An Artificial Brain Mechanism to Develop a Learning Paradigm for Robots

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Need for Biological Brain Inspired Ultra-Low Energy Computing

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Human vs. Robot for Space Exploration

Humans hold a number of advantages over robots. They can make quick decisions in response to changing conditions or new discoveries, rather than waiting for time-delayed instructions from Earth.

http://www.wired.com/2012/04/space-humans-vs-robots/

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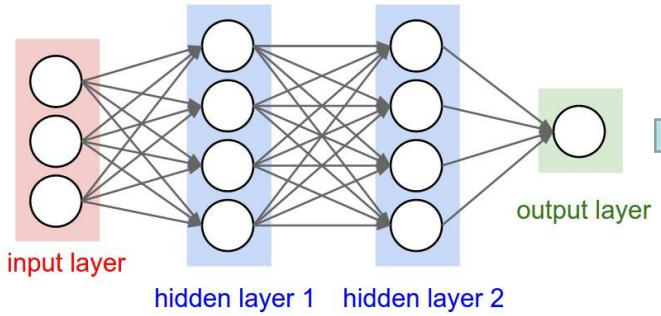
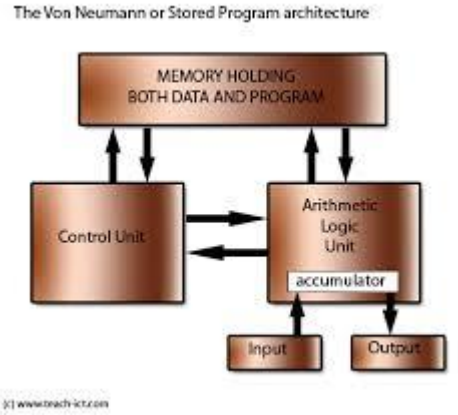
Limitations of Currently Available Machine Learning: Deep Neural Network (DNN)





DNN on conventional computing architecture are compute intensive, power hungry, need a large set of training data , and are trained to solve just some specific sets of problems.

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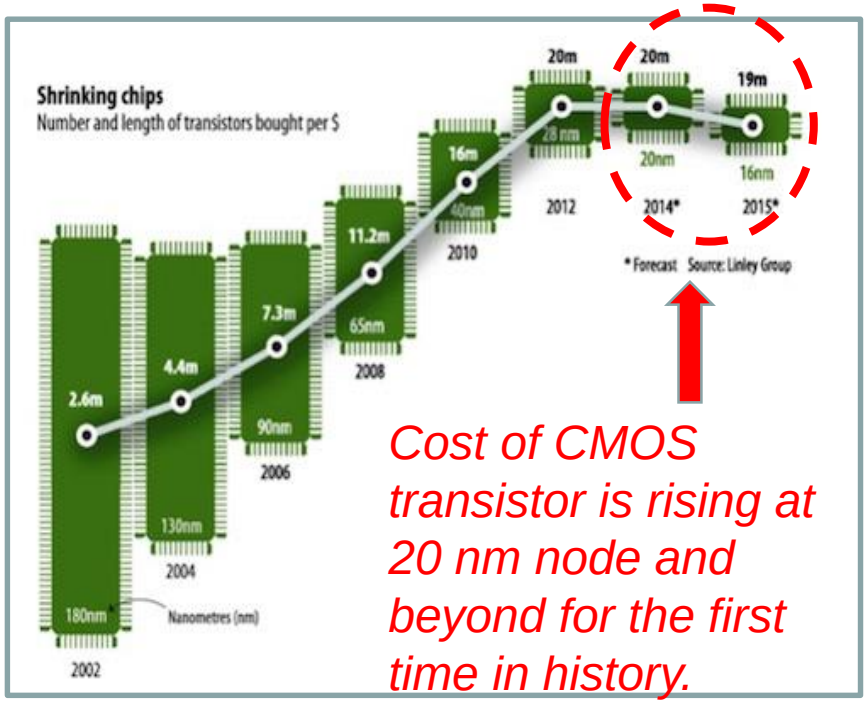
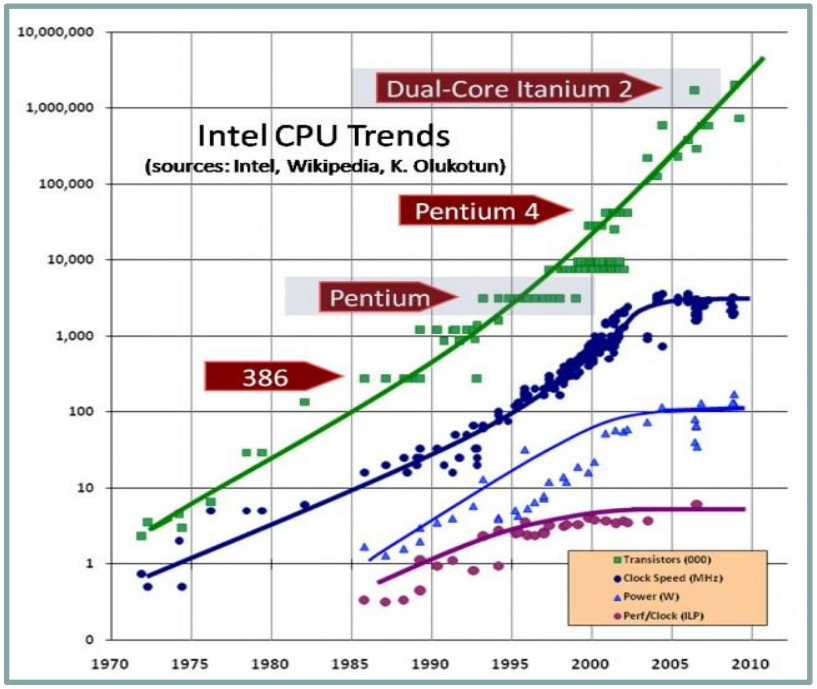
Limitations of Traditional CMOS Transistor Scaling and Computing



Cost of CMOS transistor is rising at 20 nm node and beyond for the first time in history.



http://epc-co.com/epc/EventsandNews/FastJustGotFasterBlog/Issue11.aspx

http://www.extremetech.com/computing/116561-the-death-of-cpu-scaling-from-one-core-to-many-and-why-were-still-stuck

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Motivation for Artificial Brain

"Challenge is to create an exascale computing system by 2018 that consumes only 20 megawatts (MW) of power."- DOE grand challenge.

Supercomputers

Scalable

Ultra Low-Energy

Brain

"Taking advantage of the almost 83,000 processors of one of the world's most powerful supercomputers, the team was able to mimic just one percent of one second's worth of human brain activity—and even that took 40 minutes." – *Gizmodo, 2013*

"10^{14} Neurons, 10^{15} Synapses, 10^{13} to 10^{16} Instructions per sec, 10 W of Power (e.g. retinal operation)."

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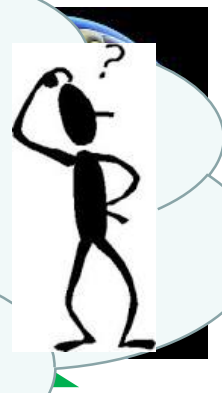
Motivation for Artificial Brain

"Challenge is to create an exascale computing system by 2018 that consumes on megawa power." challenge

Supercomputers

Brain



- How does a biological "Brain" work ??
- How can we make an artificial brain on chip???

"Taking advanta processors of one of the world's fa powerful supercomputers, the team was able to mimic just one percent of one second's worth of human brain activity—and even that took 40 minutes." – *Gizmodo, 2013*

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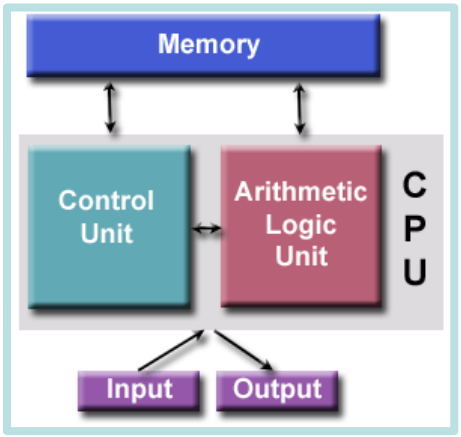
How Does a Biological Brain Process Information?

