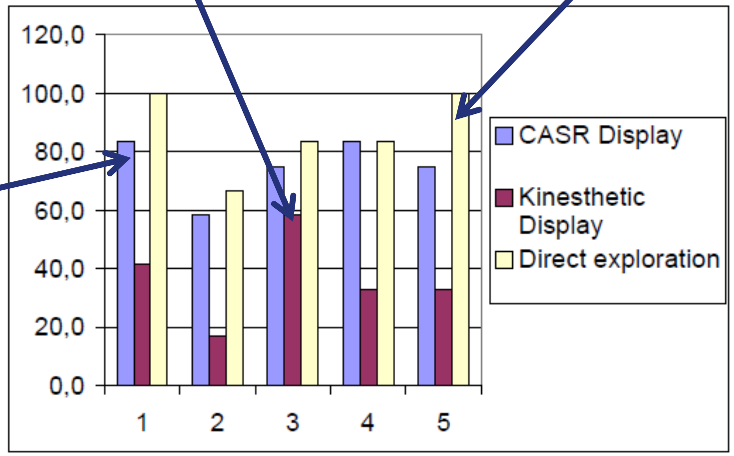
- CASR for softness discrimination

IEEE TRANSACTIONS ON ROBOTICS & AUTOMATION 1

Haptic Discrimination of Softness in Teleoperation: The Role of the Contact Area Spread Rate

Antonio Bicchi, Enzo Pasquale Scilingo, Danilo De Rossi





- CASR is analogous to time-to-contact for tactile flow

Fig. 14. Percentage of successfull recognition of 5 different levels of softness by direct exploration, and by remote exploration using the CASR haptic and the kinesthetic displays.

Constraint Equation and Tactile Flow

$$\frac{d\upsilon}{dP} = 0 = \frac{\partial \upsilon}{\partial x}\varphi_x + \frac{\partial \upsilon}{\partial y}\varphi_y + \frac{\partial \upsilon}{\partial z}\varphi_z + \frac{\partial \upsilon}{\partial P}$$

$$\nabla \upsilon \cdot \varphi = -\frac{\partial \upsilon}{\partial P};$$

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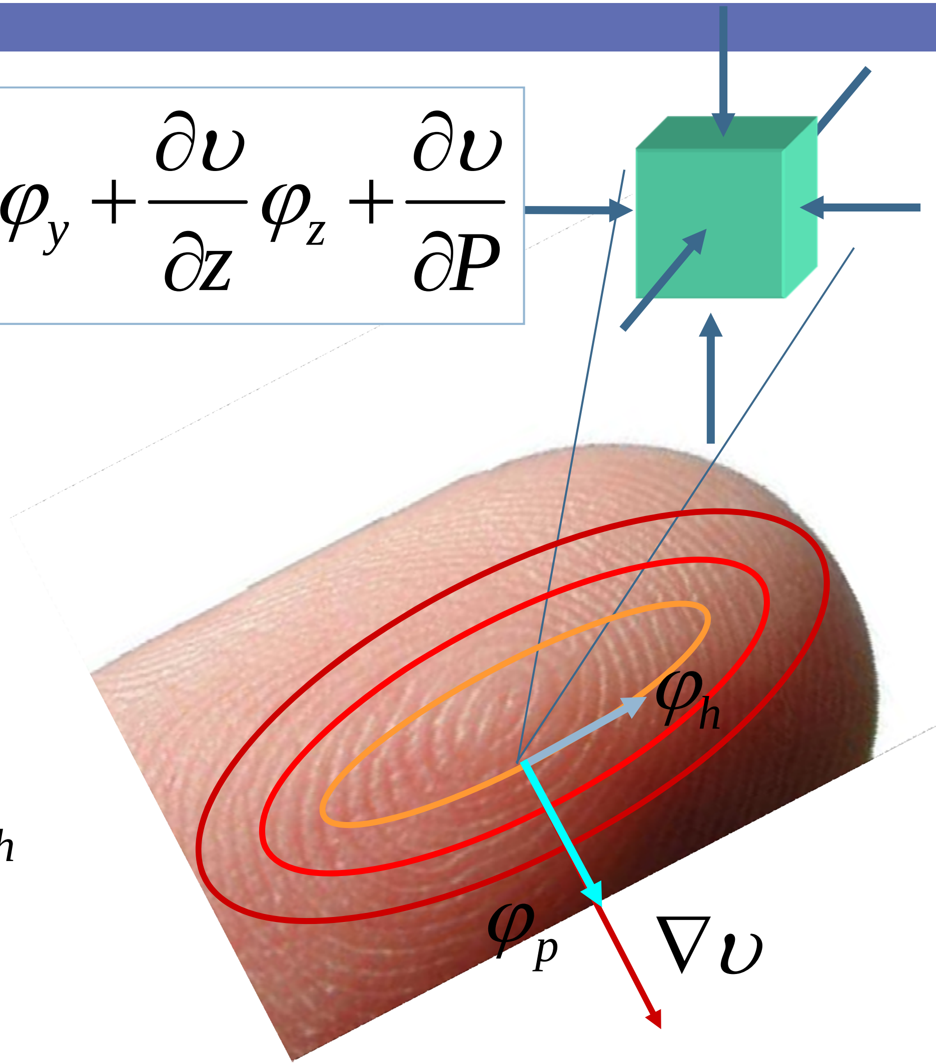
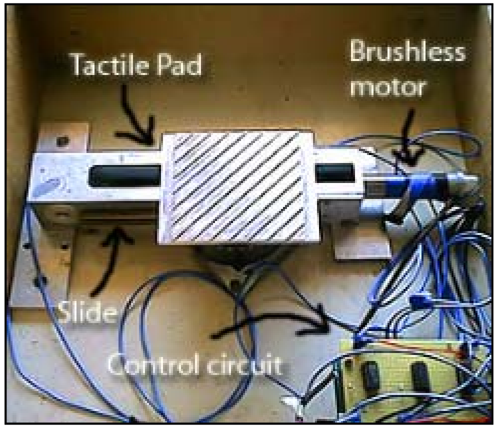
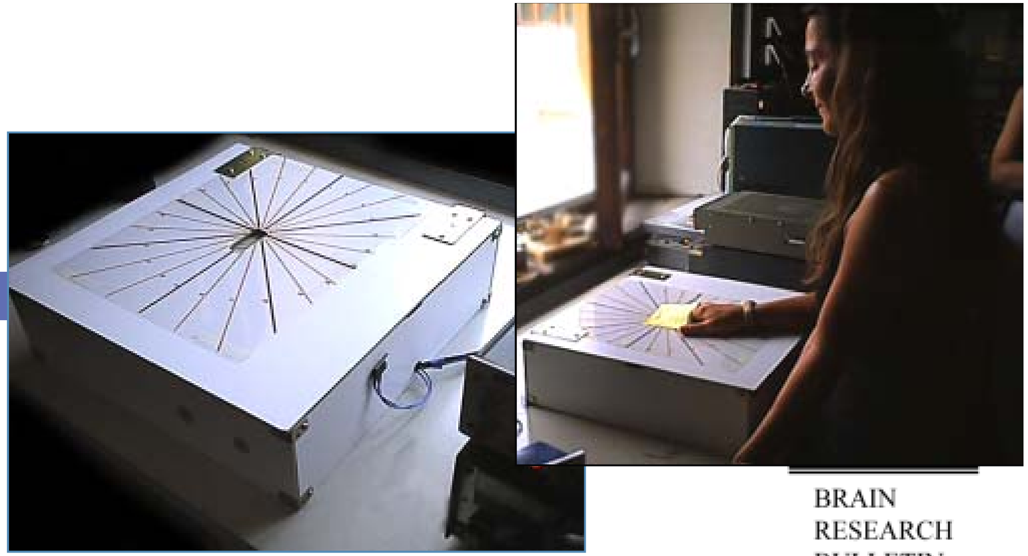


Tactile Flow Illusions

- Tactile Barber Pole





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Brain Research Bulletin 75 (2008) 737–741

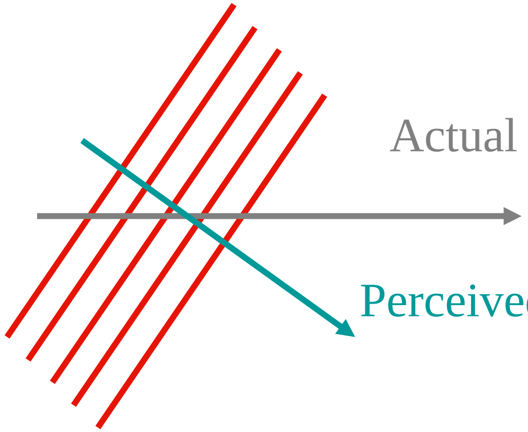
BRAIN RESEARCH BULLETIN

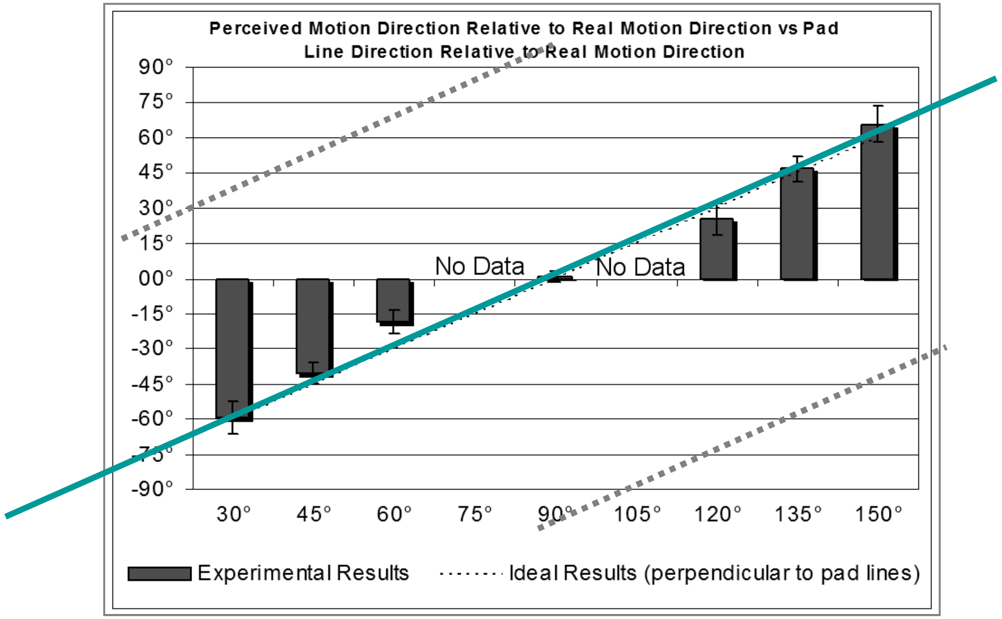
www.elsevier.com/locate/brainresbull

Research report

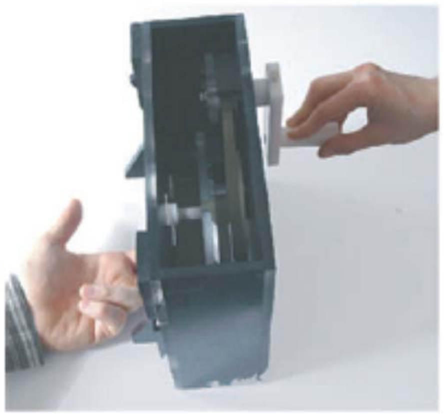
Tactile flow explains haptic counterparts of common visual illusions

Antonio Bicchi[a,b,*], Enzo P. Scilingo[a], Emiliano Ricciardi[a,c,d], Pietro Pietrini[c]





