

# TINNE- Techniques for Innovative Nanoscale Neuromorphic Electronics

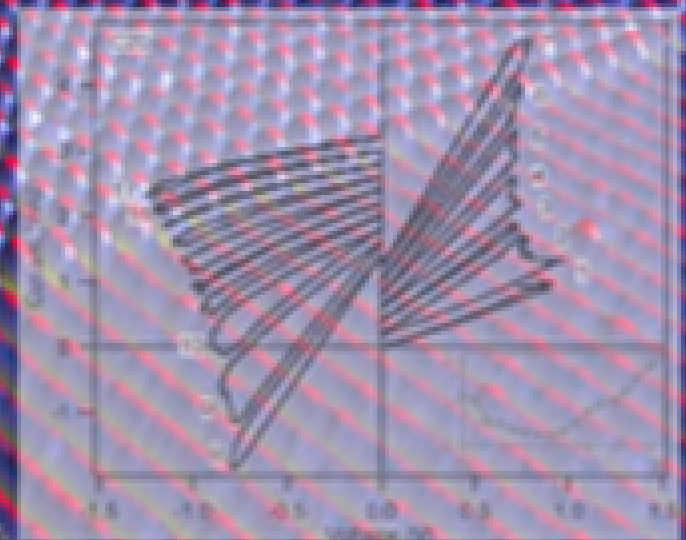
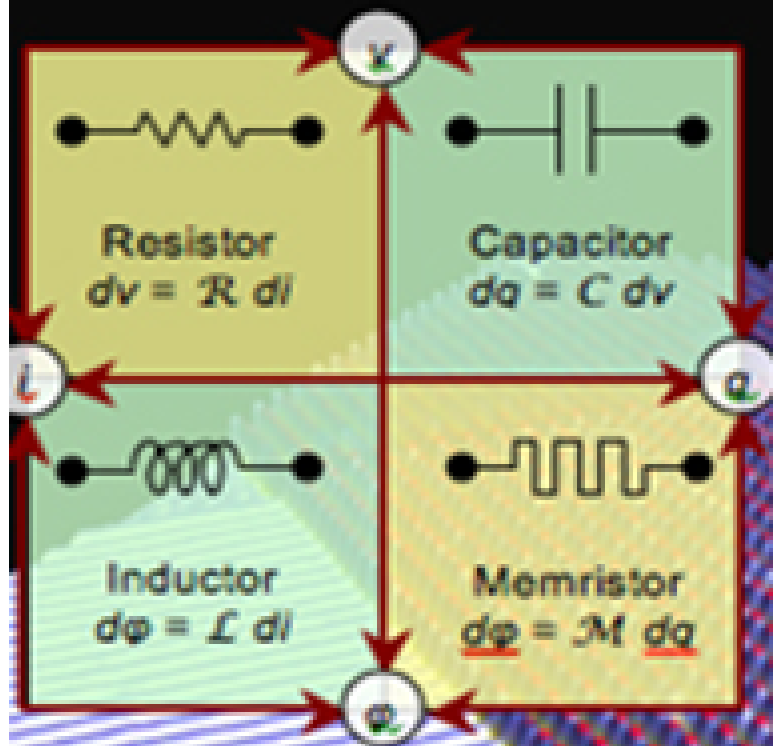


