

Biological and Artificial Neural Networks

Neural Nets Lecture, May, 2012

Presentation: Pascal Kaufmann

Dipl. sc. nat. ETH, Neurosciences

Artificial Intelligence Laboratory, AND 2.21

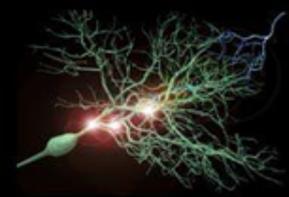
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Presentation: Topics

I. Neural Networks foundations: Abstracting Principles

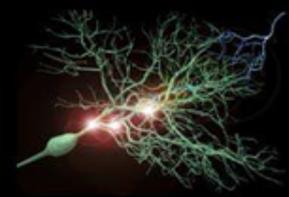
- Artificial Brains and Bird Wings
- Principles and Design Strategies

II. Applying principles: Example - Growing Artificial Neural Networks

- Introducing the architecture
- Ant Analogy

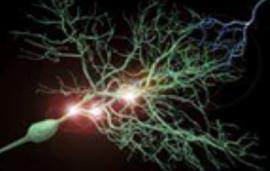
III. Binding Spiking Artificial Neurons through Sensory Input

- Results
- Conclusions



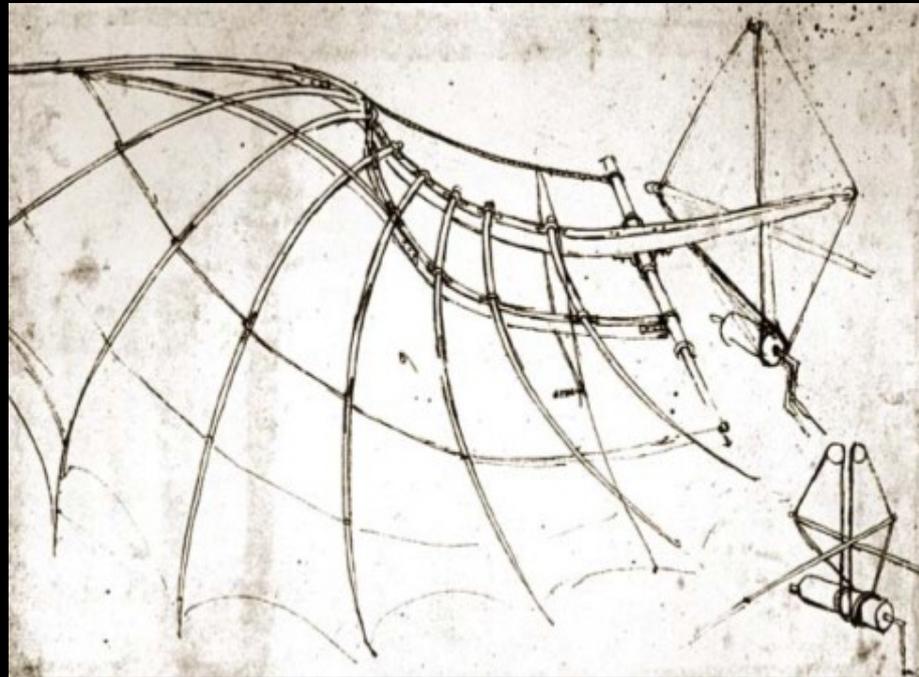
I. **Motivation: Abstracting and Applying Principles for Applications**

- Artificial Brains and Bird Wings
- Principles and Design Strategies

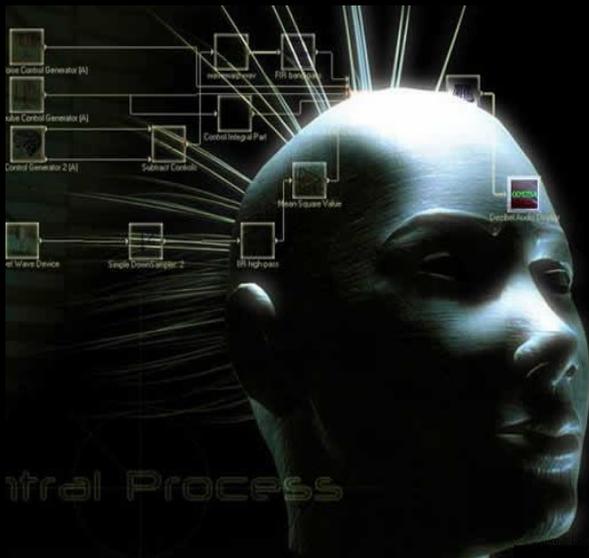


On Artificial Brains and Bird Wings: An Analogy

Many sought to realize their dream to fly by mimicking birds. Man-crafted machines that much resembled artificial birds were envisaged, and in spite of numberless attempts pursued over centuries the mystery of flight could not be unravelled.



Study of the Structure of a Wing. Pen and ink "Dissect the bat (...) and on this model arrange the machine". Leonardo da Vinci (1452-1519), "Codice sul volo degli uccelli", 1505, Original at the Biblioteca Reale, Turin, Italy.



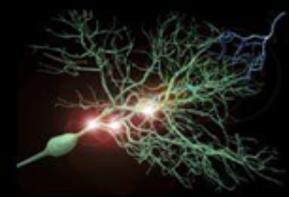


Example: Cronos humanoid robot in Shanghai



How could we steer a robot with human-like body dynamics?

Can we give life to Cronos? ☺

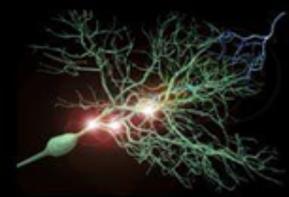


Example: Interfacing Brains with Machines

- “The physically handicapped (paraplegics and quadriplegics) will have their ability to walk and climb stairs restored. Methods to accomplish this will be controlled by finger motion, head motion, speech, and perhaps eventually thoughts.”

In ‘The Age of Spiritual Machines‘ by R. Kurzweil, MIT-Press 1990

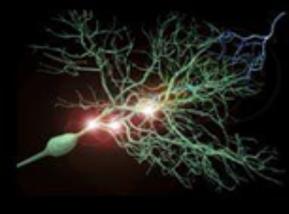
- The Scientific Bottleneck Problem
- Working at the interface between Neuroscience, Cybernetics and Computer-Science



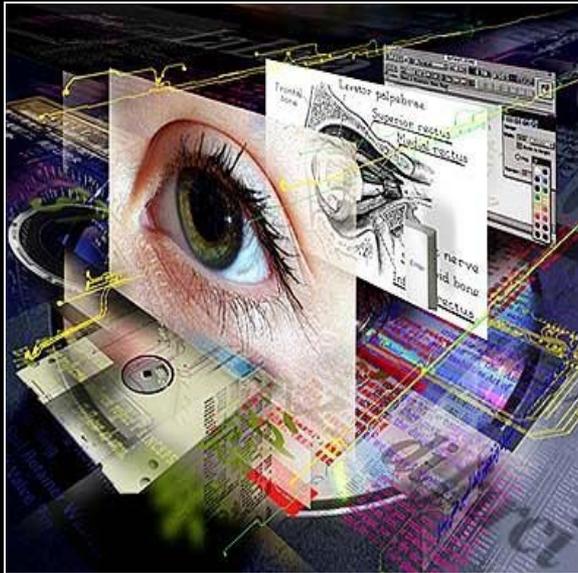
The Scientific Bottleneck Problem



A monk copying the bible (anno 1300).



The Scientific Bottleneck Problem



Today, accessing information is no longer a problem.



Still, the transition of knowledge into our brain is exhaustive and time consuming.

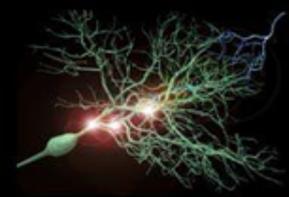


Example: Interfacing Brains with Machines

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In “The Age of Spiritual Machines“ by R. Kurzweil, MIT-Press 1990

- The Scientific Bottleneck Problem
- Working at the interface between Neuroscience, Cybernetics and Computer-Science may shed light on the phenomenon of biological Learning and Memory.



Virtual Neural Tissue: Foundations

Neural Tissue

Neurites

Growth Cones

Dendrites

Neural Plasticity

Synchronizity

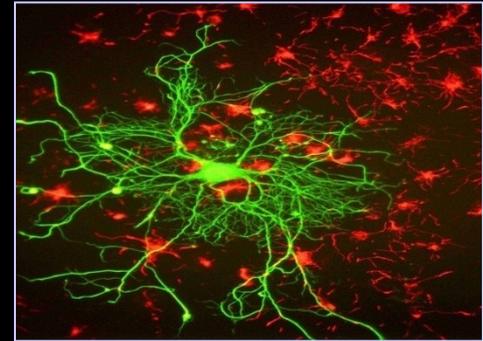




Virtual Neural Tissue: Foundations

Neural Tissue

Neurons are embedded in a chemical environment, where the interplay between morphology, the environment and physics determine circuitry and connectivity and thence neural dynamics.



Neurites

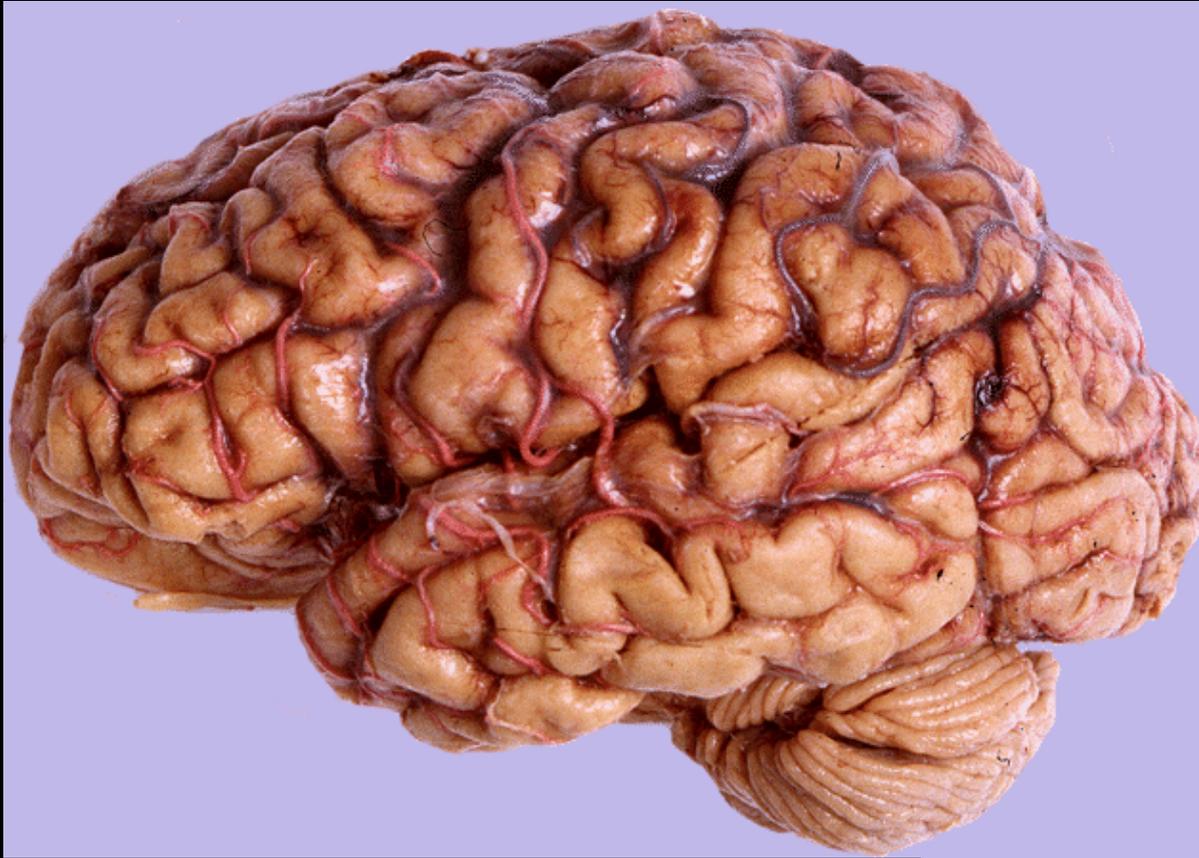
Growth Cones

Dendrites

Neural Plasticity

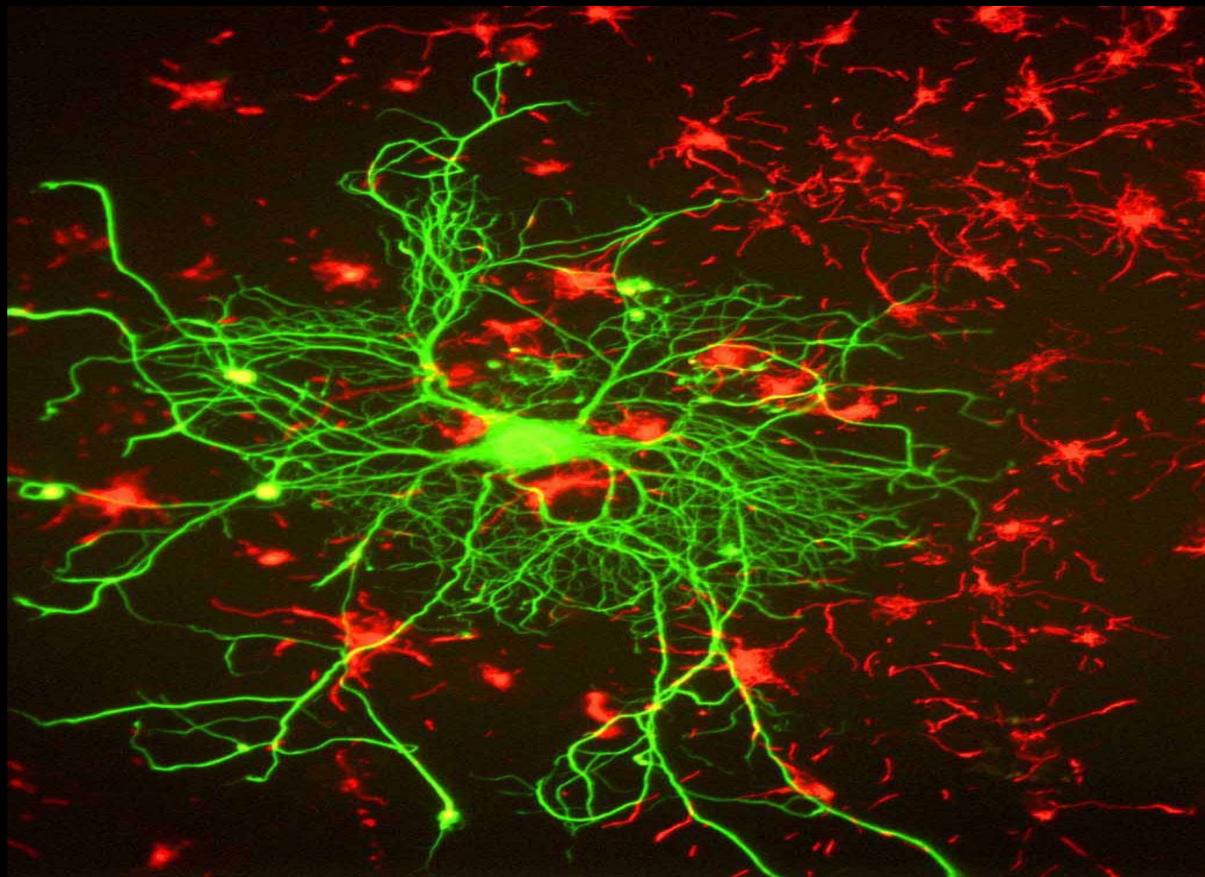
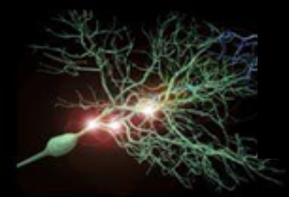
Synchronizity

Some Neuroscientific foundations



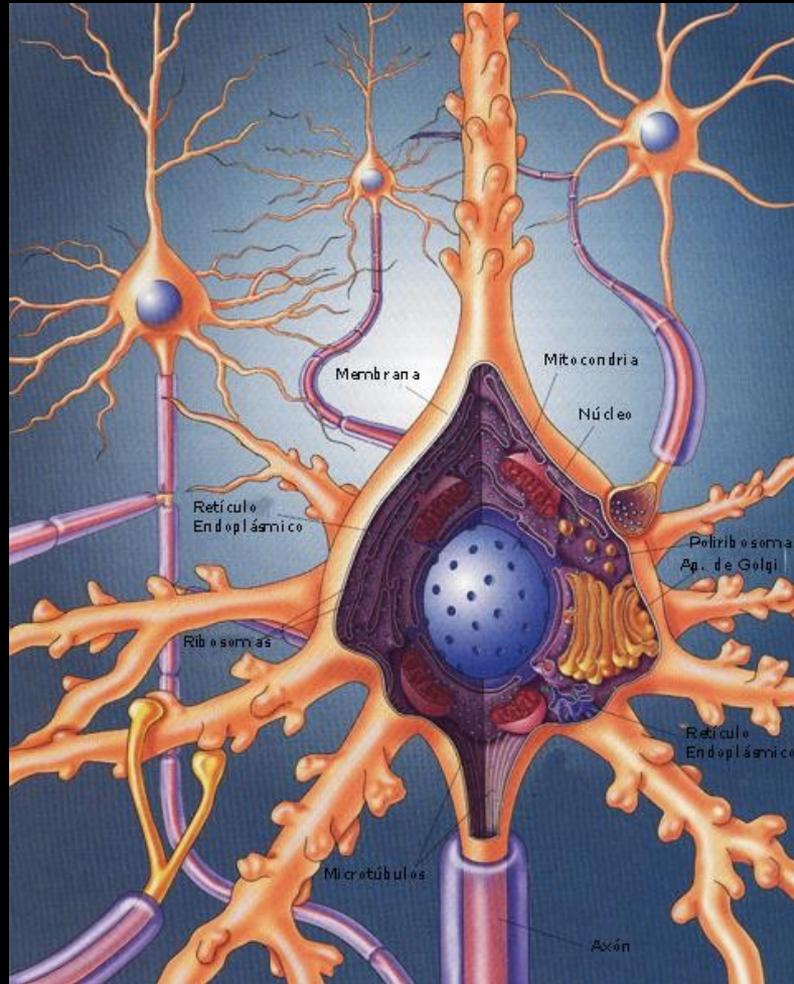
human brain

the neuron



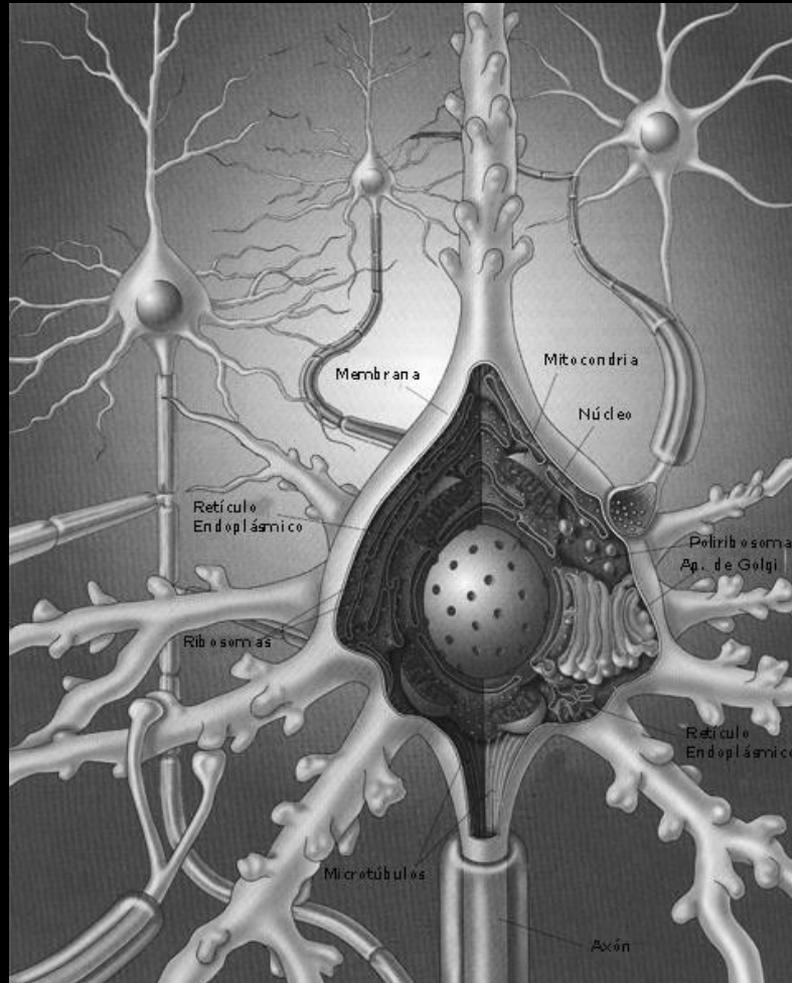
a single neuron: branching astrocyte

the neuron

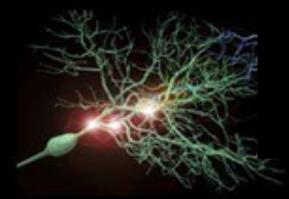


a single neuron: branching astrocyte (schematic)

