What can robots teach us about the brain?

Report

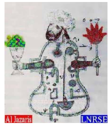
Author(s):
Voegtlin, Thomas; Althaus, Philipp; Verschure, Paul F.M.J.

Publication date:
2001

Permanent link:
https://doi.org/10.3929/ethz-a-004266495

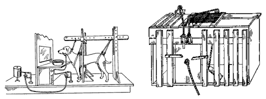
Originally published in:
INI's posters

What can robots teach us about the brain?



Thomas Voegtlin, Philipp Althaus, Paul F.M.J. Verschure
Laboratory of Neuromorphic Robotics and Synthetic Epistemology (LNRSE)
Institute of Neuroinformatics, University/ETH Zürich, Winterthurerstrasse 190, CH-8057 Zürich
www.ini.unizh.ch

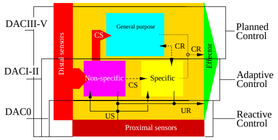
1



The first systematic studies on learning were reported by Thorndike in 1898. His most influential experiments were those based on the "puzzle box". In the same period Pavlov developed his studies on so called *classical conditioning*. This paradigm refers to learning phenomena where initially neutral stimuli, or *conditioned stimuli* (CS), like lights and bells, are through their simultaneous presentation with motivational stimuli, *unconditioned stimuli* (US), like footshocks or food, able to trigger a *conditioned response* (CR).

2

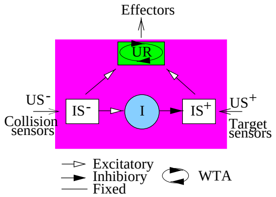
Thorndike's experiments are an example of *operant, or instrumental, conditioning*, in which the UR is contingent on a particular action displayed by the organism.



We make the assumption that both experimental paradigms address complementary subcomponents of one *complete learning system* which we study in our modeling work on **Distributed Adaptive Control** (DAC).

3

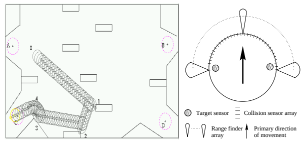
DAC assumes that learning systems are constructed on the foundation of an automatic prewired *reactive control structure* which consists of reflexes and stereotypic behavioral patterns. It provides the organism with a basic level of competence and contraints any learning process.



DAC0 is our implementation of a **Reactive Control System**.

4

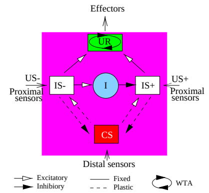
Bugworld is a 2-dimensional environment containing elements associated with reflexes: Targets (A-D), and obstacles. The simulated robot uses 3 types of sensors: A range finder, collision detectors and two target detectors.



A collision triggers an avoidance reaction (US^-) (1,2,3). Targets disperse a gradient that can be detected by the sensors (appetitive unconditioned stimulus, US^+). These can trigger approach actions.

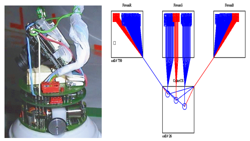
5

The *adaptive control structure*, DAC2, learns to correlate CS events (distal sensor) with internal states (IS). It proposes that a central element of classical conditioning is *CS identification*.

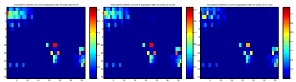


The DAC2 learning rule categorizes CS events, using a reconstruction of these events as feedback to the sensors; **Predictive Hebbian Learning**.

6

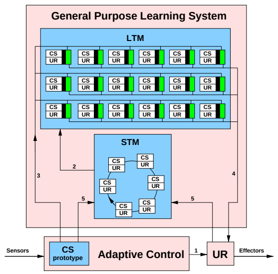


The real-world version of DAC runs on a Khepera robot [K-team, Lausanne]. The knowledge of the system is expressed in synapses connecting the CS and IS populations. In this example it associated colors with collisions and light events.



7

Learning about ones actions means to pursue plans. DAC3 uses a short-term and a long-term memory system to acquire its knowledge and to make plans based on its experience. It is built on top of a DAC2 level of control.



8

Since DAC3 implements a supplemental level of control as compared to DAC2, one can wonder if it organizes its behavior in a different way.

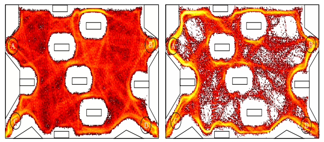
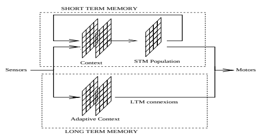


Figure 1: positions visited over 10^6 time steps. Left: DAC2. Right: DAC3

By plotting the distribution of probabilities to find the robot at a certain location in the environment over 10^6 time steps we observe that DAC3 exhibits more structured behavior. This structuring of behavior affects the way perception organizes itself at its DAC2 level.

9

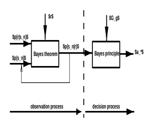
STM and LTM of DAC3 are ring buffers and chained lists. The question whether DAC3 could be implemented by a biologically plausible neural network raises some important challenges: A natural neuron can only use local information, both spatially and temporally.



DAC4 is a fully neural implementation of DAC3 where STM and LTM are implemented by recurrent networks where the temporal context is represented by a pattern of activity.

10

Human decision making follows so-called Bayesian inference principles. Bayesian theory provides a framework to choose optimal actions given limited knowledge.



DAC5 is a model of the general purpose learning system which was demonstrated to obey Bayesian inference principles in its decision making.

Supported by SPP-SNF