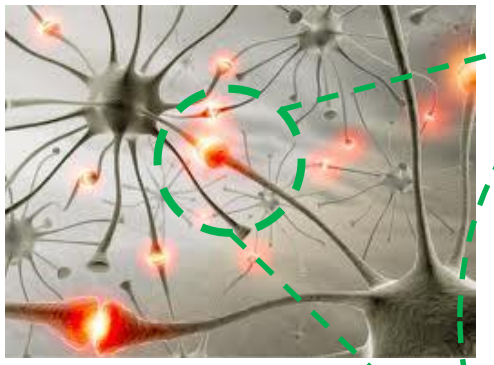
Today's Computing

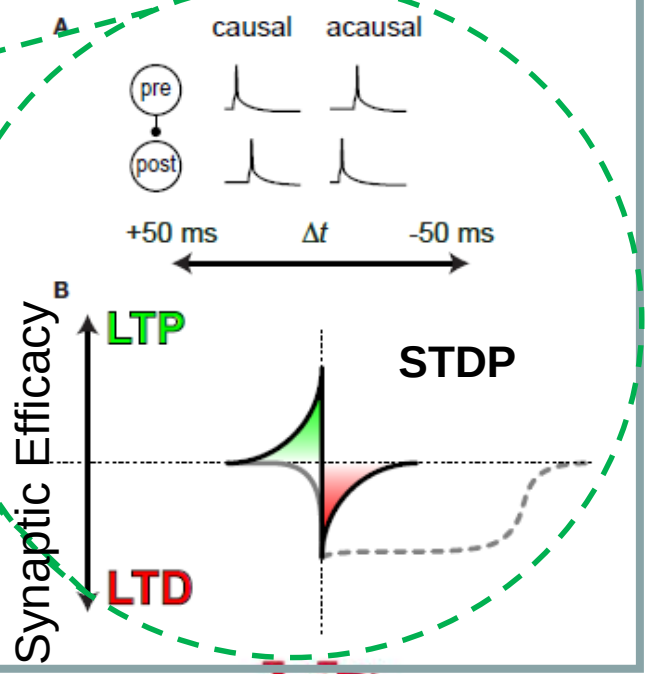


Von-Neumann Architecture

https://computing.llnl.gov/tutorials/parallel_comp/

Brain-Inspired Paradigm of Computing





Components: Neurons, Reconfigurable Synapses, Interconnects

Markram et. al., Front. Synp. NeurosSc. 2011

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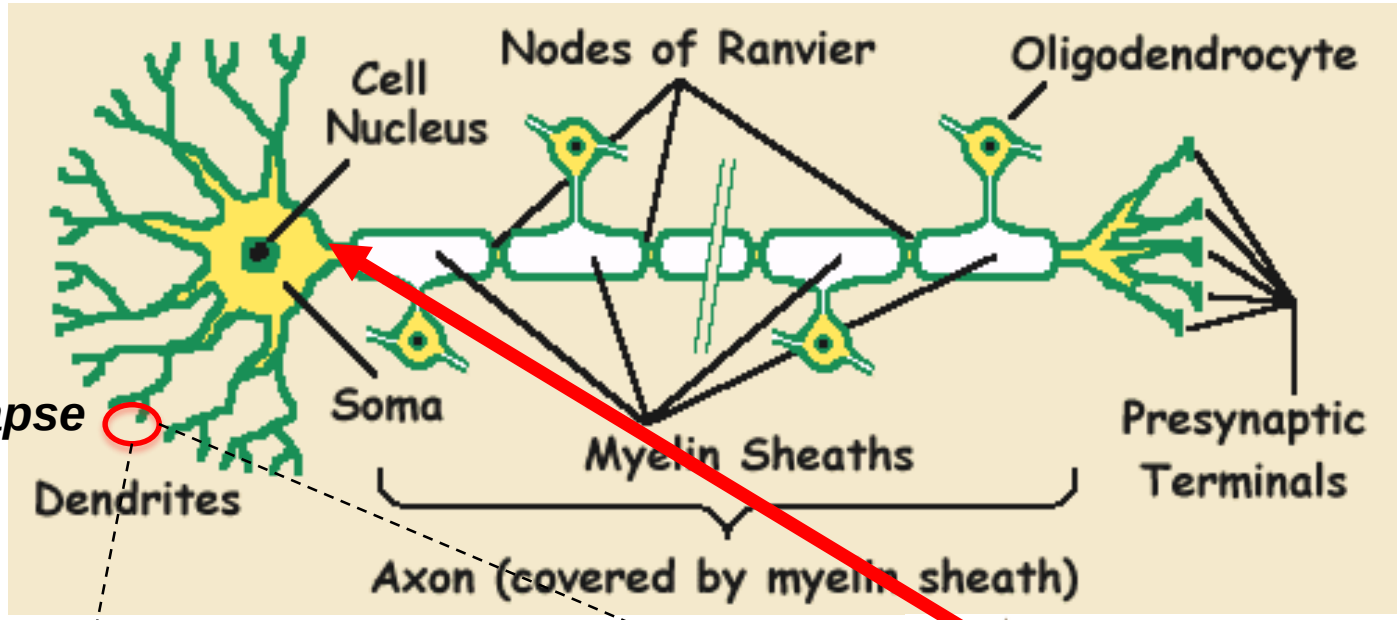
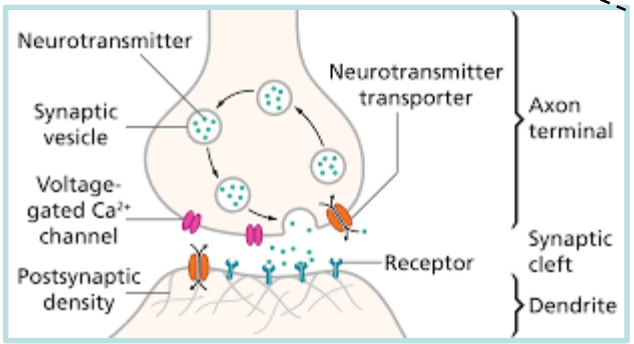
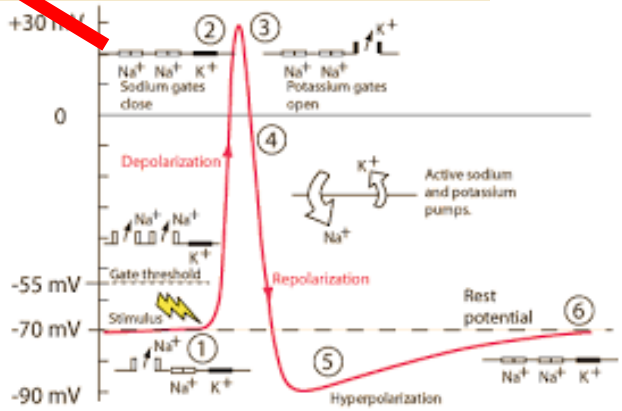
Neuron Operation and Action Potential Firing







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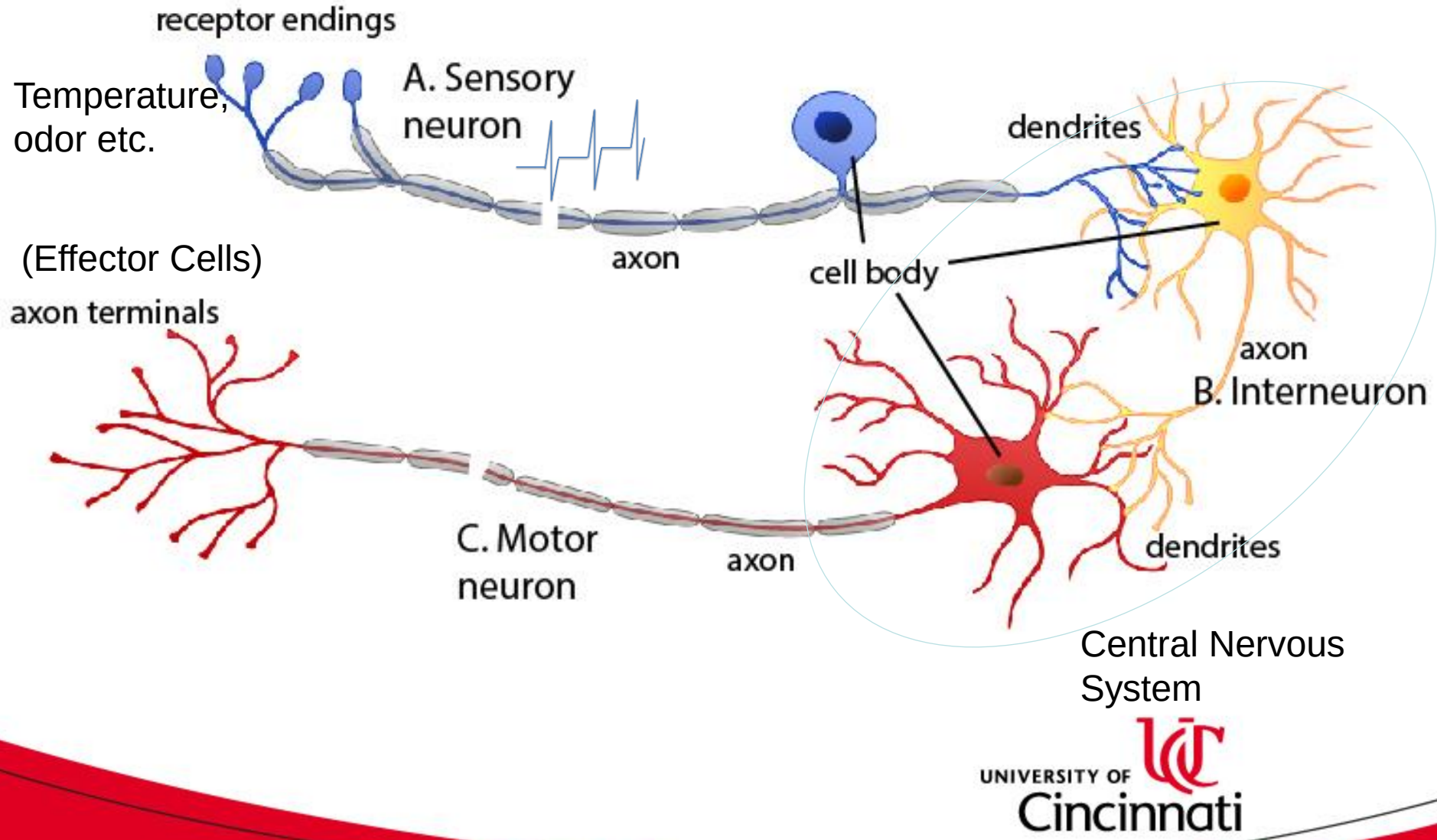
Sensory Signal Processing



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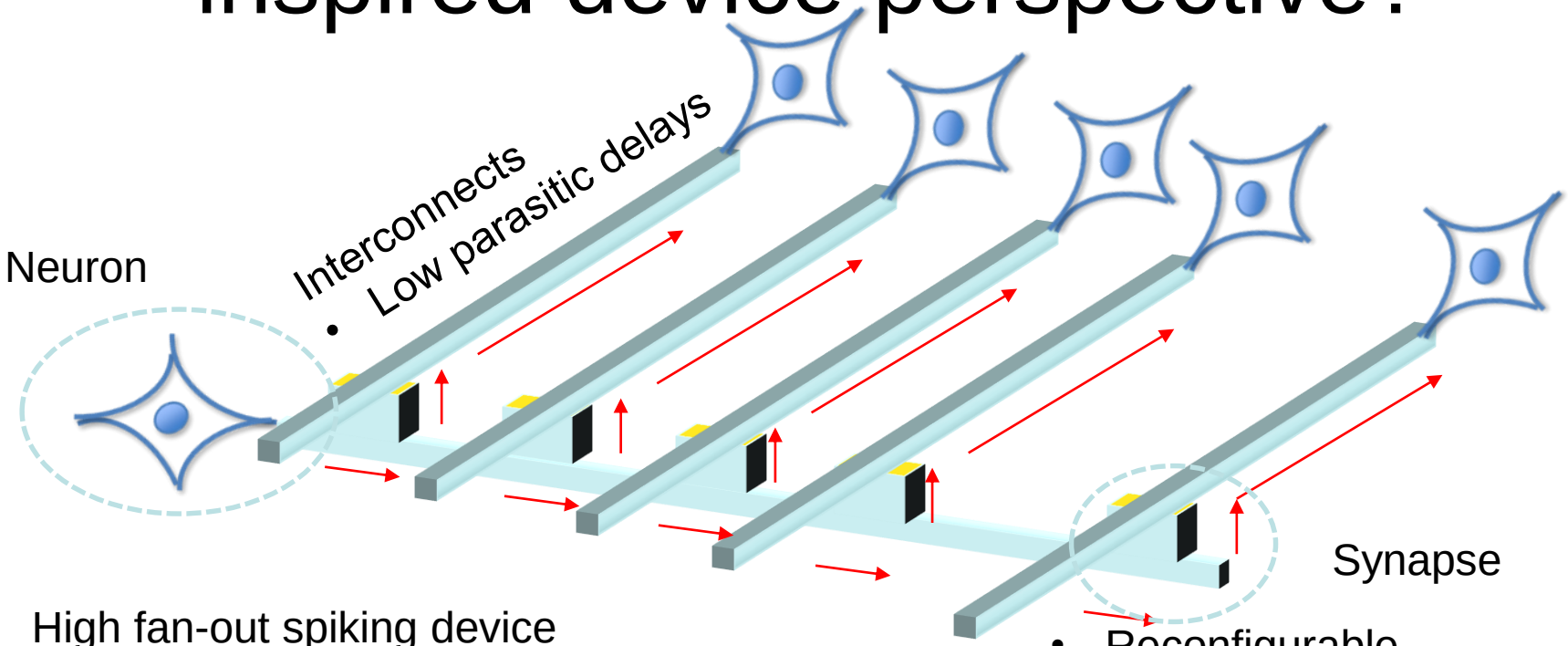
What does it mean from neuro-inspired device perspective?



