Toward Cognitive Integration of Prosthetic Devices

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Brain Machine Interfaces (BMI)

A man made device that either substitutes a sensory input to the brain, repairs functional communication between brain regions or translates intention of movement.

Only the joint work of engineers, neurophysiologists and neuro scientists can realize this dream!

How did we get here?

Computational Models of Neural Intent

Neural Coding

- Spike Timing

  Information is carried by the time of firing

- Rate

  Information is carried by the intensity of neural firing (estimated over an appropriate window)

This gives rise to two very different types of models:

Spike timing $\Longrightarrow$ Point process models

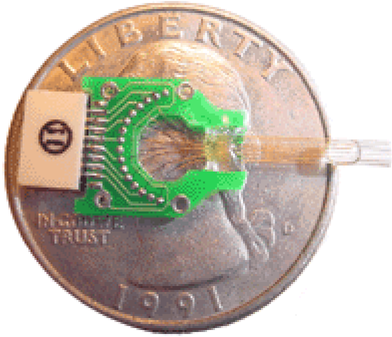
Rates $\longrightarrow$ Time series models

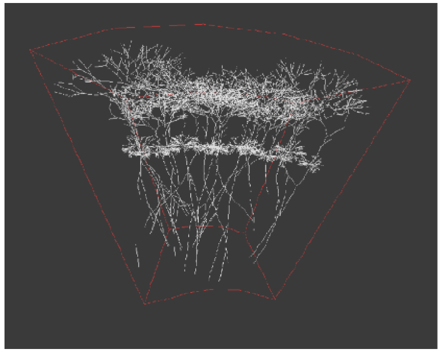
Science and Technology Enablers

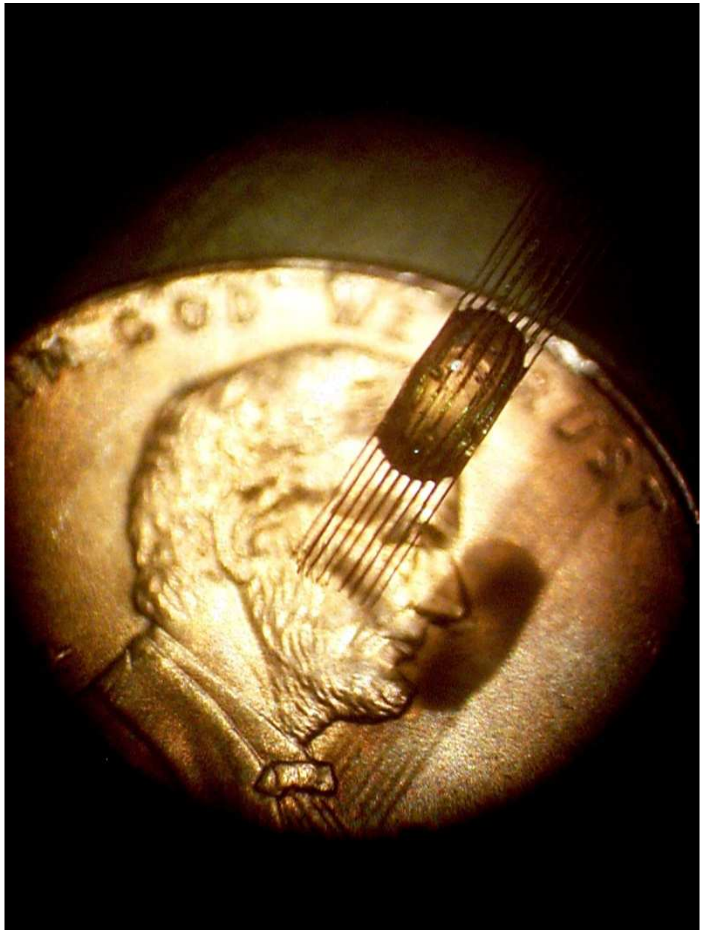
- Neuroscience knowledge and paradigms – from neurons to cell assemblies to cognition
- Massive sensing (microelectrode arrays and optogenetics)
- Biocompatibility
- Miniaturization of electrodes and electronic systems
- Signal Processing and Machine Learning
- Novel control frameworks for engineering design

Sanchez J., et al., "Technology and Signal Processing for BMIs", IEEE SP Magazine, vol 25, #1, pp 29-40, 2008