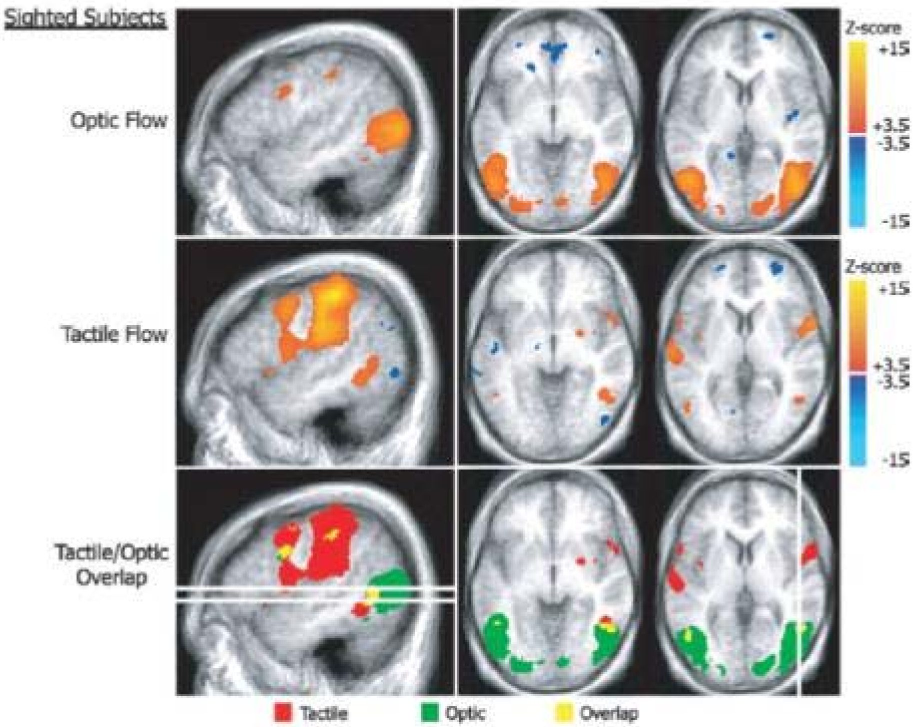
Cerebral Correlates of Tactile Flow

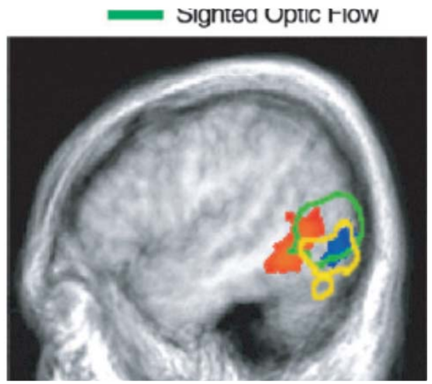


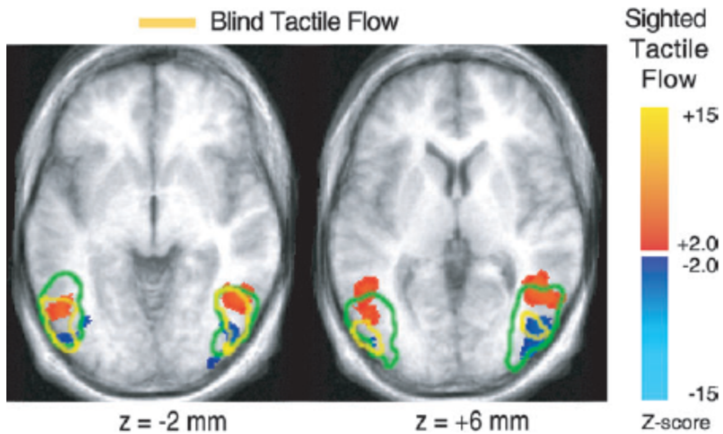
Cerebral Cortex
doi:10.1093/cercor/bhm018

The Effect of Visual Experience on the Development of Functional Architecture in hMT+

Emiliano Ricciardi[1,2,3], Nicola Vanello[2,3], Lorenzo Sani[1], Claudio Gentili[2,4], Enzo Pasquale Scilingo[3], Luigi Landini[2,3], Mario Guazzelli[4], Antonio Bicchi[3], James V. Haxby[5] and Pietro Pietrini[1]





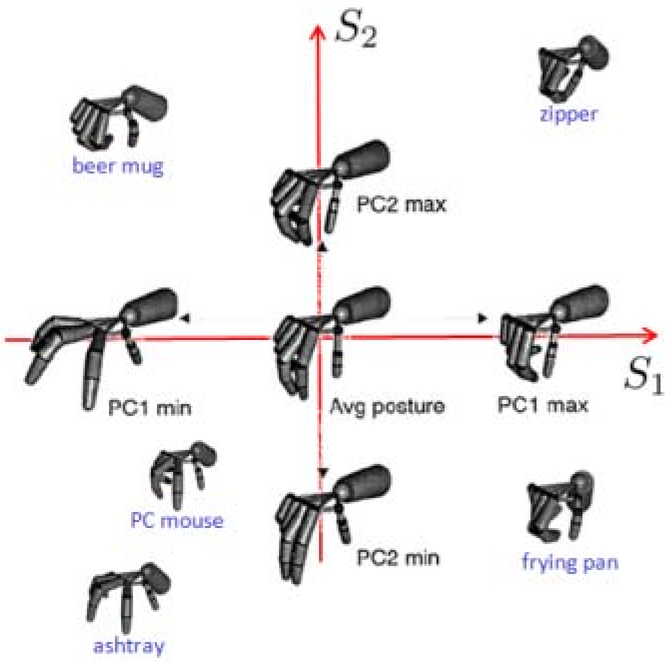


Synergies in the Hand Motor System

- Extensive neuroscientific evidence for the ***existence of sensorimotor synergies and constraints***
  Babinski (1914!), Bernstein, Bizzi, Arbib, Jeannerod, Wolpert, Flanagan, Soechting, Sperry, …

- Quantitative work on hand postural synergies dates back a decade only

Postural Synergies



Santello, Flanders, Soechting
J. Neuroscience, 1998

- Santello et al. (1998) investigated the hypothesis that "*learning to select appropriate grasps is applied to a series of inner representations of increasing complexity, which varies with experience and degree of accuracy required.*"
  - 5 subjects were asked to shape their hands in order to mime grasps for a large set (57) of familiar objects;
  - Joint values were recorded with a CyberGlove;
  - Principal Components Analysis (PCA) of these data revealed that the first two Principal Components or postural synergies account for $\sim 84\%$ of the variance, first three $\sim 90\%$;
  - PCs (eigenvectors S_i of the Covariance Matrix) can be used to define a basis for a subspace of the joint space.

The Shape of Synergies

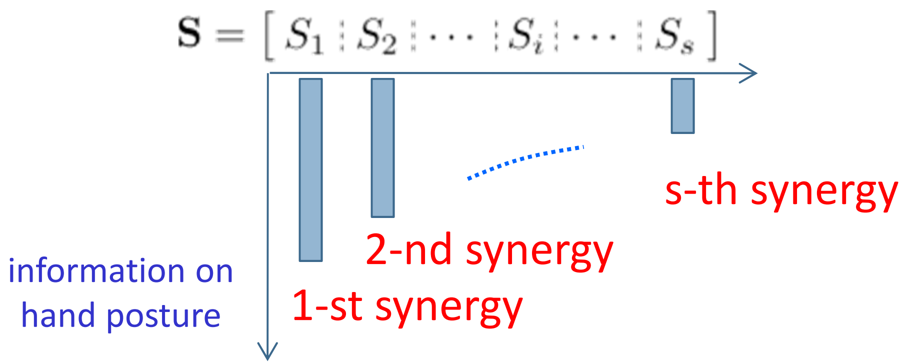
Postural ***synergies*** (aka **primitives**, ***eigengrasp***
components) are the eigenvectors of the join

First synergies contain most of hand posture in
Higher-order synergies used for fine adjustmen

PCs can be collected in a synergy matrix: $S = \left[\begin{array}{c:c:c:c:c} \vdots & \vdots & \vdots & \vdots & \\ S_1 & S_2 & S_3 & \cdots & S_n \\ \vdots & \vdots & \vdots & \vdots & \end{array}\right]$

S_1 (1-st synergy) S_2 (2-nd synergy) S_3 (3-rd synergy)

Model of a Hand with "*s*" synergies



Straightforward Kinematic interpretation:

- Joint configurations must belong to s-dimensional manifold

$$\mathbf{q} = \mathbf{q}(\sigma), \;\; \sigma \in \mathbb{R}^s$$

- Hand velocities belong to tangent bundle

$$\dot{\mathbf{q}} = \mathbf{S}(\mathbf{q})\dot{\sigma}, \;\; \mathbf{S}(\cdot) \in \mathbb{R}^{n \times s}$$

- Fingers move according to Hand jacobian

$$\dot{\mathbf{c}}_f = \mathbf{J}\dot{\mathbf{q}} = \mathbf{J}\mathbf{S}\dot{\sigma}$$

Grasp Force Distribution & Optimization

- External load (wrench) $\mathbf{w}$
- Grasp matrix $\mathbf{G}$ (*fat*)
- Contact forces $\mathbf{p}$

$$\boxed{\mathbf{w} = \mathbf{G}\mathbf{p},}$$

- Friction Constraints

$$\boxed{\sigma_{i,f}(\mathbf{p}_i) \; = \; \alpha_i \|\mathbf{p}_i\| - \mathbf{p}_i^T \mathbf{n}_i < 0}$$

- Given $\mathbf{w}$ which $\mathbf{p}$?

$$\boxed{\mathbf{p} = \mathbf{G}^R \mathbf{w} + \mathbf{A}\mathbf{x},}$$

- $\mathbf{G}^R$ (any) right inverse of $\mathbf{G}$
- $\mathbf{A}$: a basis of internal forces subspace
- By changing $\mathbf{x}$, squeezing forces are changed: if for every $\mathbf{w}$ it is possible to find $\mathbf{x}$ such that friction constraints are verified, than one has FcC
- **This only holds for fingertip grasping with a large number of synergies!**

Controllability of Grasping with Synergies

- Hand joint torques τ
- Hand Jacobian $\mathbf{J}$

- Hand with synergies

$$\boxed{\tau = \mathbf{J}^T \mathbf{p},}$$

$$\boxed{\tau_\sigma = \mathbf{S}^T \mathbf{J}^T \mathbf{p}}$$

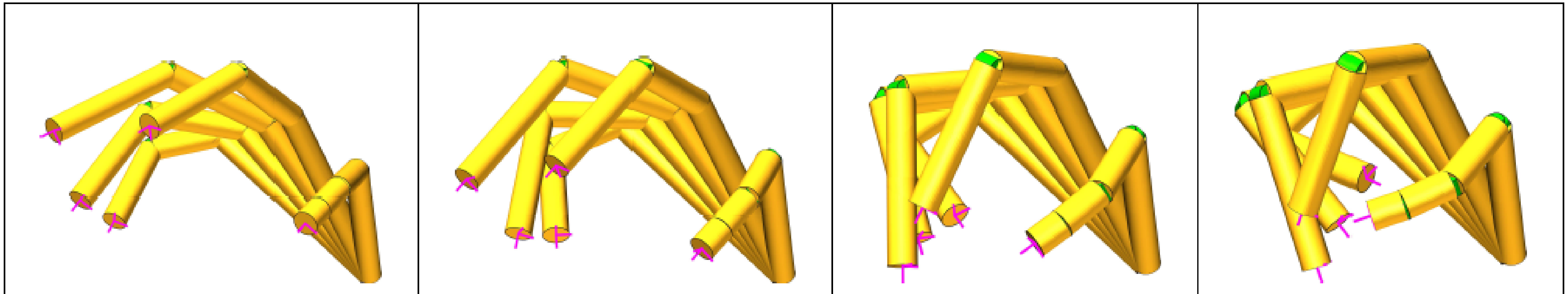
$$\mathbf{S}^T \mathbf{J}^T \in \mathbb{R}^{s \times p}$$

$$s < p$$

Not controllable in general → can not apply arbitrary contact forces $\mathbf{p}$!