the neuron



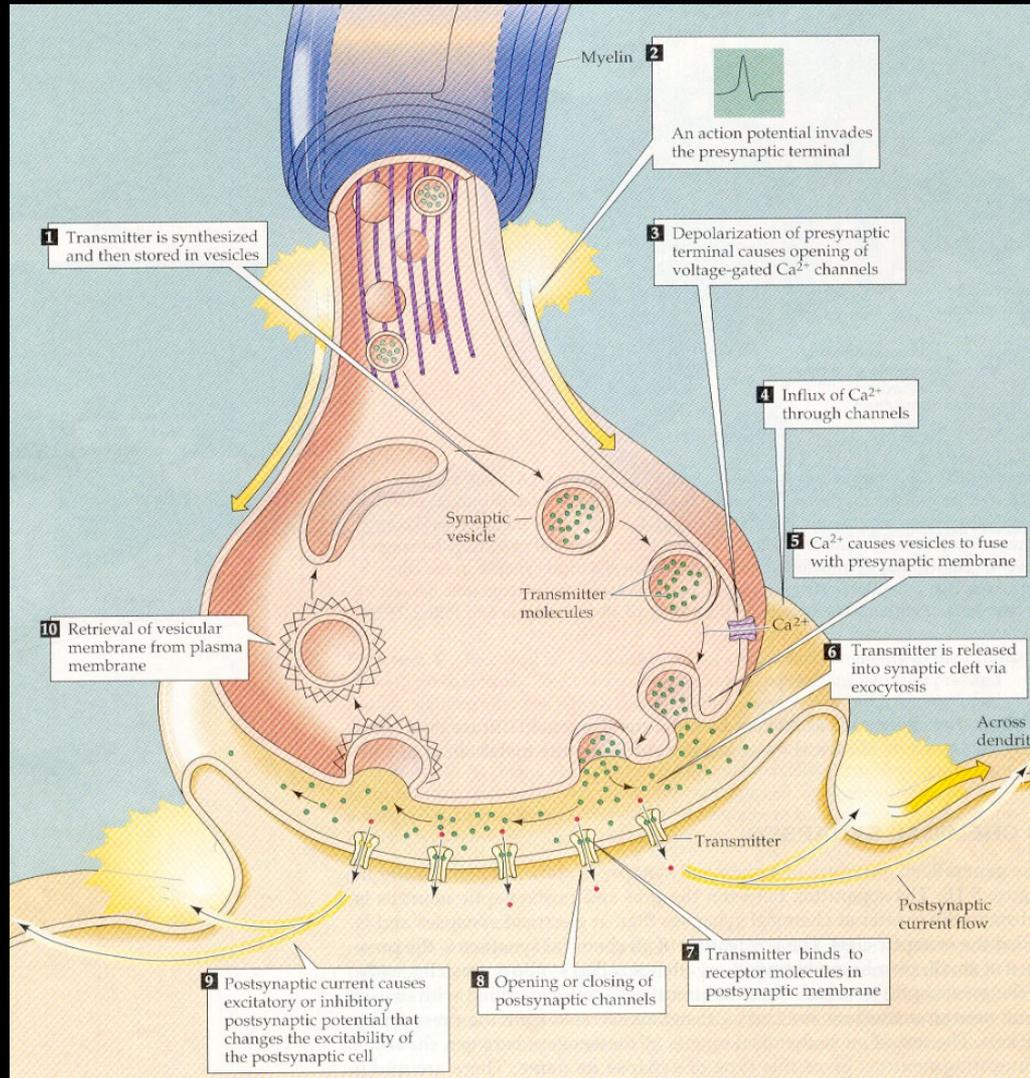
a single neuron: branching astrocyte (schematic)



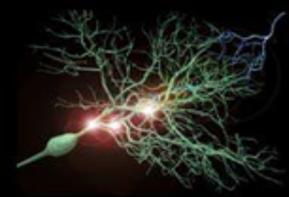
the neuron

a single neuron: branching astrocyte (schematic)

the synapse



transmitter release at the synaptic cleft

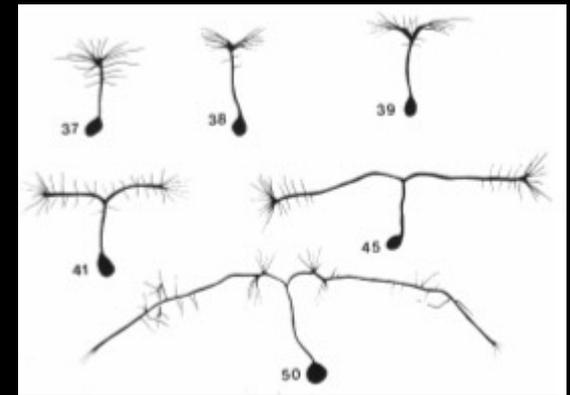


Virtual Neural Tissue: Foundations

Neural Tissue

Neurites

The observation that axons may grow and branch dependent on the dynamics of underlying micro-elements (microtubuli) promotes the implementation of local assembling strategies that are both interesting from a conceptual and computational viewpoint.



Growth Cones

Dendrites

Neural Plasticity

Synchronizity



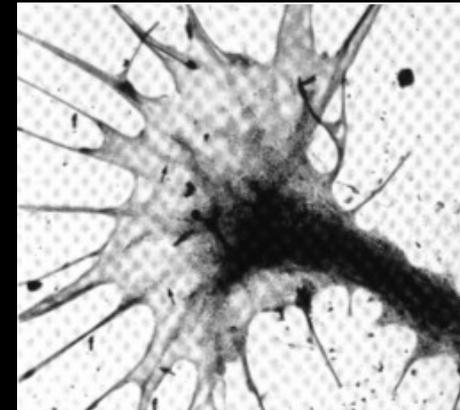
Virtual Neural Tissue: Foundations

Neural Tissue

Neurites

Growth Cones

The scanning of the local environment for chemical gradients performed by the growth cone occurs ceaselessly and constitutes an interesting strategy that is widely applied in nature. By varying the sensitivity of surface receptors the growth cone may select distinct pathways embedded within a chemical environment.

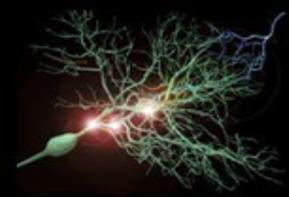
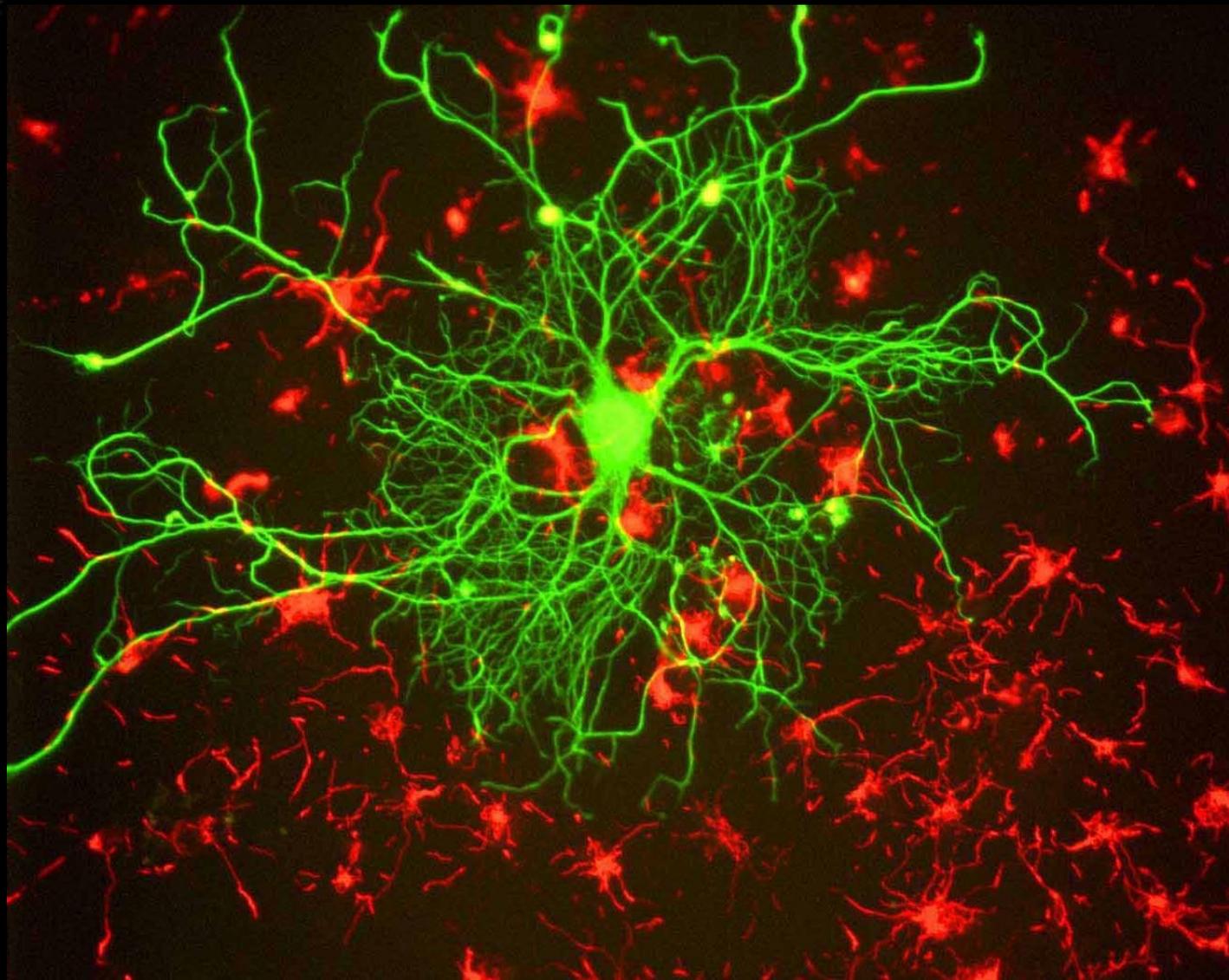


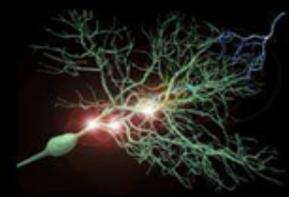
Dendrites

Neural Plasticity

Synchronizity

Diploma Thesis: Growing an Intelligent Artificial Neural Network





Motivation : biological Neurons





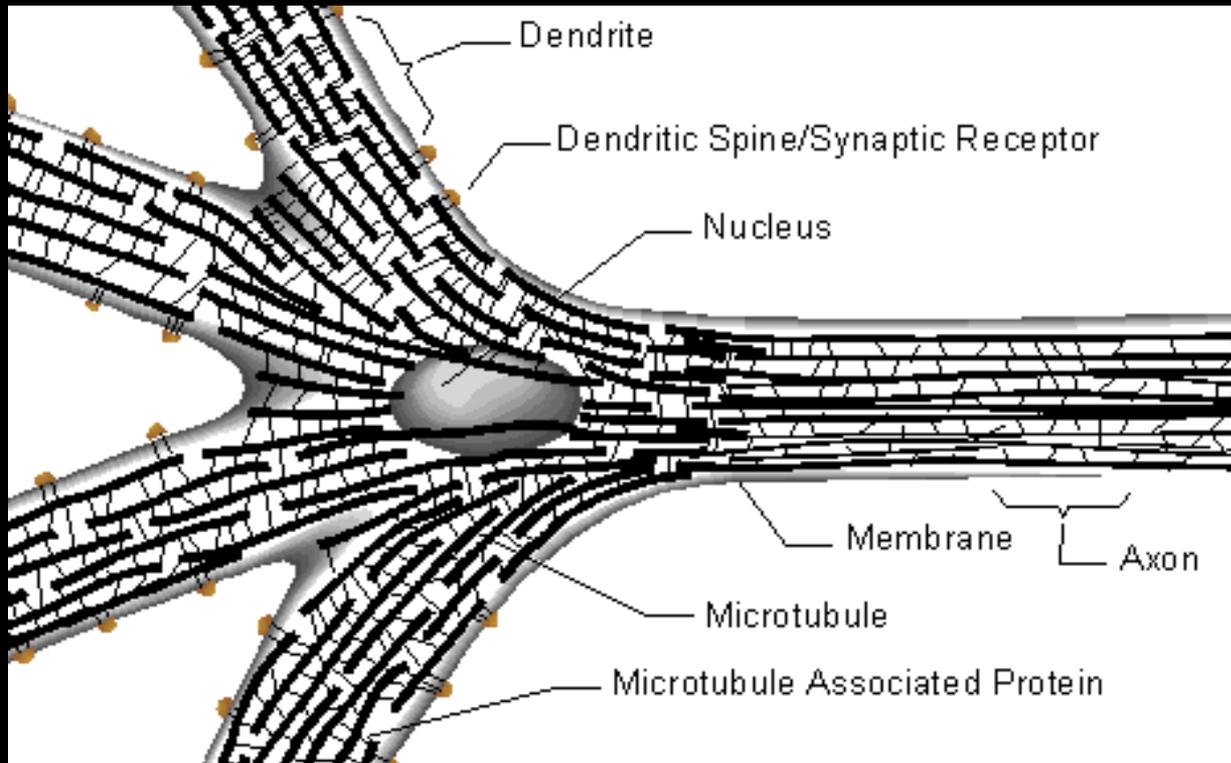
Diploma Thesis: Growing an Intelligent Artificial Neural Network



The ant analogy: intelligent microtubuli ?

Kalil, K. et al. (2000) "*Common Mechanisms Underlying Growth Cone Guidance and Axon Branching*", J. Neurobio. 44:145-158.
Penrose, R., (2000) "*The Large, the Small and the Human Mind*", UK, Cambridge University Press

Diploma Thesis: Growing an Intelligent Artificial Neural Network



- How does a neuron grow?
- What are the underlying principles?
- How does nervous tissue emerge?
- How does it process information?
- Where are the roots of Intelligence?



Virtual Neural Tissue: Foundations

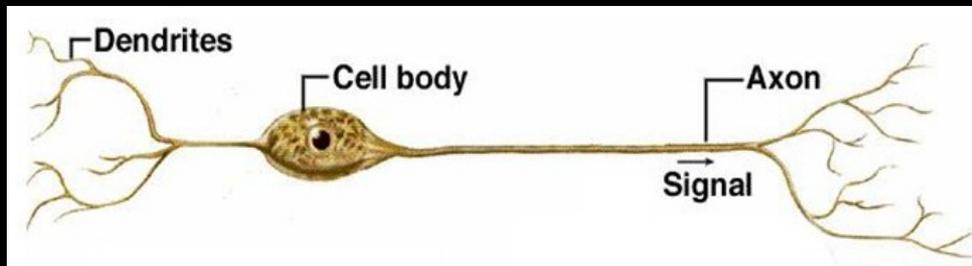
Neural Tissue

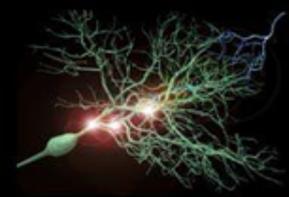
Neurites

Growth Cones

Dendrites

Dendrites could act as coincidence detector in that they exclusively amplify signals that arrive within a certain time window. Current hypotheses underscore the importance of the interplay between dendrites and cellbody. The fact that they are interacting through backpropagating action potentials was referred to as 'Handshake' between cellbody and dendrites (Koch et al., 2000) and may thus directly support Hebb's postulate of learning.





Virtual Neural Tissue: Foundations

Neural Tissue

Neurites

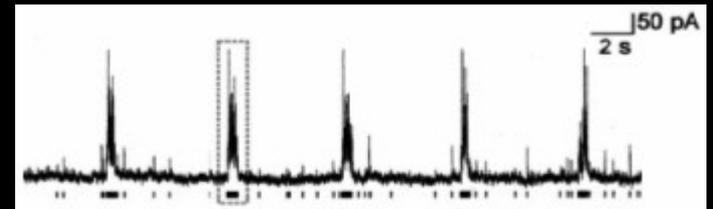
Growth Cones

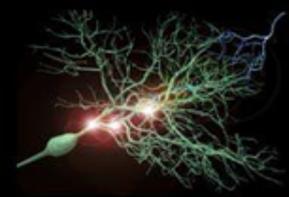
Dendrites

Neural Plasticity

Synchronizity

Tononi and Edelman showed in simulations that fast changes in synaptic efficacy and spontaneous activity may rapidly establish a transient but globally coherent process. They then pointed out the possibility of solving the 'binding problem' by neuronal synchronization and thus neuronal coherence (Singer, 1995; Edelman et al, 2000).





