DRONES Workshop @ FIT
May 13, 2016

Integrated Platforms and Algorithms of Multisensory Data Capture & Decision Support for Autonomous Vehicles

A biologically-inspired Model and Control Algorithm for Decision Support of Mobile Robots

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Project Research Objectives

Development of an autonomous navigation and control system for a vehicle using:

- **Integrated platforms** and algorithms of **multisensory data capture**;
- **Robust decision support systems** in dynamically changing, complex environments.

Extending on results achieved in NSF DMS-13-11165 project:

- US-German research on **strategy change** in complex dynamically changing environments

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Talk Outline

1. Introduction to Framework of Autonomous Decision Support
2. Foundations of Learning in Cognitive/Biology Domains
    - The “AHA” moment of learning/decision making
3. Main Results in Math/Graph Theory
    - Sudden changes (phase transitions) in structure and dynamics
4. Robotics Implementation Domain
    - Establish a link with biological and theoretical results
5. Conclusions

Research Tasks

1. A mathematical and computational model of multi-sensory channels for robust navigation, and decisions support (strategy change).
2. Robot platform to implement and test the conceptual integration model.
3. The performance of the developed system will be evaluated using quantitative metrics, such as:
    - Robustness to noise and incomplete data;
    - Fast and efficient evaluation using limited resources;
    - Generalization to unforeseen scenarios;
    - Resistance to system degradation.

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Biological/Cognitive Framework

Intentional Control Cycle (WJ Freeman)

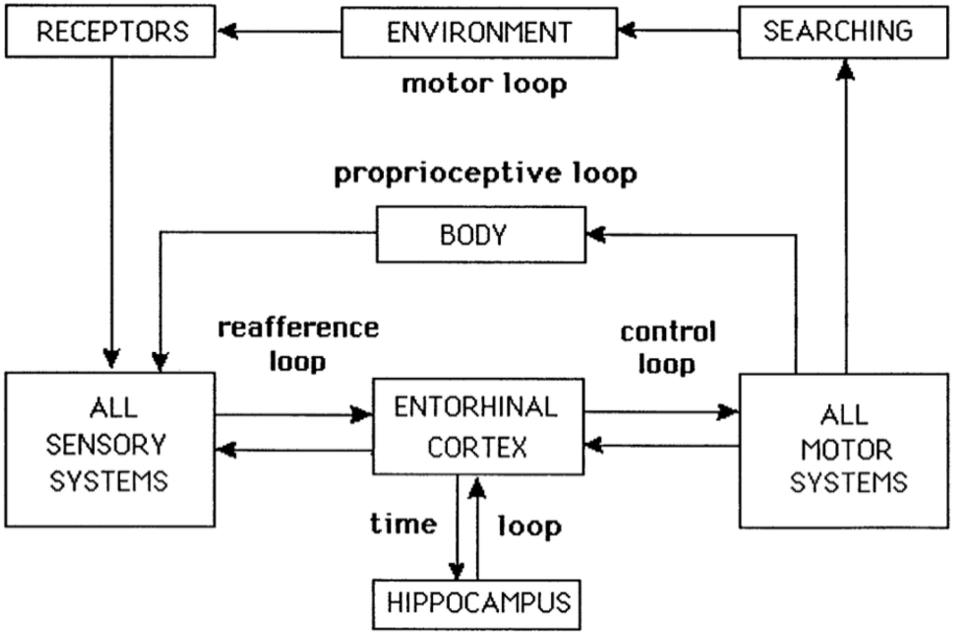
1. **PREDICT:** Form hypotheses about expected future states, and express these as goals such as safety, fuel, or temperature control.

2. **TEST BY ACTION:** Formulate a plan of action, and they must inform their sensory and perceptual apparatus about the expected future input.

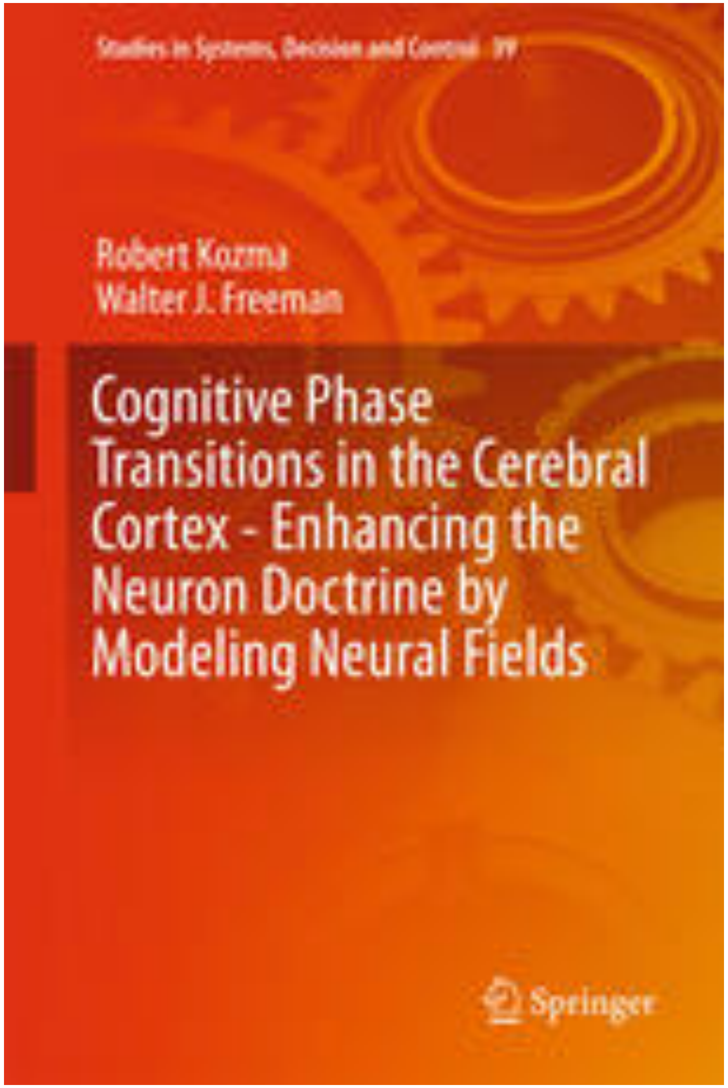
3. **SENSE:** Manipulate sensing channels, take information in the form of samples from all of their sensory ports.