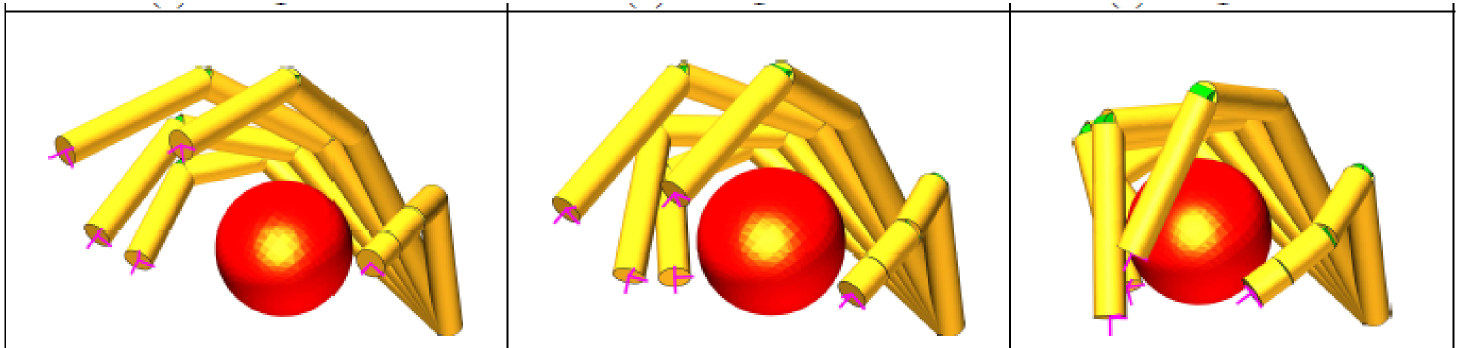
Grasping objects with synergies

- First synergy only



(a) $\sigma_1 = 0$ (b) $\sigma_1 = 0.35$ (c) $\sigma_1 = 0.70$ (d) $\sigma_1 = 1.0$

- Grasping an object



(e) $\sigma_1 = 0$ (f) $\sigma_1 = 0.35$ (g) $\sigma_1 = 0.70$

Soft Synergies

- Internal Forces: $\mathbf{p} \in ker(\mathbf{G})$
- Not all internal forces are active (controllable) acting on the joints

TH: The set of contact forces which can be actively controlled is a linear subspace of $ker(\mathbf{G})$

- $$\mathbf{A}\mathbf{x} = \mathbf{KJS}\Delta\sigma - \mathbf{KG}^T\Delta\mathbf{u}$$

  PLV →

  $$\begin{bmatrix} \mathbf{A} & -\mathbf{KJS} & \mathbf{KG}^T \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ \Delta\sigma \\ \Delta\mathbf{u} \end{pmatrix} = 0.$$

- hence

  $$\mathbf{p}_a = (\mathbf{I} - \mathbf{G}_K^R \mathbf{G})\mathbf{KJS}\Delta\sigma$$

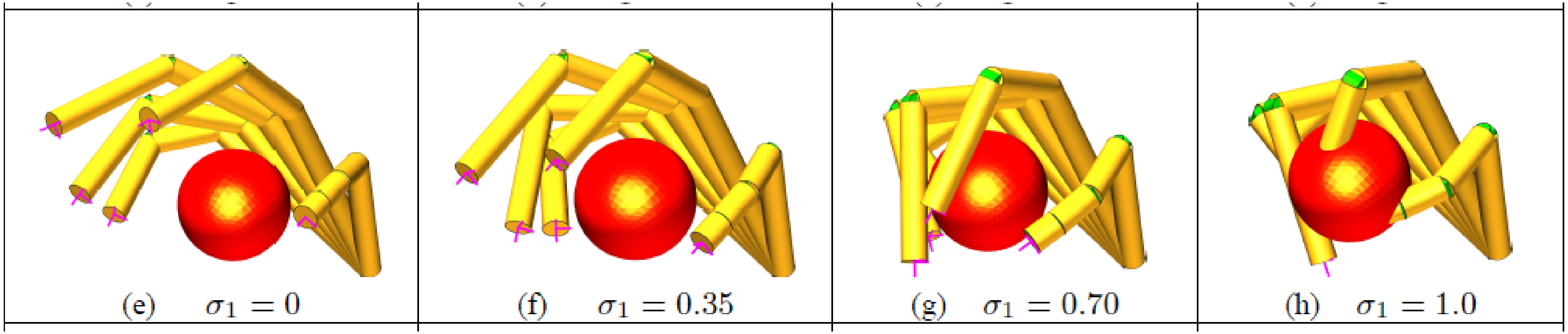
- or $\boxed{\mathbf{p}_a = \mathbf{E}_\sigma \mathbf{y}}$

Feldman's Equilibrium Point Hypothesis

λ?

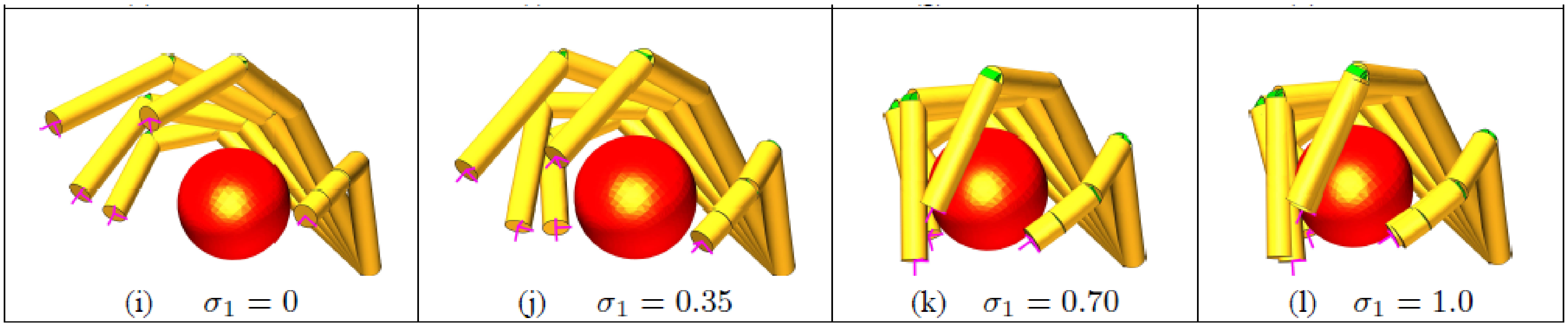
Soft Synergies

- ❑ Rigid Synergy = Reference Hand



(e) $\sigma_1 = 0$ (f) $\sigma_1 = 0.35$ (g) $\sigma_1 = 0.70$ (h) $\sigma_1 = 1.0$

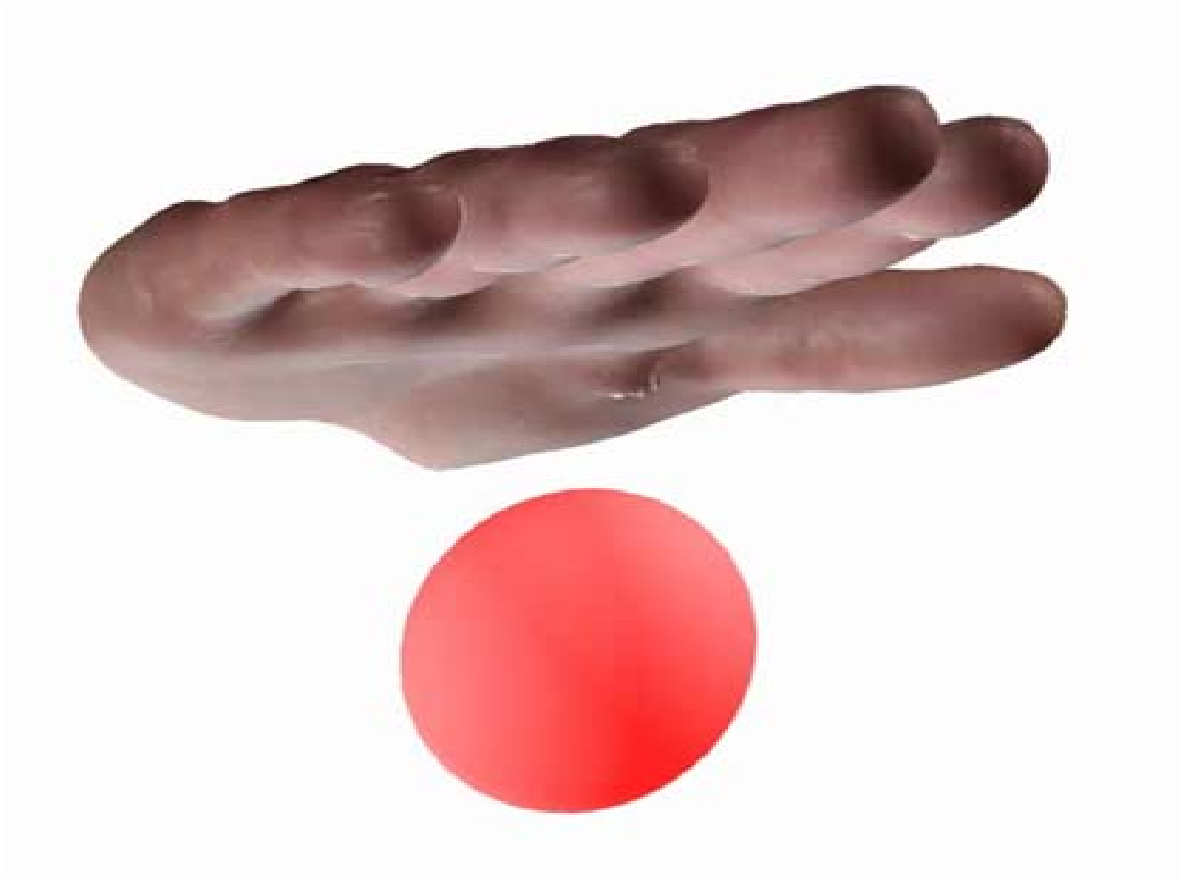
- ❑ Soft Synergy = Equilibrium Hand

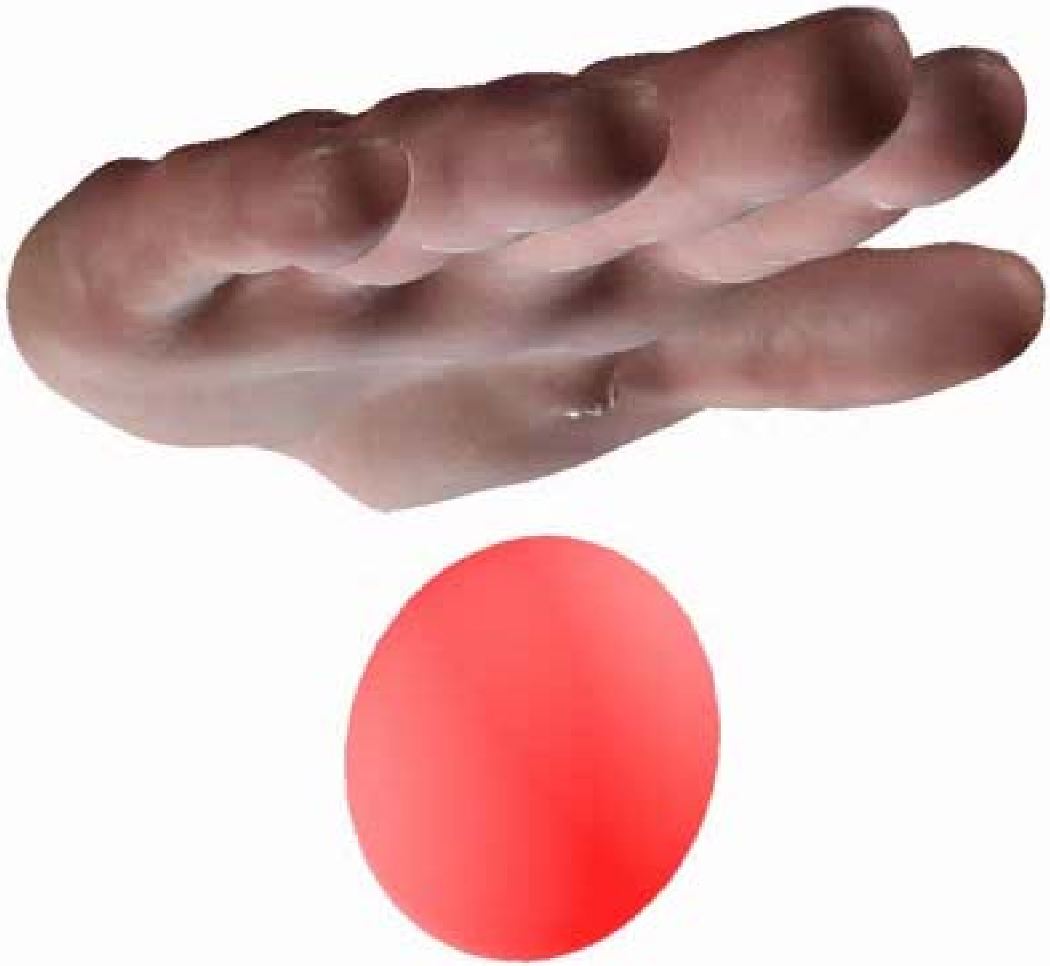


(i) $\sigma_1 = 0$ (j) $\sigma_1 = 0.35$ (k) $\sigma_1 = 0.70$ (l) $\sigma_1 = 1.0$