- High fan-out spiking device
- Ultra-low energy consumption ~10 fJ/spike
- Scalable
- High reliability and endurance

- Reconfigurable
- Ultra Low-power
- Scalable
- High endurance and reliability
- Minimal Variability

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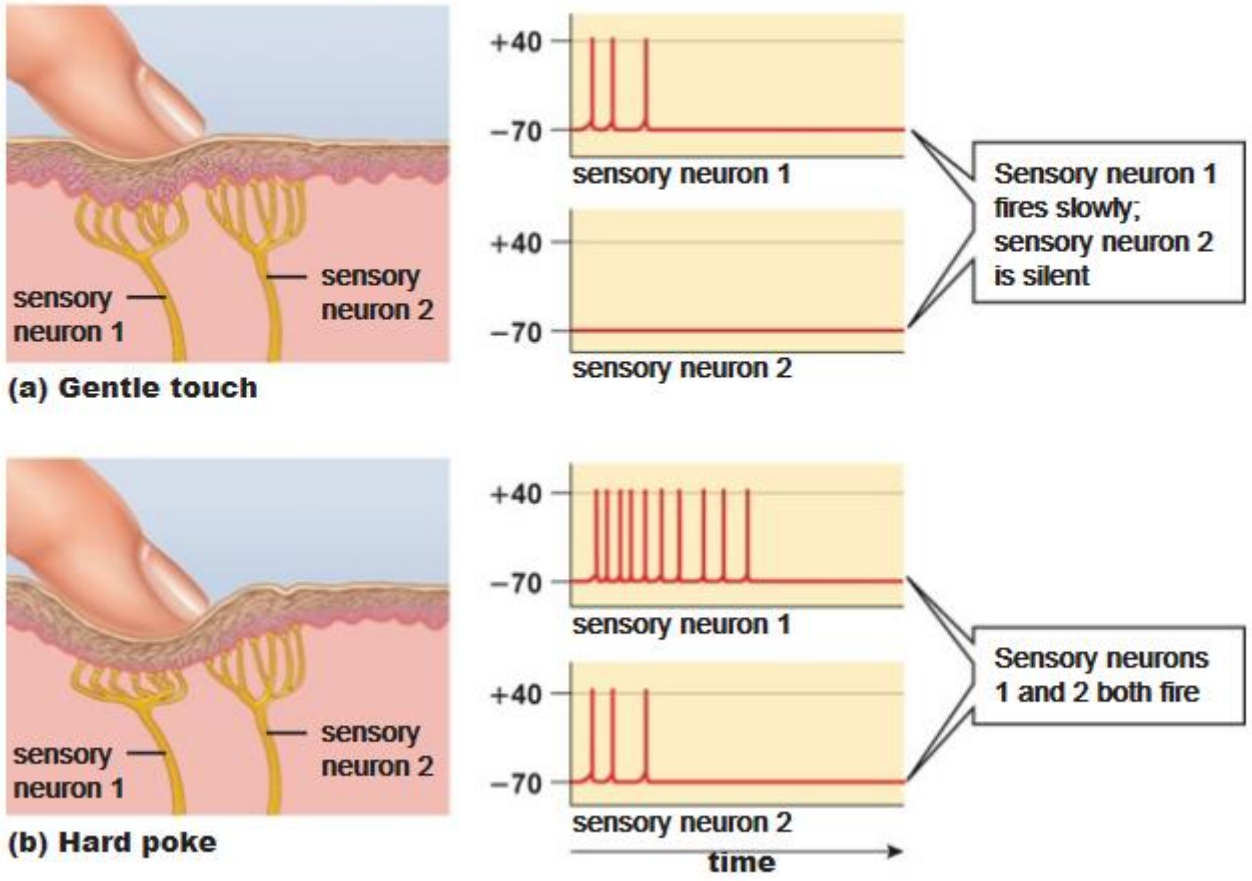
Sensory Information Coding

Signaling Stimulus Intensity



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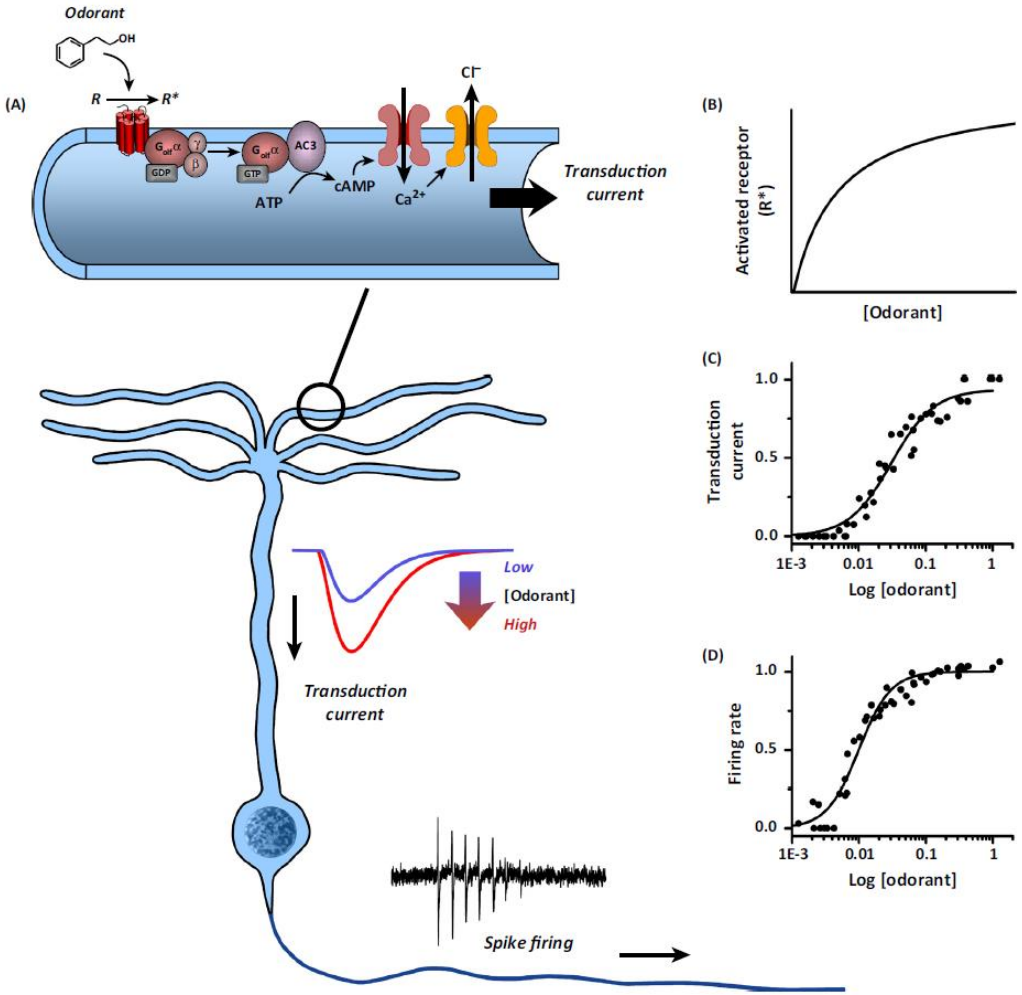
Spike Coding of Odor



TRENDS in Neurosciences

Mainland et. al., Trends in Neurosciences August 2014, Vol. 37, No. 8

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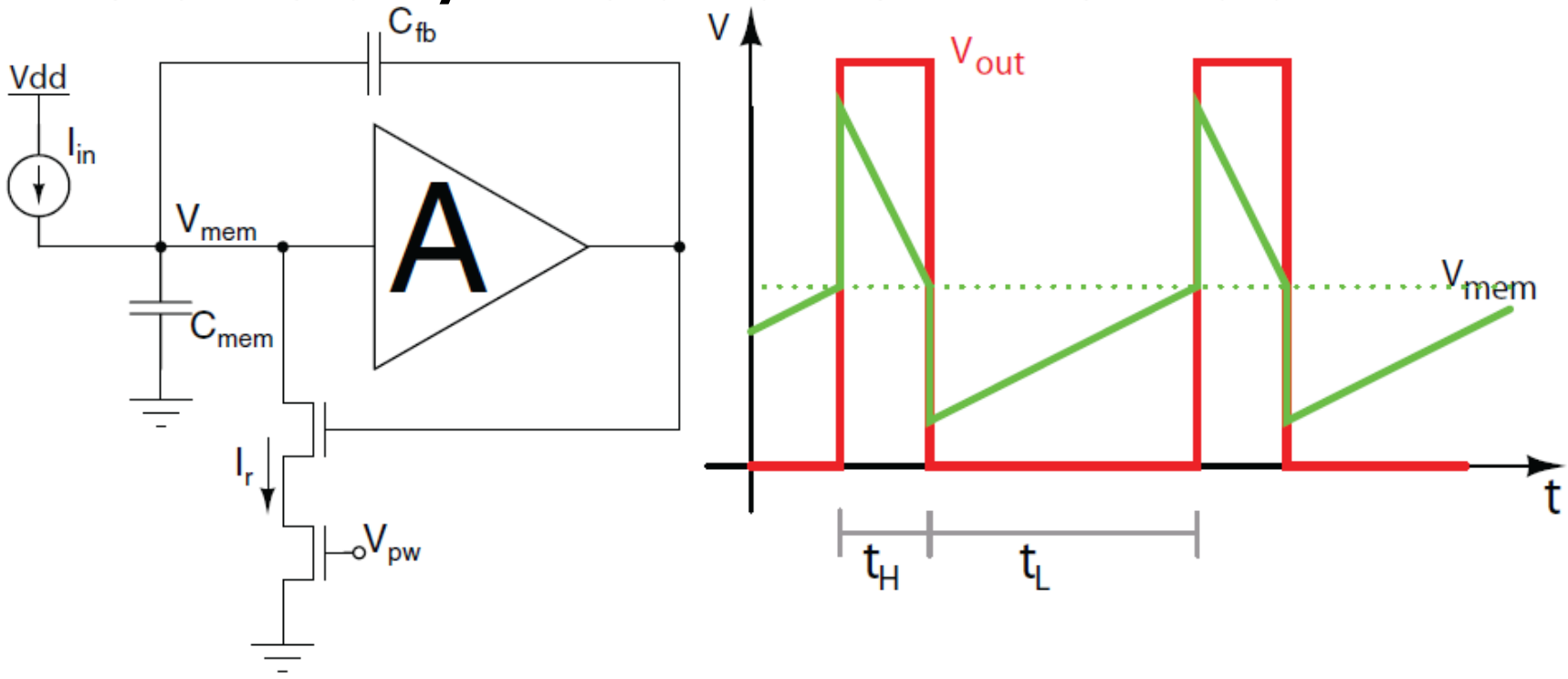
Sensory Neurons in Silicon