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# Project goals

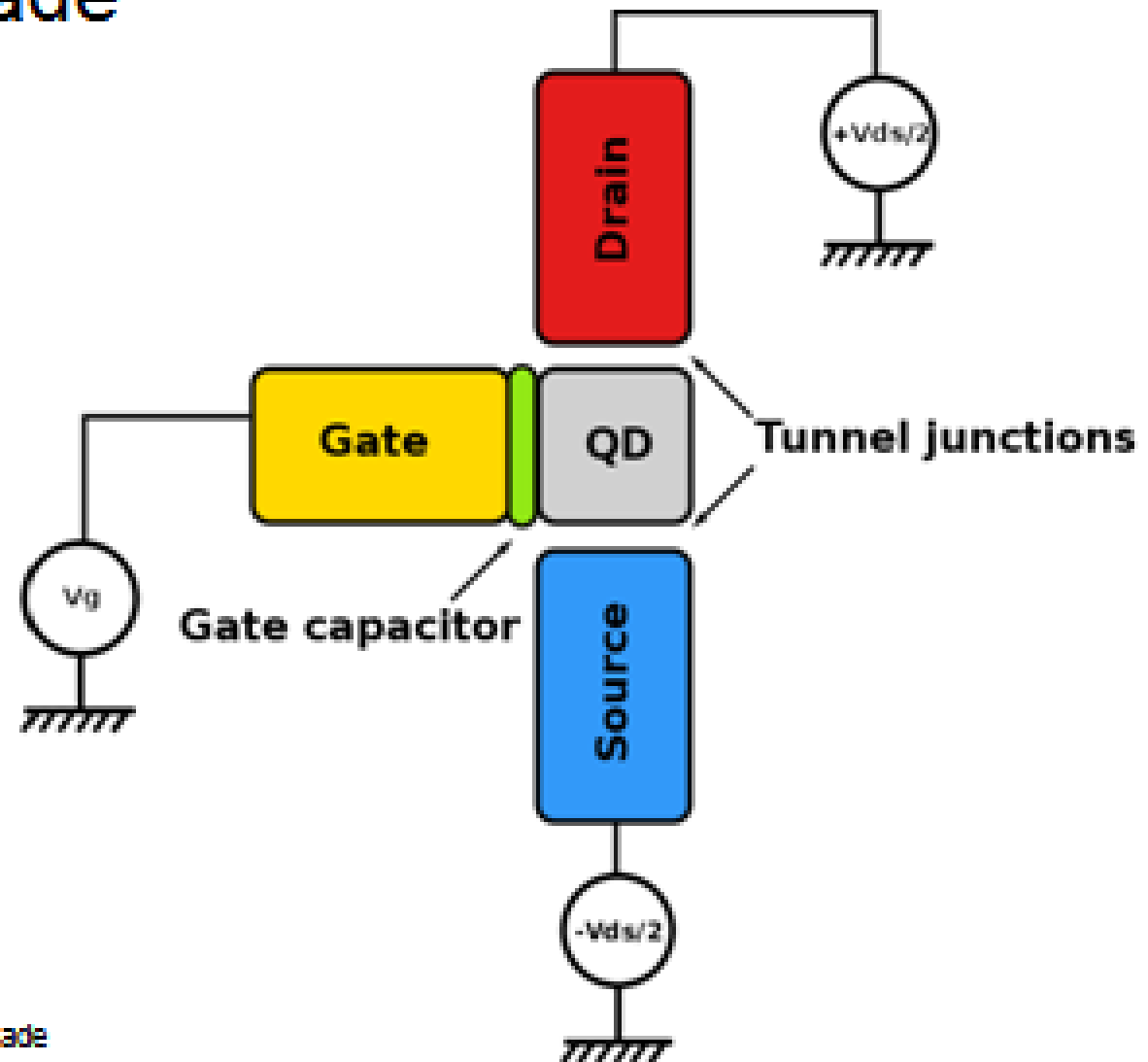
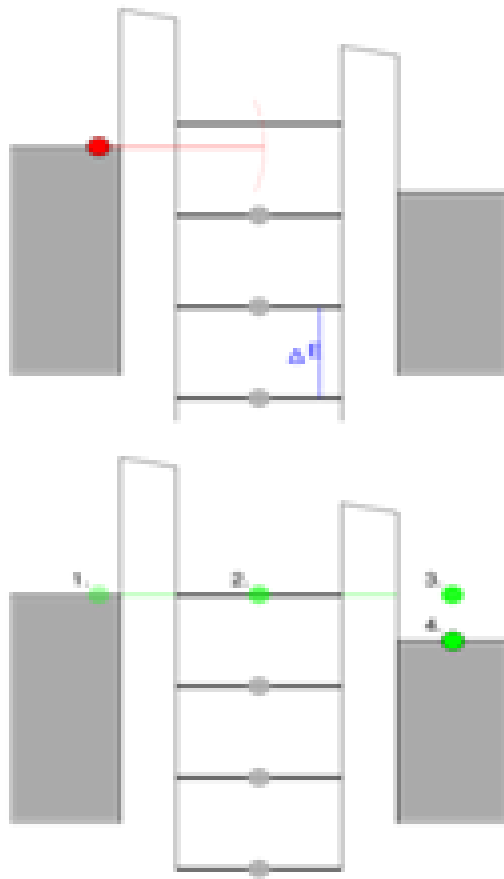
- establish collaboration model for Neuromorphic system research
- accomplish feasibility studies of adiabatic computation and interpulse interval coding for Neuromorphic systems
- lay the foundation for a design and simulation infrastructure that can be used for large and scalable Neuromorphic systems
- establish the needs of a larger faculty and student team for follow-up research
- explore collaboration with industry for Neuromorphic applications
- explore funding opportunities at DARPA, NSF, NRI, NIH