Pinch Grasping with 3 soft Synergies

- Cherry



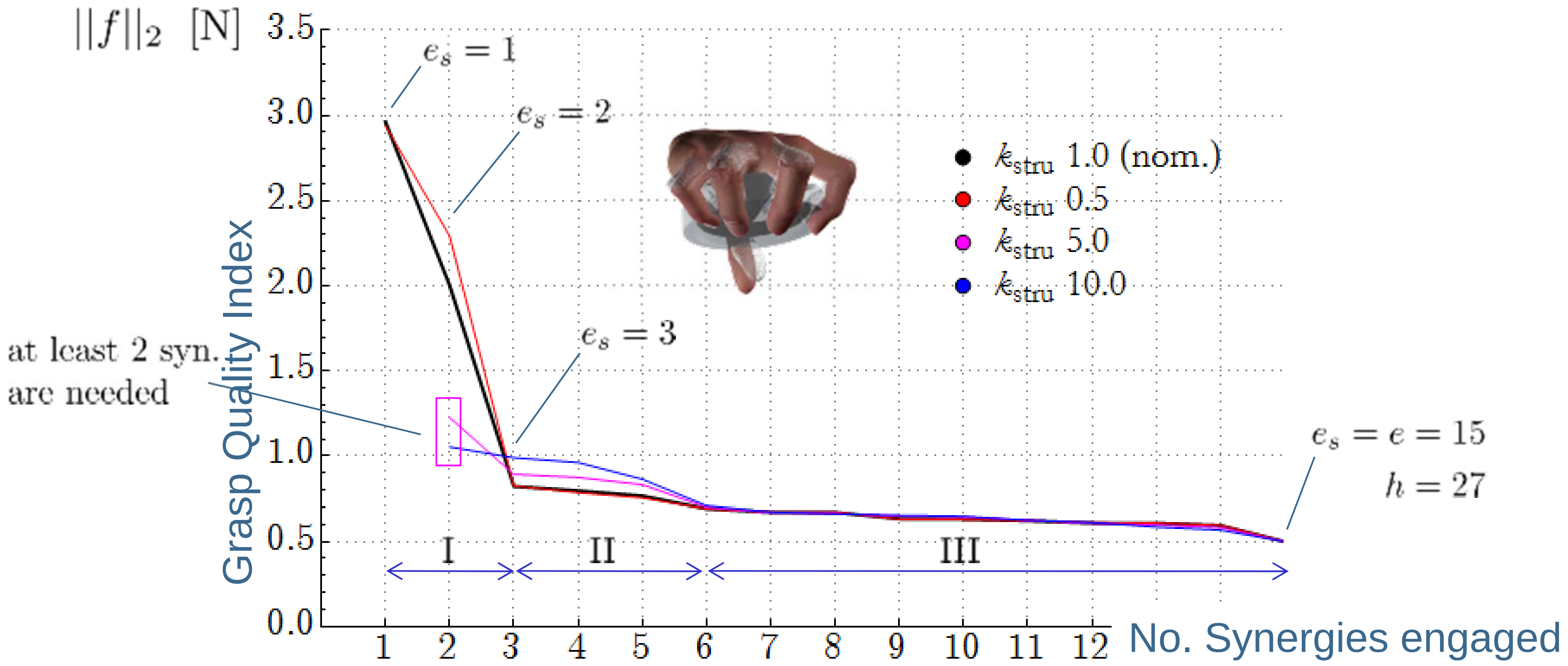


Power Grasping with 3 soft Synergies

- Ashtray

Predictions

- Variation of grasp quality measure with # synergies engaged in grasp
- Dimension of Internal Force subspace: 27
- Grasp is not always force-closure with the 1-st synergy only
- Limited effect of contact stiffness variation

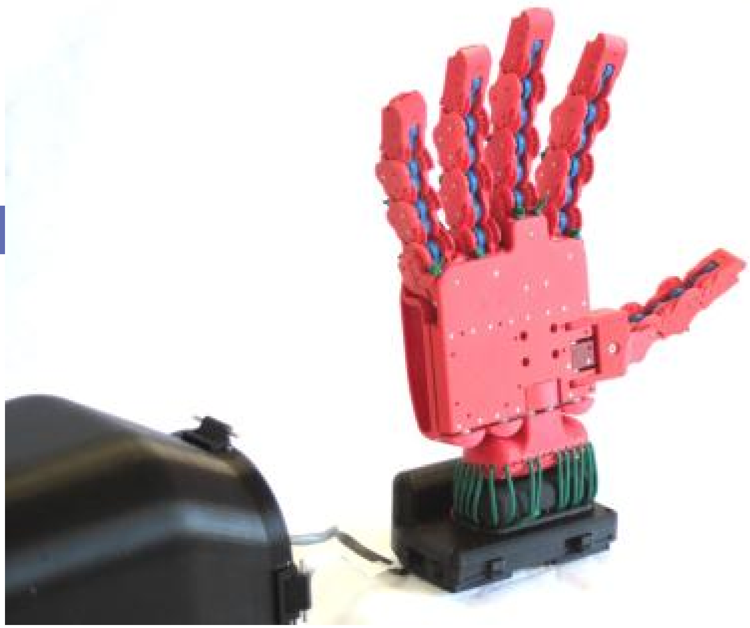


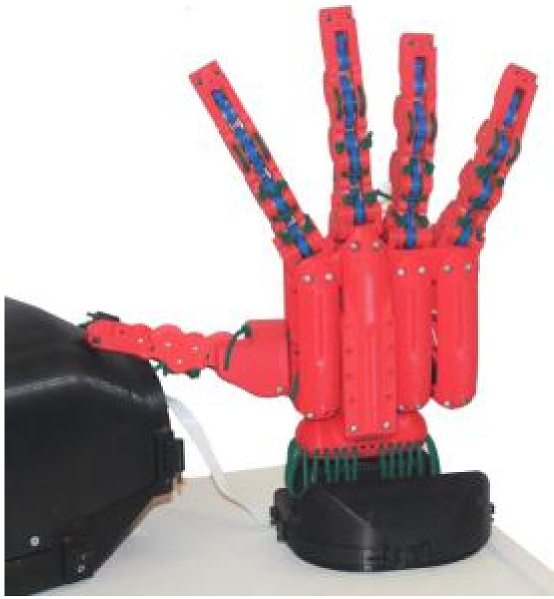
Design

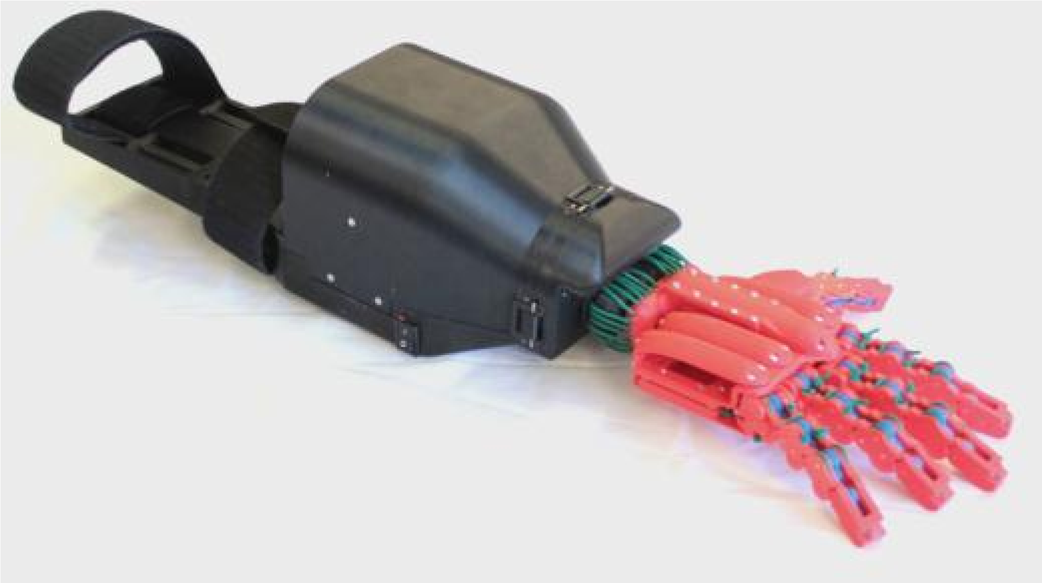

Berkley
Whiplash
Tough & Powerful
for Extreme Fishing
100LB 300YD
44.9kg 274m
NEW

One Synergy, one Motor!

THE Third Hand







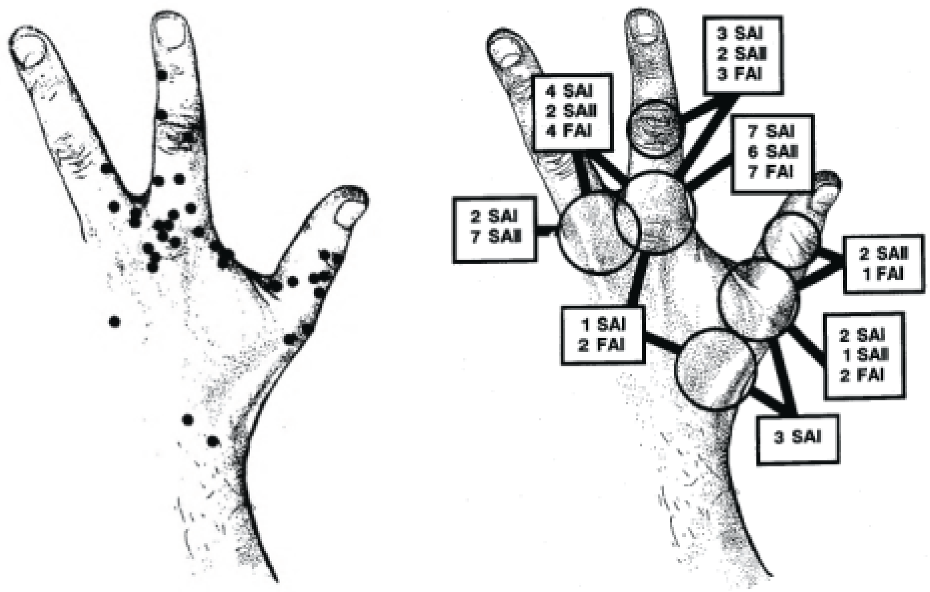
The dual point of view:
Synergies for Optimal Observers

Glove-based HPR Systems:
- Mass market (entertainment)
- Few, low cost, low accuracy sensors
- Many joints

[Dipietro et al.,2008]

The dual point of view: Synergies for Optimal Observers

- Humans do not have homogeneous distribution of receptors...