Axon-Hillock Circuit, proposed by Prof. Carver Mead, 1980's

Indiveri et. al., Frontiers in Neuroscience, 2011

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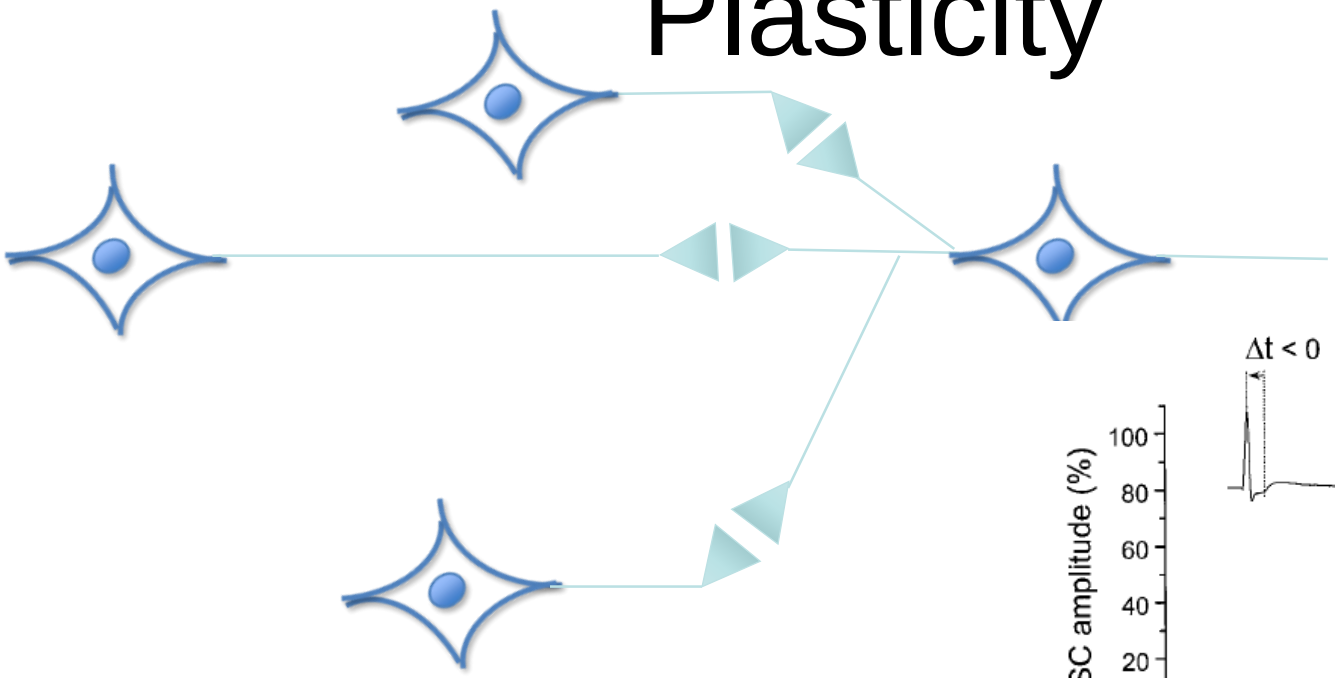
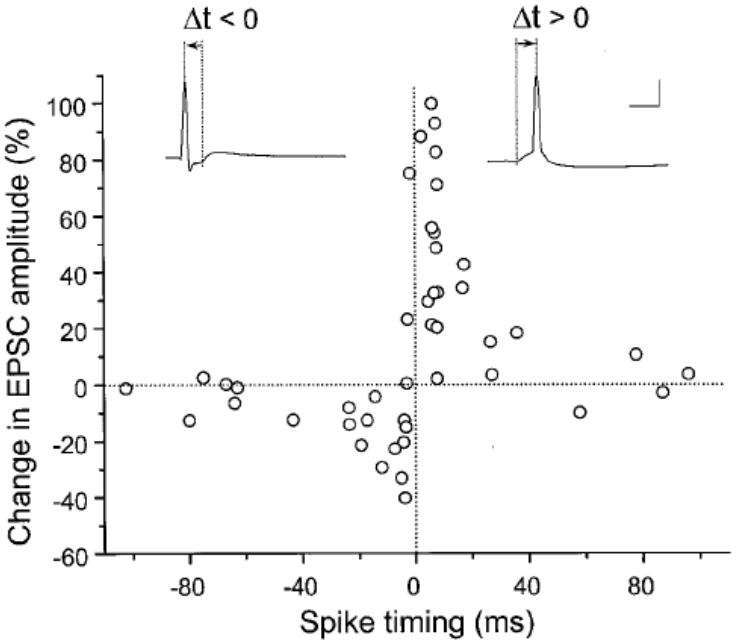
Learning Algorithms

- Supervised Learning
  - Feed-Forward
  - Back-Propagation
  - Gradient-Descent
- Unsupervised Learning for Spiking Neural Network
  - Hebbian Learning (Spike Timing Dependent Plasticity)
    - Neurons that fire together, wire together
    - Basis of Associative Memory

Spike Timing Dependent Plasticity





Which synapses are strengthened? Which ones are depressed?

Bi et. al. J. of NeuroSci, 1998

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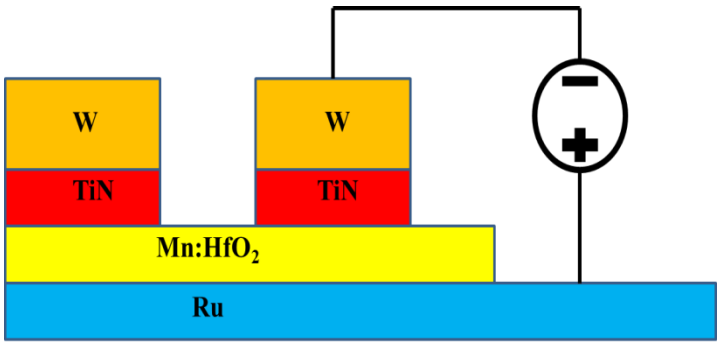
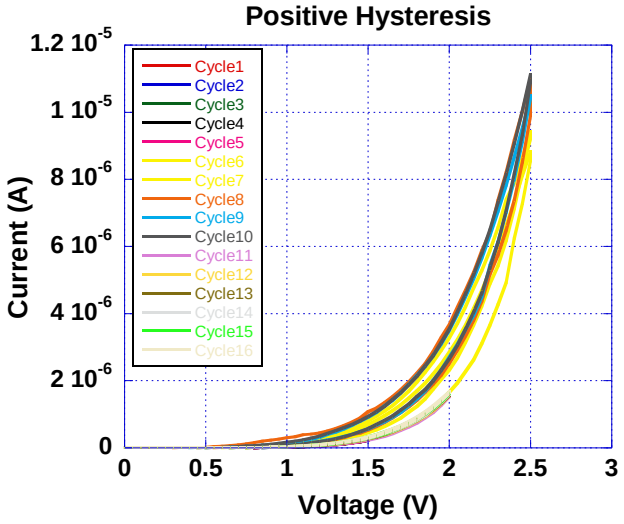
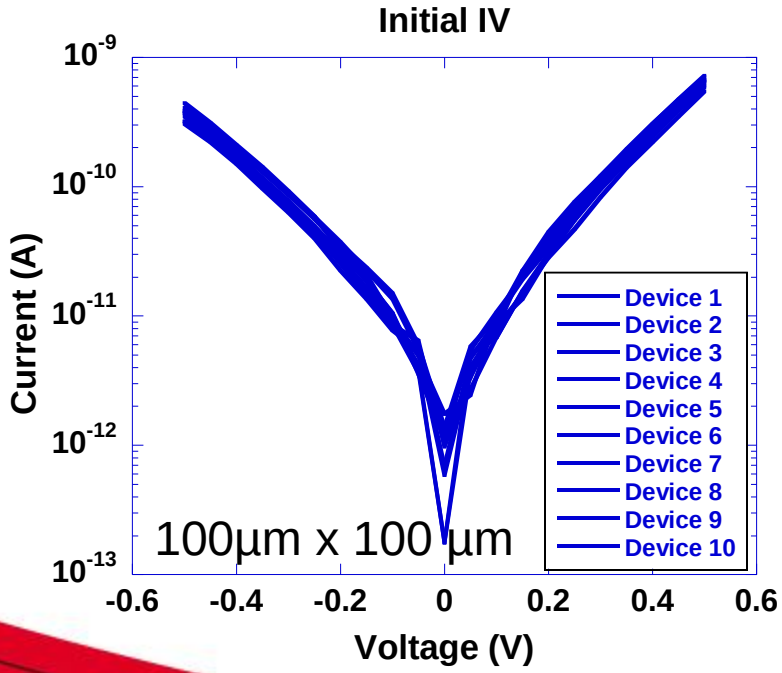
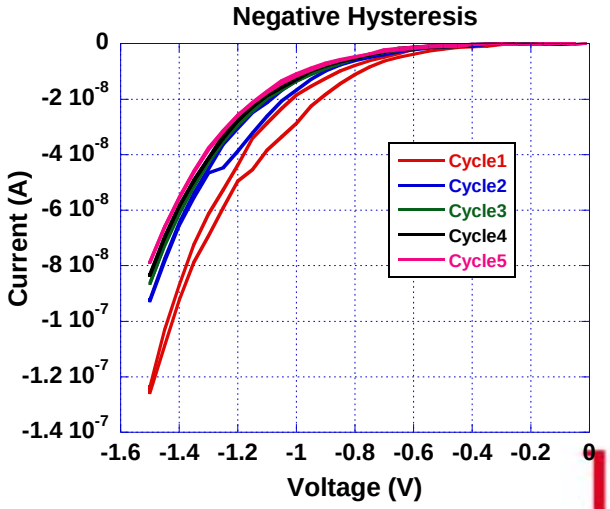
Doped Oxide Dynamics for Synaptic Memory