Electrophysiology: Electrode Arrays

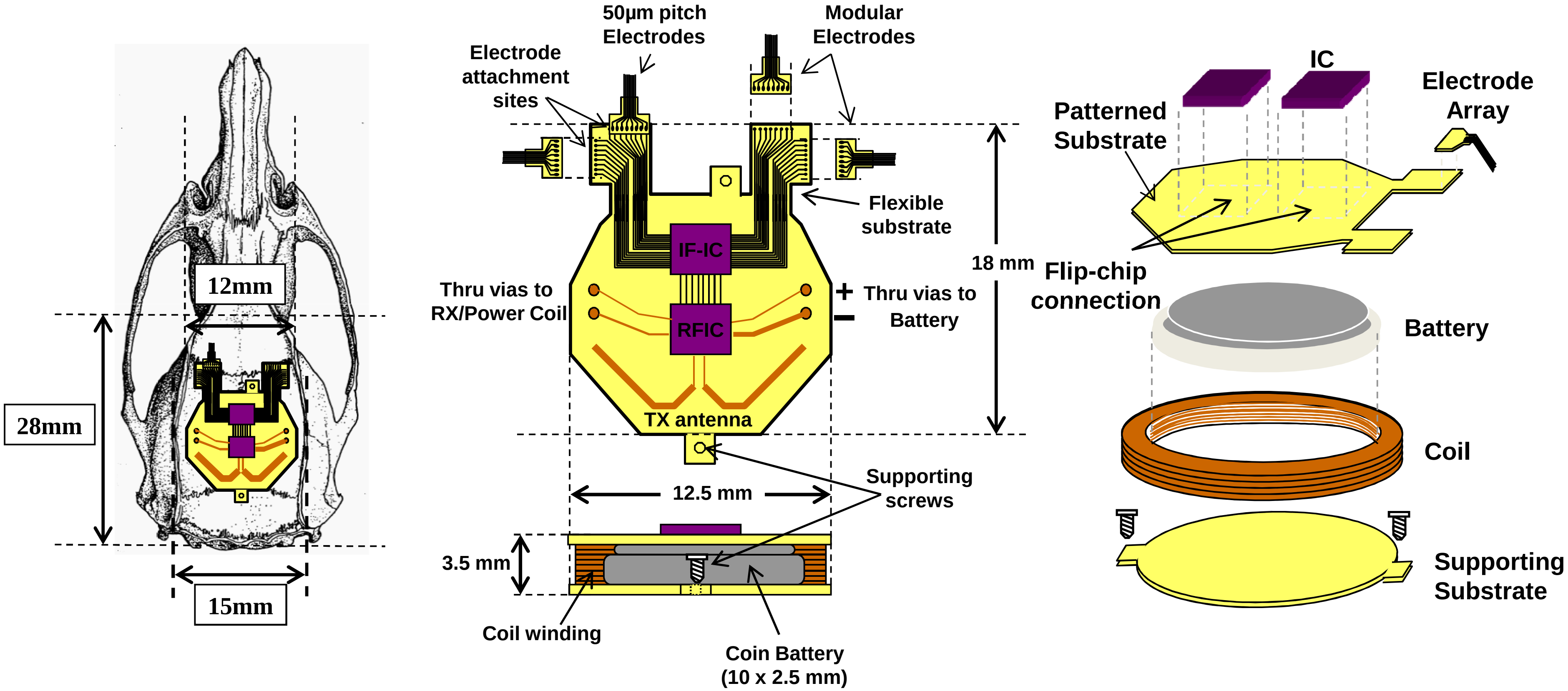






- 50µm polyimide insulated tungsten
- 250µm separation
- Wire impedance of 500K – 1.5M Ω

FWIRE: Florida Wireless Implantable Recording Electrodes



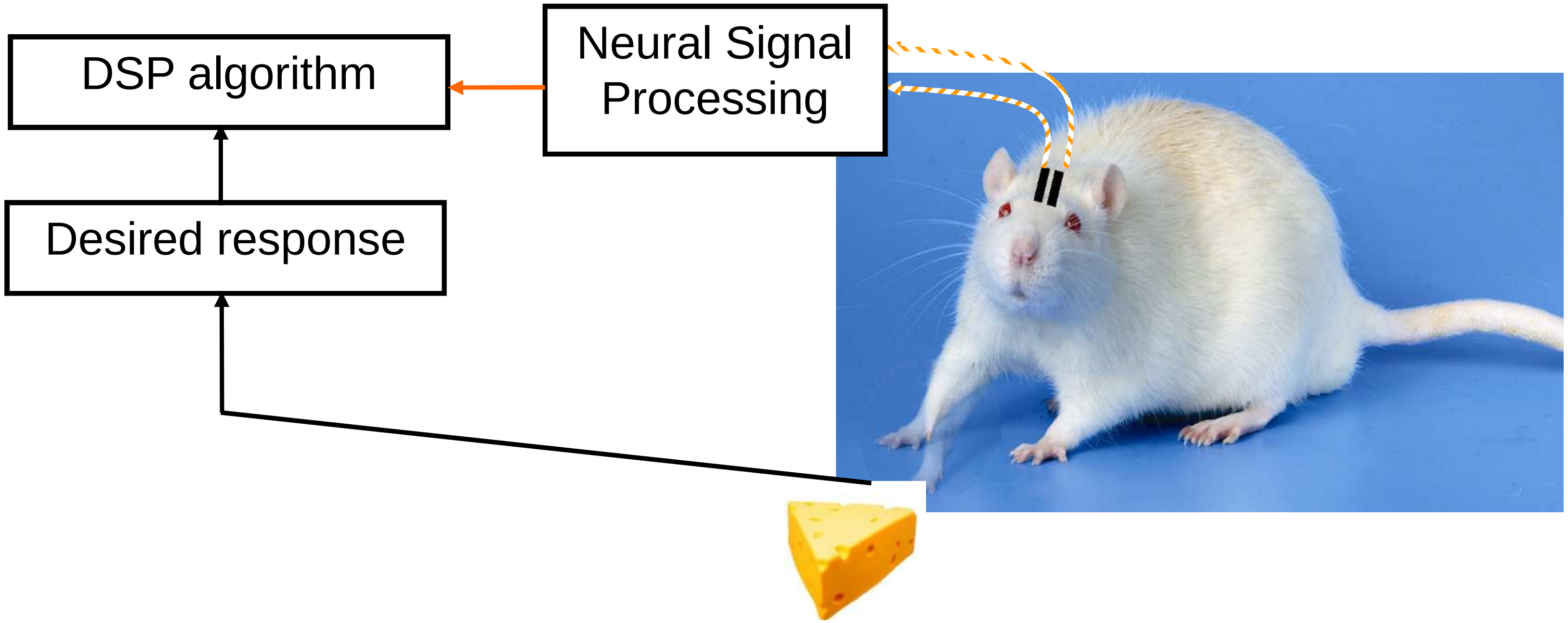
Specifications:

16 flexible microelectrodes (40 dB, 20 KHz)

Wireless (500 Kpulse/sec)

2mW of power (72-96 hours between charges)

Conventional BMIs!