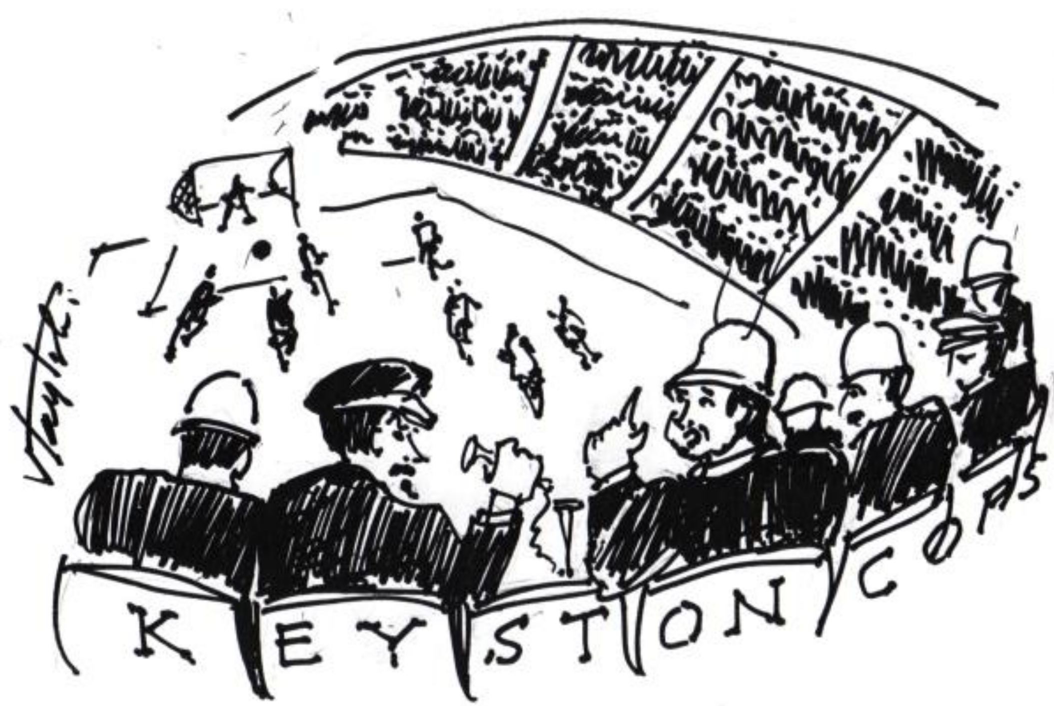
4. **PERCEIVE:** Generalize, abstract, categorize, and combine into multisensory percepts (Gestalts).

5. **ASSIMILATE & UPDATE:** Use new data to verify or negate the hypotheses and update the brain state, including information about the location in the environment.



Book on Cognition & Decision Making
(RK, WJF, 2016)

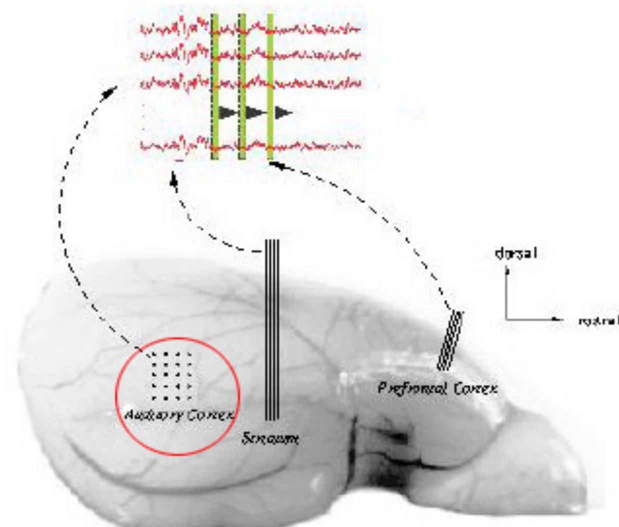




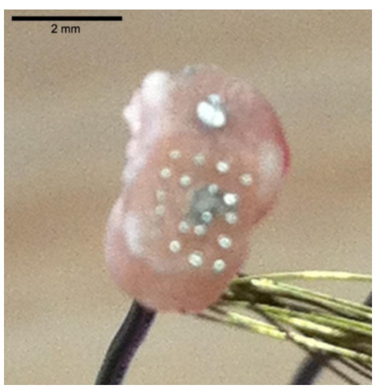
Collective dynamics in a football stadium
Emergent self-organized dynamics with many interacting components