Virtual Neural Tissue: Foundations

Neural Tissue

Neurites

Growth Cones

Dendrites

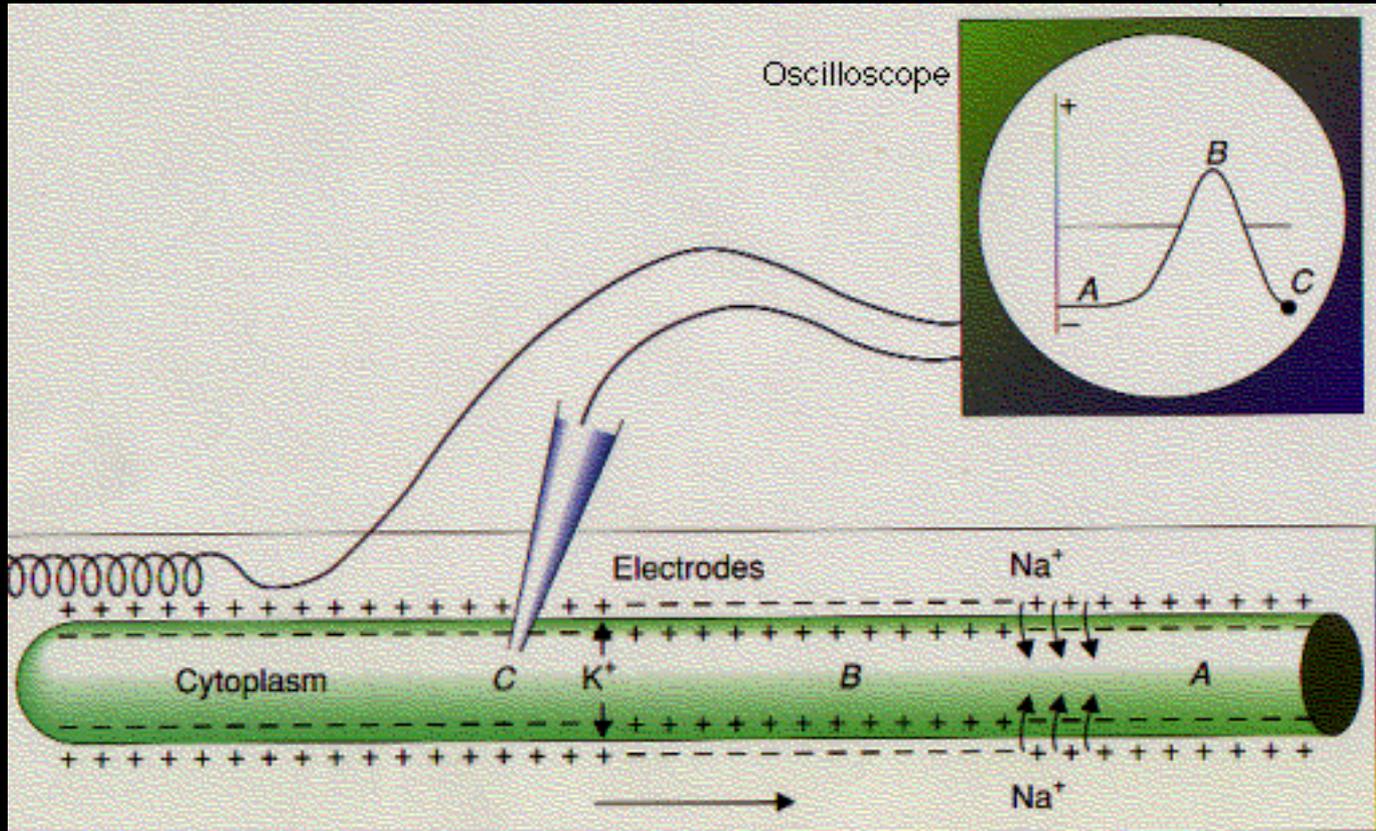
Neural Plasticity

Synchronizity



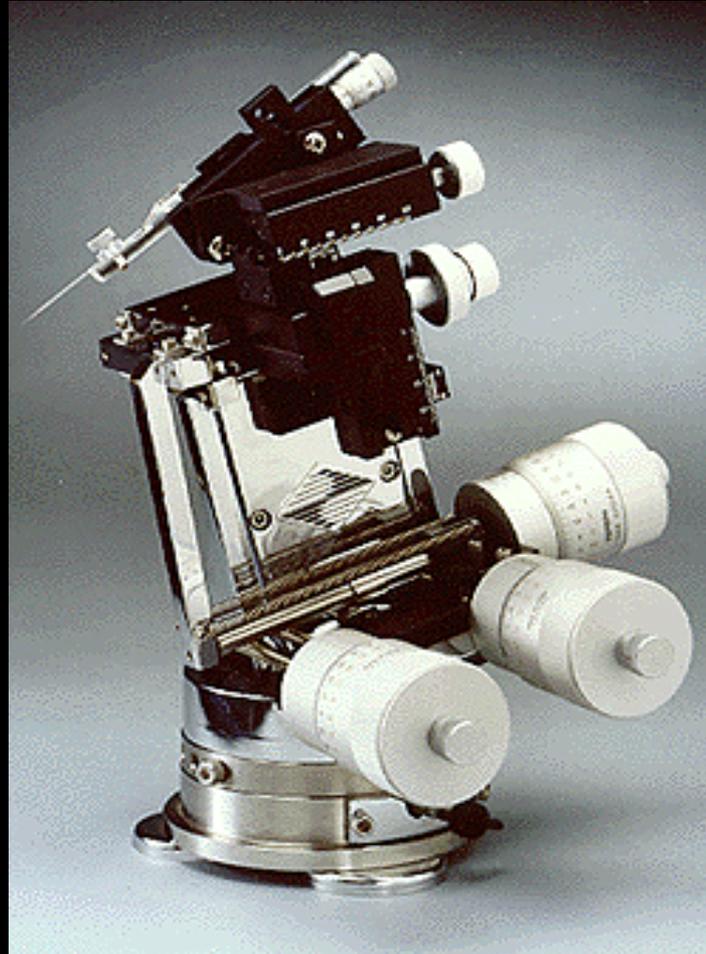
The Virtual Neural Tissue (VNT) architecture is designed to implement recent neuroscientific findings and to investigate adaptive growing artificial neural networks for its future application in robotics research. VNT is detailed in the following by examining recent investigations on synchronizity.

recording signals in nerve cells



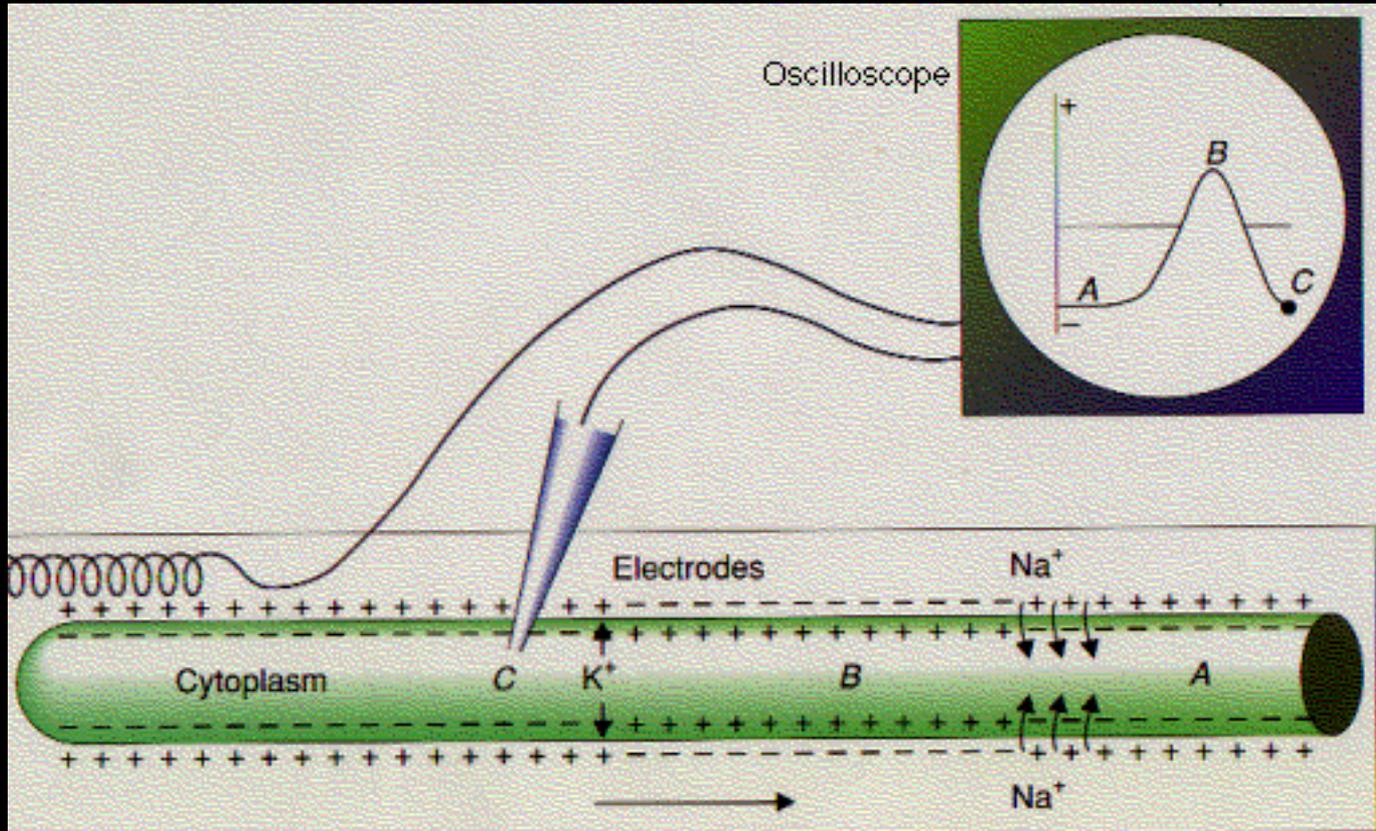
recording neural signals: action potentials

recording signals in nerve cells



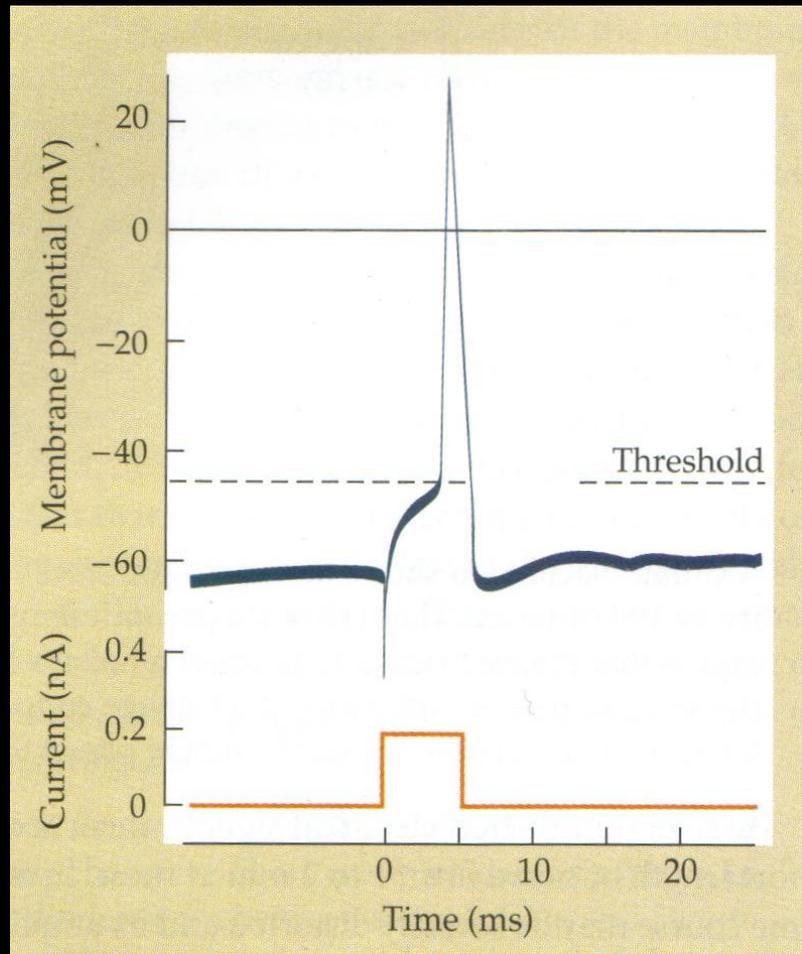
high-precision glass electrode for electrophysiological recording of neural activity.

recording signals in nerve cells



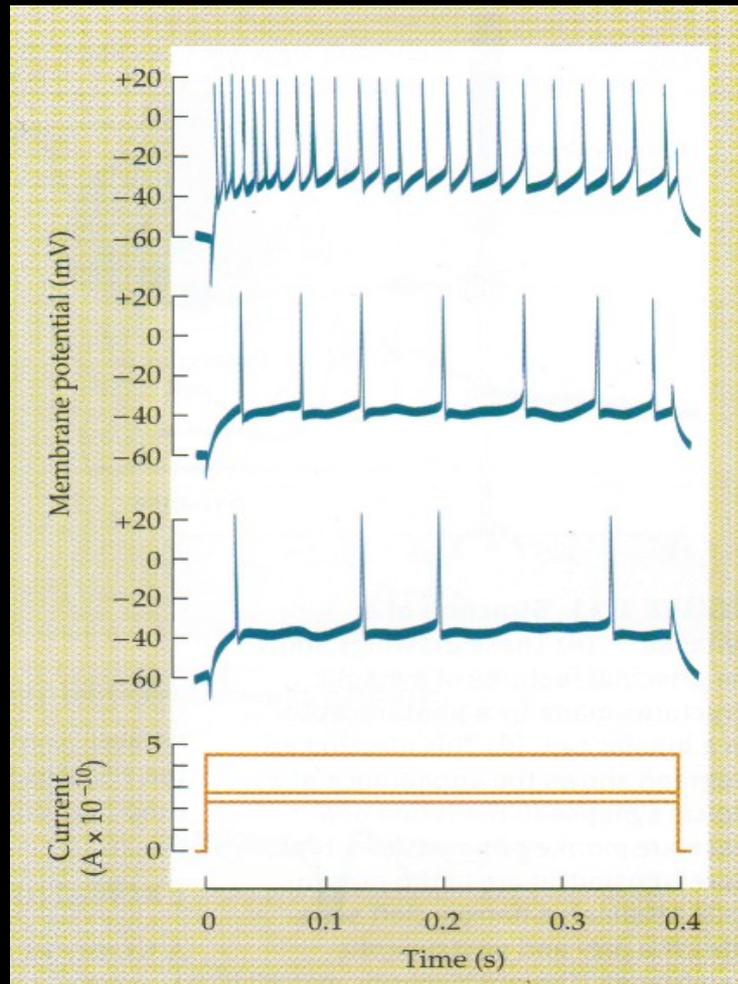
recording neural signals: action potentials

triggering signals in nerve cells



triggering an action potential by depolarization.

signal encoding in nerve cells



triggering a burst of action potentials

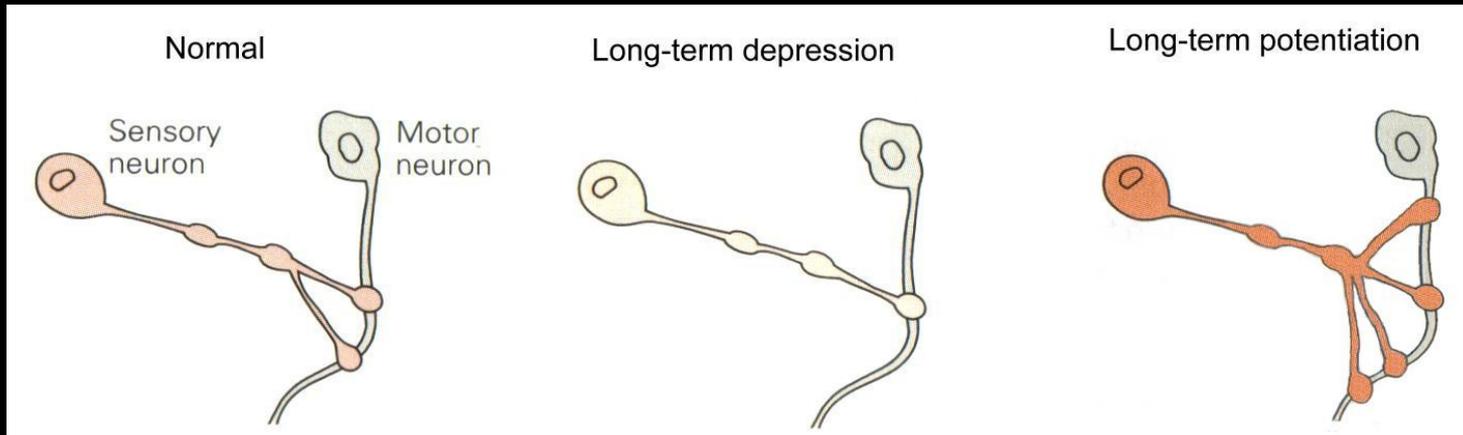


Learning and Memory

- “The mechanisms of Learning and Memory is still a very controversial and extensively treated issue in Neuroscience.”
- “There is not yet any conclusive evidence for any theory suggested.”
- “However, activity dependent plastic changes are still the best candidate for Learning and Memory.”
- “There is strong empirical support that synapse specific changes accompany the learning process.”

Kandel et al. (2000) *"Principles of Neural Science"*, New York: McGraw-Hill.

Longterm Potentiation (LTP)



no stimulation (3)

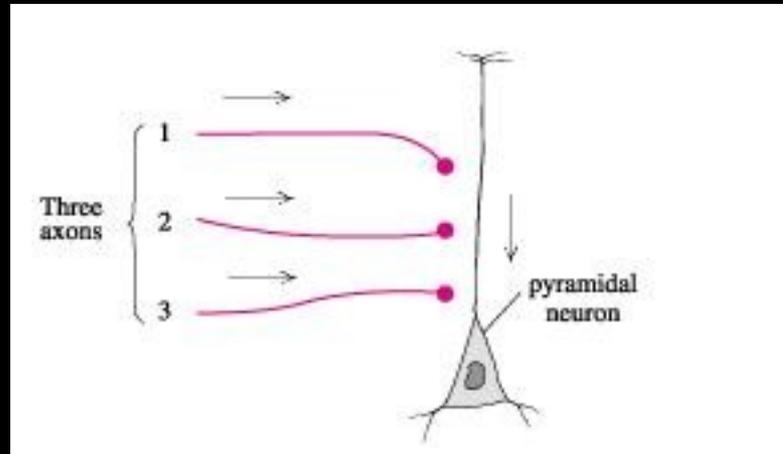
weak stimulation (2)

tetanic stimulation (1)

Problem:

Relating plasticity to behavior is very difficult: Behavioral studies cannot be performed while precisely recording cellular responses. Any movement prevents accurate electrophysiological recordings.

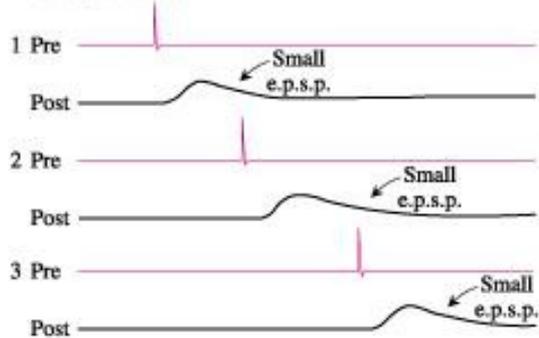
Longterm Potentiation (LTP)



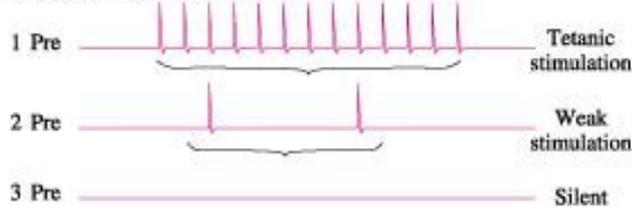
Axons 1, 2 and 3 (pre) transmitting signals to a pyramidal neuron (post).

Longterm Potentiation (LTP)

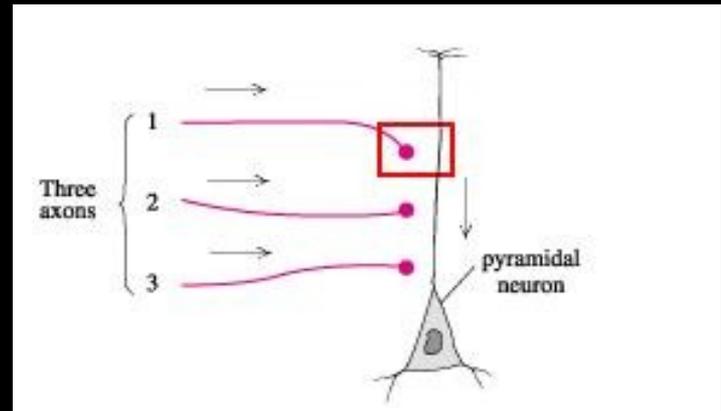
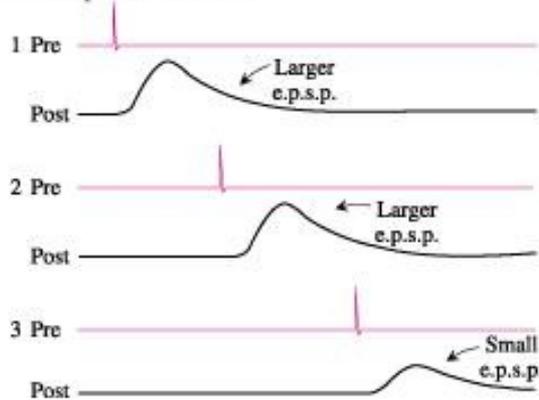
B. Before potentiation



C. Potentiation stimulus



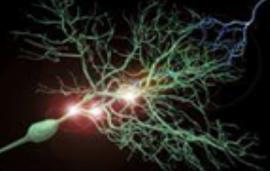
D. Test response 1 hour later



B: Current applied to axons 1, 2 and 3.
-> equivalent post-synaptic spikes.

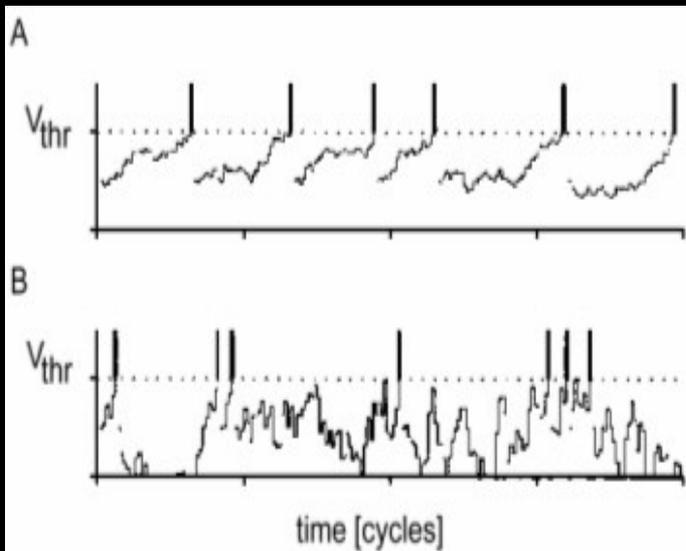
C: 3 different stimulation protocols applied.
-> equivalent post-synaptic spikes

D: After one hour application of same current as at the beginning.
-> Potentiated, long-lasting response.