Mandal/Jha et. al., Nature Sci. Rep, 2014

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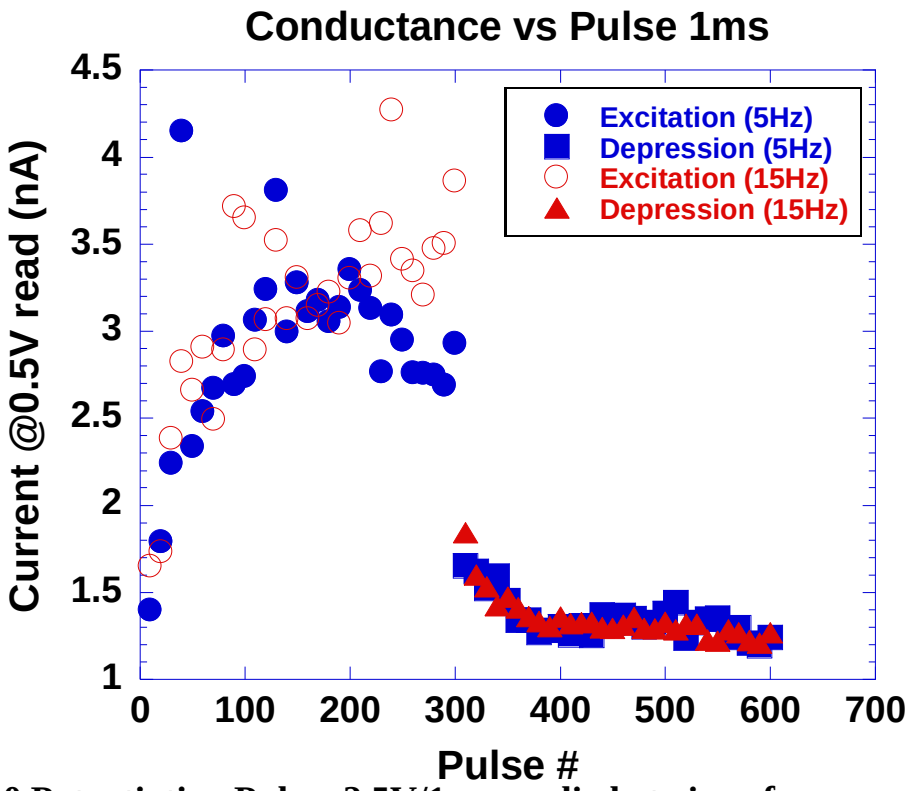
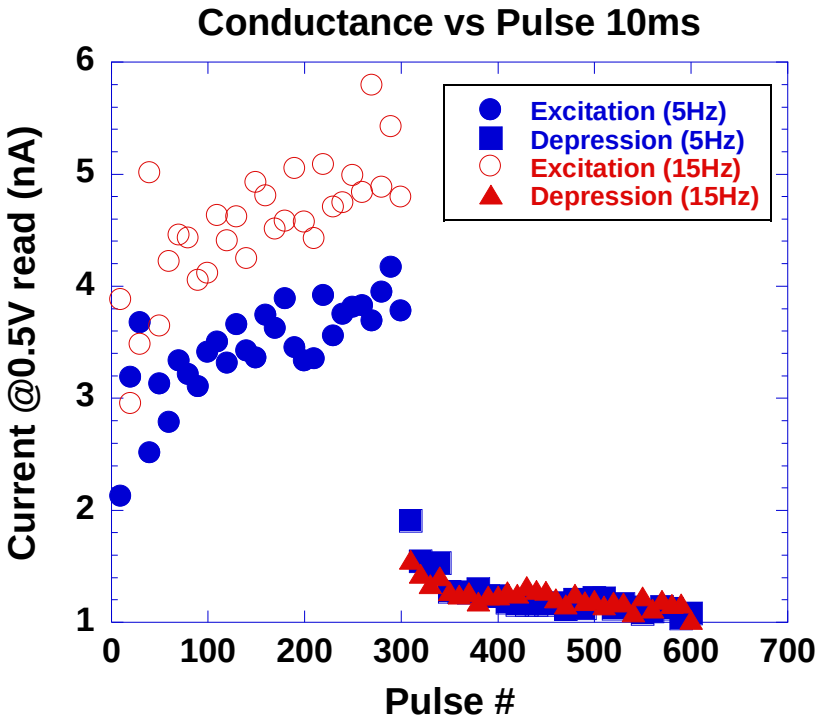
Potentiation and Depression with Pulses





10 Potentiating Pulses 2.5V/1ms applied at given frequency and Current measured at 0.5V read after excitation. Potentiation was repeated 30 times (total 300 pulses) with conductance measuring intervals of 10 pulses. After potentiation for 300 pulses, 300 depression pulses at -1.5V/1ms were applied at the given frequency and measurement of current at 0.5V read was done in intervals of 10 pulses.

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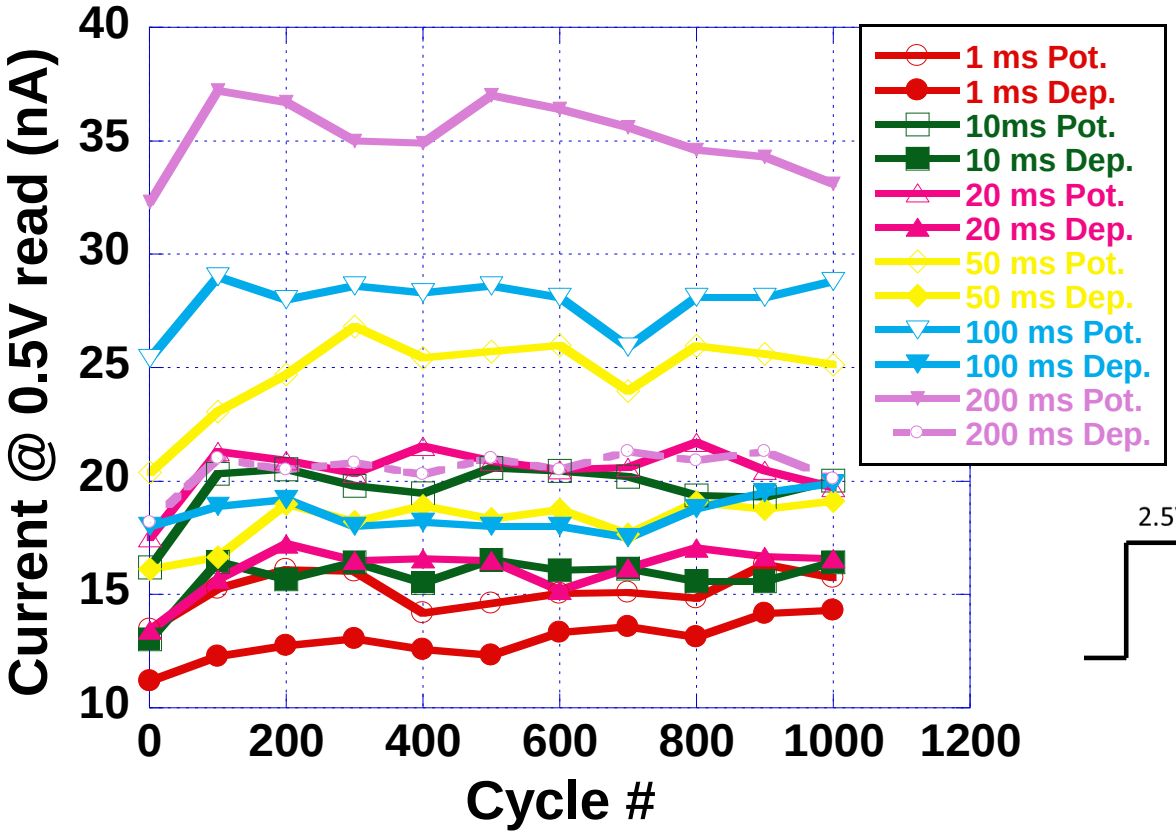
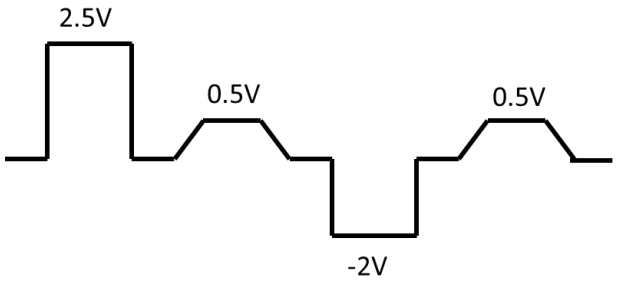
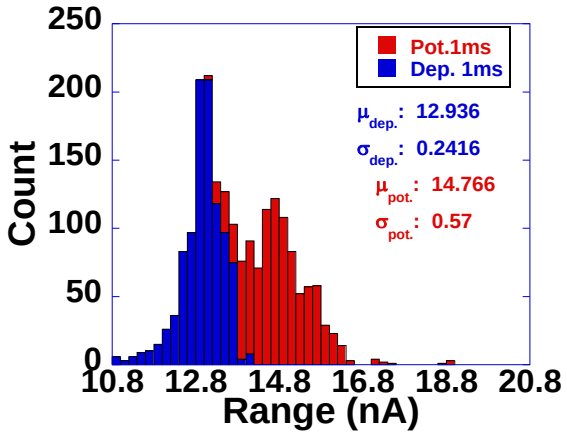
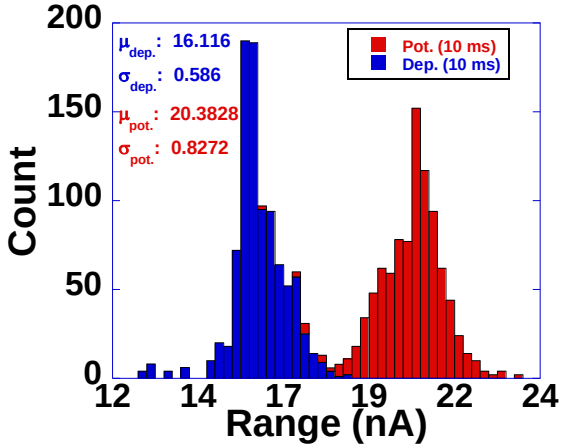
Endurance with Pulses of Different Pulse-Widths