Gerbil Experiments

@Leibniz Institute of Neurobiology, Magdeburg, Germany
Prof Frank Ohl's Group



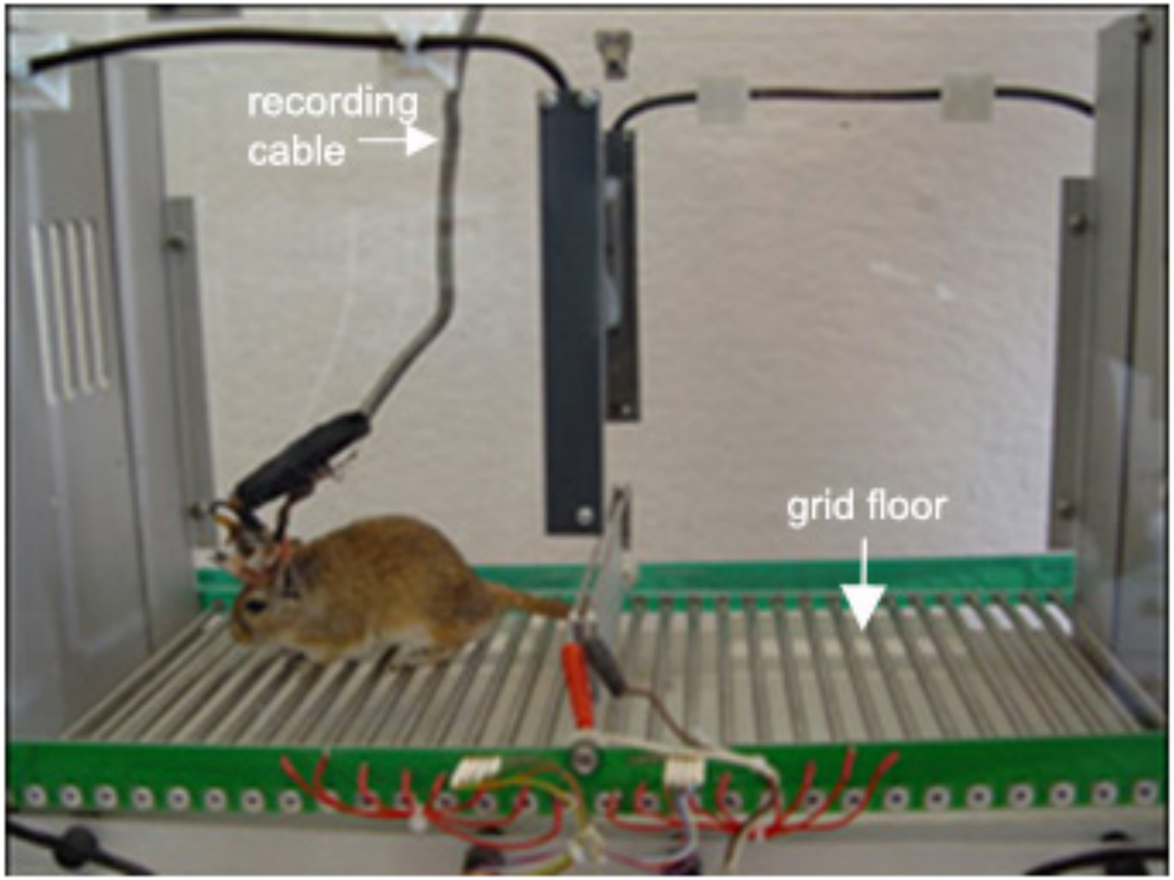
Ohl, Scheich, Freeman, Nature (2001)



- Rectangular electrode array w/ 20 channels (5 x 4 matrix)
- Stainless steel wire, Ø 76.2 μm, impedance: 50 – 500 kΩ
- Chronic implantation of 5 x 4 electrode array on top of primary auditory cortex (A1)
- Recording of epidural potentials during behaviour

Learning Paradigm

Discrimination of frequency modulated tones in the shuttle box

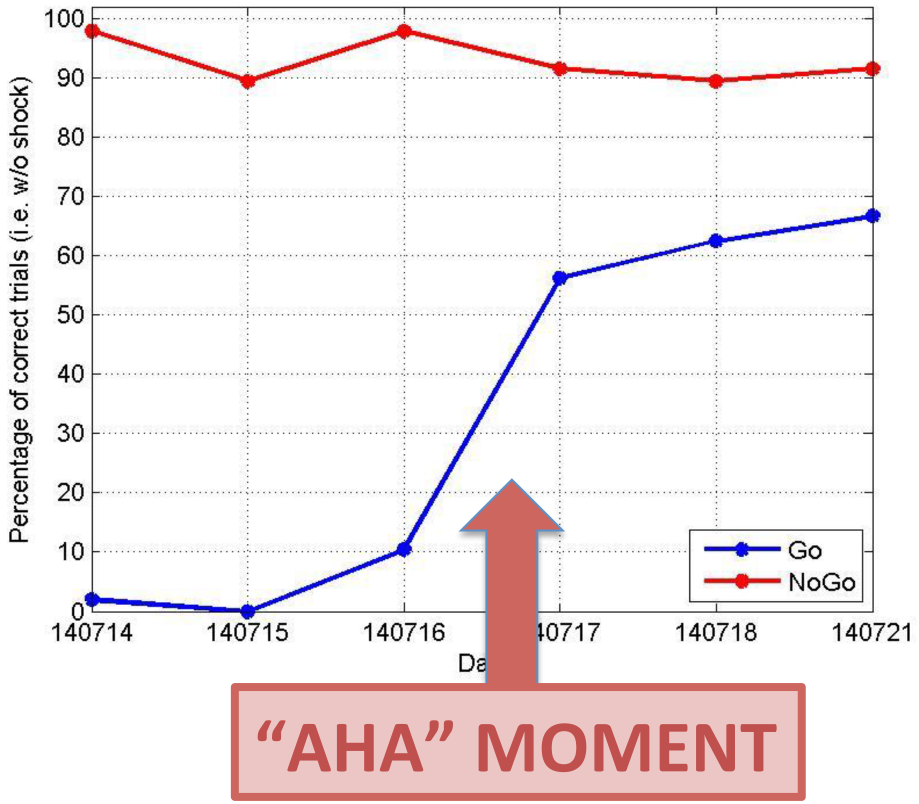


Go-tone:
sequence of *'rising'* FM-tones (2–4 kHz, 200 ms duration)