Spiking Neurons: Integrate and Fire Units

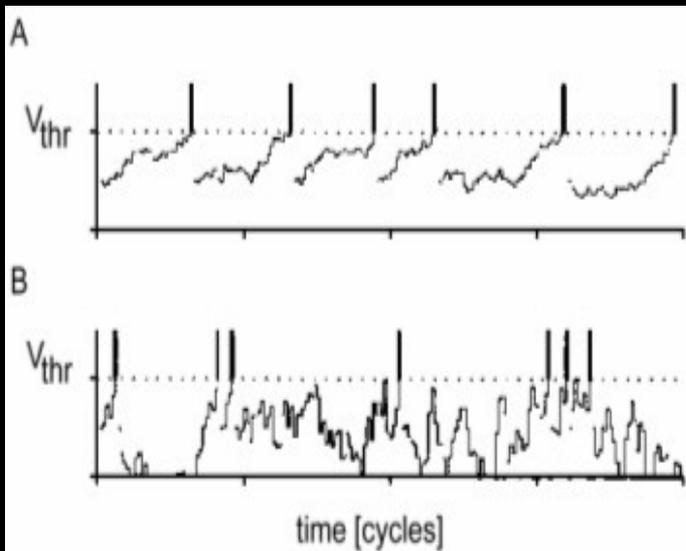
Integrate and Fire Units...



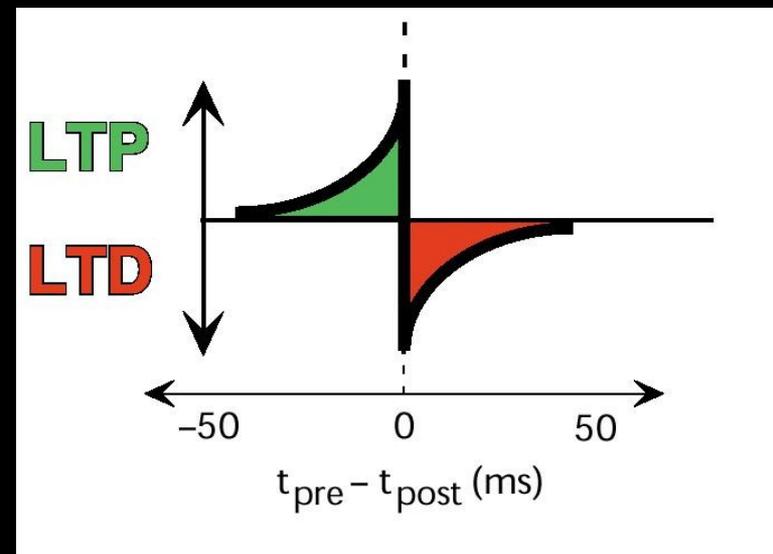
Left Panel: Traces illustrate how the accumulated number of net excitatory spikes affects the potential of a given neuron. When the potential V_{thr} is reached a single spike is emitted (vertical bars) and the potential reset to V_{reset} . A: A high drift of activity dominates over the fluctuations so that the neuron engages in regular firing. B: Irregular firing emerges as the neuron is exclusively driven by fluctuations (after Salinas et al., 2000).

Spiking Neurons: Integrate and Fire Units

Integrate and Fire Units...



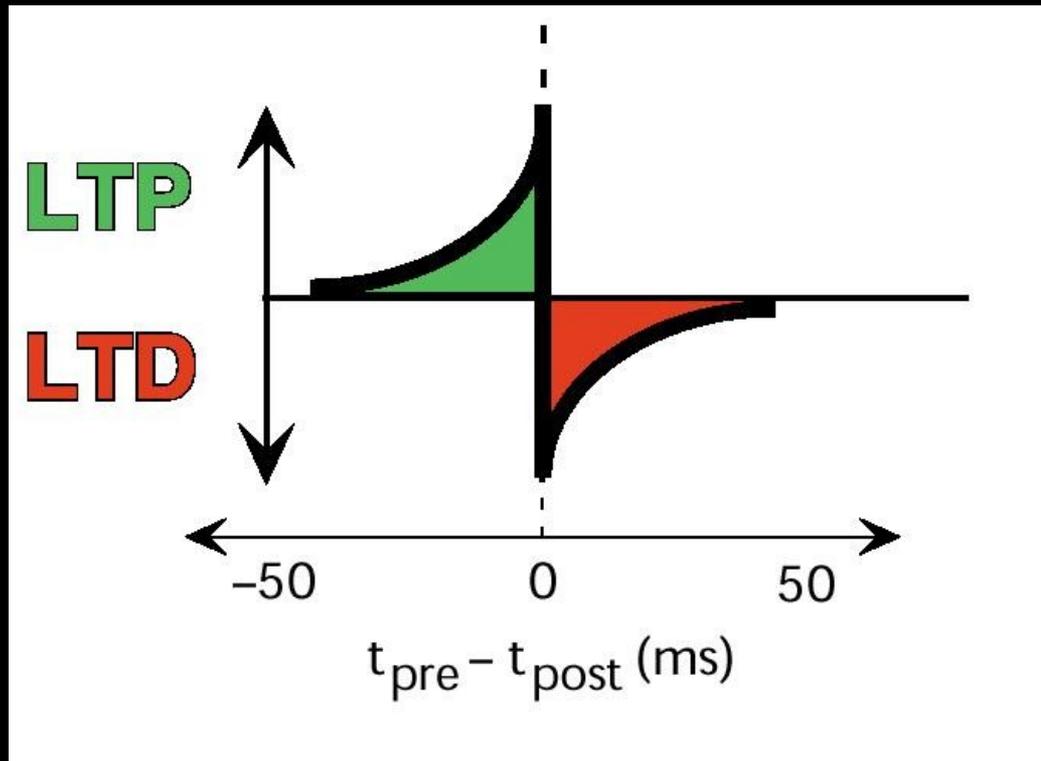
...underlying STDP



Right Panel: Spike Timing Dependent Plasticity as a universal learning rule? Adapted from L. F. Abbott and Sacha B. Nelson (2000), "Synaptic plasticity: taming the beast", Nature Neuroscience 2000.

VNT Neurons underlying Spike Timing Dependent Plasticity

VNT Integrate and Fire Units underlying STDP



Adapted from L. F. Abbott and Sacha B. Nelson (2000), "Synaptic plasticity: taming the beast", Nature Neuroscience 2000.

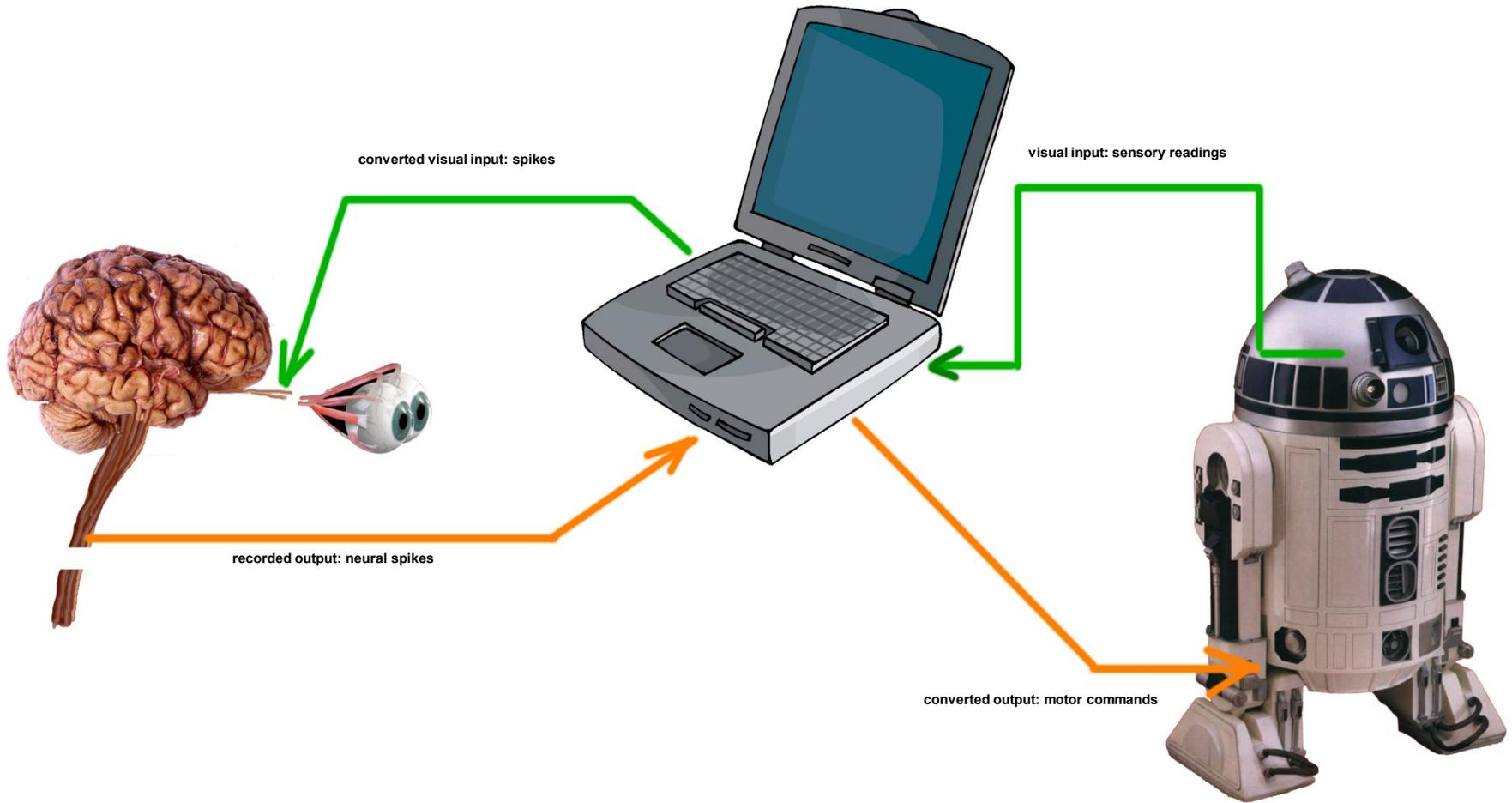
Neural Interfacing: Connecting Brains to Robots

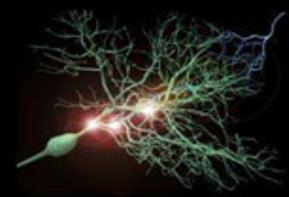


In collaboration with Mussa-Ivaldi, S., Alford, S., Sanguineti, V., Reger, B., Fleming, K., Kaufmann, P., 2001
Northwestern University, University of Illinois, University of Genova, Swiss Federal Institute of Technology



Pascal Kaufmann
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Artificial Intelligence Laboratory, Sect. Neural Interfacing
University of Zurich, Switzerland

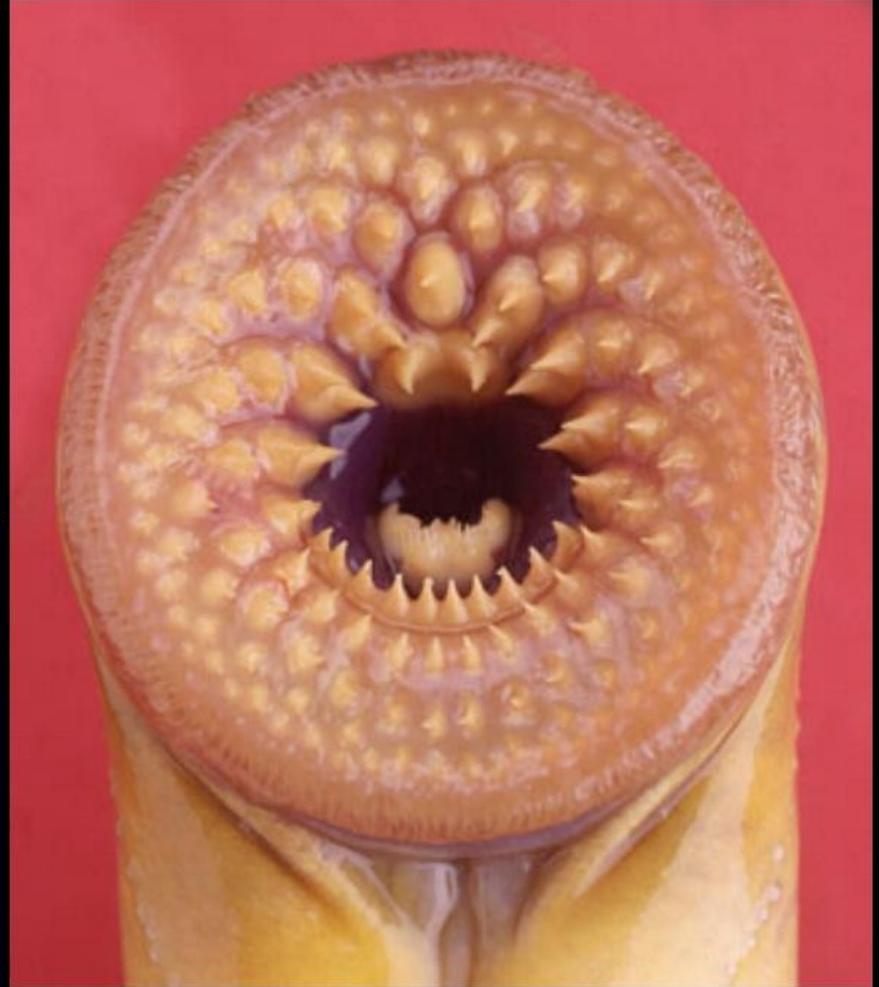




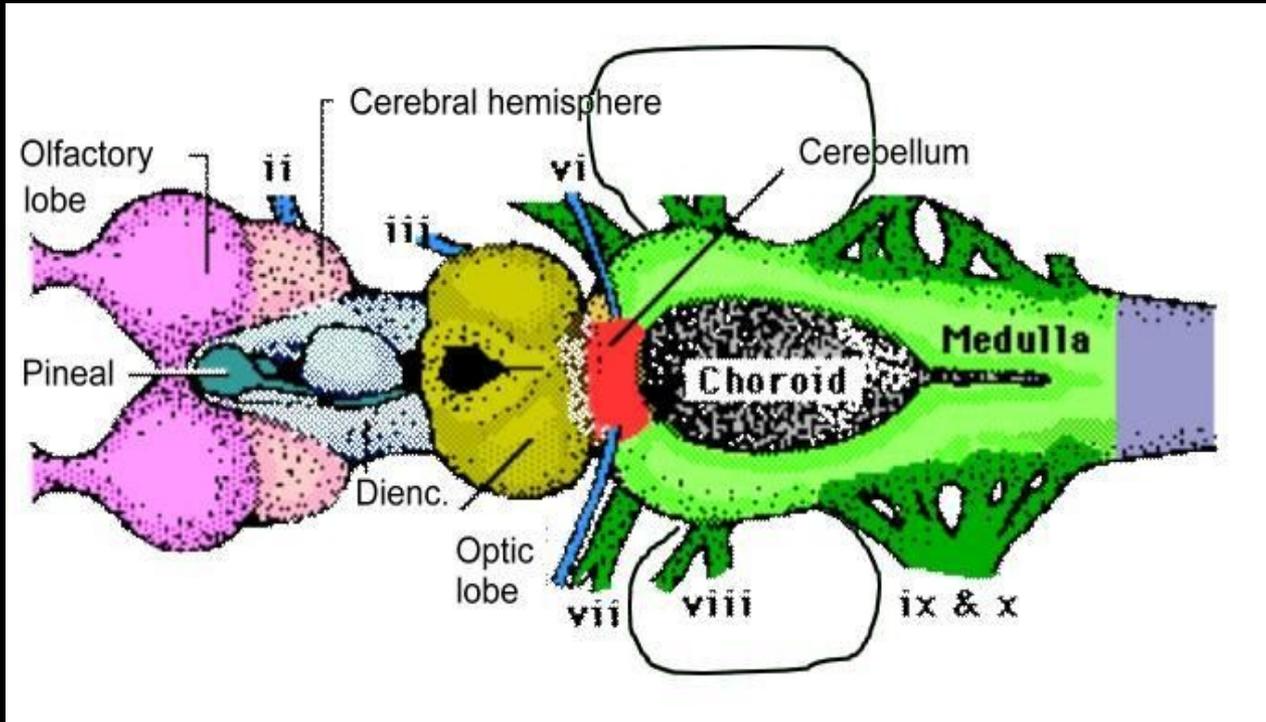
III. The Neurointerface: Connecting the Lamprey-Brain with Khepera

- Concepts and goals
- Experimental setup: the Brain, the Robot and its interface
- Preliminary findings and results
- Conclusions

