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

Antonio Bicchi
Centro “E. Piaggio”
Università di Pisa

with L Greco, A. Chaillet, M. Gabiccini, S. Falasca, M. Gamba
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

Antonio Bicchi
Centro “E. Piaggio”
Università di Pisa
&
Italian Institute of Technology
ADVanced Robotics Dept.
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
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
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
"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 into 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.
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.

(c) Winged vehicle with side-looking sensors.

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

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

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.”

Mens et Manus

- “The modern human brain came after the hominide hand”
  Sherwood Washburn, Scientific American, 1960
Tendons
Under a pin’s head

Merkel Cell
Meissner corpuscle
Ruffini corpuscle
Pacini corpuscle

Epidermis
Dermis
Subcutaneous layer
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

Inference and Anticipation

Sensorimotor primitivies

cognitive sensorimotor synergies

Sensor synergies

Motor synergies

early touch

early grasp

cue processing

multifinger integration

cue integration, selection, ...
Images for Hands
Images for Hands

Johansson, 2005
Dynamic Constraints: Surfaces of Iso-Strain

Let $\nu$ Strain Energy Density

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

Consider the ISO-SED curves when $P$ varies

$$\frac{d\nu}{dP} = 0 = \frac{\partial \nu}{\partial x} \varphi_x + \frac{\partial \nu}{\partial y} \varphi_y + \frac{\partial \nu}{\partial z} \varphi_z + \frac{\partial \nu}{\partial P}$$
Dynamic Touch and Tactile Flow

\[
\frac{d\nu}{dP} = 0 = \frac{\partial \nu}{\partial x} \phi_x + \frac{\partial \nu}{\partial y} \phi_y + \frac{\partial \nu}{\partial z} \phi_z + \frac{\partial \nu}{\partial P}
\]

\[
\nabla \nu \cdot \phi = -\frac{\partial \nu}{\partial P};
\]

\[
\phi = \begin{pmatrix}
\phi_x \\
\phi_y \\
\phi_z
\end{pmatrix} = \phi_p + \phi_h
\]
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

\[ \frac{dV}{dP} = \int \text{div}(\phi) \, dV \]
\[ \frac{dA}{dP} = \int \text{div}(\phi_s) \, dA \]

“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

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 successful 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

\[
\frac{d\nu}{dP} = 0 = \frac{\partial \nu}{\partial x} \varphi_x + \frac{\partial \nu}{\partial y} \varphi_y + \frac{\partial \nu}{\partial z} \varphi_z + \frac{\partial \nu}{\partial P}
\]

\[
\nabla \nu \cdot \varphi = -\frac{\partial \nu}{\partial P};
\]

\[
\varphi = \begin{pmatrix} \varphi_x \\ \varphi_y \\ \varphi_z \end{pmatrix} = \varphi_p + \varphi_h
\]
Tactile Flow Illusions

- **Tactile Barber Pole**

The Barber Pole illusion involves a stationary object that is perceived as moving when observed under certain conditions. This is often perceived in situations where the intensity of the sensation experienced at a given location is modified by the proximity of one or more other locations.

**Diagram:**
- Actual motion and perceived motion are illustrated, showing a deviation between the two due to the illusion.

**Research Report:**

Tactile flow explains haptic counterparts of common visual illusions

Antonio Bicchi\(^{a,b,*}\), Eno Scilingo\(^a\), Emiliano Ricciardi\(^{a,c,d}\), Pietro Pietrini\(^e\)

**Graph:**

Perceived motion direction relative to real motion direction vs pad line direction relative to real motion direction.

- **Legend:**
  - Experimental results
  - Ideal results (perpendicular to pad lines)

*Note: Images and charts are not fully transcribed due to the format limitations.*
The Effect of Visual Experience on the Development of Functional Architecture in hMT+
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.
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 ~84% of the variance, first three ~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, eigengrasps, or principal grasp components) are the eigenvectors of the joint data covariance matrix.

First synergies contain most of hand posture information; higher-order synergies used for fine adjustments.