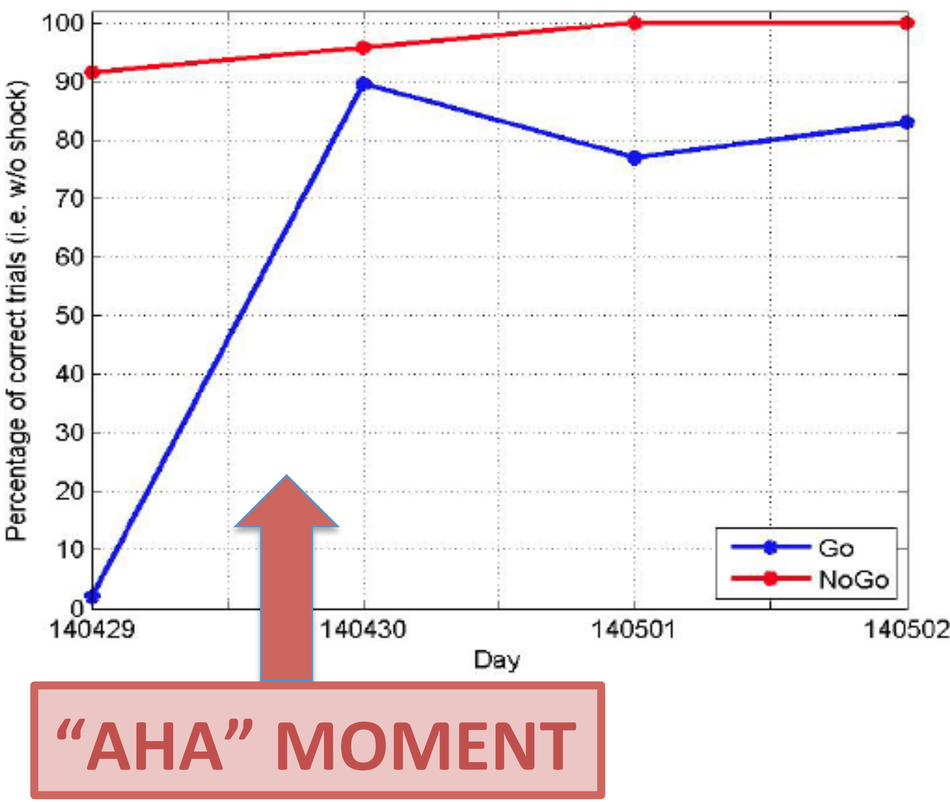
NoGo-tone:
sequence of *'falling'* FM-tones (4-2 kHz, 200 ms duration)

Original Motivation of Strategy Change Manifested in Learning - Examples

Gerbil #6
(training sessions for 6 days)



Gerbil #4
(training sessions for 4 days)



Lessons Learned from Animal Experiments

- Understanding Strategy Change

- **Strategy change** can be defined as the change in action selection and/or action planning while a previously established overarching goal is maintained.
- Strategy change is often **manifested via significant "sudden" variation** in behavior and performance.
- Such behavior can be **interpreted as the "AHA" moment** of sudden understanding and deep insight. There are experimentally observable changes in the neural structure associated with strategy change.
- The structural changes can be modeled through **phase transitions in the neural network as a large graph** and the dynamics of an activation propagation process.
- → NEXT: Use **Graph Theory** in mathematical modeling.

Graph Theory Approach to Learning in Networks

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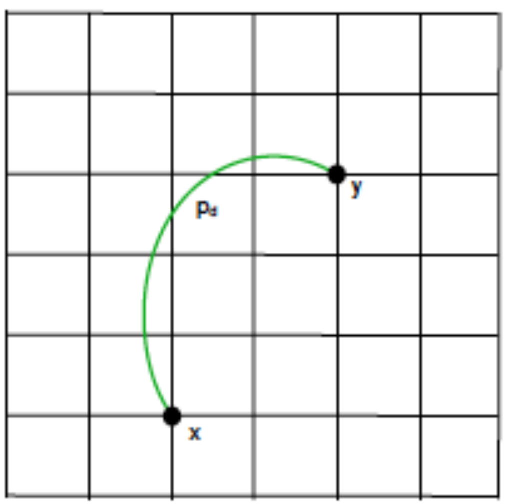
Random Graph Model over 2D Lattice

Start first with $\mathbb{Z}^2$ lattice. We take a $(N+1) \times (N+1)$ grid and for simplicity assume periodic boundary condition. Thus, we have a torus $\mathbb{T}^2 = (\mathbb{Z}/N\mathbb{Z})^2$, with the short notation $\mathbb{Z}_N^2$. The set of vertices of G consists of all the vertices of $\mathbb{Z}_N^2$ and we will not change them. All the edges from the torus $\mathbb{Z}_N^2$ are presented in the graph.



Additionally, we introduce the random edges. For any pair of vertices that are at distance d apart of each other we assign probability of edge that depends on the graph distance d:

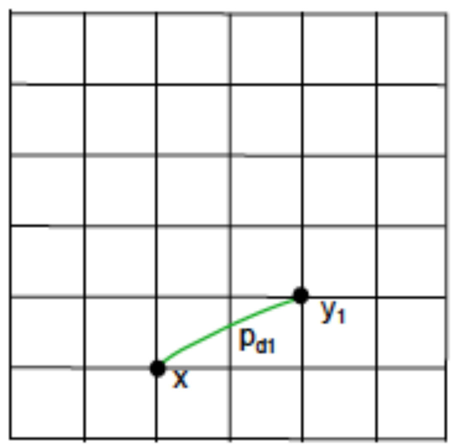
$$p_d = \mathbb{P}\Big((x,y) \in E(G_{\mathbb{Z}_N^2,p}) \text{ and } dist(x,y) = d\Big) = \frac{c}{Nd},$$

Graph Model: Short and Long Edges

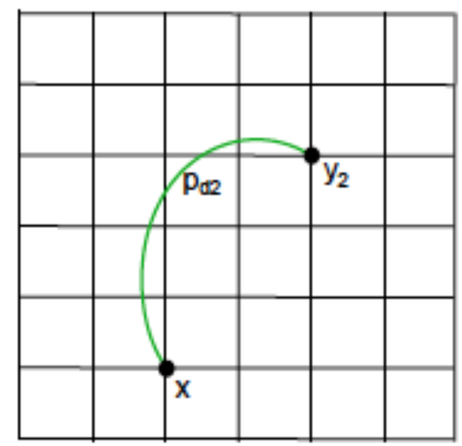
Random edges of $G_{\mathbb{Z}_N^2,p}$ are called **long**, s.t., there is an edge between a pair of vertices with probability

$$p_d = \mathbb{P}\left((x,y) \in E(G_{\mathbb{Z}_N^2,p}) \text{ and } dist(x,y) = d\right) = \frac{c}{Nd}, \quad (1)$$

The edges of the grid are called **short**.



