Neural control – Layers, Loops, Learning and Predictions

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Biological locomotion control

**Biomechanics:**

**Neural control:**

- Central Pattern Generator (CPG)
- Reflexes (local motor response to a local sensation)
- Higher control centers (brain for e.g., posture, direction)
Adaptive Control during Walking

**Three Loops**

- **Central Control (Brain)**
- **Spinal Cord (Oscillations)**
- **Motorneurons & Sensors (Reflex generation)**
- **Muscles & Skeleton (Biomechanics)**

**Feedback loops:**
- Step control
- Terrain control
- Ground-contact
- Muscle length
RunBot’s Network of the lowest loop

Motor neurons & Sensors
(Reflex generation)

Muscles & Skeleton
(Biomechanics)

Muscle length
Leg Control of RunBot
Reflexive Control

Leg Control

Left Leg

Right Leg

Motor neuron
Sensor neuron/receptor
Excitatory synapse
Inhibitory synapse

Hip
Knee

Hip Motor M
Knee Motor M
Long-Loop Reflex of one of the upper loops

Before or during a fall:
Leaning forward of rump and arms
Body (UBC) Control of RunBot

Leaning Reflex triggered by a fall.
(accelerometer signal AS)
Long-Loop Reflexe der obersten Schleife

Central Control
(Brain)

Terrain control

Backward leaning UBC

Forward leaning UBC
Leg Control as Target of the Learning
Learning in RunBot

Differential Hebbian Learning related to Spike-Timing Dependent Plasticity

Target neurons

Body control
UBC

Leg control
Left, Right
Hips

Knees

Sensor

Learner neurons

Fixed reflex synapses

Learning synapses

Changeable synapse
Inhibitory synapse (shunting, divisive)

Excitatory synapse
Inhibitory synapse

\( \Sigma \)

\( \frac{d}{dt} \)

\( u_0 \)

\( u_1 \)

L6

\( \rho^6_0 = 1 \)
RunBot: Learning to climb a slope

BBC, July 07
New York Times July 07
AAAS Sci Update July 07

Manoonpong et al PLoS CB, July 07
Passive Walking Properties
Weight stabilize together with the behaviour as the robot avoids the leaning-reflex. Too late, Early enough.

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Such a controller assures behavioral stability ("weak homeostasis") as well as stability during the learning ("fall-back behavior").

But: Reflexes are always too late!
Cerebellar-Like Reflex-Avoidance Learning

During learning the primary reflex re-action has effectively been eliminated and replaced by an earlier anticipatory action.
Predictive Learning

Sniff sniff

Smell predicts Taste!

Yummy Yummy
IR-Signal (ramp) predicts AS-Signal (fall)
The Basic Control Structure

Schematic diagram of a pure reflex loop

Systems Theoretical Analysis

This is a closed-loop system before learning

The Basic Control Structure
Schematic diagram of a pure reflex loop
The $T$ represents the temporal delay between vision and bump.
Antomically this loop still exists but ideally it should never be active again!
This is the system after learning.

The inner pathway has now become a pure feed-forward path.

What has happened in engineering terms?
Formally:

Delta pulse Disturbance $D$
Calculations in the Laplace Domain!

\[
X_0 = P_0[V + D e^{sT}] \\
X_1 = \frac{P_1(D + P_{01}X_0H_0)}{1 + P_1P_{01}HV} \\
X_0 = e^{sT}D + H V \frac{P_1(D + P_{01}X_0H_0)}{1 + P_1P_{01}HV}
\]

\[
H V = \hat{r} \frac{P_1 e^{sT}}{1 + P_{01}e^{sT}}
\]
The Learner has learned to **predict** the inverse transfer function of the outer loop and can compensate the disturbance therefore at the summation node!

\[ H_V = \dot{r} P_1 e^{sT} \]
Some closed-loop Subtleties:
Agents as (linear) Systems with Transfer Functions

(Porr & Wörgötter, Kybernetes, 2006)
On Transfer Functions

Necessary condition:
Every entity who's effects are fully predictable could be part of your body!

Unpredictable disturbances always belong to (come from) the world

Some random examples:
Predictable pain can be to some degree ignored, unpredictable pain not.
Well fitting prostheses can be ignored (bodily integrated).
A race-car pilot becomes “one” with his machine.
Everything which is fully predictable could be part of your body (Necessary condition)

Sufficient Conditions:

1) To be part of your body the entity, from which a predictable event arises, should be proximal and causally linked to your currently existing body.

Some examples:
The sun’s motion is fully predictable but the sun certainly cannot be integrated into your body.
A robot’s hand is linked to a robot’s arm.
Two computers are linked by a wireless connection.
On Transfer Functions

Everything which is fully predictable could be part of your body (Necessary condition)

Sufficient Conditions:

2) To be part of your body any (newly integrated) entity should be part of your body “for a longer time” (Bodies are continuous over some time).
How might this be reflected at the nervous system?