- During training the user actions create a desired response to the DSP algorithm.
- During testing the DSP algorithm creates an approximation to the desired response.
- The DSP algorithm is a simple mapper. i.e. design still follows the **Master-Slave** tool concept

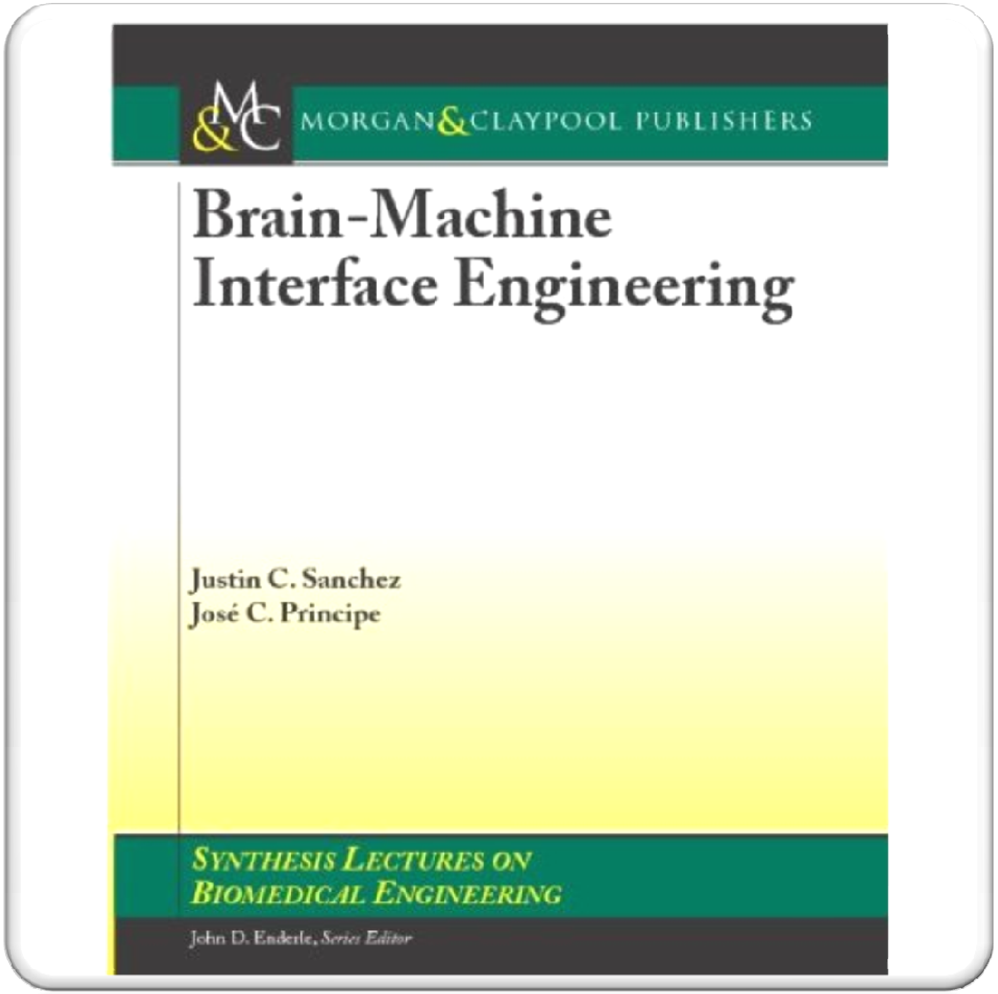
BMI lessons learned

Current decoding methods use kinematic-training signals - not available in the paralyzed patients

I/O models cannot contend with new environments without retraining

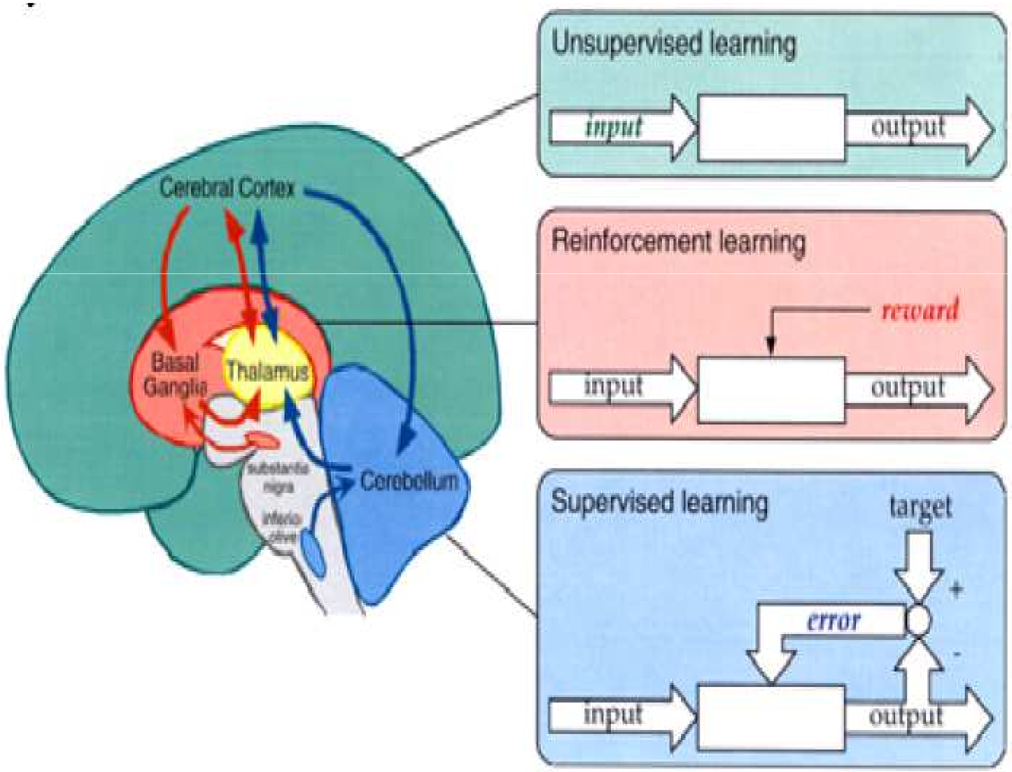
Laboratory BMIs are NOT yet the design blue print for the clinical setting