$d_1 = 3$

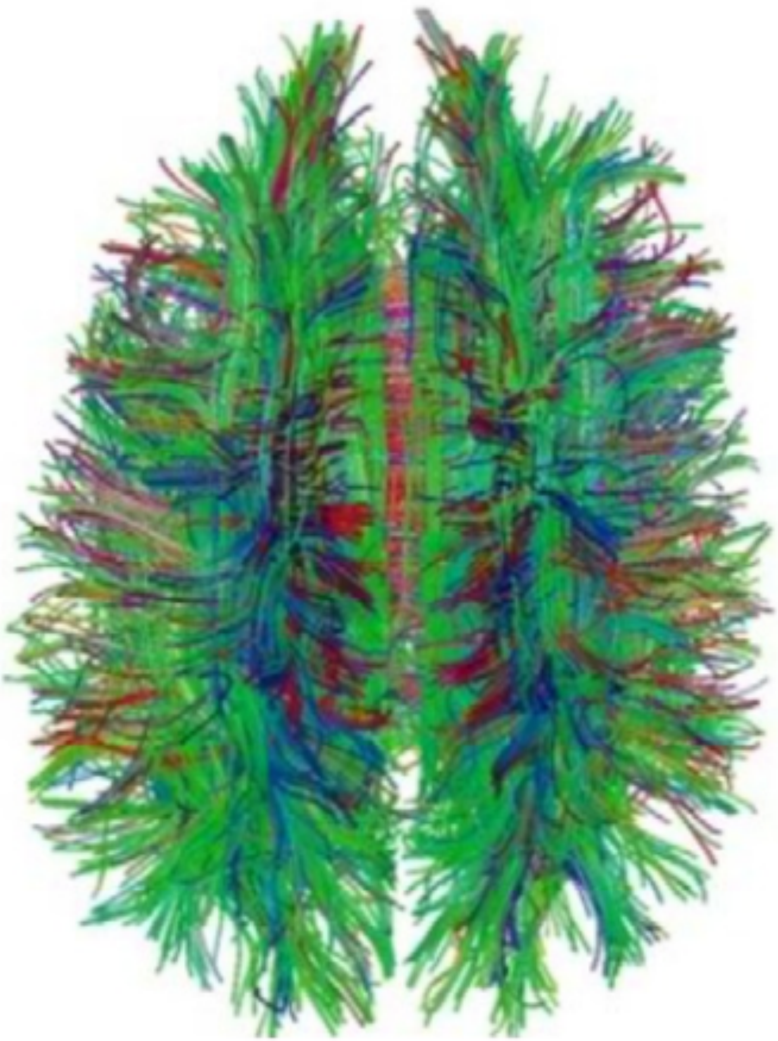


$d_2 = 5$

$$p_{d_1} > p_{d_2},$$

that is, for long edges it is more likely to have a shorter edge than a longer one.

Brain Connectivity



There is one long connection (axon) out of 1000 synapses of a neuron. If we consider two sets of connections between neuropopulations where the first set contains only axons and the second set have all the others then the ratio will still be the same 1:1000.

Fig.: de la Iglesia-Vaya, M., Molina-Mateo, J., Escarti-Fabra, J., Kanan, A.S., Marti-Bonmati, L., (2013)

Previous Random Graph Models

- "Small world I": Starting from a circle lattice with n vertices and k edges per vertex, rewire each edge at random with probability p, regularity for $p = 0$ and disorder for $p = 1$. (Watts, D. J., and Strogatz, S. H., Nature, (1998))
- "Small world II": Again an n-cycle with its edges is considered. In contrast to the original formulation, however, random edges were added with some p instead of rewiring the edges. (Newman, M. E. J., and Watts, D. J., Phys. Rev. E, (1999))
- "Long-range percolation graph": An undirected graph with the node set $\{0, 1, \ldots, N\}^d$, has edges (x, y) selected with probability $1 - exp(-\beta/|x - y|^s) \approx \beta/|x - y|^s$ if $|x - y| > 1$, and with probability 1 if $|i - j| = 1$, for some $\beta, s > 0$. (Benjamini, I., and Berger, N., RSA (2001); Coppersmith, D., Gamarnik, D., and Sviridenko, M., RSA

Diameter is of Logarithmic Order in the System Size

Observation. Signals in networks spread fast, hence, the diameter of any graph modeling networks has to be small. The diameter $D(G_{\mathbb{Z}_N^2,p})$ is logarithmic in the number of vertices, i.e., it has small world property.

Theorem (JKRS'15)

There exist constants C_1, C_2, which depend on c only, such that for the diameter $D(G_{\mathbb{Z}_N^2,p})$ the following holds

$$\lim_{N\to\infty} \mathbb{P}\left(C_1 \log N \leq D(G_{\mathbb{Z}_N^2,p}) \leq C_2 \log N\right) = 1.$$

Thus, it is easy to turn c for big networks with, e.g., 10^8 nodes, e.g., www. So that it is represented by $10^4 \times 10^4$. Diameter w/o long edges $= 10{,}000$, but w/ long edges 4!

Poisson Degree Distribution

The probability that a vertex has degree k considering only the long edges is given by

$$\mathbb{P}(W = k) = \sum_{k_2+\ldots+k_N=k} \prod_{i=2}^{N} \binom{\Lambda_i}{k_i} \left(\frac{c}{Ni}\right)^{k_i} \left(1 - \frac{c}{Ni}\right)^{\Lambda_i - k_i}. \quad (2)$$

However, we can approximate it by Poisson $\mathrm{Po}(\lambda)$ distribution with $\lambda = 4c \ln 2$, that is

$$\mathbb{P}(W = k) = \frac{e^{-\lambda}\lambda^k}{k!} + O\left(\frac{1}{N}\right). \quad (3)$$