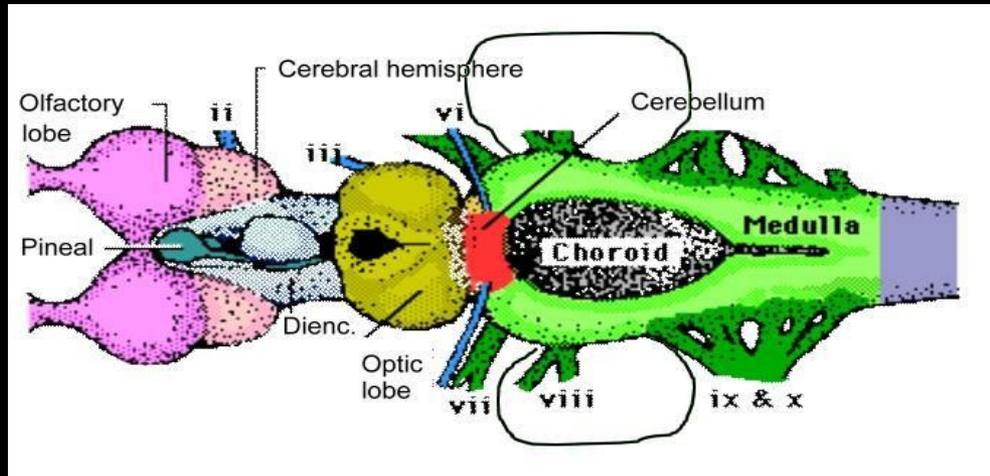
The lamprey: a brain to chat with



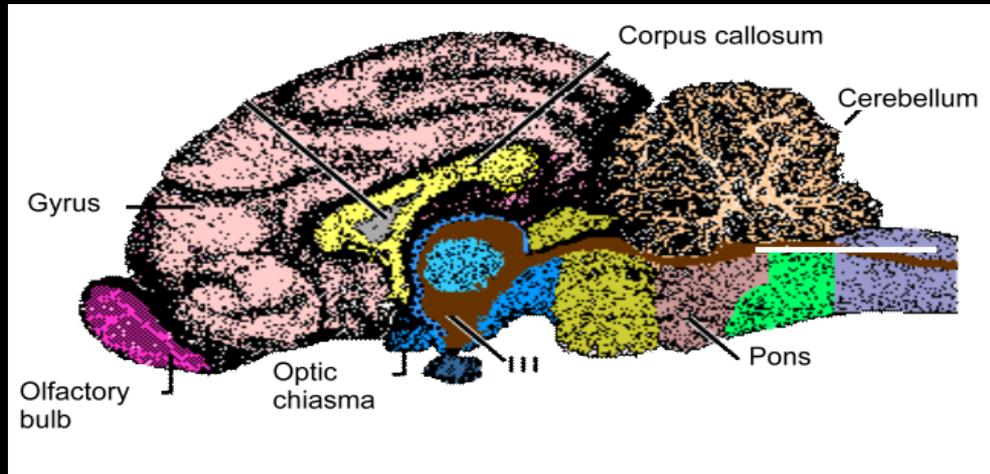
The lamprey: a brain to chat with



The lamprey: a brain to chat with



Lamprey Brain

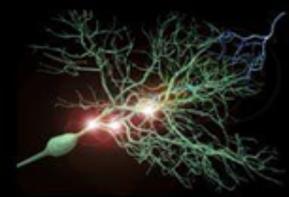


Cat Brain



Neurointerfacing: the concept

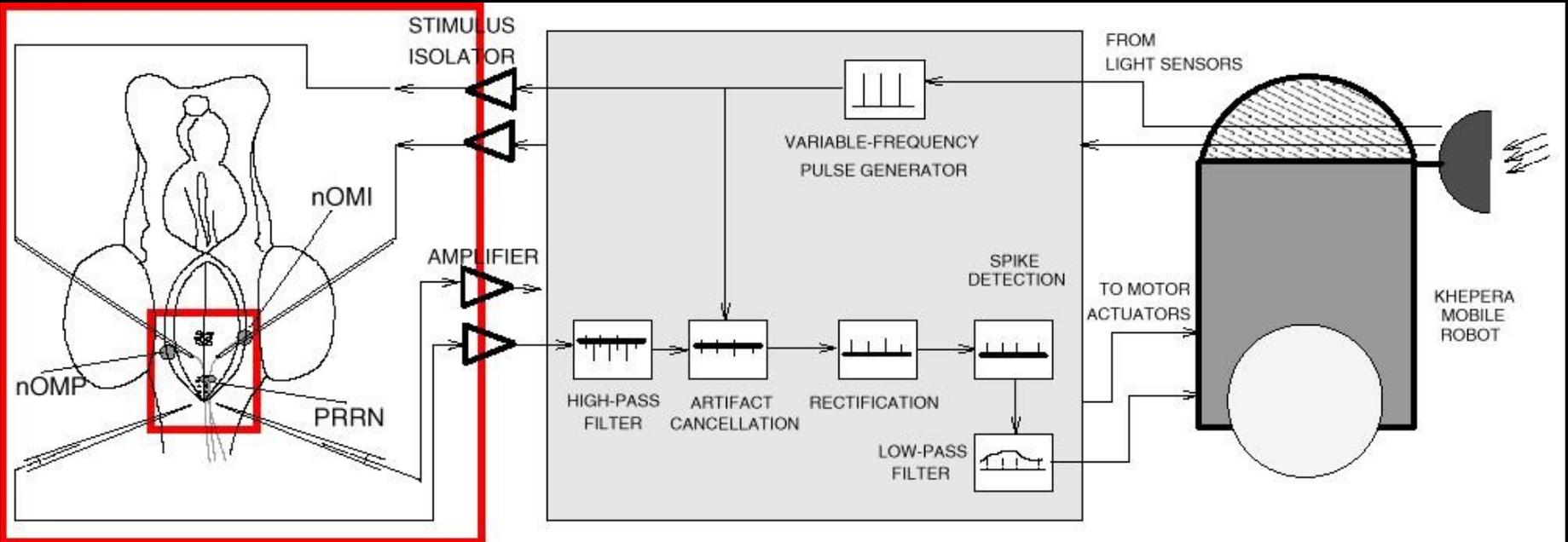
1. Connect the brain of the lamprey to Khepera while translating the neural activity in the reticular formation into wheel motor signals of the robot.
2. Completely detach the brain of the lamprey from its body in order to avoid perturbations by tweeking muscles.
3. Khepera conveys light signals to the reticular formation, thus functioning as artificial eyes of the naturally blind lamprey larvae.
4. An artificial behavior is obtained by replacing natural vestibular signals with artificial light singals, sensed by Khepera's light sensors.



Neurointerfacing: the goals

1. Creation of a hybrid system between Brain and Machine.
2. The lamprey 'learns' behavioral responses that are executed by the artificial body, i.e. Khepera.
3. Equipping the brain with sensors and actuators to interact with the real world.
4. Providing a potent tool for the investigation of LTP and its effect on behavioural responses.

Neurointerface: Experimental Setup



in vitro preparation

converter (Matlab)

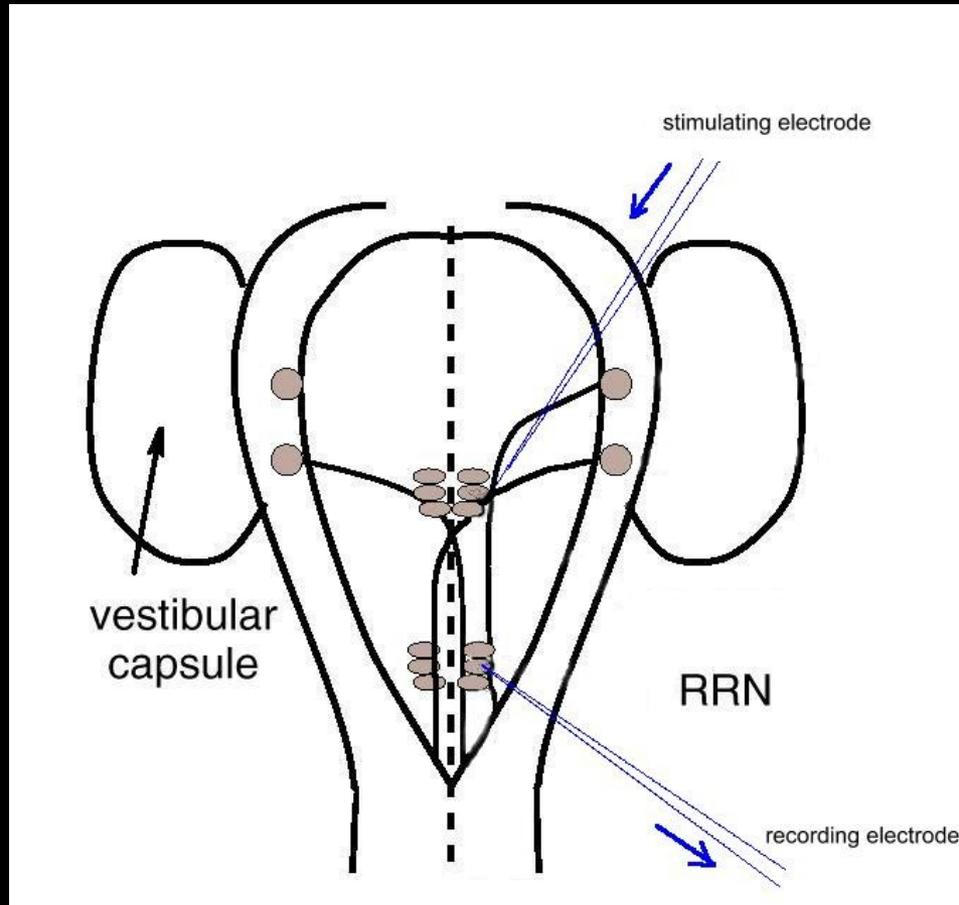
Khepera

Neurointerface: Experimental Setup



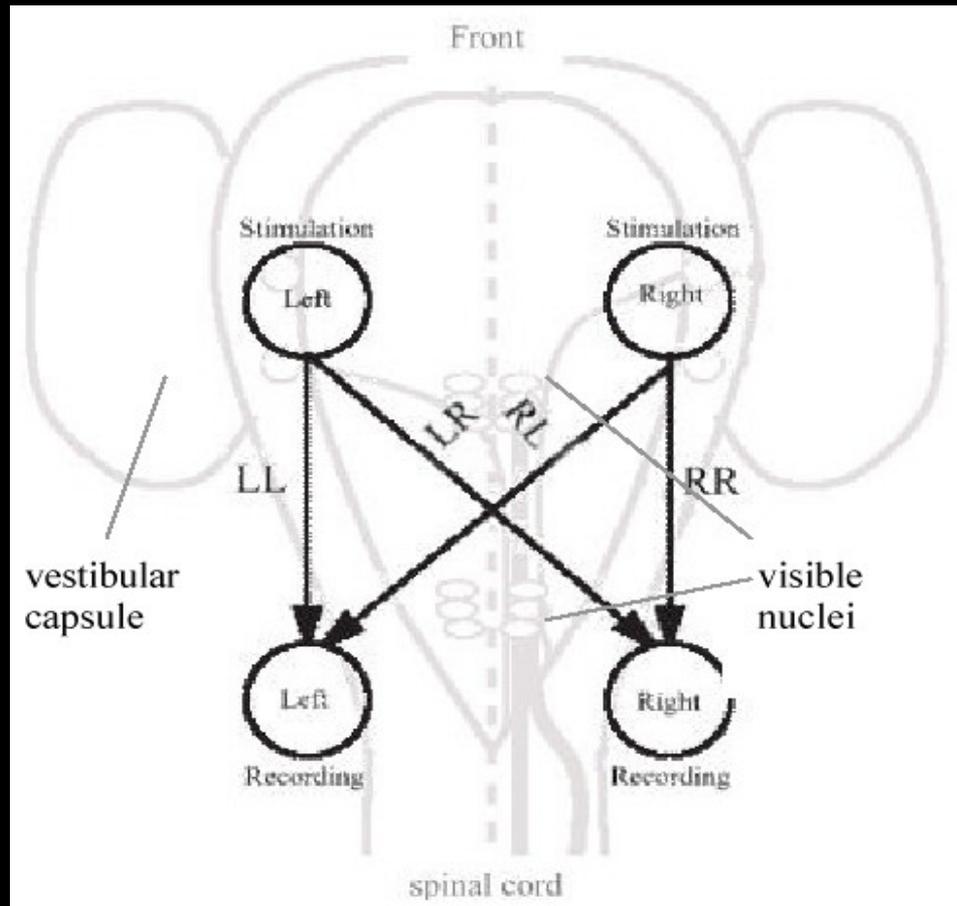
Core of the neuro-robotic interface: Stimulating electrodes and recording electrodes. The former deliver and the latter sense electrical stimulation that was modified by the brain of the lamprey sitting in the recording chamber.

Neurointerface: Experimental Setup



abstracted network for predicting the lamprey's behavioral responses.

Neurointerface: Experimental Setup



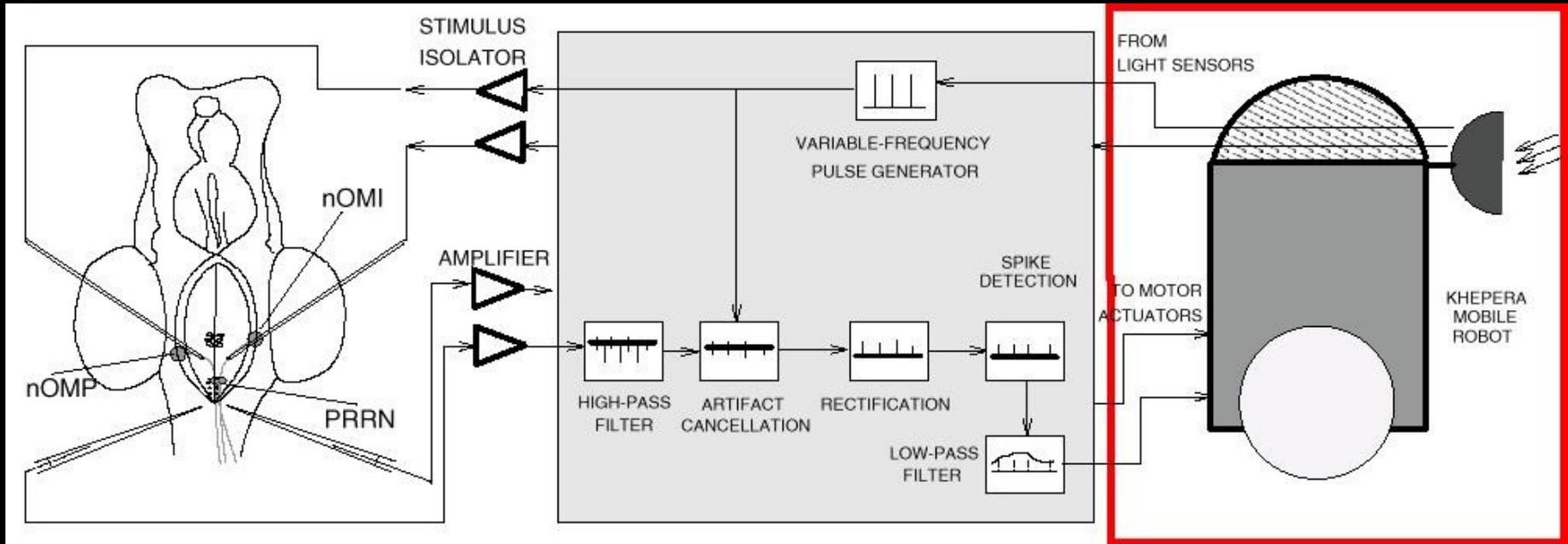
abstracted network for predicting the lamprey's behavioral responses.



Neurinterfacing: the artificial behavior

1. The axons of the vestibular system are delivered artificial (visual) signals sensed by the robot's eyes.
2. Instead of adjusting the body's position in space, the lamprey controls a robot.

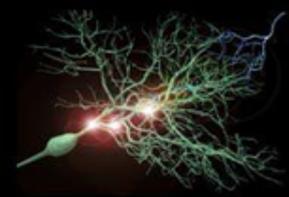
Neurointerface: Experimental Setup



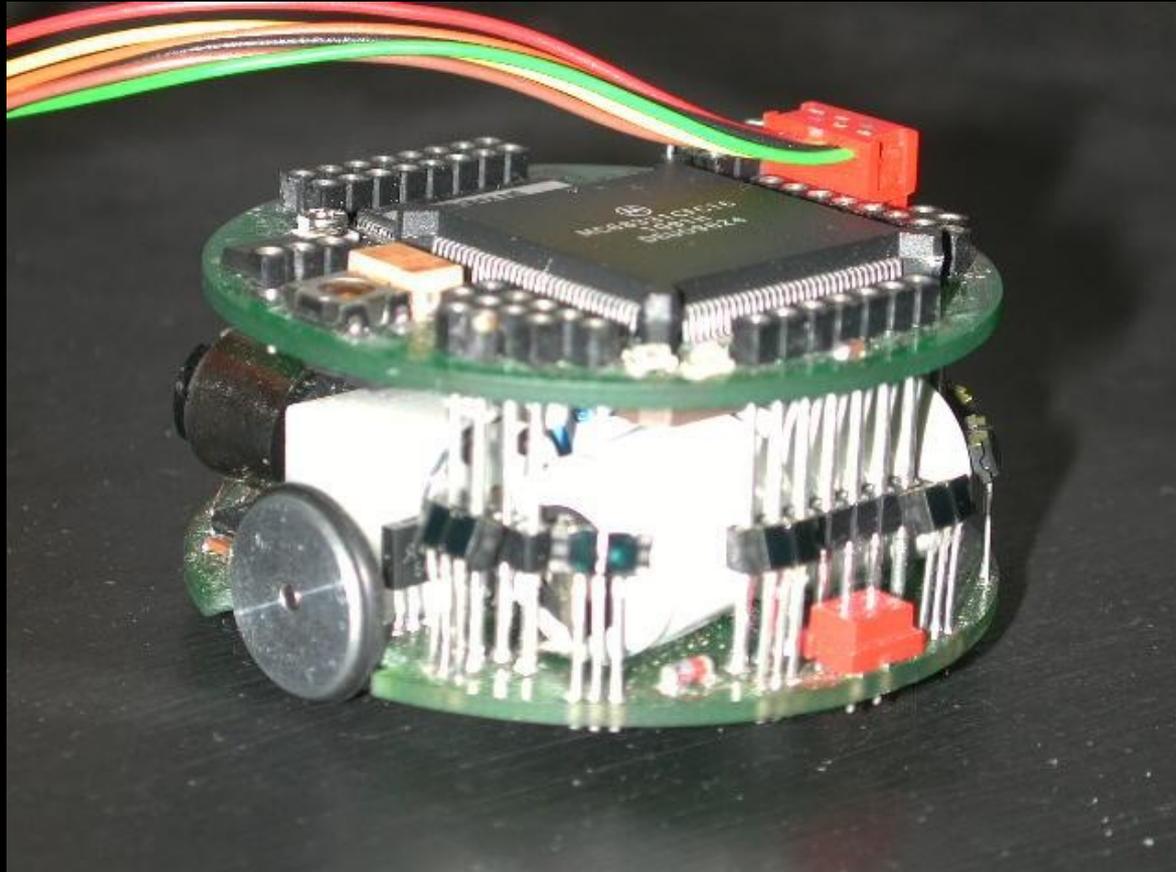
in vitro preparation

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Khepera

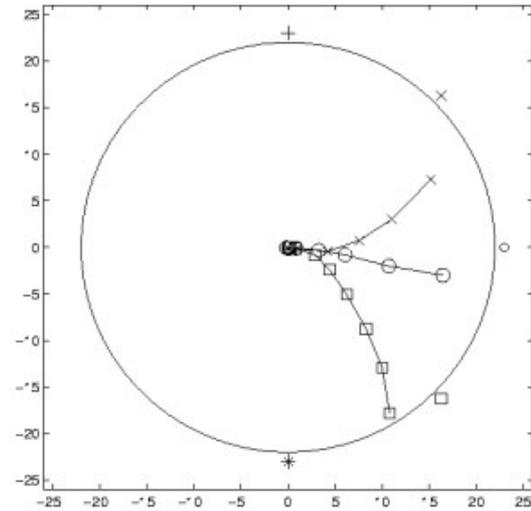
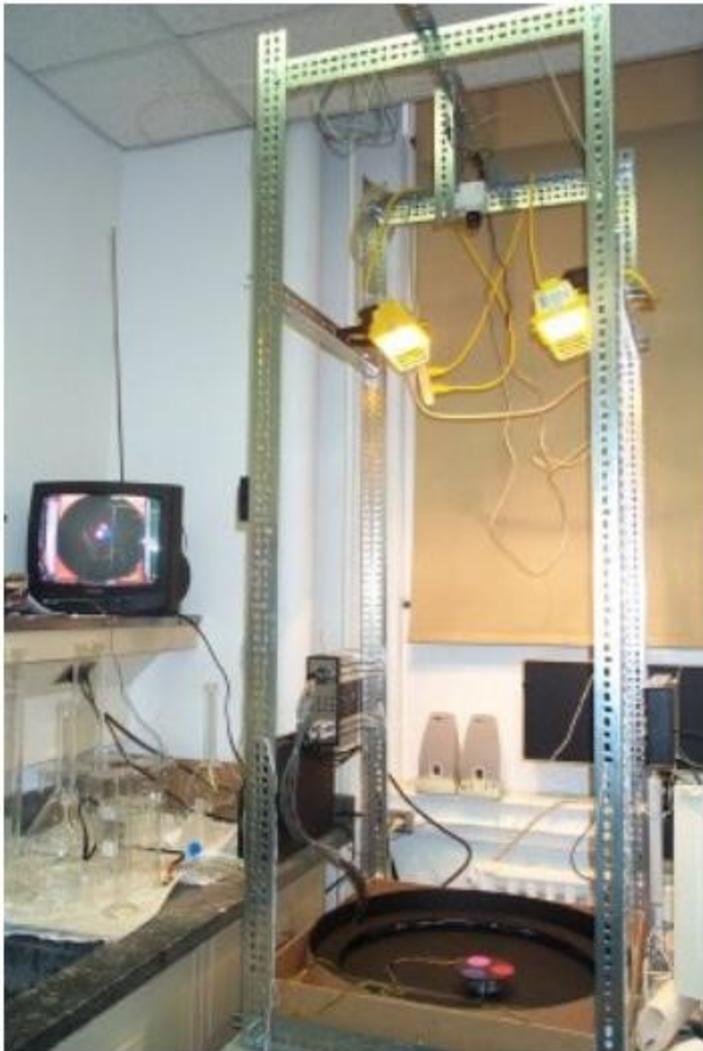