BMIs should be more than a passive decoder – exploit user's cognitive abilities



Symbiotic Learning

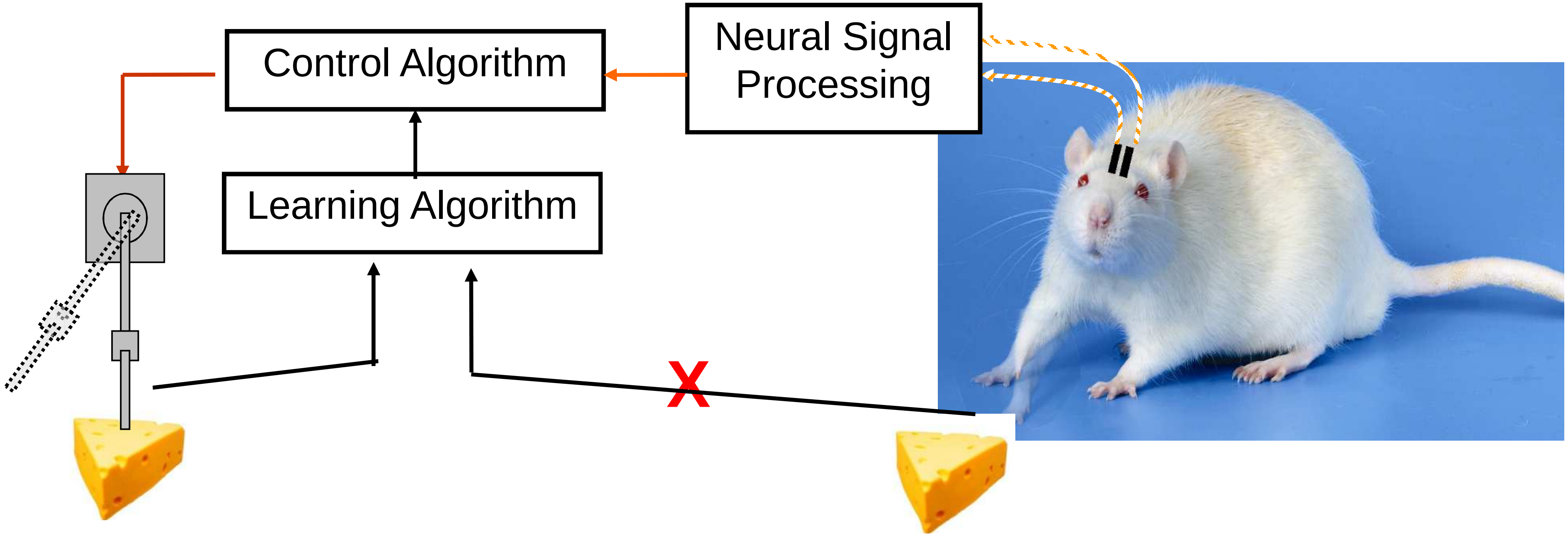
Understand + model the Perception-Action-Reward Cycle (PARC)



- Intelligent behavior arises from the actions of an individual seeking to maximize received reward in a complex and changing world.
- Why have rewards?
  - Provide rules of the game
  - Give incentive toward long-term over short-term gain
  - Rewards are necessary but not sufficient…must learn through experience how to use them.

Sanchez J., et al. ,"Exploiting Co-Adaptation for the Design of Symbiotic Neuroprosthetic Assistants", Neural Networks, vol. 22, pp. 305-315, 2009

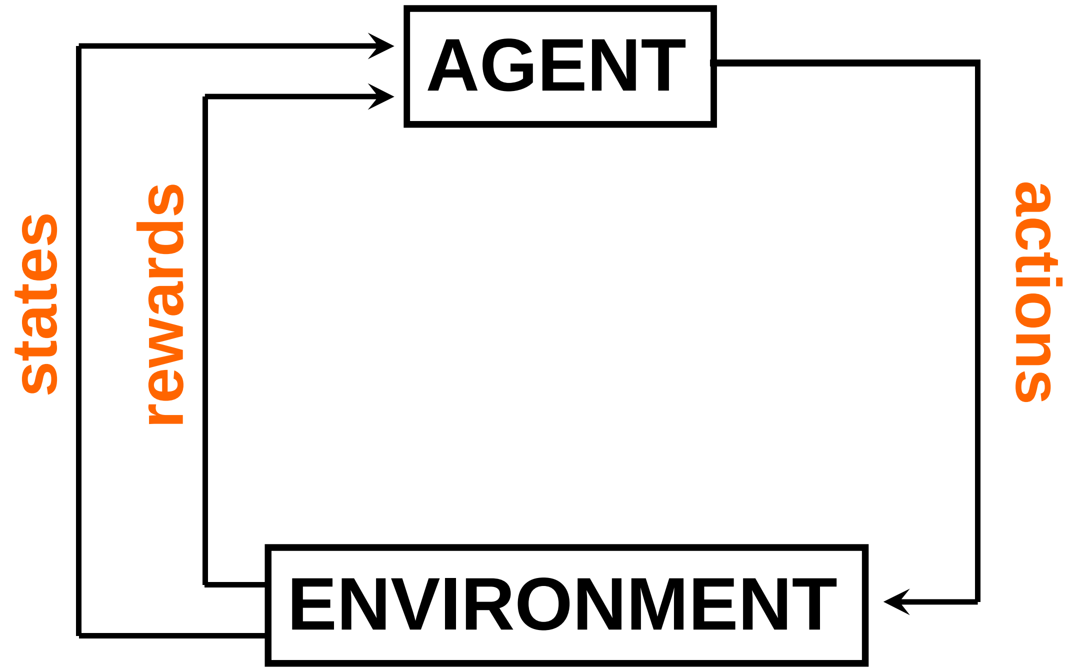
A Paradigm Shift for BMIs!