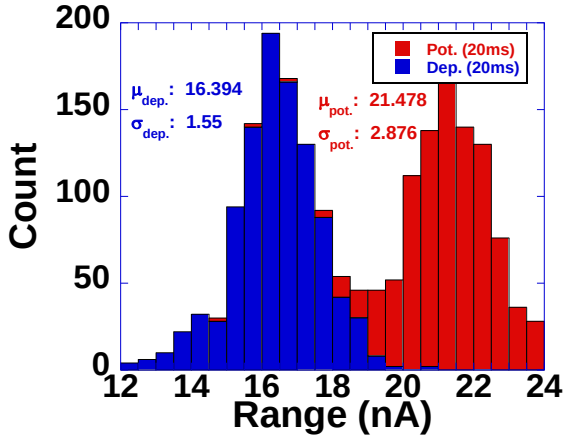


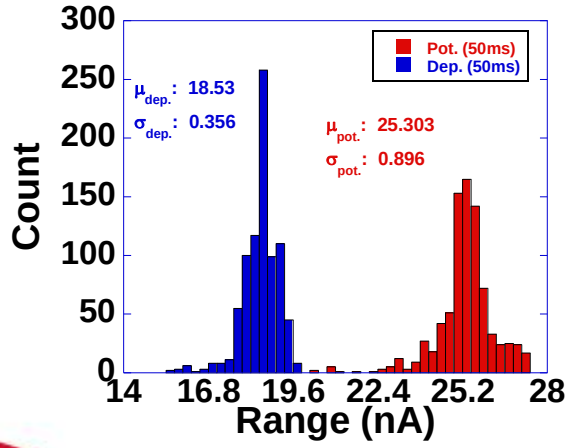


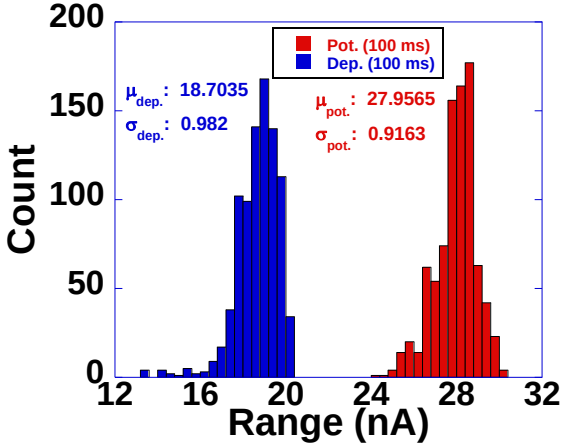
Distribution over Cycle to Cycle

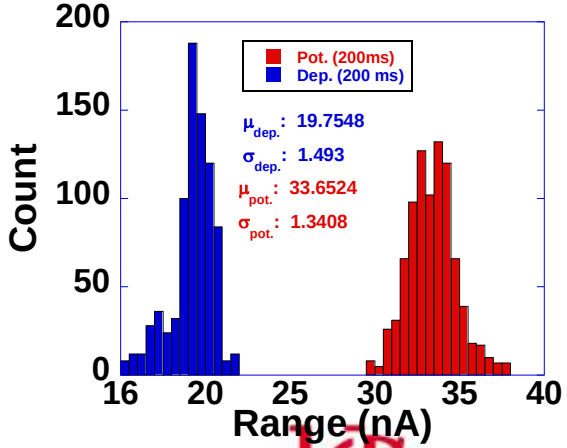












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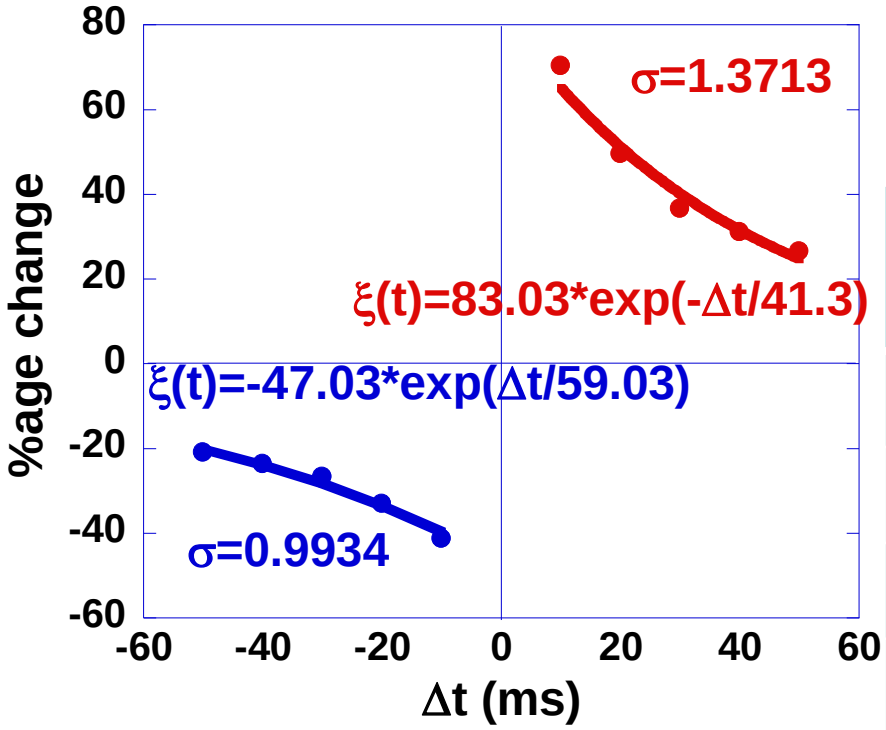
Spike Timing Dependent Plasticity



Δt (+/-)	Feedback (2.5V/-1.5V)
10 ms	200 ms
20 ms	100 ms
30 ms	50 ms
40 ms	20 ms
50 ms	10 ms

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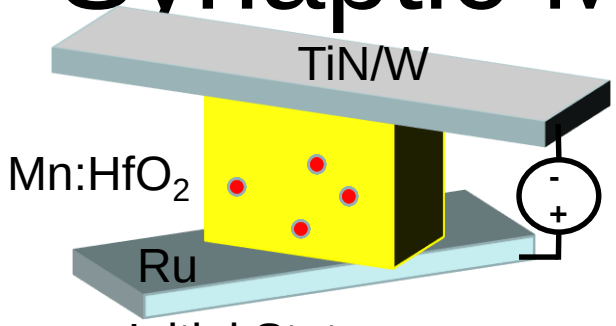
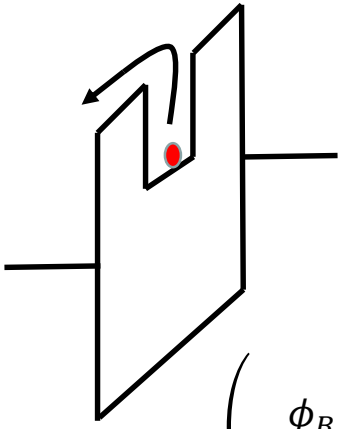
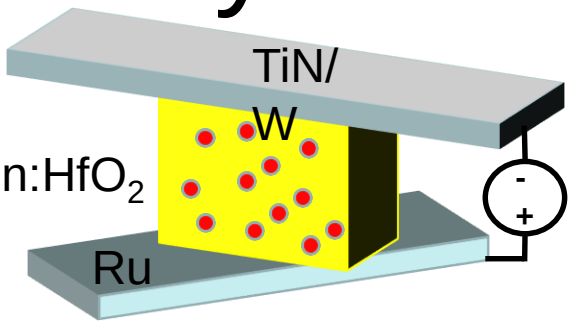
Synaptic Memory Device Model



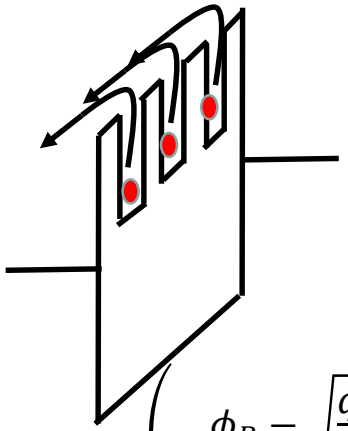
Initial State



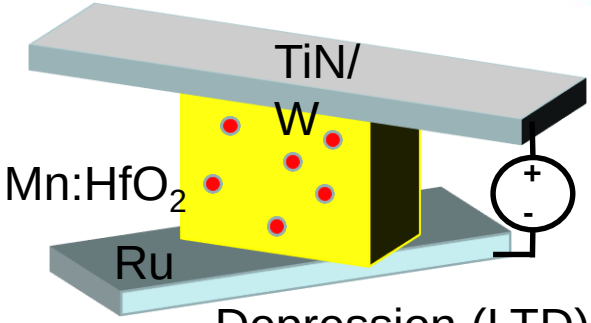
$$I = q\mu EAn_0 \exp\left(-\frac{\phi_B - \sqrt{\frac{qE}{\pi\varepsilon}}}{kT}\right)$$



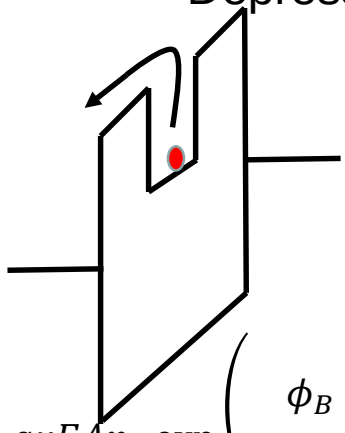
Potentiation (LTP)



$$I = q\mu EAn_1 \exp\left(-\frac{\phi_B - \sqrt{\frac{qE}{\pi\varepsilon}}}{kT}\right)$$



Depression (LTD)



$$I = q\mu EAn_2 \exp\left(-\frac{\phi_B - \sqrt{\frac{qE}{\pi\varepsilon}}}{kT}\right)$$

Mandal/Jha et. al., Nature Sci. Rep, 2014
Sarim/Kumar/Jha et. al., NAECON, 2016

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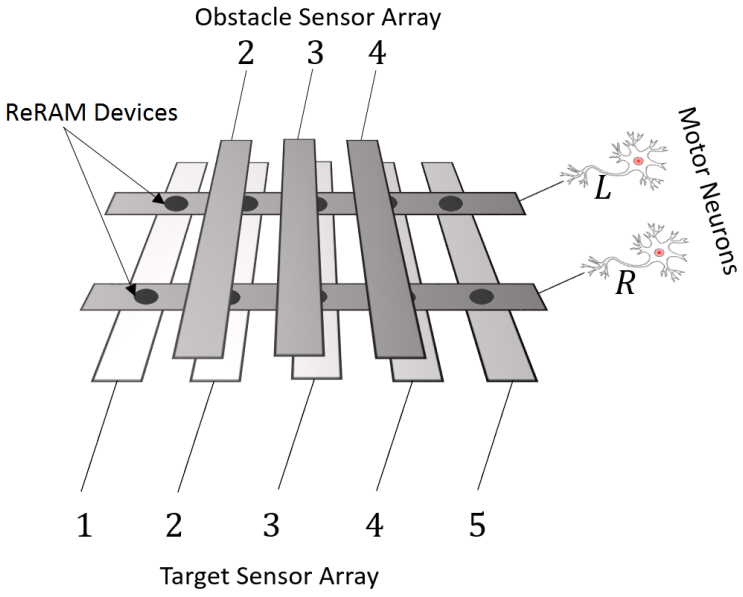
Neuromorphic Platform

- A neuromorphic platform is configured as an array of several Synaptic Memory devices arranged as shown.
- The arrays are connected to proximity sensors that send in the information about the vicinity of the robot. The motor neuron circuits move the robot wheels.