Neurointerface: Experimental Setup



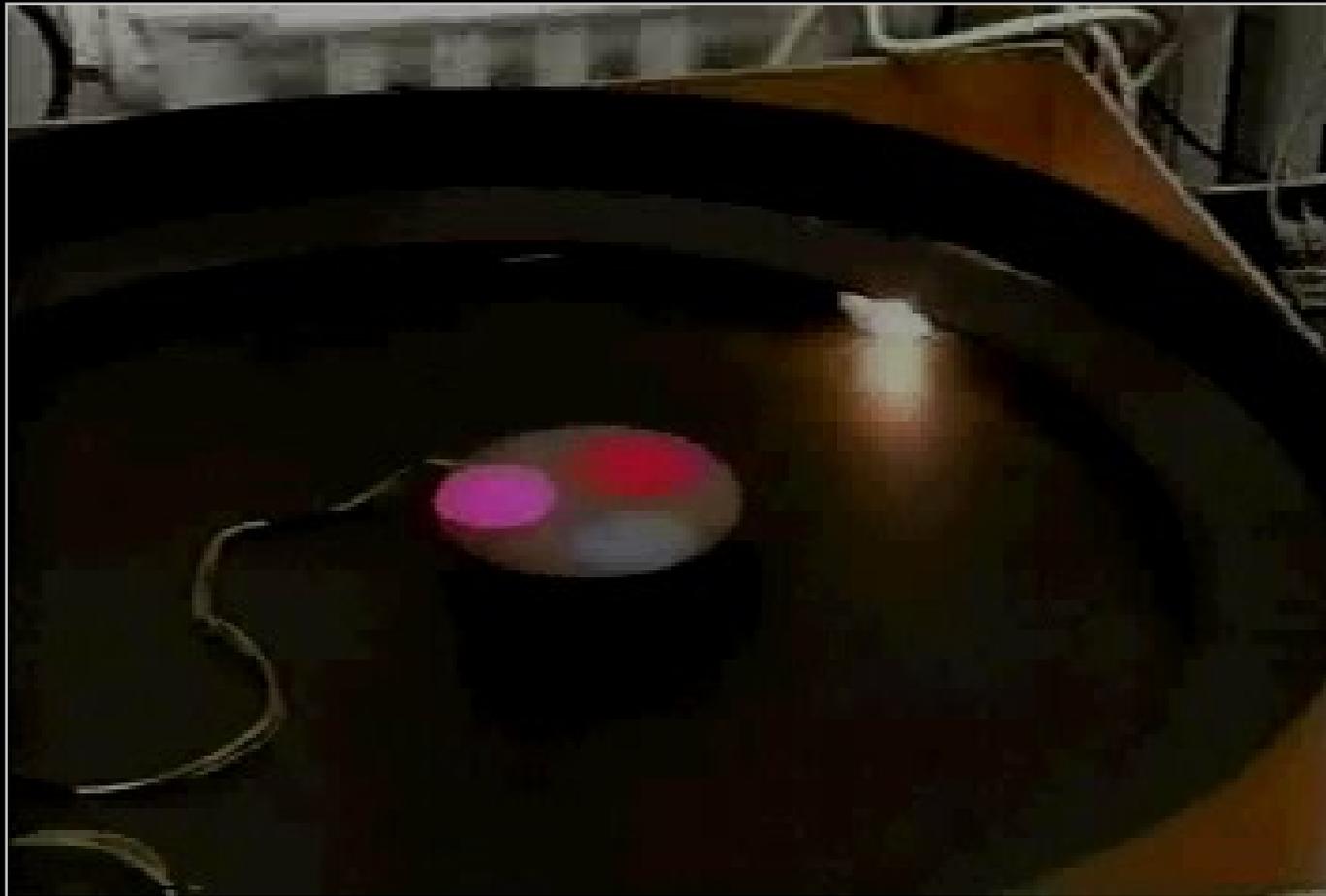
Khepera: star-guest from Switzerland

Neurointerface: Experimental Setup

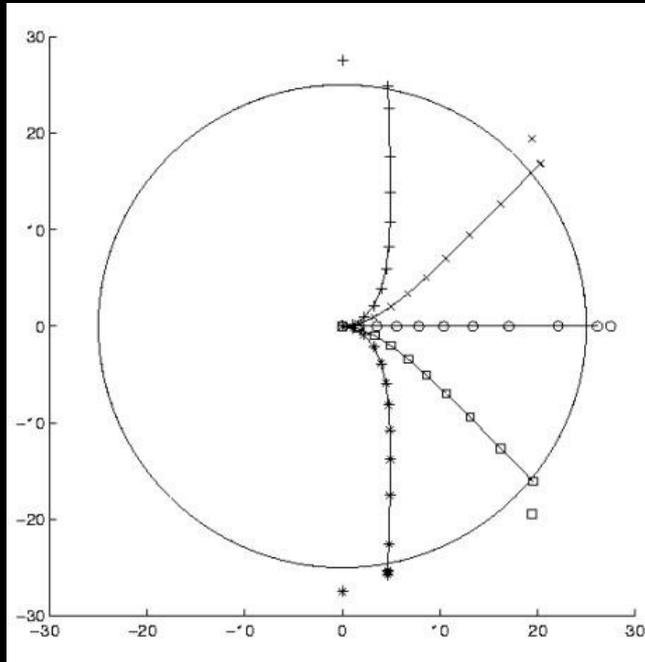




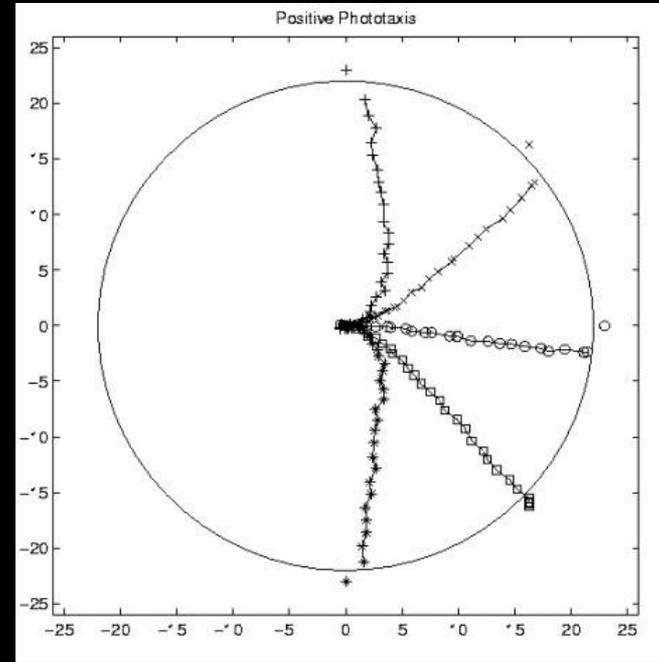
Neurointerface: Experimental Setup



Neurointerface: Theory versus Experiment

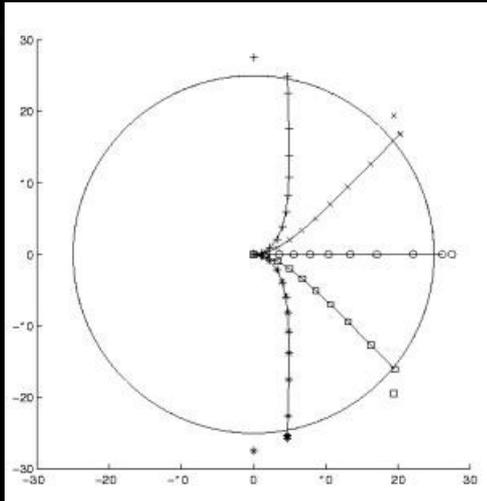
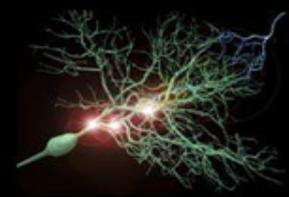


computer simulated behavior



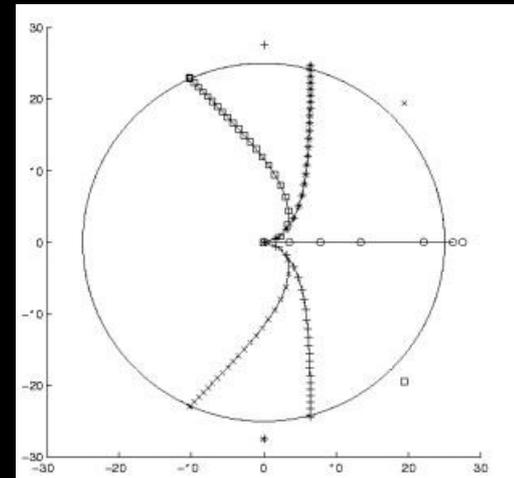
experimentally recorded behavior

Neurointerface: Computer simulated behavior

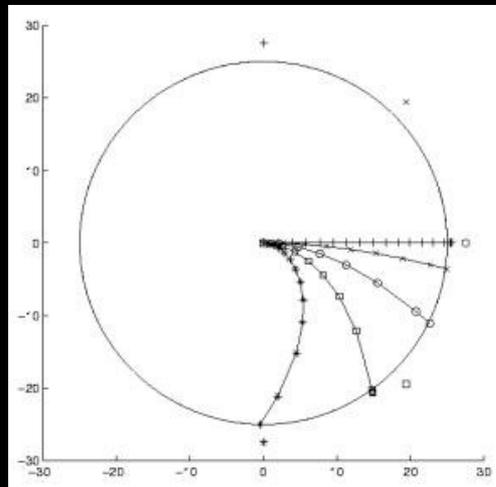


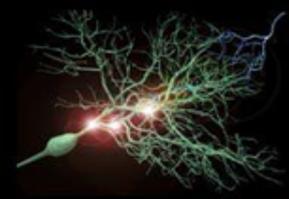
positive phototaxis

mixed taxis



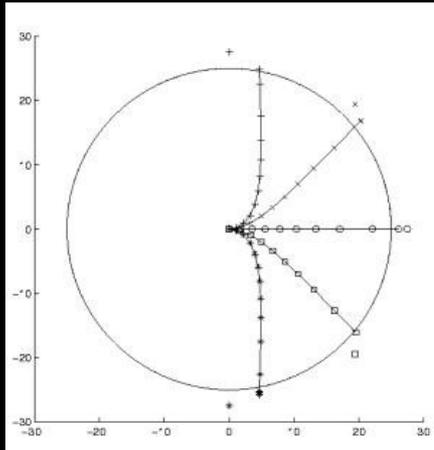
negative phototaxis



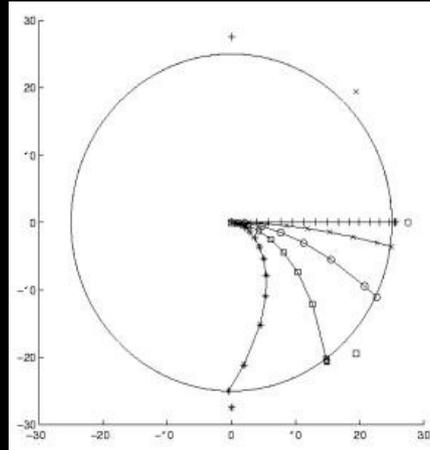


Neurointerface: Theory versus Experiment

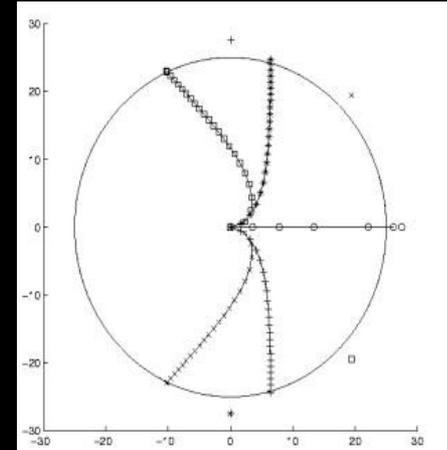
computer simulation



positive phototaxis

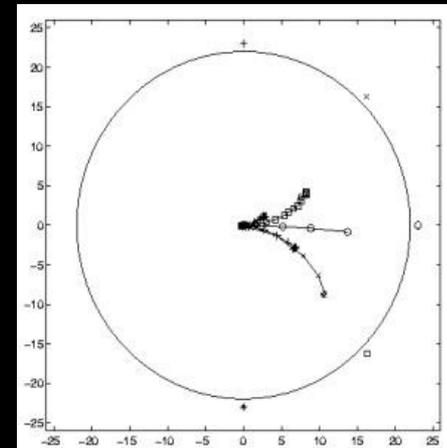
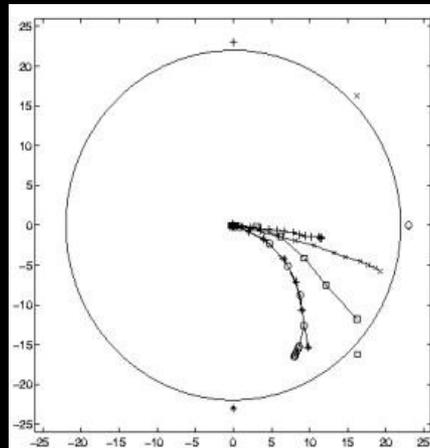
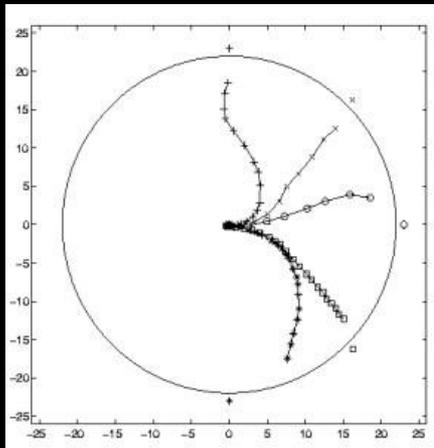


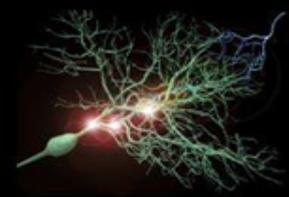
mixed taxis



negative phototaxis

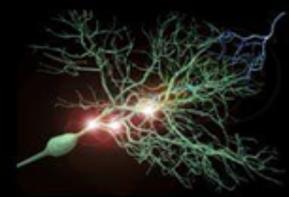
experimentally recorded behavior





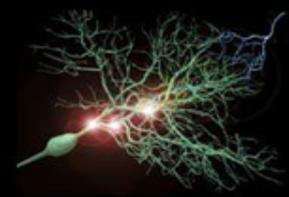
Connecting Brains to Robots: Conclusions

1. Behavioral changes remain for several hours if asymmetric illumination is applied.
2. Adaptive compensation can be measured both on behavioural and synaptic level. Synaptic plasticity is observable.
3. Long-term compensation can be accounted for by an unsupervised Hebbian regulation of synaptic plasticity that was triggered through moving in response to light stimuli.
4. Environmental conditions are controllable and various stimulation protocols are applicable to the lamprey's brain.
5. Principally, behavioural changes are completely determined by the nervous tissue.



Connecting Brains to Robots: Problems

- Experimental conditions are difficult to control (brain stage, dissection quality, healthiness of the lamprey, brains are individual).
- Human interference has to be minimized to avoid non-reproducible errors.
- Applied currents need to be adjusted to natural currents (nano scale).
- More positional information is required to place the stimulating electrodes at reproducible locations.
- The nutritious solution need to be optimized.



Connecting Brains to Robots: Problems

However, several open questions remain:

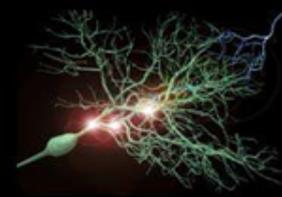
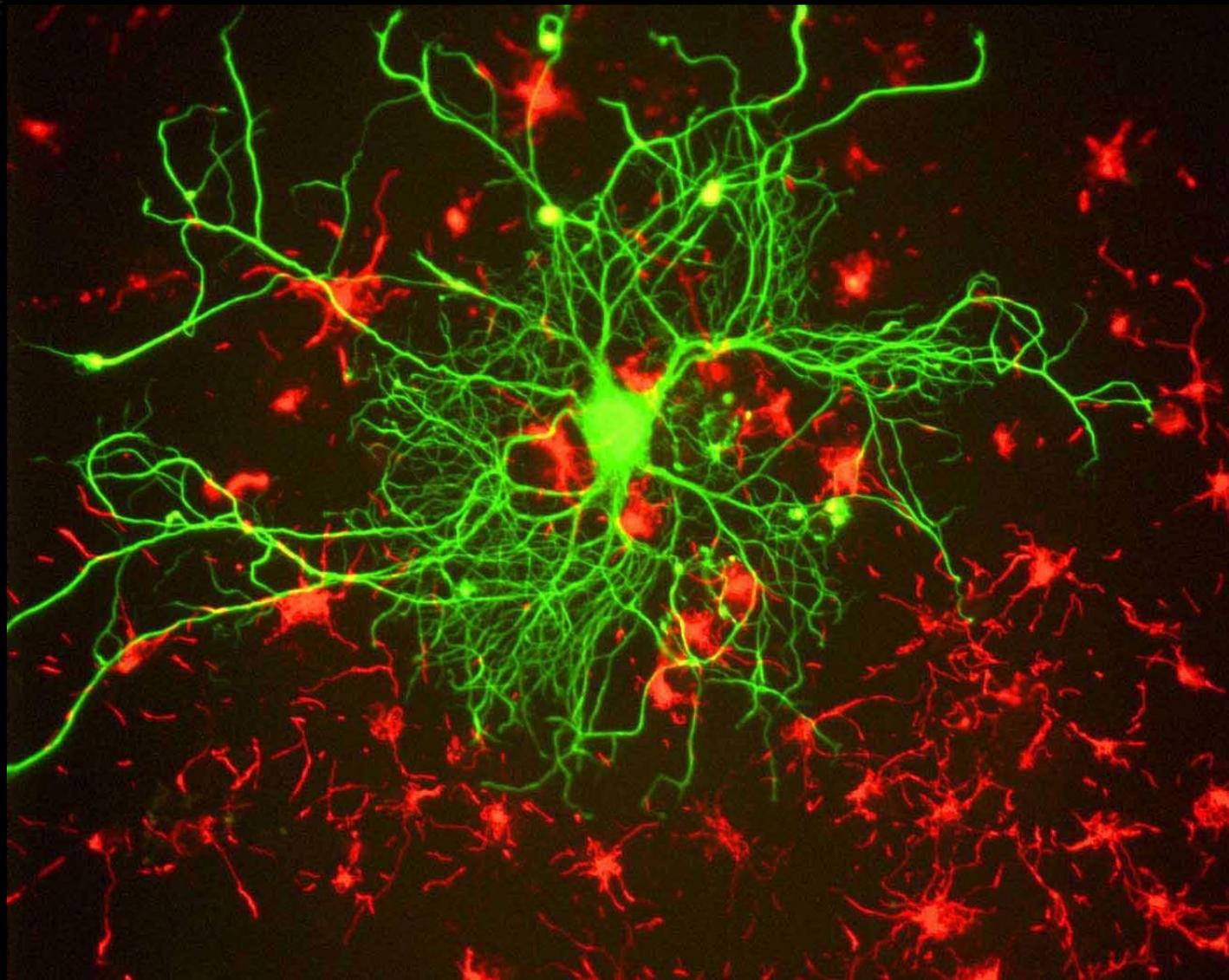
- The brain cannot be kept alive longer than for several days. Why does the brain die? What is the nutritious solution lacking?
- How can one unequivocally identify the corresponding axonal region in different brain preparations?
- How to improve the electrophysiological tools? Intracellular recording destroys the axon while extracellular recordings are too unspecific.
- How to refine the electrophysiological setup in order to get signals from several thousand neurons (instead of just a few)?
- How to capture the dynamic potential of the brain (instead of punctually sticking an electrode into the brain)?