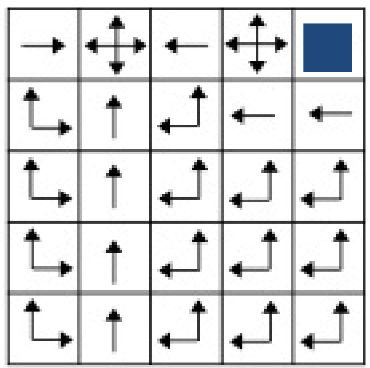
- The control algorithm learns through reinforcement to achieve common goals in the environment.
- Shared control with user to enhance learning in multiple scenarios and acquire *the net benefits of behavioral, computational, and physiological strategies*

Reward Learning Involves a Dialogue

- Relation between the agent and its environment.
- **Environment:** You are in state 14. You have 2 possible actions**.**
- **Agent:** I'll take action 2.
- **Environment:** You received a reinforcement of 17.8 units. You are now in state 13. You have 2 possible actions.
- **Agent:** I'll take action 1.
- **repeat**



22.0	24.4	22.0	19.4	17.5
19.8	22.0	19.8	17.8	16.0
17.8	19.8	17.8	16.0	14.4
16.0	17.8	16.0	14.4	13.0
14.4	16.0	14.4	13.0	11.7



Goal

Start

Basic Reinforcement Learning Components

Value Function:

Q learning is able to learn off policy!

$$Q^{\pi}(s,a) = E_{\pi}\{R_t \mid s_t = s, \quad a_t = a\}$$

policy followed

state

action

Reward Distribution: $R_t = E_{\pi}\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s, \quad a_t = a\}$

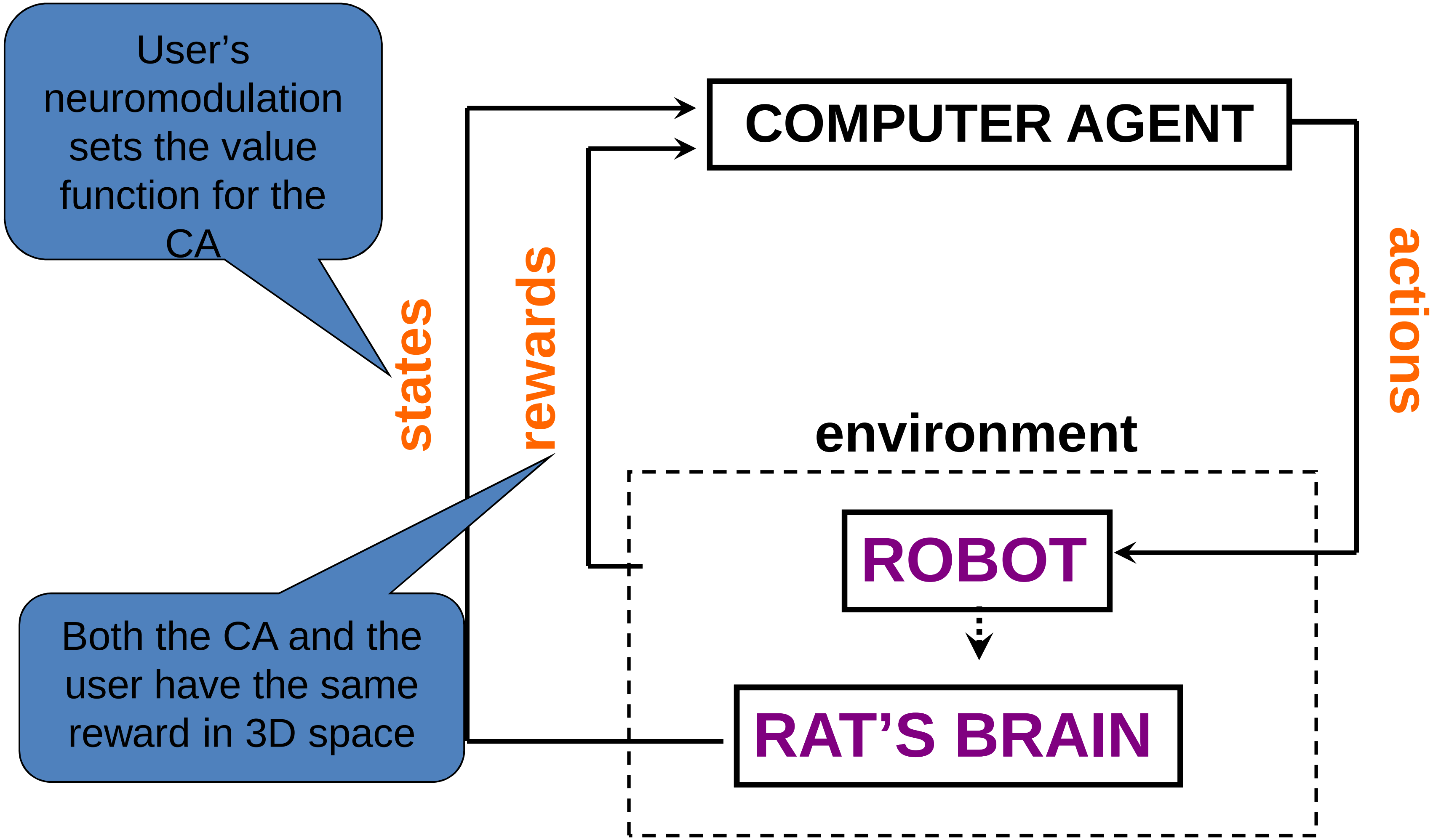
discounting factor

exploitation

Policy [ε-greedy]: $a_t = \begin{cases} \max_a Q(s_t, a) & p(1-\varepsilon) \\ rand(a) \neq \max_a Q(s_t, a) & p(\varepsilon) \end{cases}$

exploration

Symbiotic BMI involves TWO intelligent agents in a cooperative dialogue!!!