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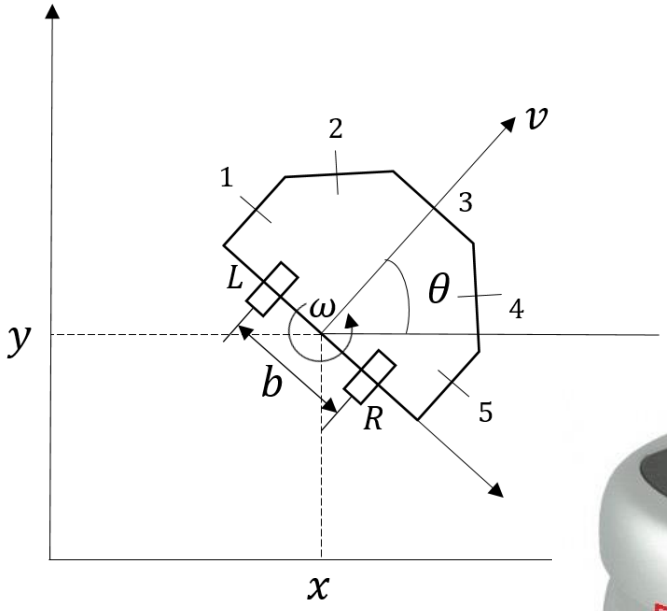
Simulation Framework

- Two different models, *viz.*, mathematical device model and experimentally derived device model, for synaptic memory devices with the neuromorphic platform were implemented to demonstrate unsupervised learning in a robot.
- This approach was validated by simulating the robot to navigate in an unknown environment with randomly placed obstacles.
- The commercially available Khepera III robot [4] is modeled with a two-wheeled differential drive robot kinematics. The robot consists of five ultrasonic sensors that give the information about the vicinity of the robot.

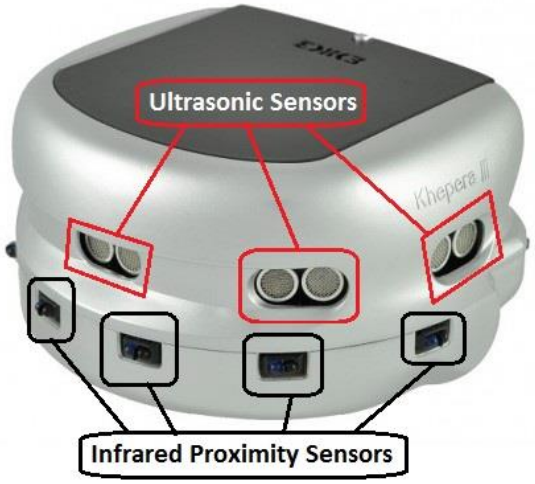
[4] http://www.k-team.com/mobile-robotics-products/old-products/khepera-iii

Robot Kinematics



$$\nu = \frac{r}{2}(\omega_R + \omega_L)$$

$$\omega = \frac{r}{b}(\omega_R - \omega_L)$$



$$\dot{x} = \nu \cos\theta$$
$$\dot{y} = \nu \sin\theta$$
$$\dot{\theta} = \omega$$

,Gianluca et. al., *IEEE Transactions on Robotics* 21.5 (2005): 994-1004.

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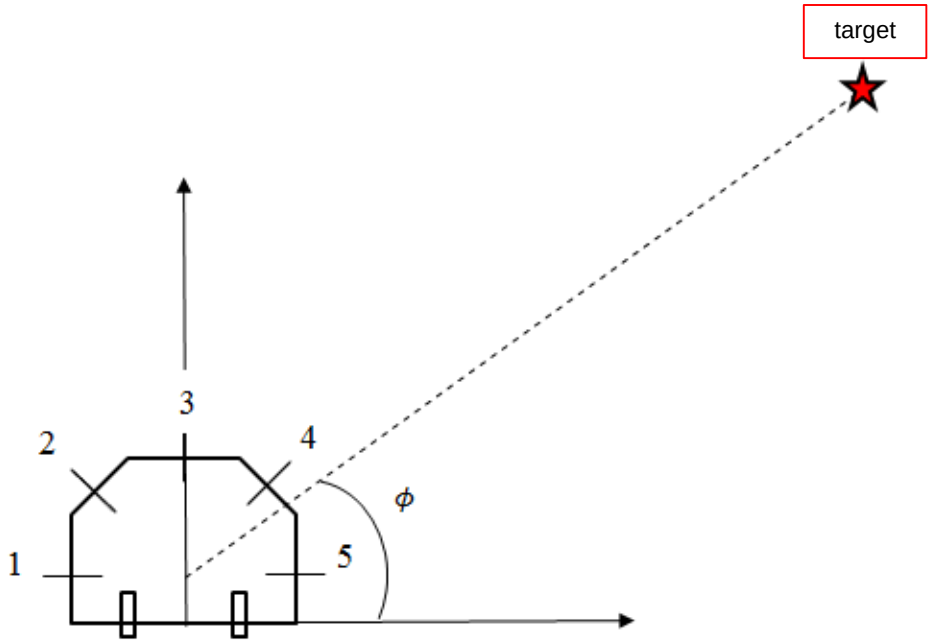
Learning Scheme



while *not reached target* **do**
    Find the target and obstacle information from the sensors.
    Send out currents based on the perceived signal.
    Add the currents from all sensors in the motor neuron circuit to generate a spike, thus moving the robot.
    Find the new position and orientation of the robot.
    Find the target and obstacle information from the sensor again.
    if *robot heading changed towards the target* **then**
        Strengthen the connection between the sensor and the spiked motor neuron.
    else
        Weaken the connection between the sensor and the spiked neuron.
    end
    if *the robot moved away from the obstacle* **then**
        Strengthen the connection between the obstacle sensor and the spiked motor neuron.
    else
        Weaken the connection between the obstacle sensor and the spiked neuron.
    end
end

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Mathematical Model

Device Model:

$$\dot{w} = f(v_{MR})$$

change in structural parameter of the device

where

$$f(v_{MR}) = I_0 sign(v_{MR})\left[e^{|v_{MR}|/v_0} - e^{v_{th}/v_0}\right]$$

memristor voltage

$$v_{MR}(t, \Delta T) = \alpha_{pos} spk(t) - \alpha_{pre} spk(t + \Delta T)$$

$spk(t)$ is the spike shape

ΔT is the difference in the spike times of pre- and post-synaptic neurons

$$\Delta w(\Delta T) = \int f\left(v_{MR}(t, \Delta T)\right) dt = \xi(\Delta T)$$

STDP learning function:

$$\xi(\Delta T) = \begin{cases} a^+ e^{-\Delta T/\tau^+} & if\ \Delta T > 0 \\ -a^- e^{-\Delta T/\tau^-} & if\ \Delta T < 0 \end{cases}$$

I_0 , v_0 are device parameters, v_{th} is the threshold voltage of the device above which it spikes, α are attenuation parameters in pre- and post-synaptic neurons. ξ is the change in the synaptic weight that is used to implement STDP.

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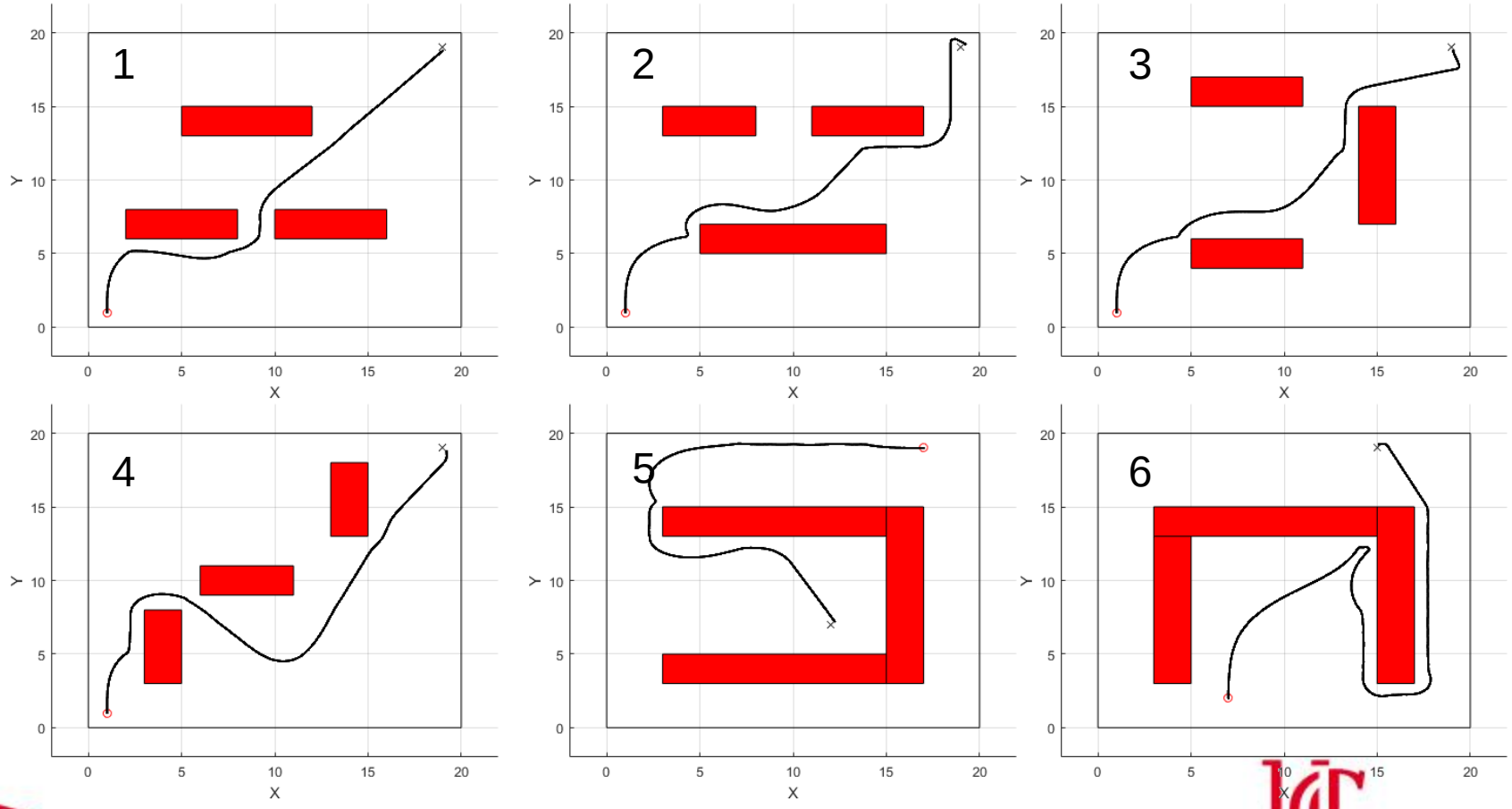
Robot Navigation Results