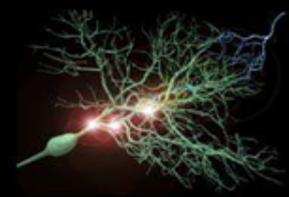


IV. A new generation of Spiking Artificial Neural Networks

- Example: Virtual Neural Tissue architectures

Diploma Thesis: Growing an Intelligent Artificial Neural Network



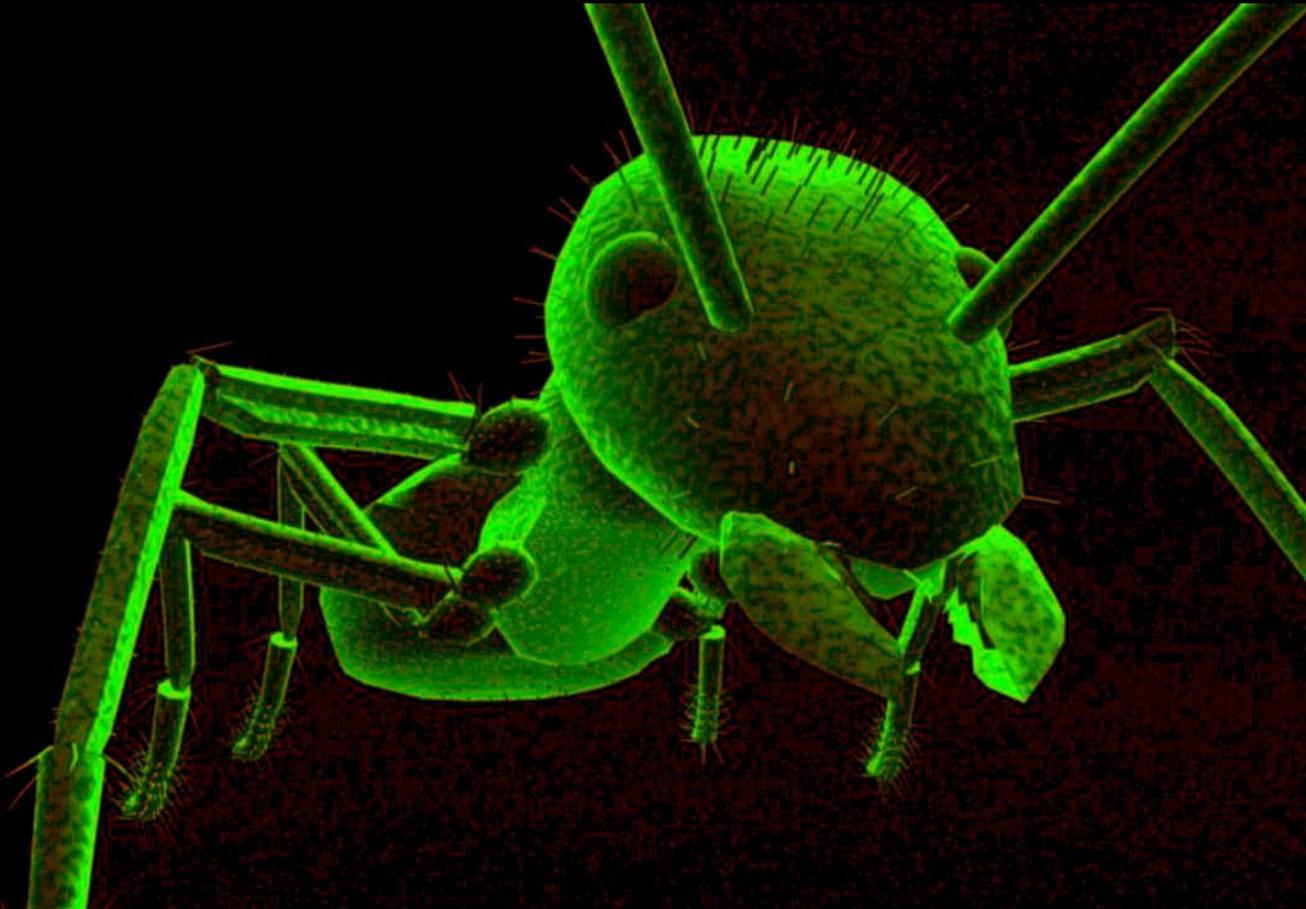


Motivation : biological Neurons





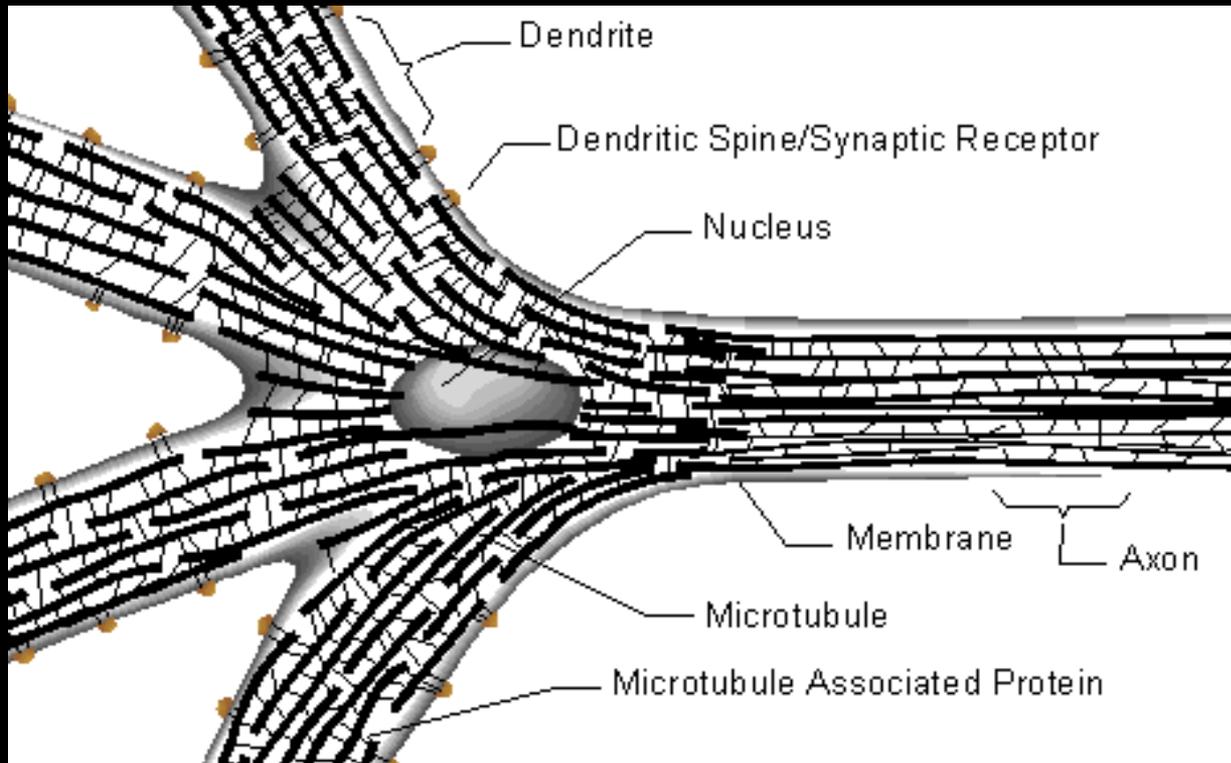
Diploma Thesis: Growing an Intelligent Artificial Neural Network



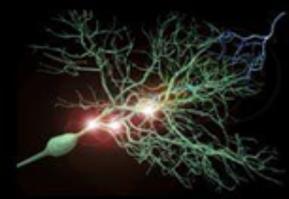
The ant analogy: intelligent microtubuli ?

Kalil, K. et al. (2000) "*Common Mechanisms Underlying Growth Cone Guidance and Axon Branching*", J. Neurobio. 44:145-158.
Penrose, R., (2000) "*The Large, the Small and the Human Mind*", UK, Cambridge University Press

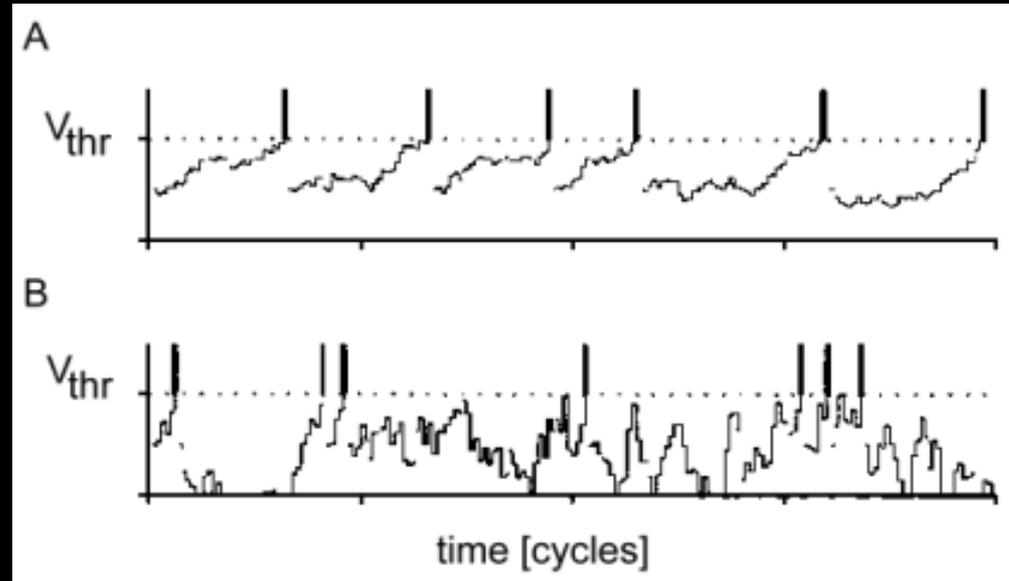
Diploma Thesis: Growing an Intelligent Artificial Neural Network



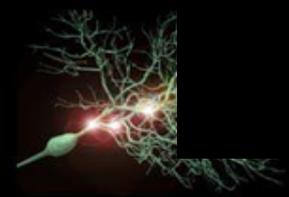
- How does a neuron grow?
- What are the underlying principles?
- How does nervous tissue emerge?
- How does it process information?
- Where are the roots of Intelligence?



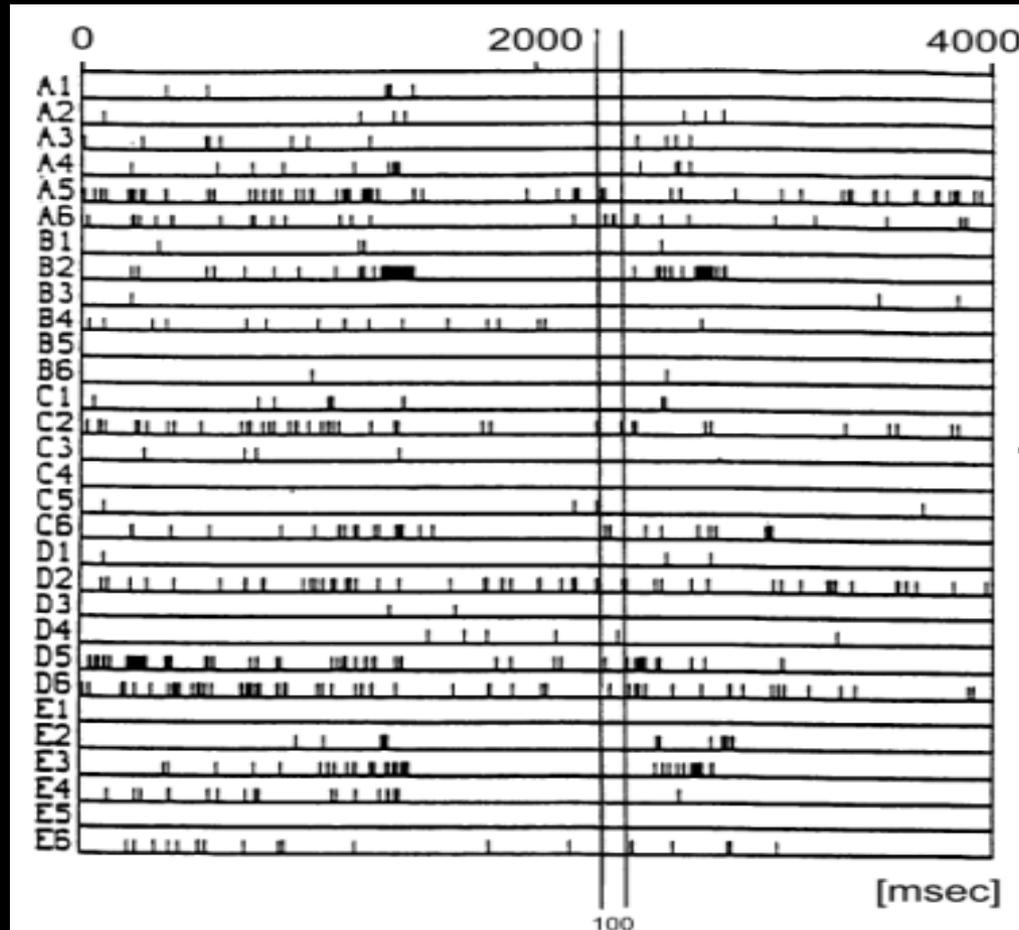
Spiking Neural Networks: Principles



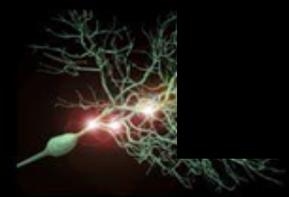
Traces illustrate how the accumulated number of net excitatory spikes may affect the potential of a given neuron. When the potential V_{thr} is reached a single spike is emitted (vertical bars) and the potential reset to V_{reset} (after Salinas et al., 2000).



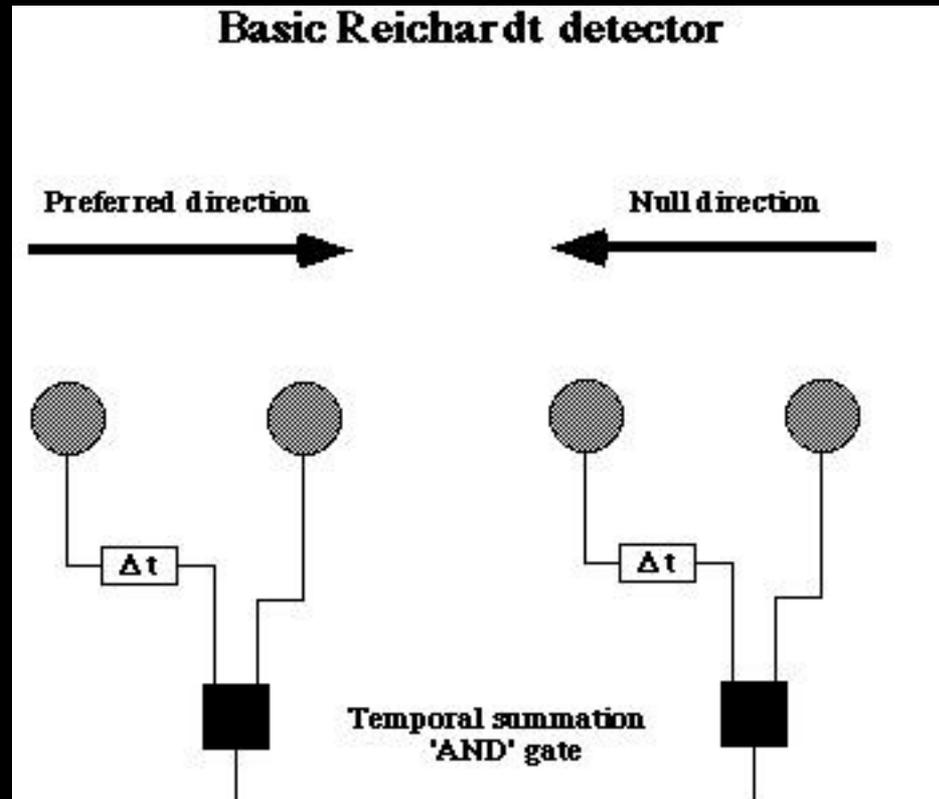
Spiking Neural Networks: Are Spikes important?



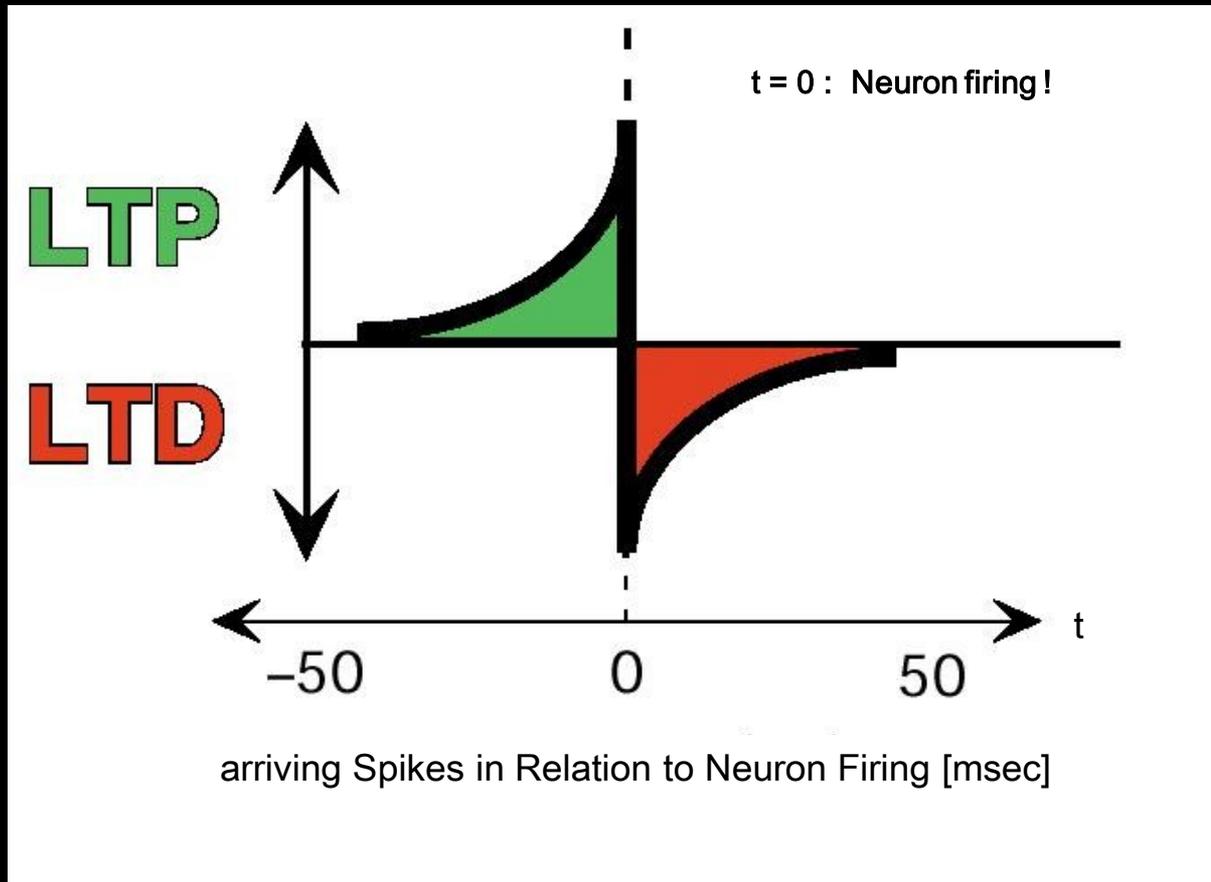
The problem of analog coding in terms of firing rates. Simultaneous recordings over 4000 msec of the firing times of 30 neurons from monkey striate cortex (Krüger et al., 1988). Each firing is denoted by a vertical bar with a separate row for each neuron. For comparison an interval of 100msec was marked and depicts the small time span that is known to suffice for the completion of complex multilayer cortical computations (adapted from Maass, 1997b).