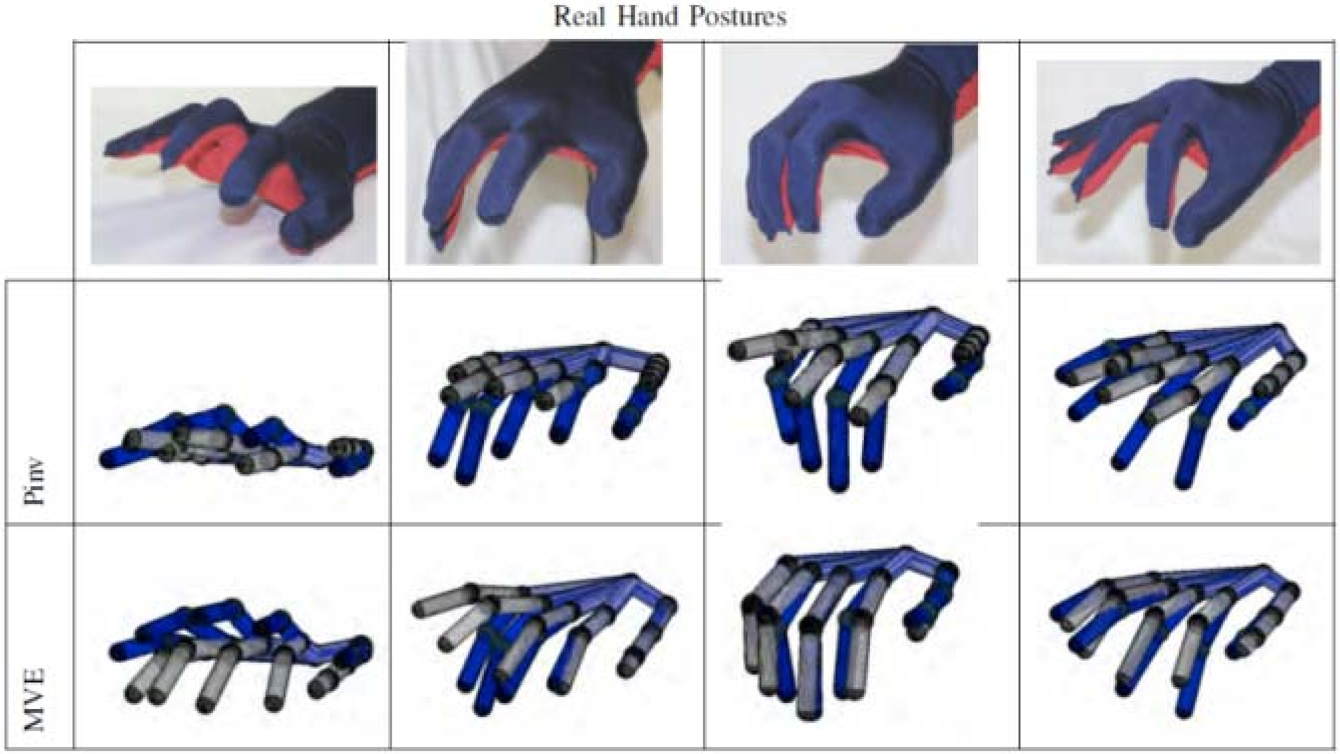


Edin and Abbs, 1991

Bianchi Salaris B., 2011

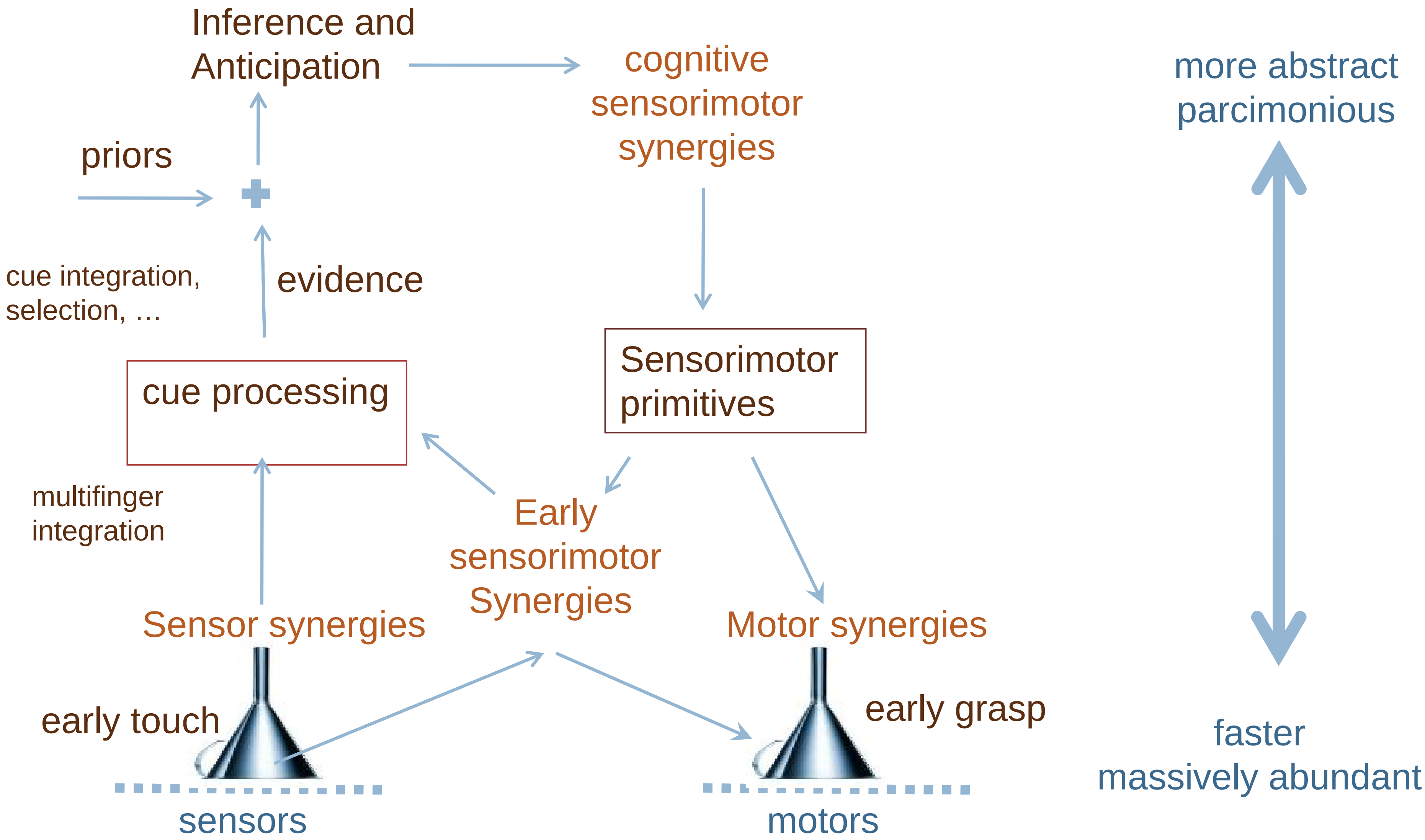
The dual point of view: Synergies for Optimal Hand Observers

- Synergies provide *a priori* information for
  - optimal Bayesian inference
  - optimal sensor placement