Principal components can be collected in a synergy matrix:

\[ S = \begin{bmatrix} S_1 & S_2 & S_3 & \cdots & S_n \end{bmatrix} \]

- \( S_1 \) (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
  \[ q = q(\sigma), \quad \sigma \in \mathbb{R}^s \]

- Hand velocities belong to tangent bundle
  \[ \dot{q} = S(q)\dot{\sigma}, \quad S(\cdot) \in \mathbb{R}^{n \times s} \]

- Fingers move according to Hand Jacobian
  \[ \dot{c}_f = J\dot{q} = JS\dot{\sigma} \]
Grasp Force Distribution & Optimization

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

Friction Constraints

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

- $\mathbf{G}^R$ (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 $\mathbf{F_c C}$

- This only holds for fingertip grasping with a large number of synergies!
Controllability of Grasping with Synergies

- Hand joint torques $\tau$
- Hand Jacobian $J$
- Hand with synergies

$$\tau = J^T p,$$

$$\tau_\sigma = S^T J^T p$$

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

$s < p$

Not controllable in general $\Rightarrow$ cannot apply arbitrary contact forces $p$.!
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: \( p \in \text{ker}(G) \)
- 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 \( \text{ker}(G) \)

\[
Ax = KJS\Delta\sigma - KG^T\Delta u
\]

PLV \( \rightarrow \)

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

hence

\[
p_a = (I - G_R^K G)KJS\Delta\sigma
\]

Feldman’s Equilibrium Point Hypothesis

\[
p_a = E_{\sigma}y
\]
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
Pinch Grasping with 3 soft Synergies
Power Grasping with 3 soft Synergies

- Ashtray
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

![Graph showing Grasp Quality Index](image)

- At least 2 synergies are needed
- $\|f\|_2$ [N]
- Grasp Quality Index
- $e_s = 1$, $e_s = 2$, $e_s = 3$
- $k_{stm}$ values: 1.0 (nom.), 0.5, 5.0, 10.0
- $e_s = e = 15$
- $h = 27$
- No. Synergies engaged
Design
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
Sensorimotor Synergies

- Inference and Anticipation
  - Priors
  - Evidence

- Cognitive sensorimotor synergies

- Sensor synergies
  - Early sensorimotor synergies
  - Multifinger integration

- Motor synergies
  - Early grasp

- Sensor synergies
  - Early touch

- Cue processing

- Inference and Anticipation

- Motor primitives

- Faster massively abundant

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

Continuous State Space

INPUT SET \{\alpha, \beta, \gamma, \ldots\}

OUTPUT SET \{A, B, C, \ldots\}

Physical world

Computer (?)
Networked Embedded Control Systems

INPUT SET \{\alpha, \beta, \gamma, \ldots\} → Control Quanta → Physical Plant(s) (continuous) → Compressor

Physical Plant(s) (continuous) → Processor(s) → Encoder

Decoder → Channel → Encoder

OUTPUT SET \{A, B, C, \ldots\}
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 diagram]

- 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-901 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 feedforward 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

- Buffer Synchronizer (Embedded Controller)
- Protocol
- Network
- Packet Filler
- Remote Controller
- PLANT
- MODEL
Network and protocol model (I)

Network Assumptions

\[
\begin{align*}
\tau_m, \tau_c & \quad \text{Bounded MATI} \\
T_m, T_c & \quad \text{Bounded MAD} \\
\varepsilon_m, \varepsilon_c & \quad \text{Bounded mTI}
\end{align*}
\]

MATI: Maximum Allowable Transfer Interval
MAD: Maximum Allowable Delay
mTI: Minimum Transfer Interval
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 \( W_0 : \mathbb{N} \times \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0} \) and constants \( a, \bar{a}, c > 0, \rho_0 \in [0, 1] \) such that:

\[
 a |e| \leq W_0(i, e) \leq \bar{a} |e| \\
 W_0(i + 1, h(i, e)) \leq \rho_0 W_0(i, e) \\
 \left| \frac{\partial W_0}{\partial e}(i, e) \right| \leq c
\]

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:

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

\(\lambda_{\hat{f} f}\) 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

- $\kappa$ guarantees the GES of $f$

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

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

$$\alpha |x|^2 \leq V(x) \leq \bar{\alpha} |x|^2$$

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

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

Local Exponential Stability of the NCS is ensured if

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

with

$$N \triangleq \left[ \frac{T_c + T_m + \tau_c}{\varepsilon_m} \right] + 1 \quad M \triangleq c N \lambda_f f (1 + \lambda_K) \quad \gamma_2 \triangleq \frac{d}{\alpha} \sqrt{\frac{N}{\alpha}} \lambda_f \lambda_K$$

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

$$R_x = R \quad R_u = \lambda_K R \quad R > 0$$

- 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 $\tau_m$: 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 $\lambda_{\tilde{f} \tilde{f}}$.

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: \( \tau^* = 2.81 \times 10^{-4} \) s

Our estimate: \( \tau_m^* = \tau_c^* = 5.58 \times 10^{-3} \) s  
20 times larger

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

Exact value (mult. commands): \( \tau_{\text{mult}}^* = 1.3105 \) s  
1160 times larger!
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.)
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-901 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".
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?
Thank you