**Predictability**

Nerve cells are almost always phasic. They respond little to constant stimulation. Instead they are change sensitive.

Predictable stimuli can be ignored: Adaptation, Habituation.

*A hypothesis*: Predictable entities can be temporarily integrated into the body of an agent. This enlarges the agent’s cause-effect horizon. *(A route to cognition?)*

*A robot experiment!*

Discovering the concept of “An Object” from manipulation
What looks like a simple “re-colouring” really is a difficult computer vision based process of using the RBM principle to “make the spoon part of the robot”
The idea that humans (and monkeys) indeed perform temporary bodily integration is supported by experimental results that over time cortical receptive fields are extended representing the tip of a stick, which a monkey had to use to obtain food for a prolonged period of time.

What has happened from a systems theoretical viewpoint?

D can be first regarded as a transfer function in the world and finally integrated in the body.
Conjecture 1: Cognitive Agents have to be (fully) situated in their world!

Conjecture 2: Cognitive Agents have to be embodied!

Some Confusions: Situated versus Embodied
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Lack of Situatedness (Open Loop)
Some Confusions: Situated versus Embodied

Conjecture 1: Cognitive Agents have to be (fully) situated in their world!

Conjecture 2: Cognitive Agents have to be embodied!

Situatedness (Closed Loop)
Case 1: NOT Situated NOT Embodied
Case 2: Embodied AND Situated
Case 3: Embodied NOT Situated
Case 4: Situated NOT Embodied

Case 1: Pure symbol manipulation systems, Cartesian attitude (GofAI-Systems)

Case 2: Most common for biological systems and robots but also A-life creatures like internet agents or computer viruses as long as they obey the necessary and sufficient conditions described above within their world.

Case 3 Open-loop systems, which do not feed their output(s) back through the environment onto themselves.

Case 4 “Strange”, Violates: Proximity and Continuity. E.g. Swarms, are a non- (or very weakly) embodied system, which will however indeed influence their environment and also receive feedback from it (situated!). Note, cognitive complexity can arise from such (social) systems, for example the building of termite mounds, etc.
Layers, Loops & Learning

- Central Control (Brain)
  - Spinal Cord (Oscillations)
    - Motorneurons & Sensors (Reflex generation)
      - Muscles & Skeleton (Biomechanics)
        - Muscle length
  - Ground-contact
  - Step control

Diagram:
- Organism
  - Environment
  - Sensor, conditioned (learned) input
  - Motor System
  - Sensor, unconditioned input
  - Organism
  - Environment
  - T: temporal delay between vision and bump
  - Open-loop system
  - Closed-loop system before learning
  - Closed-loop system during learning
Using Chaos Control to Generate Hexapod Locomotion & Foothold Searching

Silke Dreissigacker, Poramate Manoonpong, Marc Timme and Florentin Woergoetter

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Silke Dreissigacker (chaos control)
Tao Geng (RunBot design and reflex control)
Christoph Kolodziejski (3-factor learning)
Poramate Manoonpong (RunBot and hexapod design & learning)
Bernd Porr (learning theory)
Marc Timme (MPI) (chaos control)
Norbert Krüger (SDU) (computer vision)
Some Light Reading 😊 (see <http://www.bccn-goettingen.de/Groups/GroupCN for further information)

**Conceptual:**

**Computer Vision:**

**Robotics:**

**Learning**

**Reviews:**
A more complex modular, adaptive neural control network embedded in its world

The thoraco-coxal (TC-) joint enables forward (+) and backward (−) movements.
The coxa-trochanteral (CTr-) joint enables elevation (+) and depression (−) of the leg.
The femurtibia (FTi-) joint enables extension (+) and flexion (−) of the tibia.
Deterministic chaos exists in wide parameter ranges of this circuit. As usual, these domains embed an infinite manifold of unstable periodic orbits (UPOs).

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A large behavioral repertoire achieved with simple neuronal control

Using Chaos Control to Generate Hexapod Locomotion & Foothold Searching

Silke Dreißigacker, Poramate Manoonpong, Marc Timme and Florentin Woergoetter
UPOs can be stabilized by an adaptive neuronal (learning) method

\[ o_1 = \tilde{u}(11o_1 + 12o_2 + \xi_1 + c_1) \]

\[ o_2 = \tilde{u}(21o_1 + \xi_2 + c_2) \]

\[ \epsilon^{(k)} = (11d_1^{(k)} + 12d_2^{(k)}) \]

\[ \tilde{d}^{(k)} := \tilde{o} C_k \hat{(n)} x_1 - \hat{(n)} x_2 \]

\[ \hat{(n)} x_i = o_i(t + n) \quad \text{for } i = 1, 2 \]

\[ \tilde{o}^{(n)}_{t+n+1} = \tilde{o}^{(n)}_t + \tilde{o} \tilde{g}^{(n)} x \tilde{e}^2 = n \]
Switching Control On and Off with different target periods $n$ leads to the quick finding of a new UPU.
This circuit can, thus, be used as sensor-driven CPG with adjustable period.