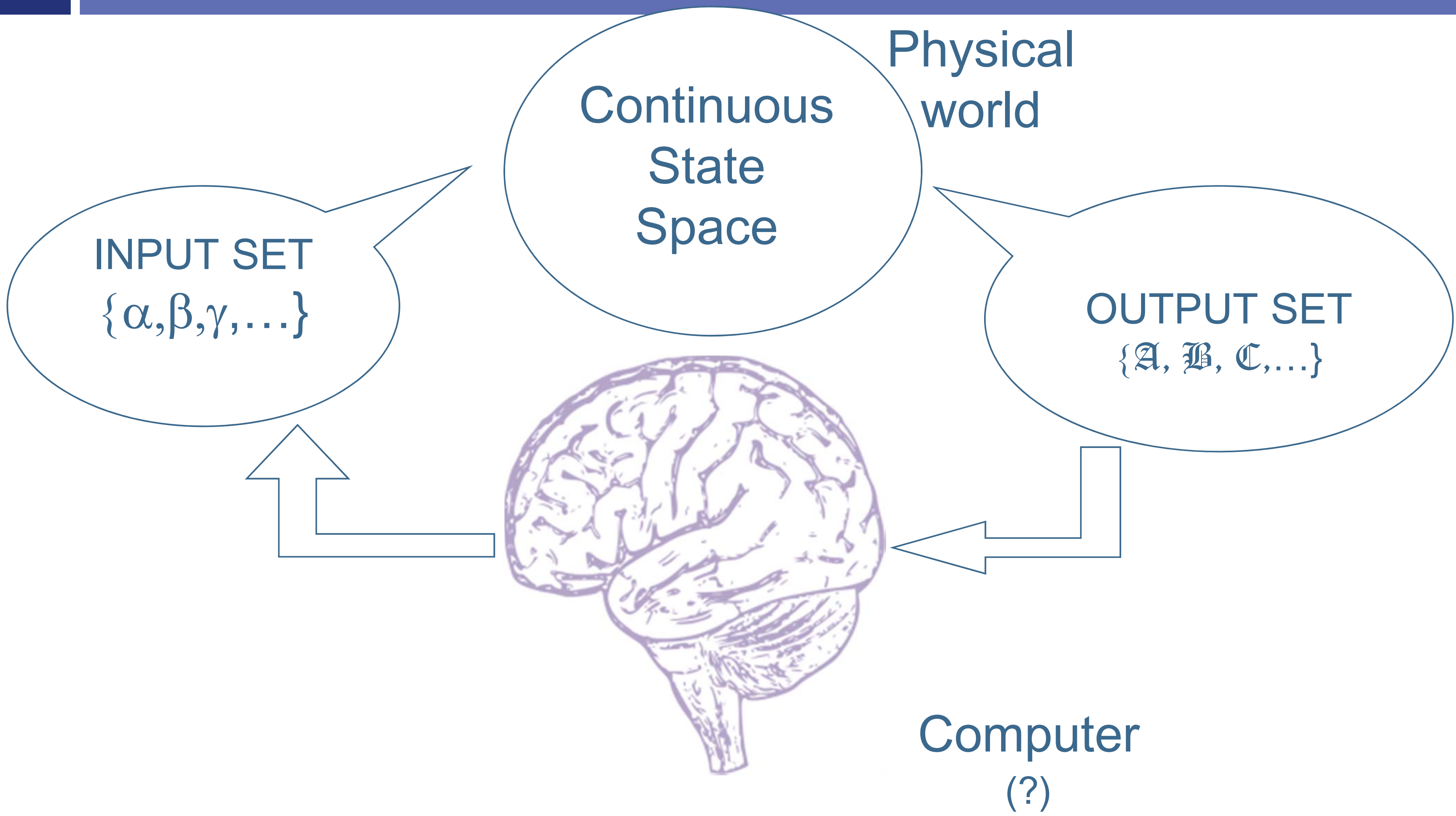


Bianchi Salaris B., 2011

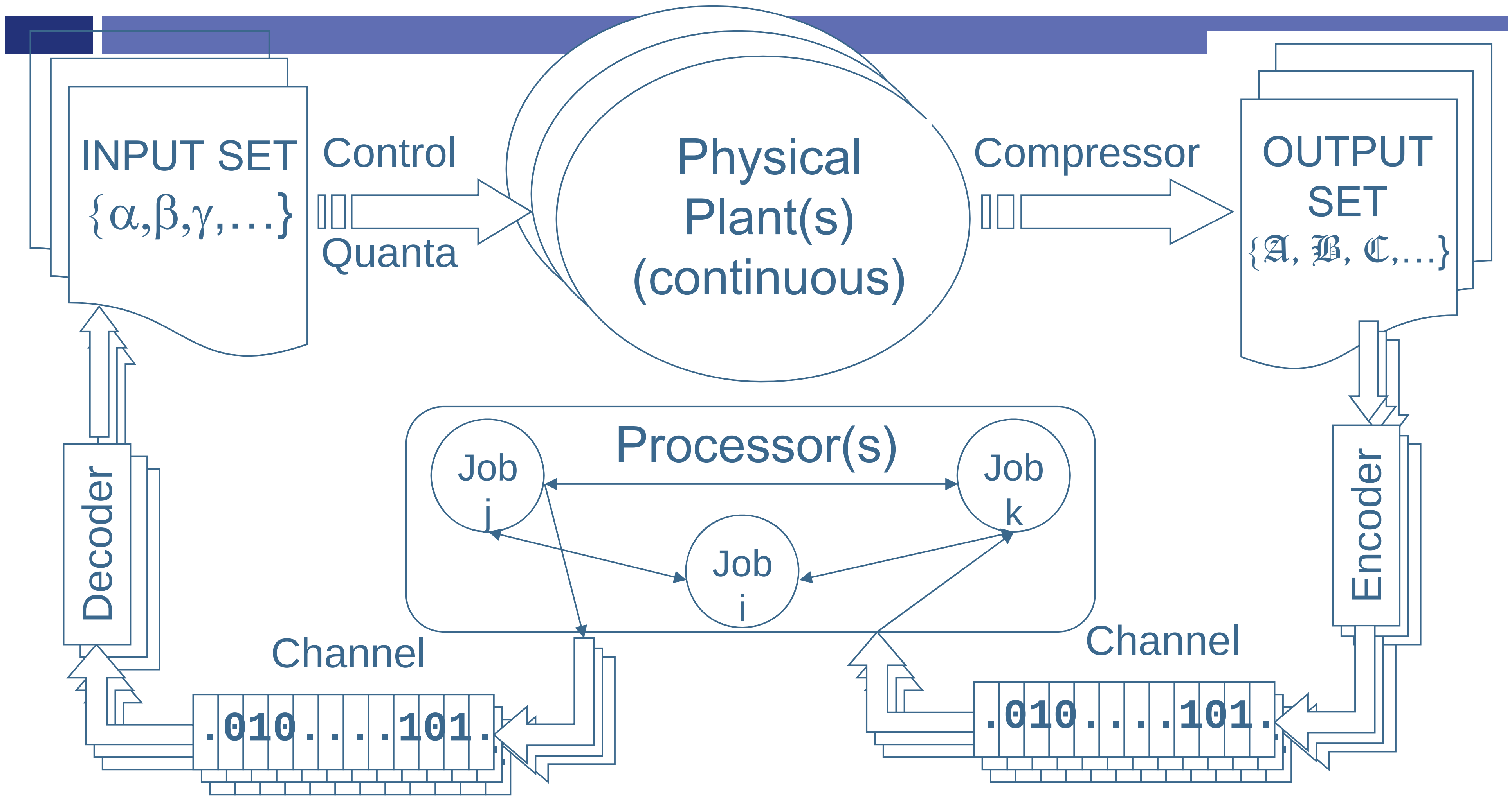
Sensorimotor Synergies



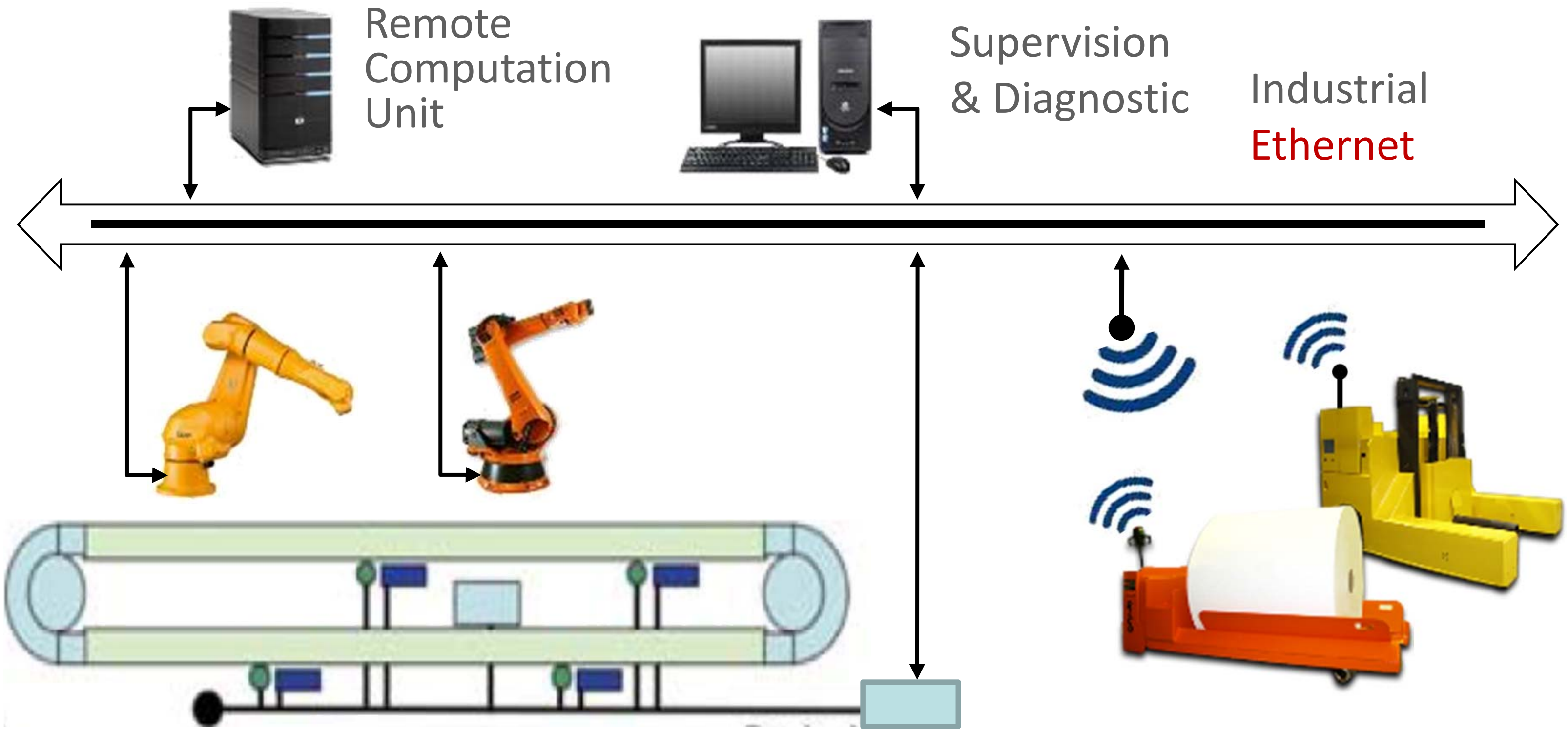
Architectures for Feedforward (Learning) and Feedback (Reflex) co-organization



Networked Embedded Control Systems

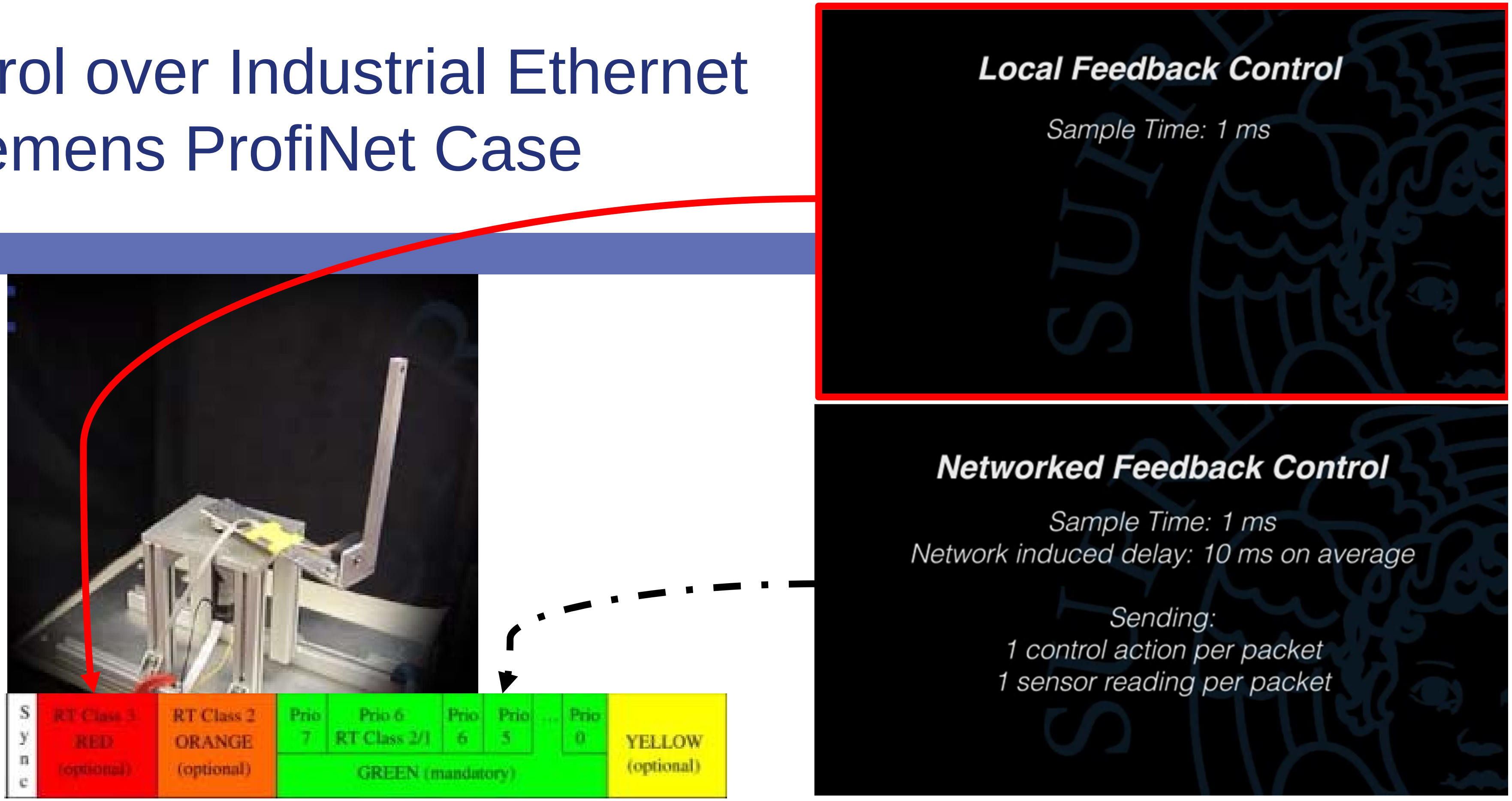


Networked Control Systems



Constraints: Limited bandwidth, variable transmission intervals, variable delays, packet dropouts, constrained access (protocol)

Control over Industrial Ethernet
A Siemens ProfiNet Case



Furuta pendulum controlled over an Industrial Ethernet:

TCP/IP with reaction times in the range of 100ms

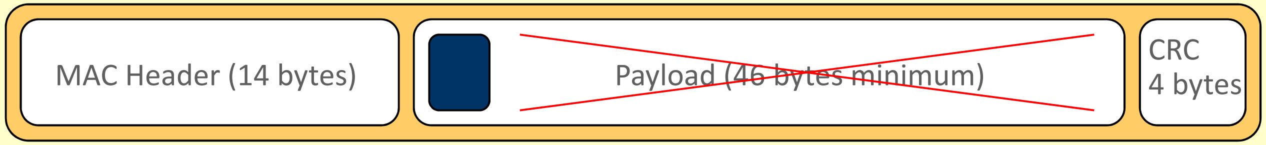
RT (Real-Time) protocol up to 10 ms cycle times

IRT (Isochronous Real-Time) cycles times of less than 1ms

Packet-switching communication

Many networks organize data transmission in *packets*

Ethernet



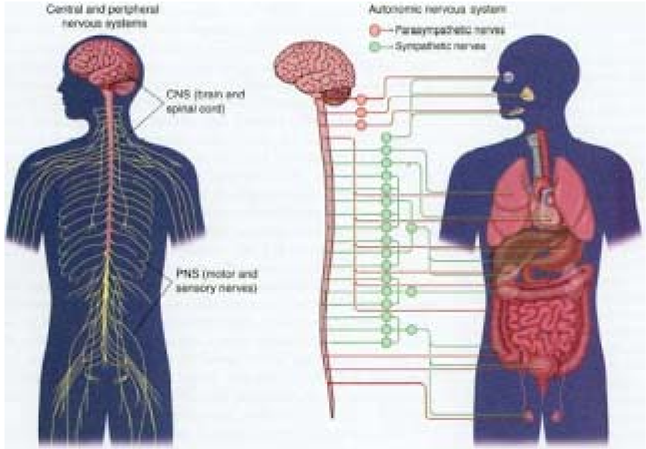
Ethernet type II frame (64 bytes)

- **38 bytes** of overhead (header + interframe separation)
- **84 bytes** of minimum packet size

Padding of payload with useless information

How can we exploit the large payload?

Ideas from another system



CNS loops ~100ms
PNS loops ~10ms

PREDICTIVE FEED-FORWARD SENSORY CONTROL DURING GRASPING AND MANIPULATION IN MAN

ROLAND S. JOHANSSON and BENONI B. EDIN
Department of Physiology, University of Umeå, S-091 87 Umeå, Sweden

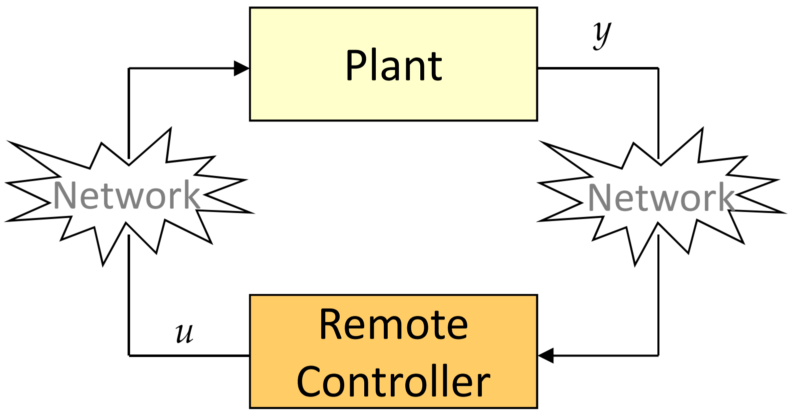
Exp. Brain Res., 1984

ABSTRACT

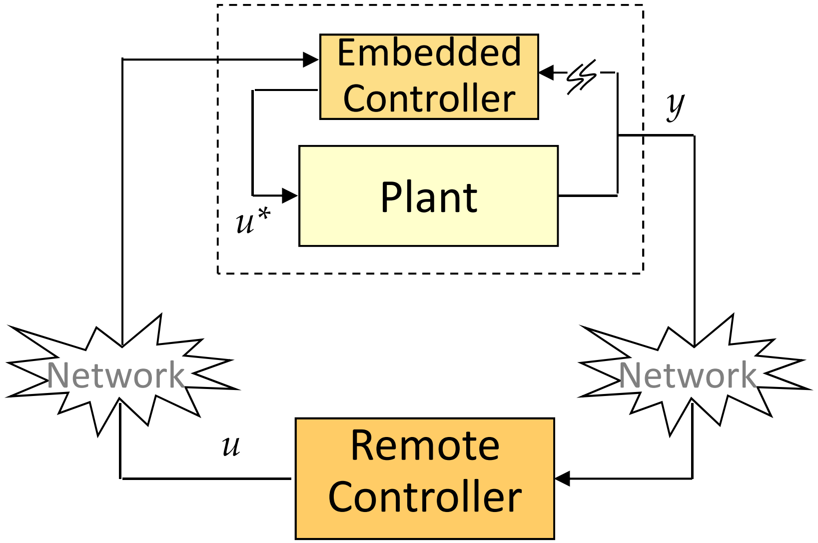
During dexterous manipulation the basal relationships expressed in the employed fundamental muscle synergies are tuned precisely not only to the manipulative intent, but also to the physical properties of the object. Recent findings indicate that the sensorimotor mechanisms involved depend largely on predictive rather than servo-control mechanisms. The CNS monitors specific, more-or-less expected, peripheral sensory events and use these to directly apply control signals that are appropriate for the current task and its phase. On a fast time scale, discrete mechanical events encoded in populations of somatosensory afferents trigger compensatory actions to task perturbations, and allow task progress to be monitored for timing the release of motor commands related to the serial manipulative phases. This type of predictive feed-forward sensory control is termed '*sensory discrete-event driven control*'. On an extended time scale, previous experience with the object at hand or similar objects is used to adjust the motor commands parametrically in advance of the movement, *e.g.* for the object's weight and surface friction. Through vision, for instance, common objects can be identified in terms of the grip and lifting forces necessary for a successful lift. This ability to directly parameterize the default motor commands is termed '*anticipatory parameter control*'.