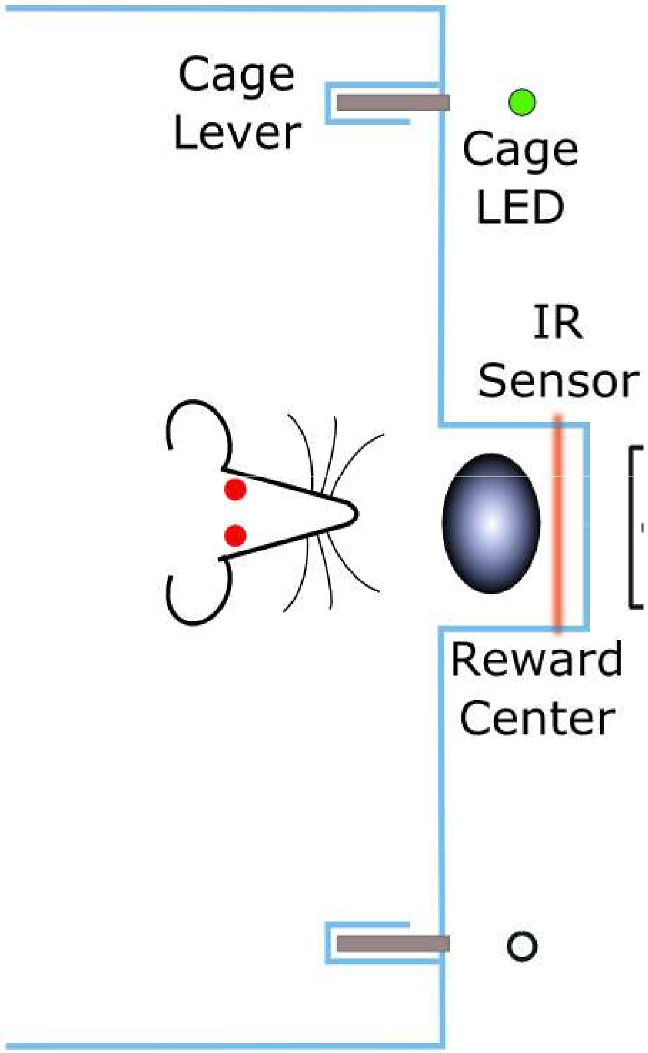


DiGiovanna J., et al "Co-adaptive Brain Machine Interface via Reinforcement Learning", IEEE Trans. Biomed. Eng., vol 56,#1, 54-64., 2009

Features of Symbiotic BMI

- Brain activity is no longer related to movement
- Enables intelligent system design in BMIs
- Both systems adapt in close loop in a very tight coupling between brain activity and computer agent (CA)
- User must incorporate the CA in its world model
- CA must decode brain activity for its value function
- We are talking about a “symbiotic” biological-computer system.

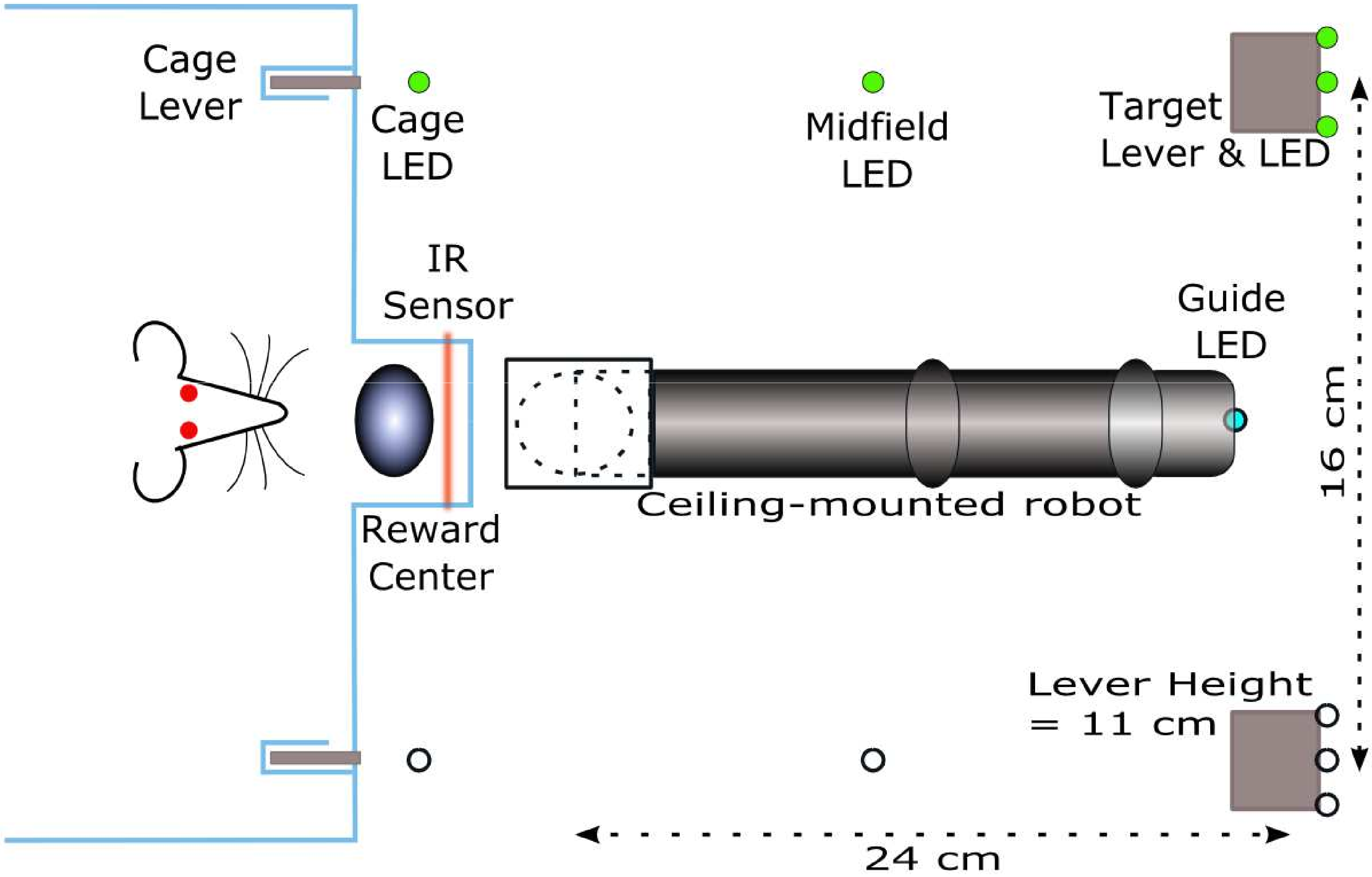
Experiment workspace [top view]