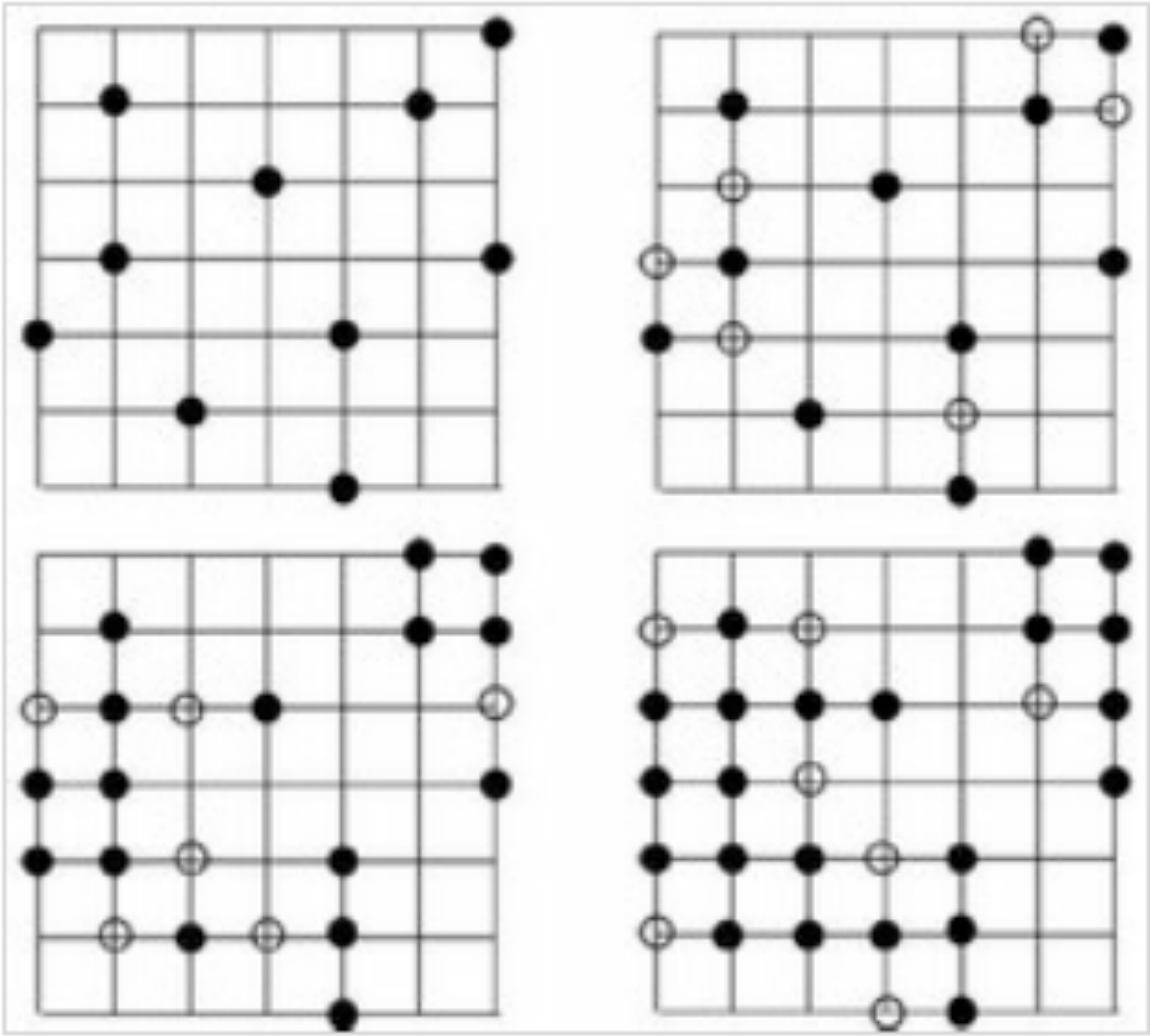
Moreover, we have that the total variation distance

$$d_{TV}(\mathcal{L}(W), \mathrm{Po}(\lambda)) = \frac{1}{2}\sum_{j \geq 0} |\mathbb{P}(W = j) - \mathbb{P}(Y = j)| = O(1/N), \quad (4)$$

Activation Process: Step-by-step Generalized Bootstrap Percolations

t=0

t=1



t=2

t=3

Mean Field Approximation – Example of Pure Excitation

Let ρ_t be a proportion of active nodes at time t, i.e. $\rho_t = A(t)/N^2$ then the evolution of ρ_t is defined as

$$N^2\rho_{t+1} = Bin(N^2\rho_t, f^+(\rho_t)) + Bin(N^2(1-\rho_t), f^-(\rho_t)) \qquad (6)$$

where

$$f^+(x) = \sum_{n=4}^{N^2-1} \mathbb{P}(\deg(v) = n-4) \sum_{i=k}^{n+1} \binom{n}{i-1} x^{i-1}(1-x)^{n-i+1} \qquad (7)$$

$$f^-(x) = \sum_{n=4}^{N^2-1} \mathbb{P}(\deg(v) = n-4) \sum_{i=k}^{n} \binom{n}{i} x^{i}(1-x)^{n-i}. \qquad (8)$$

Moreover, given ρ_t, ρ_{t+1} has mean $f(\rho_t)$ where

$$f(x) = xf^+(x) + (1-x)f^-(x), \qquad (9)$$

Main Result: Phase Transition in Mean Field Approximation

Theorem (JKRS'15)

In the mean-field approximation of the activation process $A(t)$ over random graph $G_{\mathbb{Z}_N^2, p_d}$ there exists a critical probability p_c such that for a fixed p, w.h.p., all vertices will eventually be active if $p > p_c$, while all vertices will eventually be inactive for $p < p_c$. The value of p_c is given as the function of k and λ as follows:

(i) *For $k = 0$ and any λ all vertices will become active in one step with high probability for any fixed $p > 0$.*