o : start | × : target

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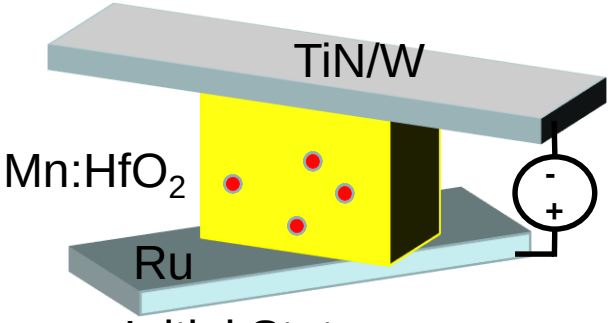
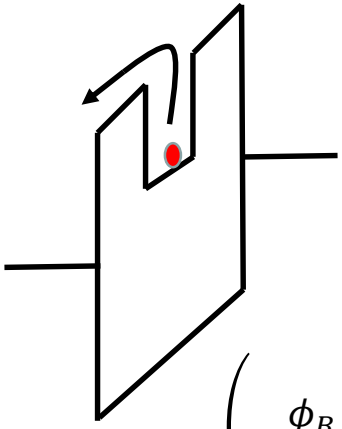
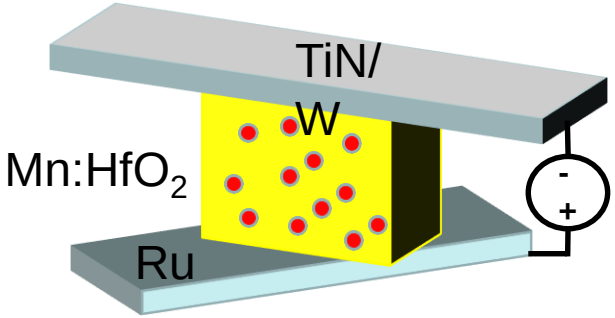
Navigation Results with Synaptic Memory Device Model



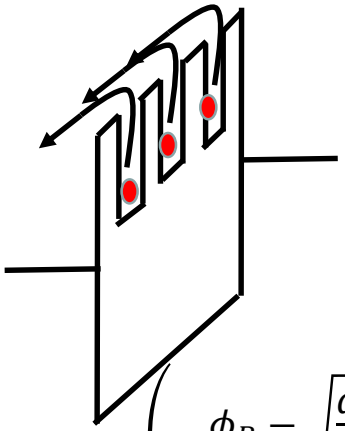
Initial State



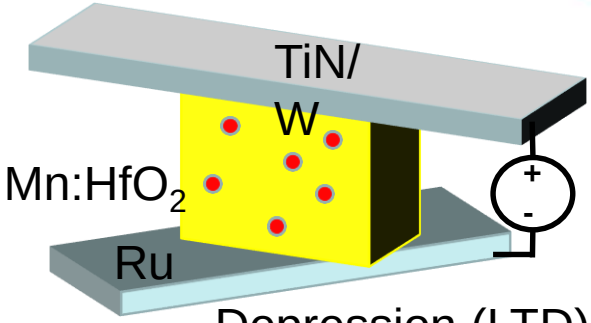
$$I = q\mu EAn_0 \exp\left(-\frac{\phi_B - \sqrt{\frac{qE}{\pi\varepsilon}}}{kT}\right)$$



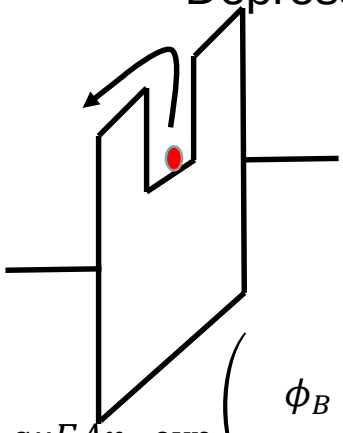
Potentiation (LTP)



$$I = q\mu EAn_1 \exp\left(-\frac{\phi_B - \sqrt{\frac{qE}{\pi\varepsilon}}}{kT}\right)$$



Depression (LTD)



$$I = q\mu EAn_2 \exp\left(-\frac{\phi_B - \sqrt{\frac{qE}{\pi\varepsilon}}}{kT}\right)$$

Mandal/Jha et. al., Nature Sci. Rep, 2014
Sarim/Kumar/Jha et. al., NAECON, 2016

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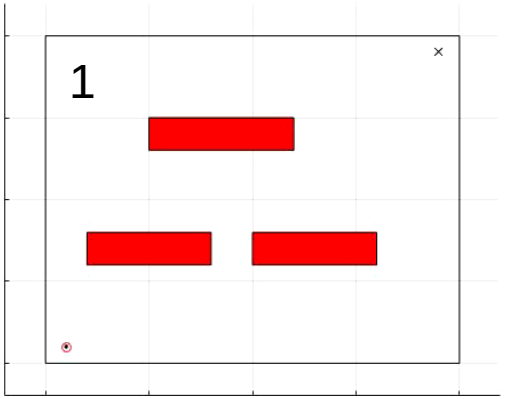
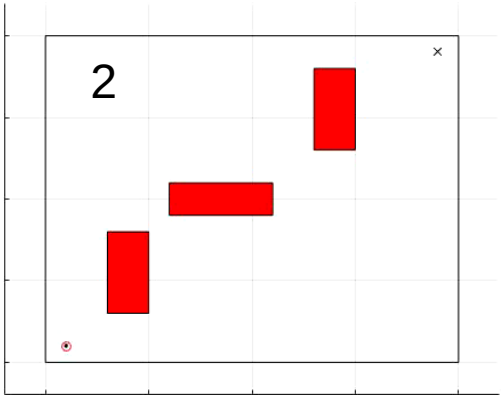
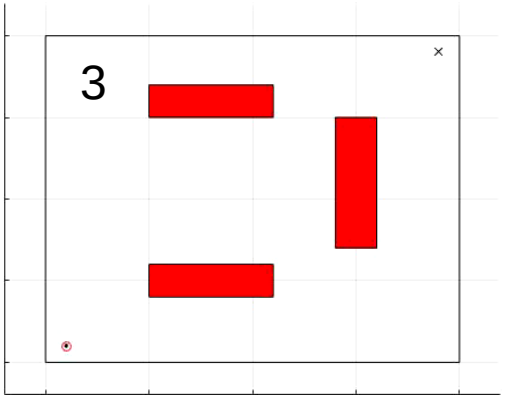
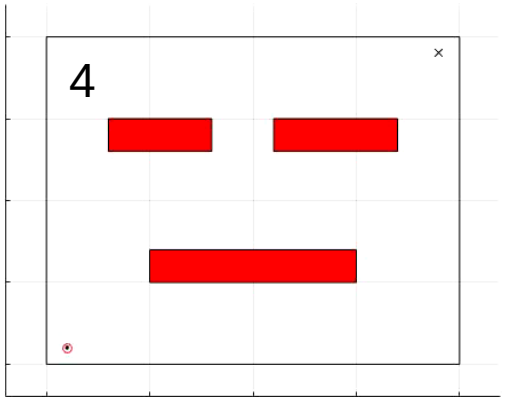
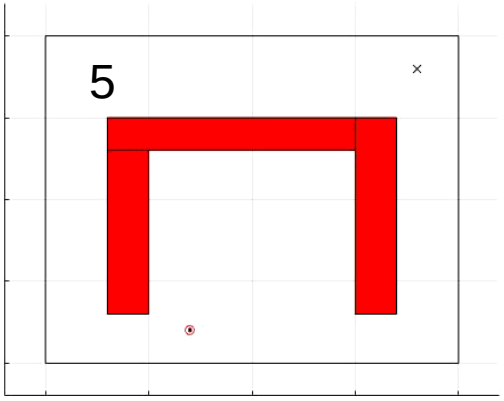
Robot Navigation Results

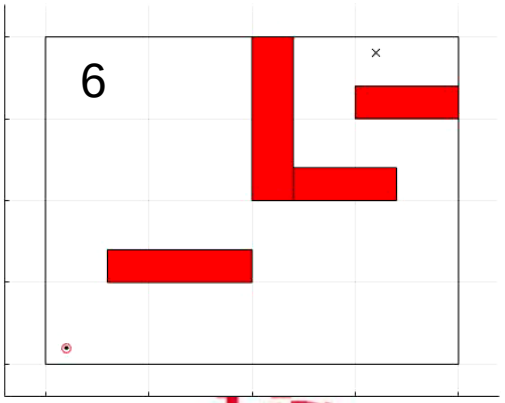












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Conclusions

- We demonstrated the potential for having an onboard “artificial brain” for Robots based on emerging neuromorphic devices.
- Using artificial brain architecture, a successful Robotic navigation was demonstrated using unsupervised learning scheme to guide the robot in complex environments using the local knowledge of obstacles only.
  - Our approach overcomes the issue of local minima which is a challenge for other navigation algorithms.
- Our approach is projected to be highly energy-efficient and scalable for implementation on any robot.
- Future work is targeted towards the actual implementation of these neuromorphic devices based artificial brain on Robots and field verification of the navigation.

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Thank You!
Questions and Suggestions?

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