Two-level architecture

From **one-level** architecture …



… to **two-level** architecture

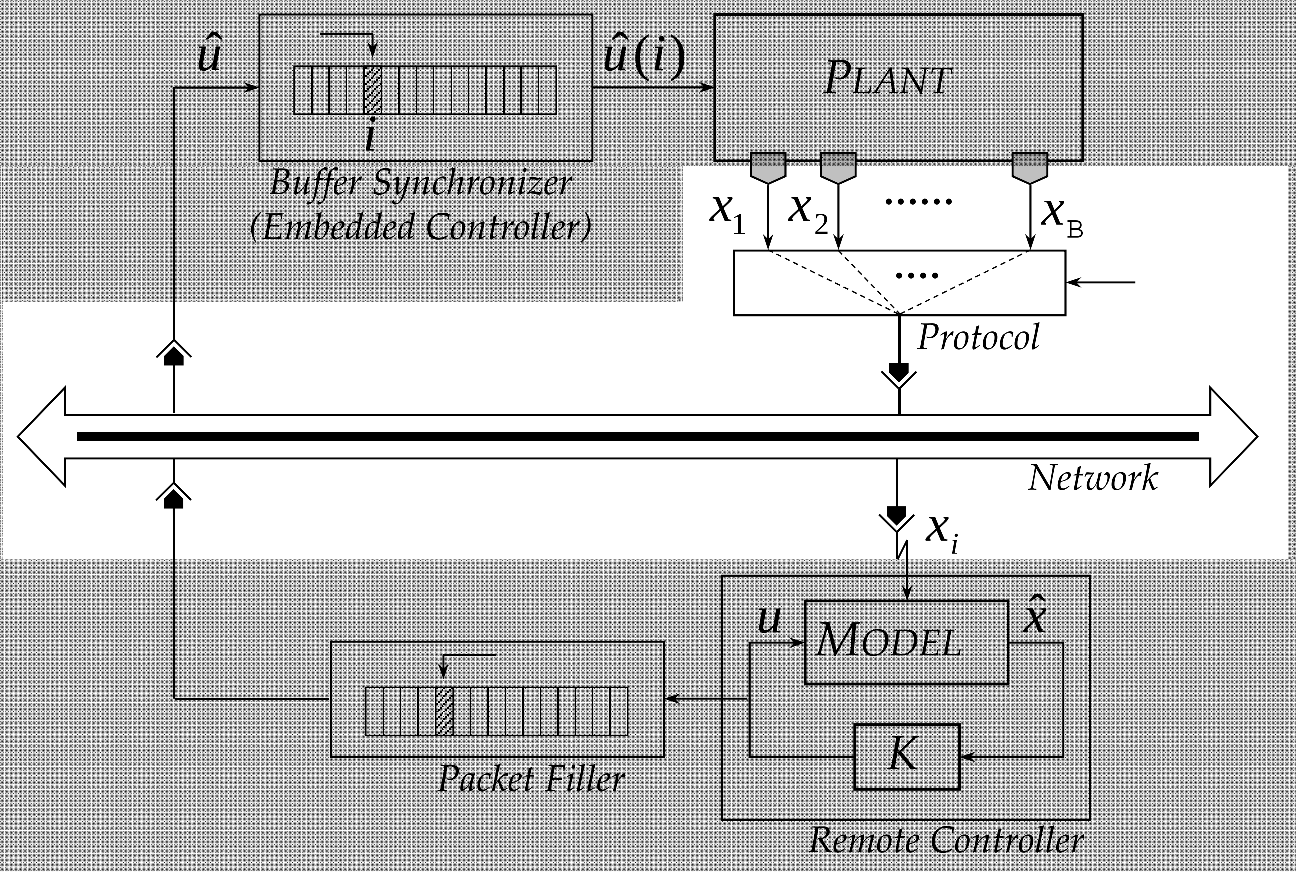


Adoption of: model-based predictive schemes
feedforward control actions

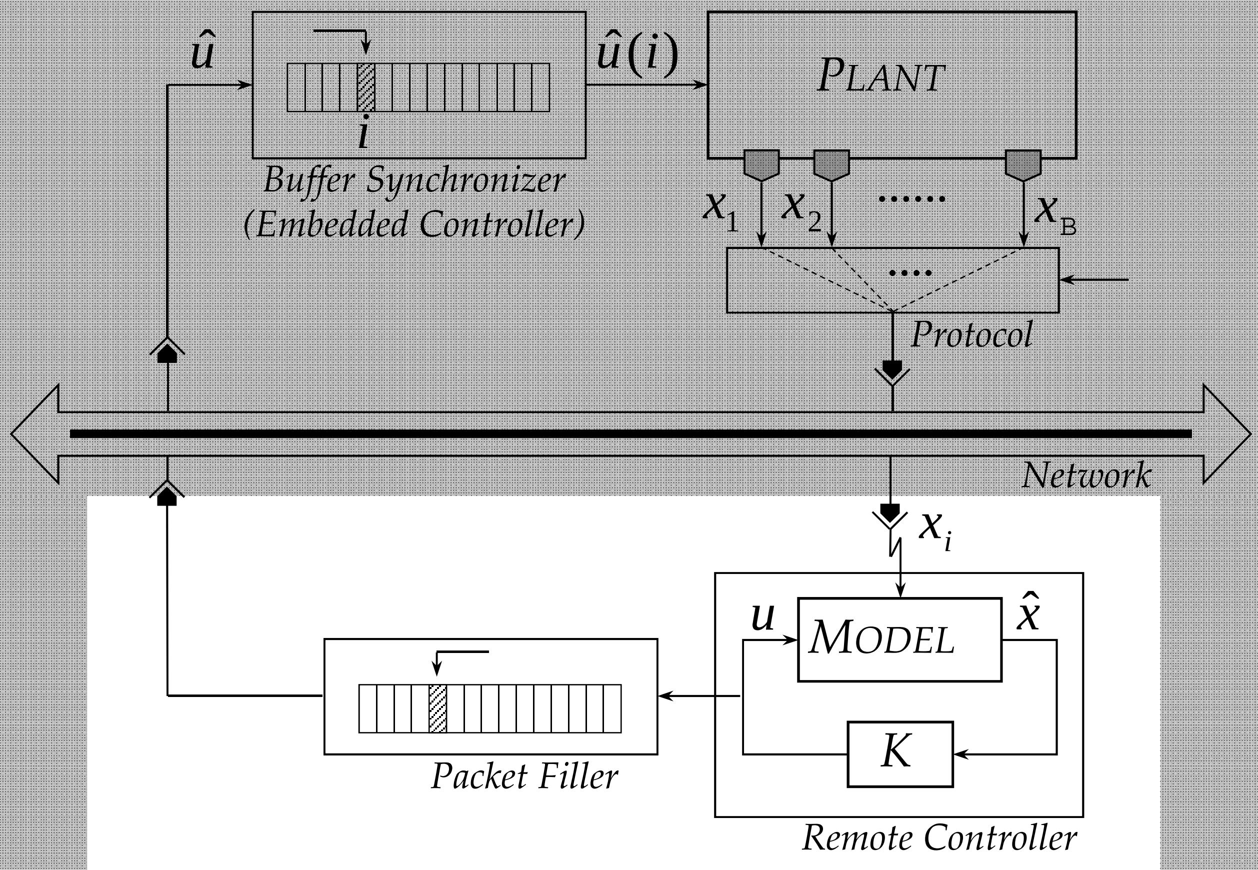
A possible answer

- *Control packets may* contain collections of "*motion primitives*" steering the system to and from a variety of states
- System would switch among primitives depending on local feedback and strategy

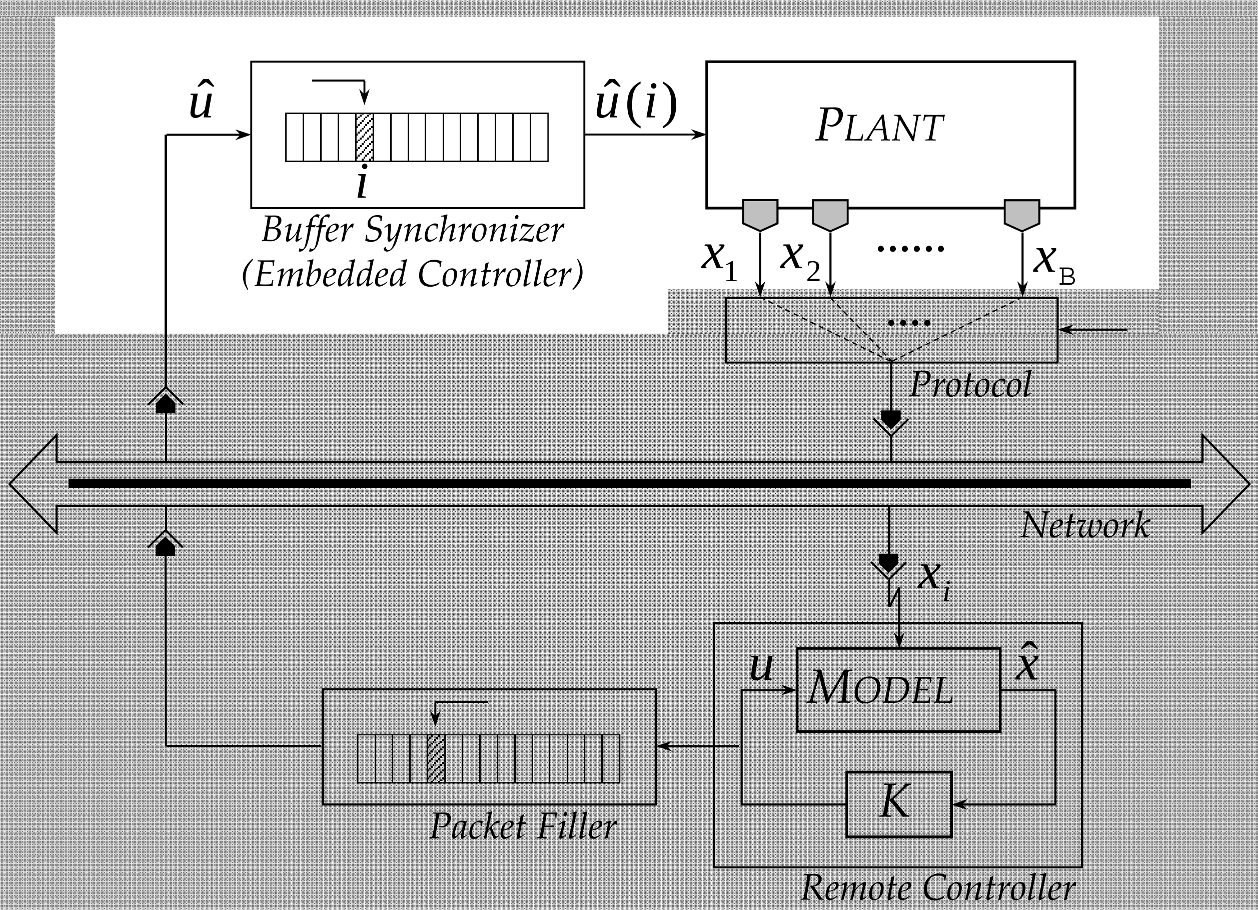
Networked control system scheme



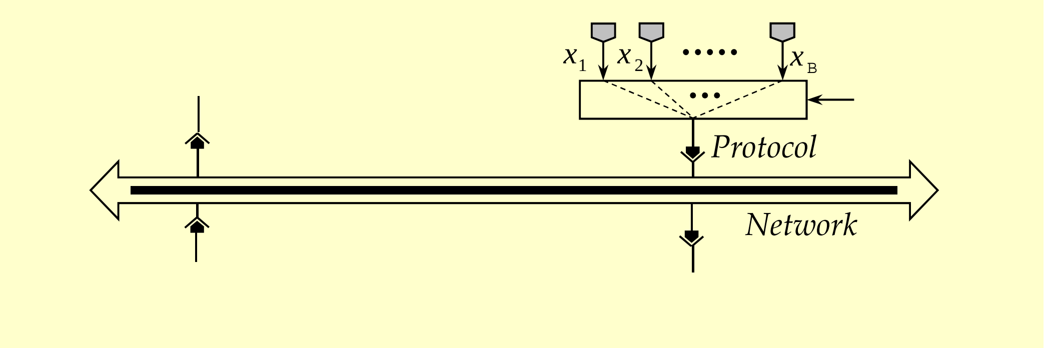
Networked control system scheme



Networked control system scheme



Network and protocol model (I)