Fast computation with single spikes: Example

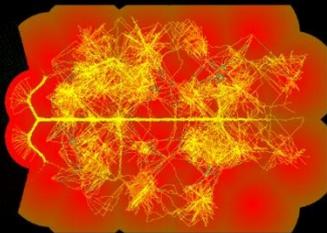
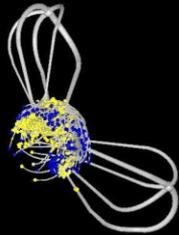
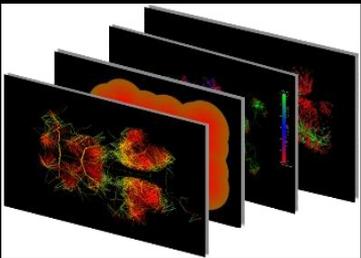
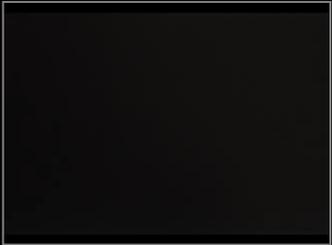
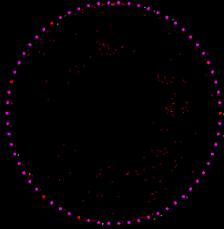
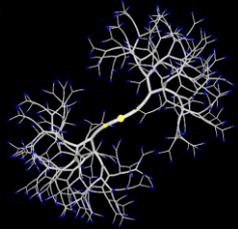
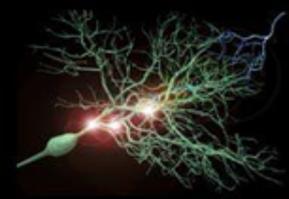


Unsupervised regulation of Neurons



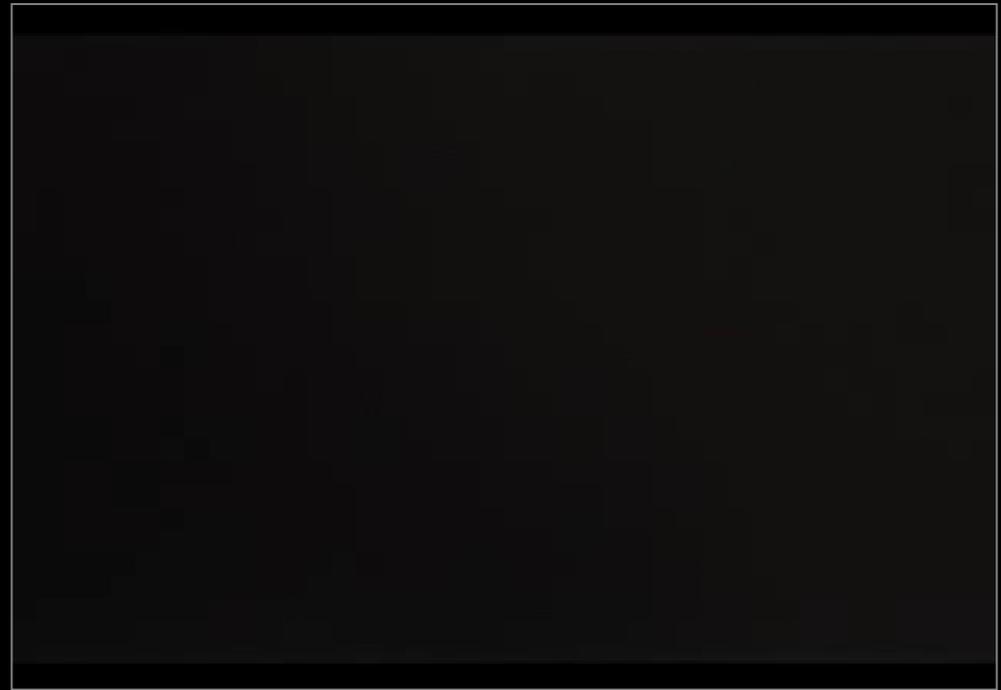
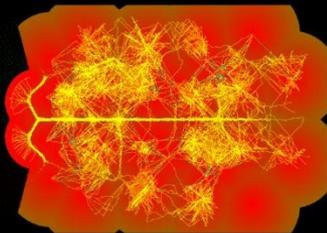
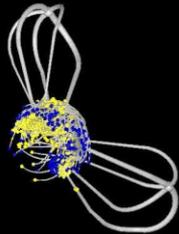
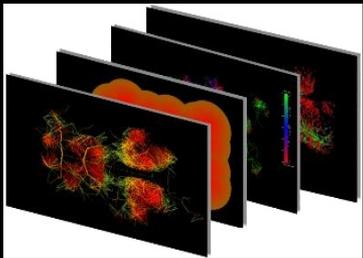
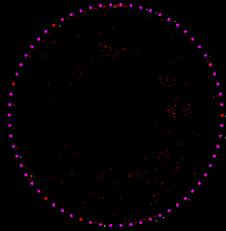
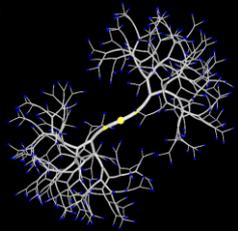
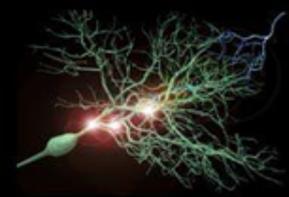
Spike Time Dependent Plasticity (STDP) as a universal learning rule?

Growing Artificial Neural Tissue: What brings the Future ?



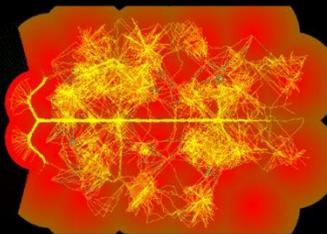
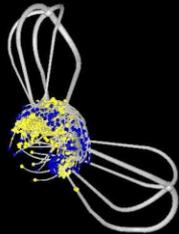
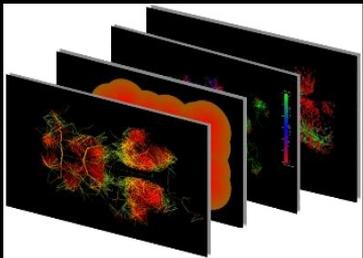
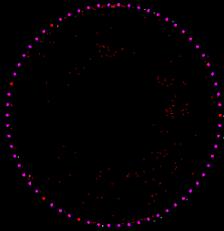
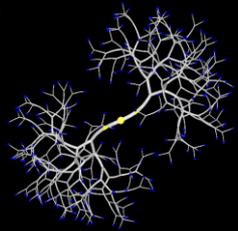
Working at the interface of computer simulations, neuroscience and robotics to tackle the phenomenon of intelligent behavior.

Growing Artificial Neural Tissue: What brings the Future ?



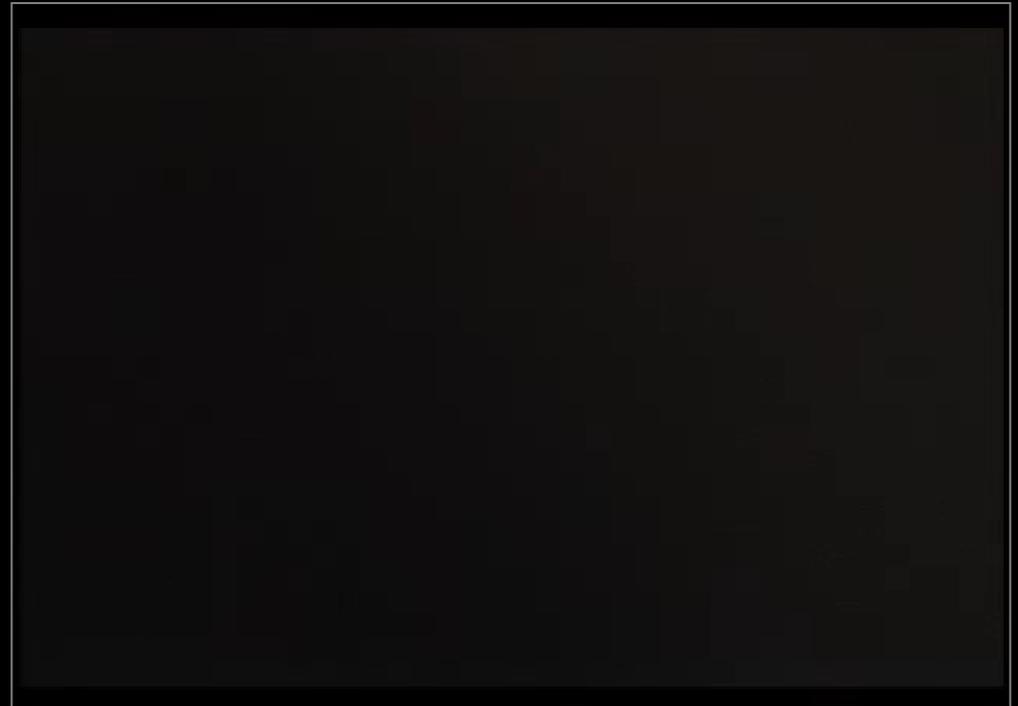
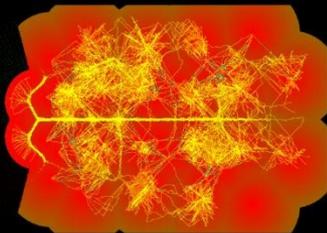
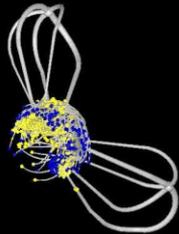
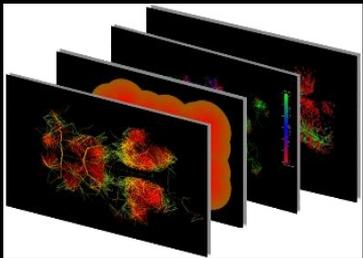
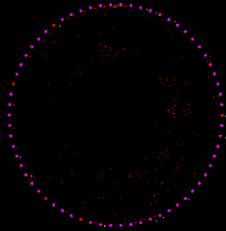
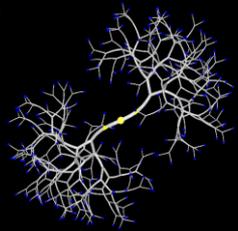
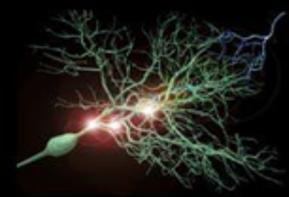
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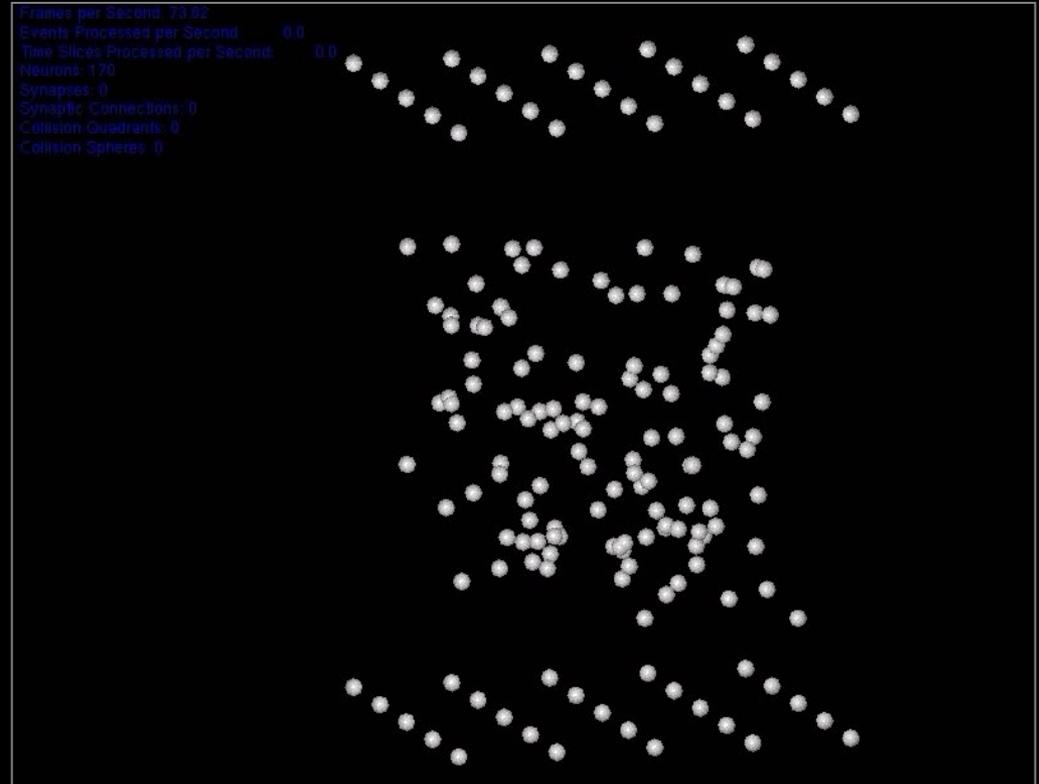
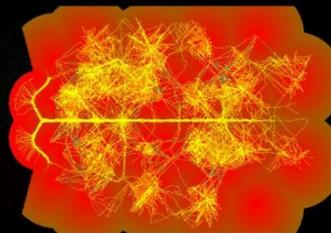
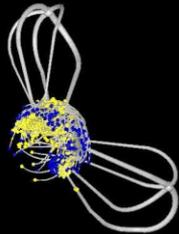
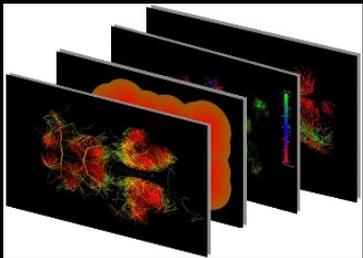
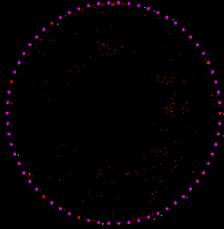
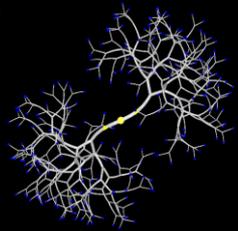
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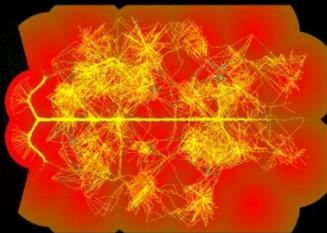
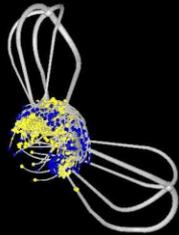
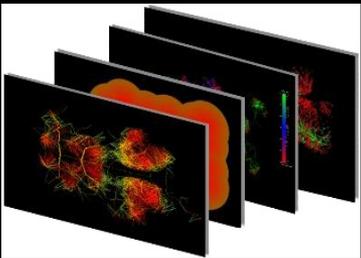
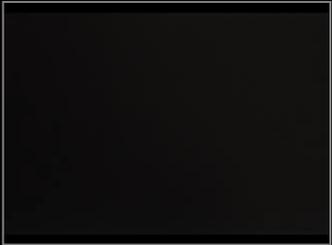
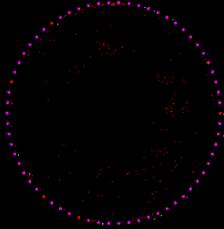
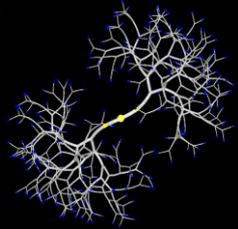
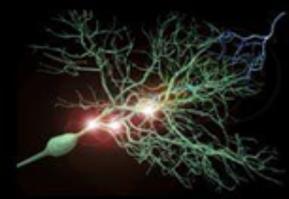
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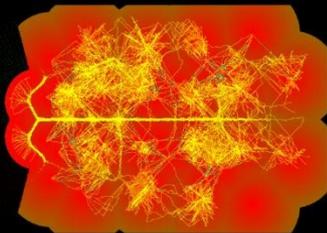
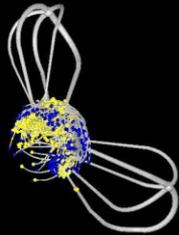
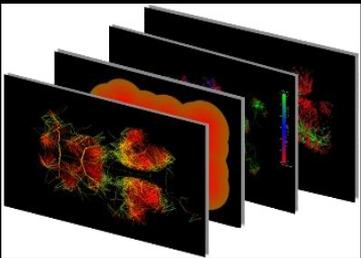
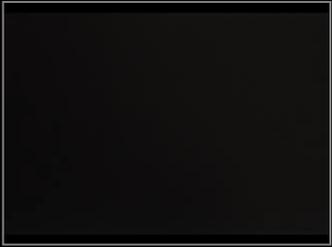
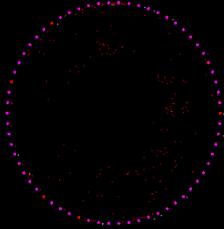
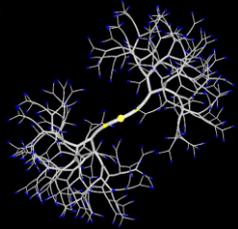
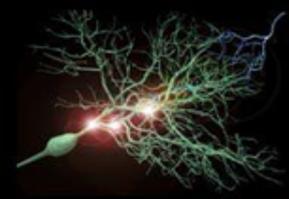
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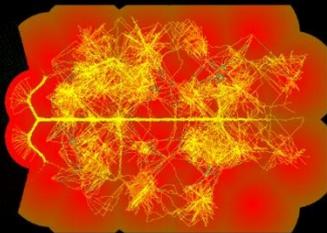
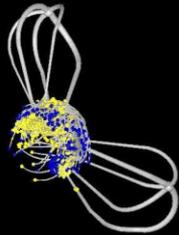
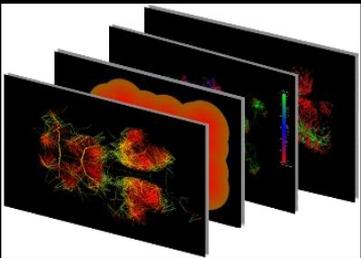
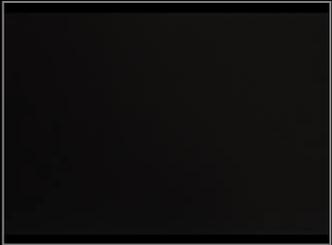
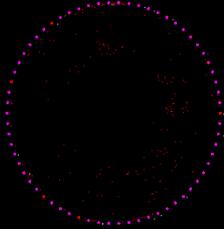
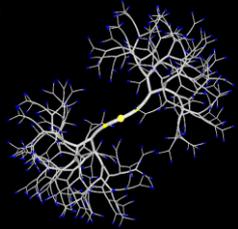
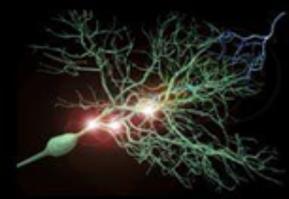
Working at the interface of computer simulations, neuroscience and robotics to tackle the phenomenon of intelligent behavior.

Growing Artificial Neural Tissue: What brings the Future ?



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Growing Artificial Neural Tissue: What brings the Future ?



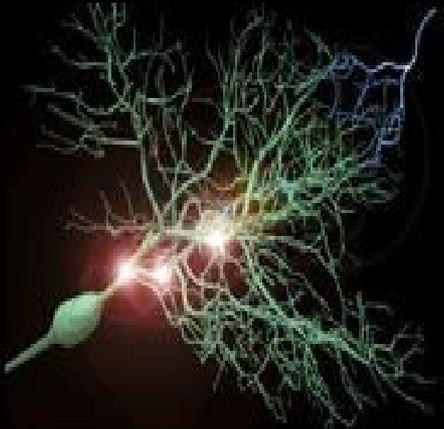
Working at the interface of computer simulations, neuroscience and robotics to tackle the phenomenon of intelligent behavior.

Thank you for your attention.

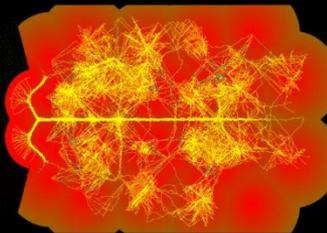
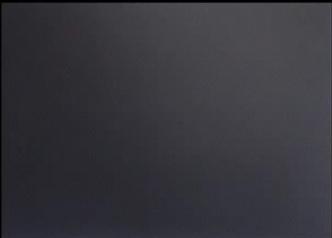
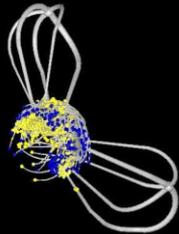
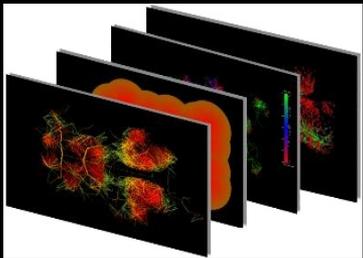
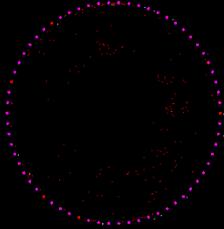
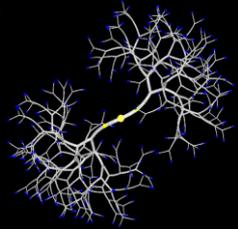
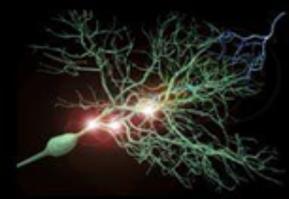
Beta

ANTIOXYDANT

- F P - 2
- T O Z - 3
- L P E D - 4
- P E C F D - 5
- E D F C X P - 6
- 7
- P E L O P H P - 7
- 8



Growing Artificial Neural Tissue: What brings the Future ?



Working at the interface of computer simulations, neuroscience and robotics to tackle the phenomenon of intelligent behavior.



F P 2
T O Z 3
L P E D 4
P E C F D 5
E D F C X P 6
P E L O P E D 7





There is still a long way to go ...