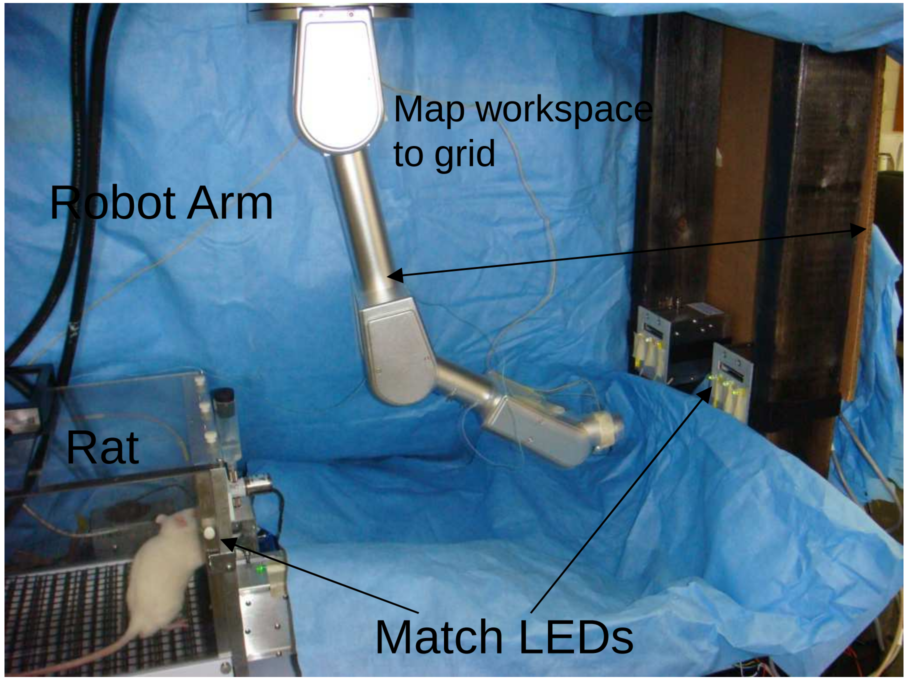
The user learns first to associate levers with water reward in a training phase.

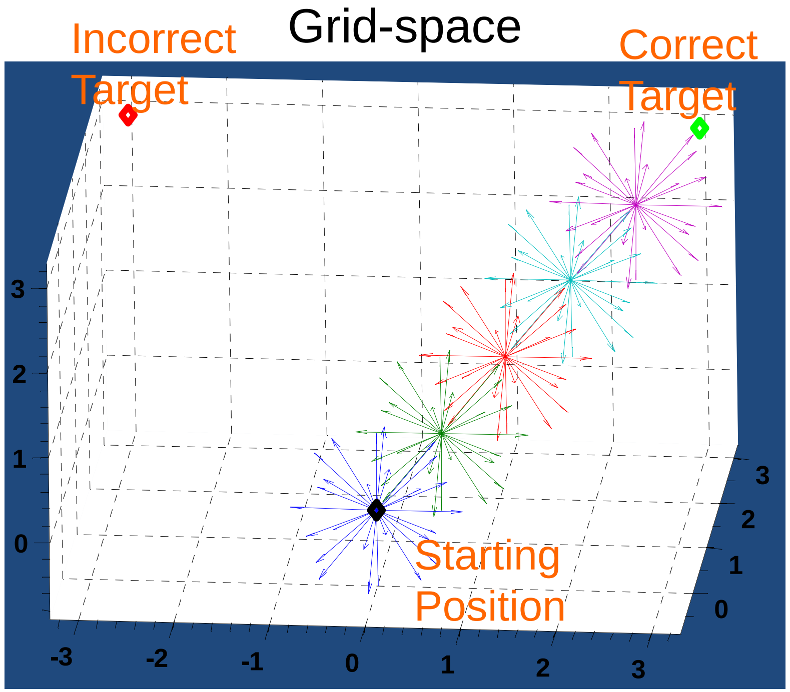
In brain control, it progressively, associates the blue guide LED of the robotic arm with the target lever LEDs.
Only when the robot presses the target lever it will get reward.

Experiment workspace [top view]



Experimental S-BMI Paradigm





27 discrete actions

- 26 movements
- 1 stationary

Rat’s Perspective

Agent – Value Function Estimation

This is the critical component of the S-BMI.