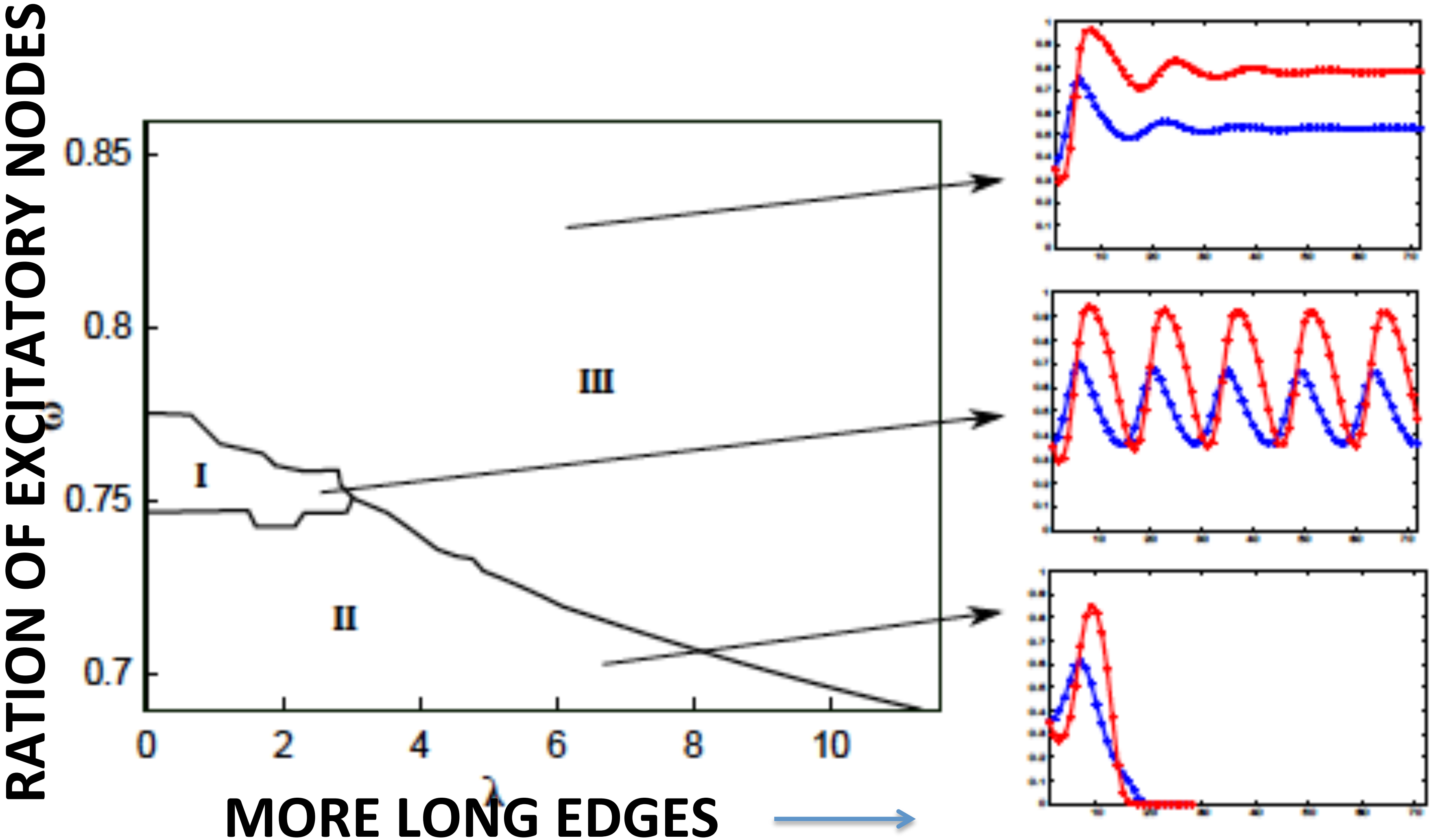
(ii) *For $k = 1$ and any λ, $p_c = 0$, i.e., for any fixed $p > 0$, all vertices will eventually become active with high probability.*

(iii) *For $k = 2$ and any λ, $p_c = x_2(\lambda)$, where $x_2(\lambda) < 0.132$ is a nontrivial solution to $x = \bar{f}_2(x)$.*

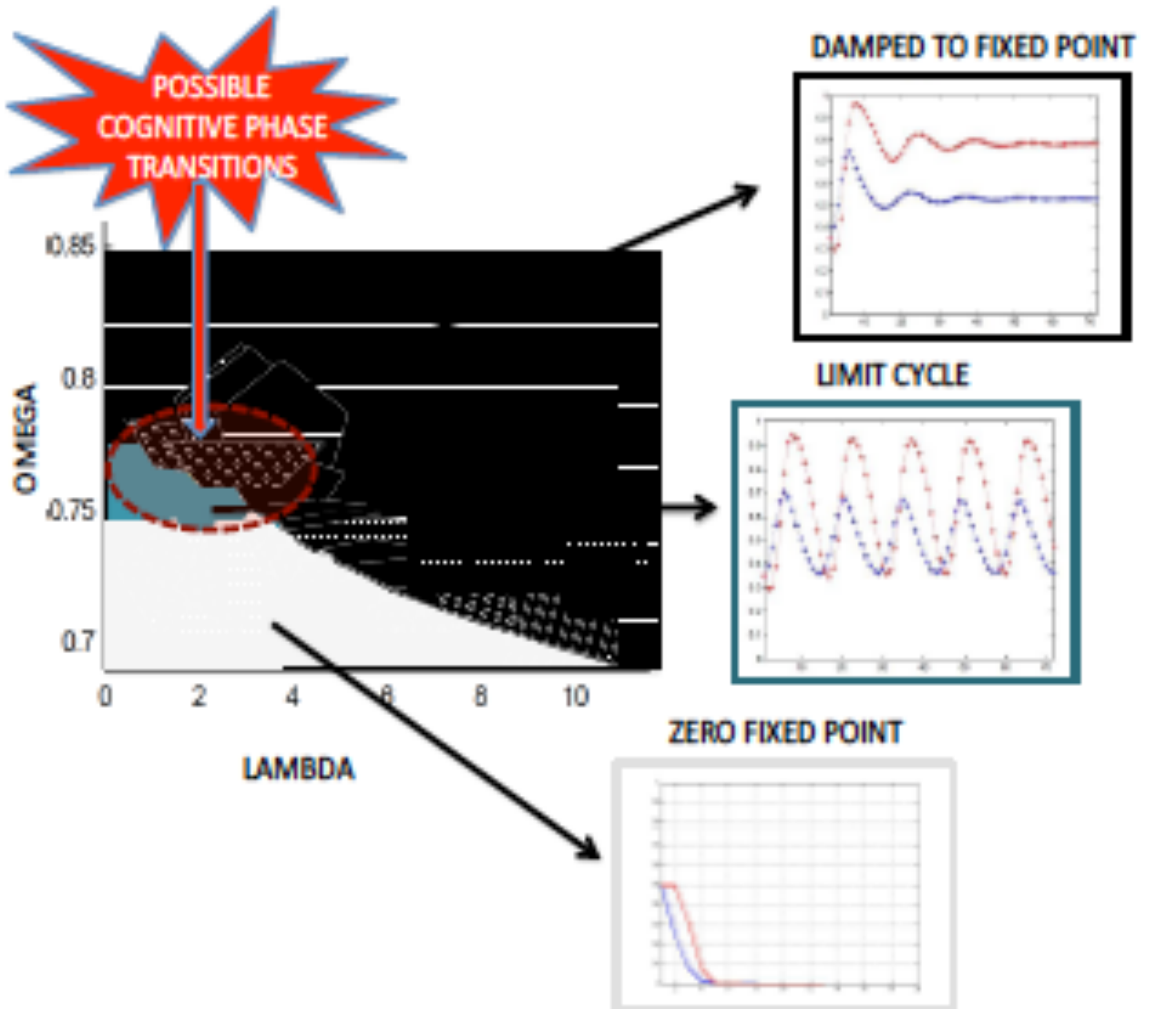
(iv) *For $k = 3$ and any λ, $p_c = x_3(\lambda)$, where $x_3(\lambda) < 0.5$ is a nontrivial solution to $x = \bar{f}_3(x)$.*