Network Assumptions

$\tau_m, \quad \tau_c$ Bounded MATI

$T_m, \quad T_c$ Bounded MAD

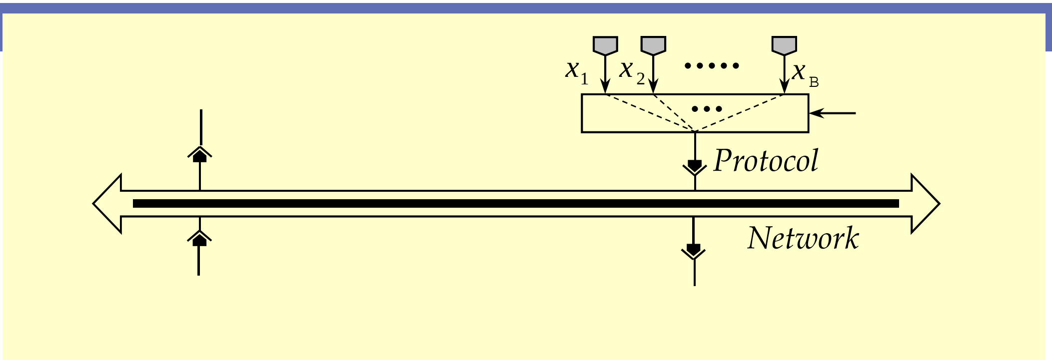
$\varepsilon_m, \quad \varepsilon_c$ Bounded mTI

MATI: Maximum Allowable Transfer Interval

MAD: Maximum Allowable Delay

mTI: Minimum Transfer Interval

Network and protocol model (II)



State partitioned in ℓ nodes: no instantaneous full reset of the network induced error $e = \hat{x} - x$

Protocol Assumptions

UGES property:

There exist a function $W_0 : \mathbb{N} \times \mathbb{R}^n \to \mathbb{R}_{\geq 0}$ and constants $\underline{a}, \overline{a}, c > 0 \quad \rho_0 \in [0,1)$ such that:

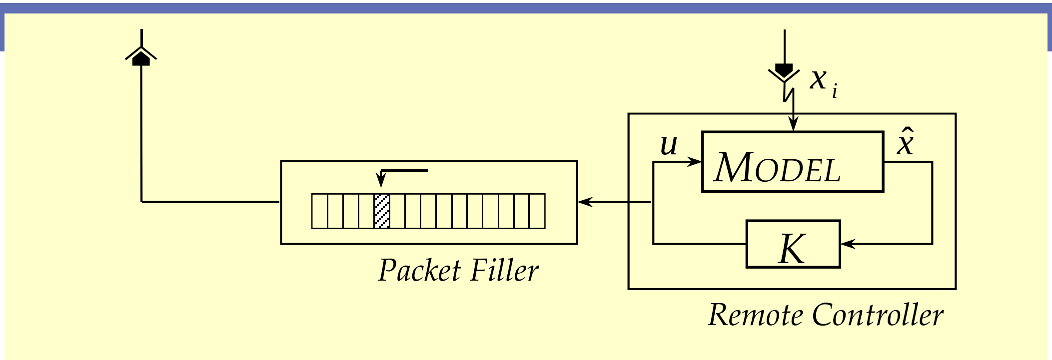
$$\underline{a}\,|e| \leq W_0(i,e) \leq \overline{a}\,|e|$$

$$W_0(i+1, h(i,e)) \leq \rho_0\, W_0(i,e)$$

$$\left| \frac{\partial W_0}{\partial e}(i,e) \right| \leq c$$

Round Robin (RR) and Maximum-Error-First Try-Once-Discard (MEF-TOD) are UGES

Remote controller



- Receive time-stamped measurements, produce time-stamped control over a fixed time horizon (feedforward)

- Model-based prediction

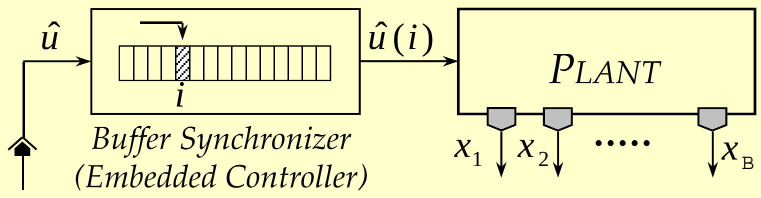
Model Assumptions

Sector-bounded model inaccuracy:

$$\left|\hat{f}(x,u) - f(x,u)\right| \leq \lambda_{f\hat{f}}\left(|x| + |u|\right)$$

$\lambda_{f\hat{f}}$ is a constant defined for every $x \in B_{R_x}$ and $u \in B_{R_u}$ with $R_x, R_u > 0$

Plant and embedded controller



- Control packets are stored in a local buffer

- An embedded controller scans the buffer and chooses the control value to apply at each instant accordingly to the time-stamp

Plant and closed-loop Assumptions

- κ guarantees the GES of f

- Regularity of f and κ measured in terms of two local Lipschitz constants $\lambda_f, \ \lambda_\kappa$ defined on B_{R_x}, B_{R_u}

There exist a function $V : \mathbb{R}^n \to \mathbb{R}_{\geq 0}$ and constants $\underline{\alpha}, \overline{\alpha}, \alpha, d > 0$ such that:

$$\underline{\alpha} \, |x|^2 \leq V(x) \leq \overline{\alpha} \, |x|^2$$

$$\frac{\partial V}{\partial x}(x) f(x, \kappa(x)) \leq -\alpha \, |x|^2$$

$$\left| \frac{\partial V}{\partial x}(x) \right| \leq d \, |x|$$

Main results

Local Exponential Stability of the NCS is ensured if

$$\tau_m \in [\varepsilon_m, \tau_m^\star), \quad \tau_m^\star \triangleq \frac{1}{L} \ln\left(\frac{M\gamma_2 + a_L L}{M\gamma_2 + a_L \rho_0 L}\right)$$

with

$$N \triangleq \left\lfloor \frac{T_c + T_m + \tau_c}{\varepsilon_m} \right\rfloor + 1 \qquad M \triangleq cN\lambda_{f\hat{f}}\,(1+\lambda_\kappa) \qquad \gamma_2 \triangleq \frac{d}{\underline{\alpha}}\sqrt{\frac{\overline{\alpha}}{\underline{\alpha}}}\lambda_f\lambda_\kappa$$

$$L \triangleq \frac{c}{a_L}\left(\sqrt{N}\lambda_{f\hat{f}}(1+\lambda_\kappa) + \sqrt{N}\lambda_f + \left(\sqrt{N-1} + N - 1\right)\lambda_f\lambda_\kappa\right)$$

$$R_x = R \qquad R_u = \lambda_\kappa R \qquad R > 0$$

- An explicit estimate of radius of attraction is provided as a function of $R > 0$

- L is a bound on the divergence rate of the system between two error updates. The larger L the smaller the τ_m : need for frequent measurement transmissions
- N binds together MATI, MAD and mTI: trade-off among them

Main results

The radius $\tilde{R}$ of the basin of attraction is a function of the radius of the ball B_R of definition of the local constants $\lambda_f, \ \lambda_\kappa$ and $\lambda_{f\hat{f}}$

For enlarging R we could have constant or even collapsing $\tilde{R}$

For semiglobal results we need a further assumption on the dependency of constants on R

Semiglobal Exponential Stability is ensured if $\exists \sigma \in [0, 1)$

$$\lim_{R \to \infty} \frac{\lambda_f(R)\lambda_\kappa(R)}{R^\sigma} < \infty$$

Example

Linearized Ch-47 Tandem Rotor helicopter

- Static output feedback
- 2-links network (measurement side)
- RR protocol
- Perfect model, no delays (same as in literature)

MATI evaluation

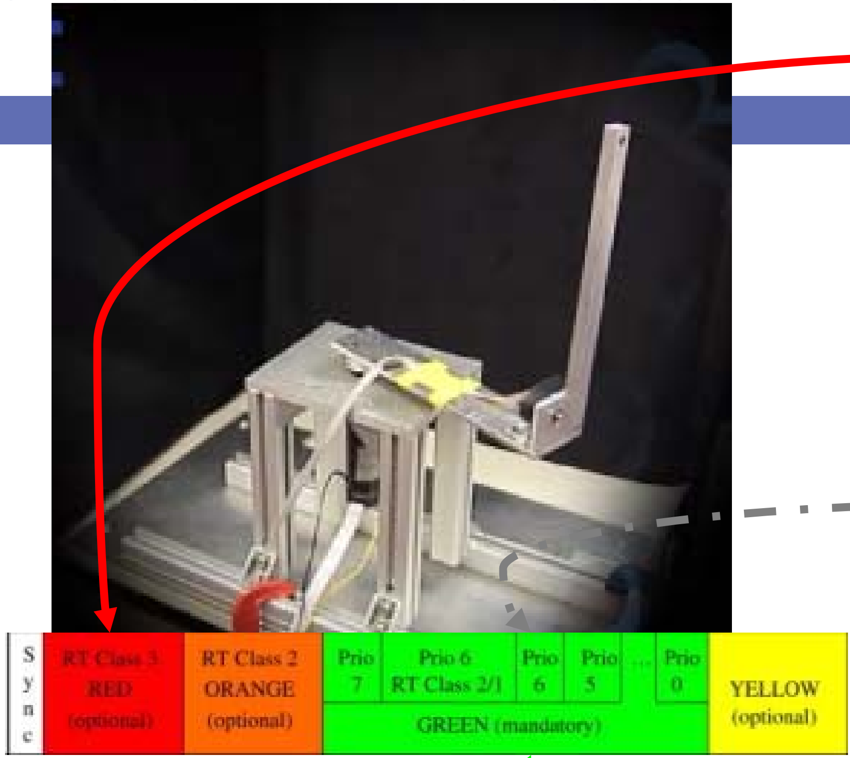
Estimate in literature: $\tau^\star = 2.81\ 10^{-4}$ s

Our estimate: $\tau_m^\star = \tau_c^\star = 5.58\ 10^{-3}$ s 20 times larger

Exact value (single command): $\tau_{\text{single}}^\star = 1.13\ 10^{-3}$ s

Exact value (mult. commands): $\tau_{\text{mult}}^\star = 1.3105$ s 1160 times larger!

Control over Industrial Ethernet: A Siemens ProfiNet Case



Packet-Based Control over the Industrial Ethernet allows to move critical system control processes from red (RT) to green (packet-switching) zone in ProfiNet

(joint work with Siemens Corp.Res..)

Local Feedback Control

Sample Time: 1 ms

Networked Feedback Control

Sample Time: 1 ms
Network induced delay: 10 ms on average

Sending:
1 control action per packet
1 sensor reading per packet

Packet Based Control

Sample Time: 1 ms
Network induced delay: 20 ms on average

Sending:
40 control actions per packet
10 sensor readings per packet

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Open Issues

- System would switch among OL/CL plans depending on local feedback and strategy
- How do you pre-compute and store feedback control ?
- ...
- How can control make good use of big data and the cloud?

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Thank you