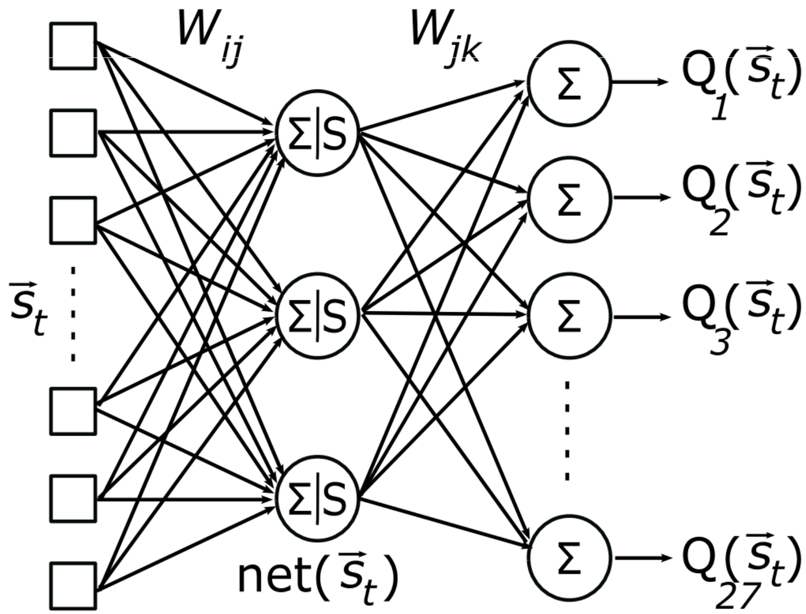
Used a 32x5x27 TDNN (with gamma memory) trained with the time difference (TD) error.

Each input is a neuron spike rate (100msec), each output is one of the 27 actions.

Careful training is needed.

$$Q_k(\vec{s}_t) = \sum_j \left(\tanh\left(\sum_i s_{i,t} w_{ij} \right) \right) w_{jk}$$

$$\delta_t = r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)$$



DiGiovanna J., et al "Co-adaptive Brain Machine Interface via Reinforcement Learning", IEEE Trans. Biomed. Eng., vol 56,#1, 54-64., 2009

Proof of concept is established, BUT…

From an engineering perspective, the biggest bottleneck is the "channel" bandwidth between the brain and the prostheses: recent papers estimate it at ~ 25 bits/minute (BCI) ~180 bits/minute (BMI), which is still very low.

So the pertinent question is: how to increase the channel bandwidth?

Neuroscientists say: increase number of probed neurons

The engineering answer should also seek:

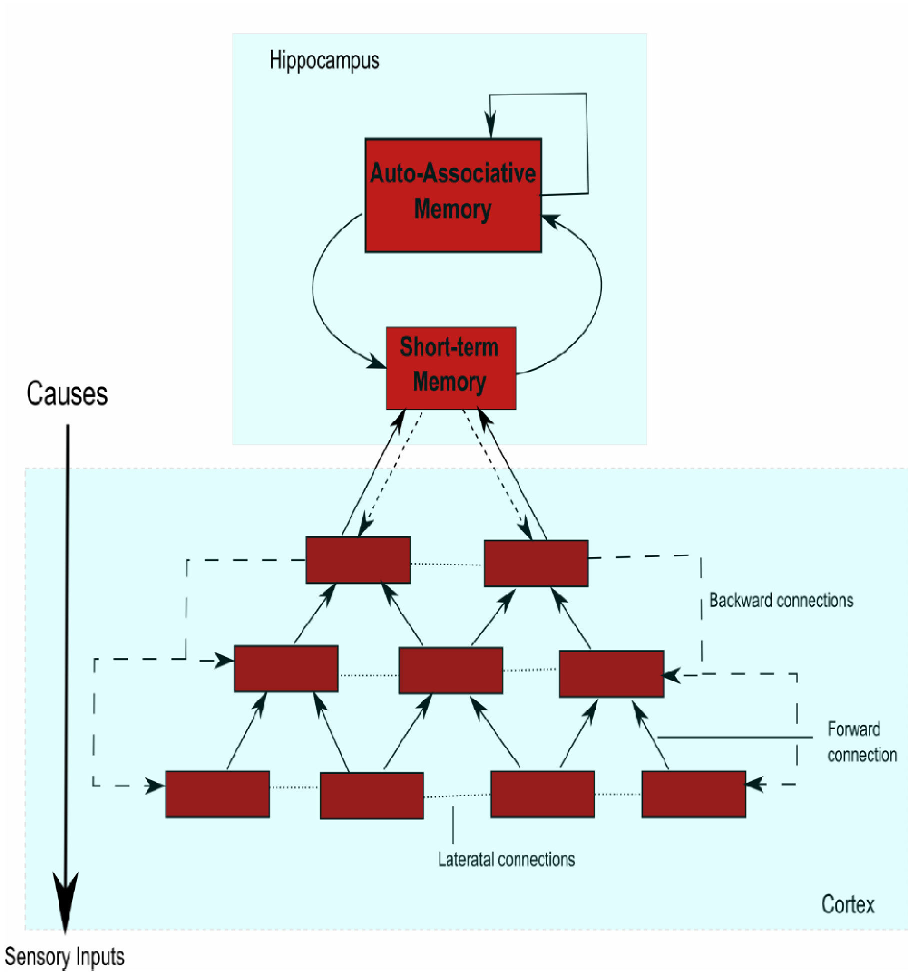
Architectures (how to use the available bits)

Signal Processing (reduce the noise in feature extraction)

Future of Brain Assistants

- The processing architecture should be similar to the human brain such that it "learns how to learn" and predict what the patient wants.
- Therefore assistants have to also be aware of the environment for context, not only subject's brain activity.
- This requires sensory processing architectures for vision, audition and haptics.
- Bidirectional hierarchical distributed architectures that are able to learn from the input sensory data and low bandwidth coded user intent in a self-organizing manner.
- We already initiated this development with a cognitive deep learning architecture for object recognition in video

Cognitive Model for Object Recognition in Video



Goal: develop a bidirectional, dynamical, adaptive, self -organizing, distributed and hierarchical model for sensory cortex processing using approximate Bayesian inference.

Principe J. Chalasani R., "Cognitive Architecture for Sensory Processing", Proc. of the IEEE, vol 102, #4, 514-525, 2014

Collaborators

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