Emergent Oscillations (Region I)

Network with Excitatory & Inhibitory Nodes



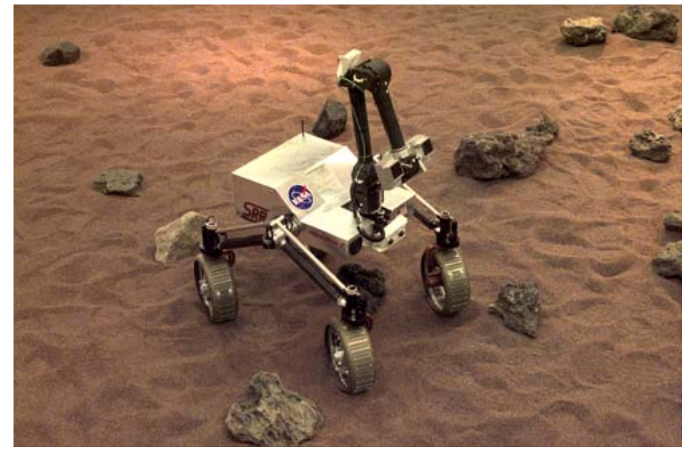
Emergent Oscillations Interpreted as Learning Effects



Concept of Implementations on Robotics Platform

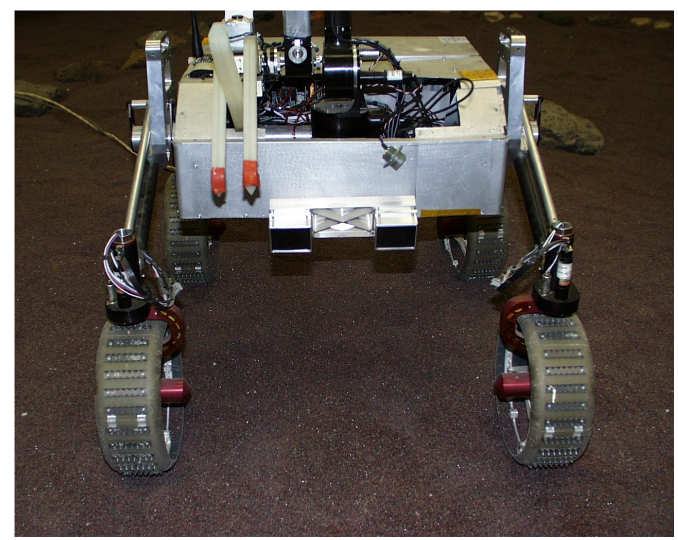
Example of Sensor Modalities
Mars Rover SRR-2K Prototype

1. **Stereo camera (Hazcam)**
   A pair of cameras
   with 130 degree FOV



2. **Goal camera (Viewcam)**
   mounted on a manipulator arm
   20 degree field of view;

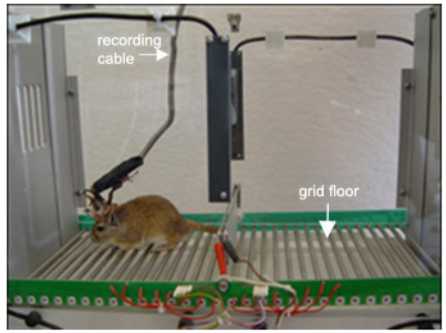
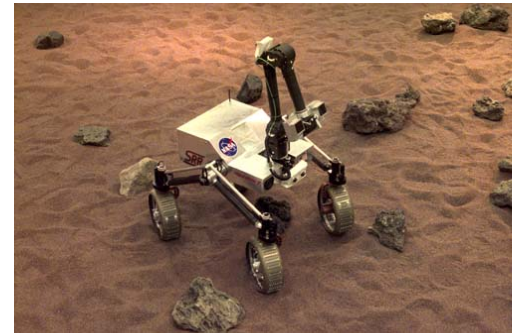
3. **Internal gyroscope (IMU)**
   registering along coordinates
   pitch, roll, and yaw



4. **Crossbow accelerometer (ACC)**
   x, y, and z coordinates

5. **Sun sensor (GPS)**
   for global positioning information

Linking Animal Experiments with Robotic Platform

	Gerbil	**Mobile Robot**
		
Task:	Move to/ stay in L/R correct compartment	Move to target using Left/Right/Forward/Back steps
Senses:	Auditory (hearing)	Visual (stereo camera)
Reinforcement:	Shock in grid	Shaking through accelerometers

Similar to phase transition in animals to a learnt state, dynamics of the rover autonomous learning (adaptation to a new environment) may be described by the same mathematical model.

This inspires the possibility to transfer tools for data analysis in biological system to an autonomous device.

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