# Memristor: the missing element found

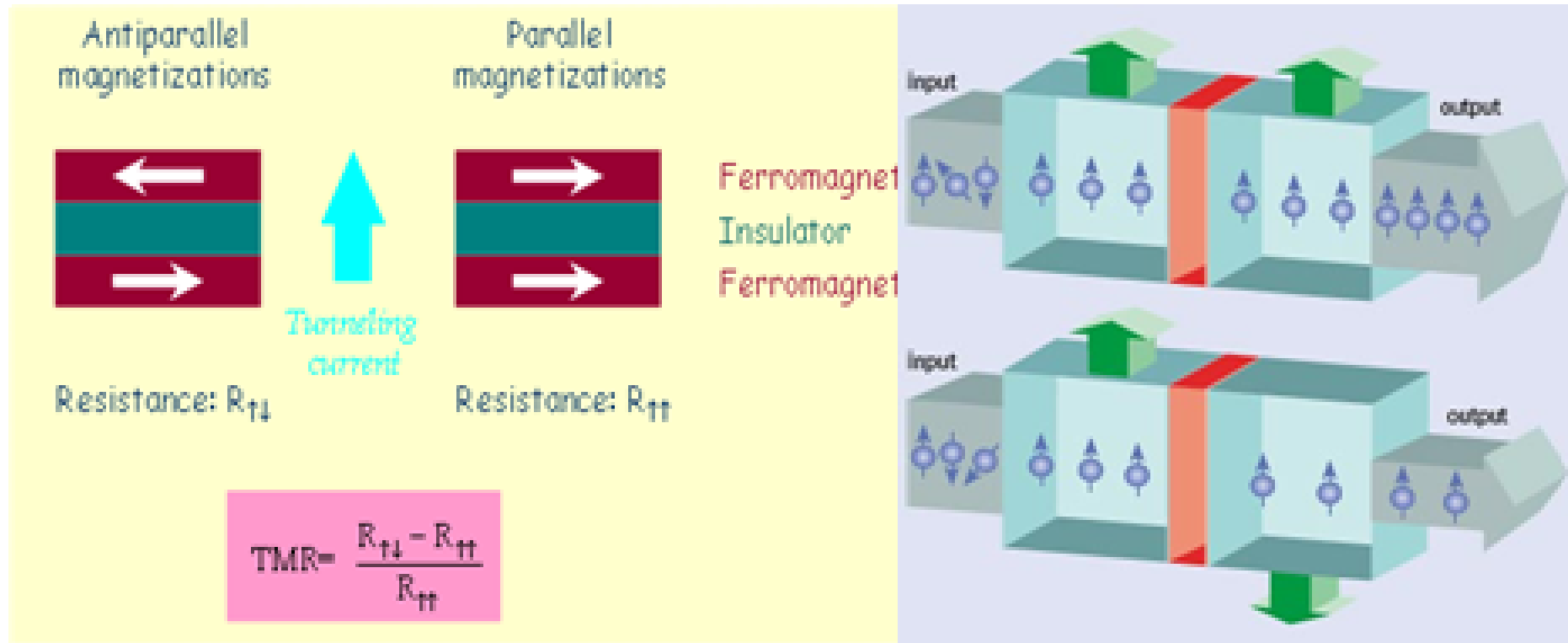


# Single electron transistor - SET

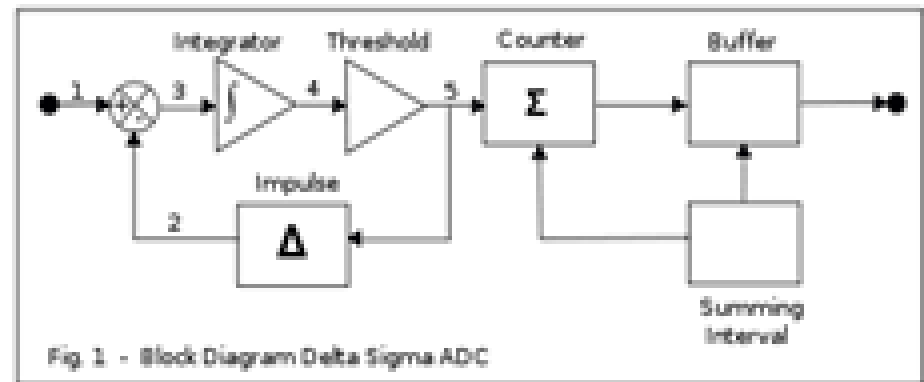
## Coulomb blockade



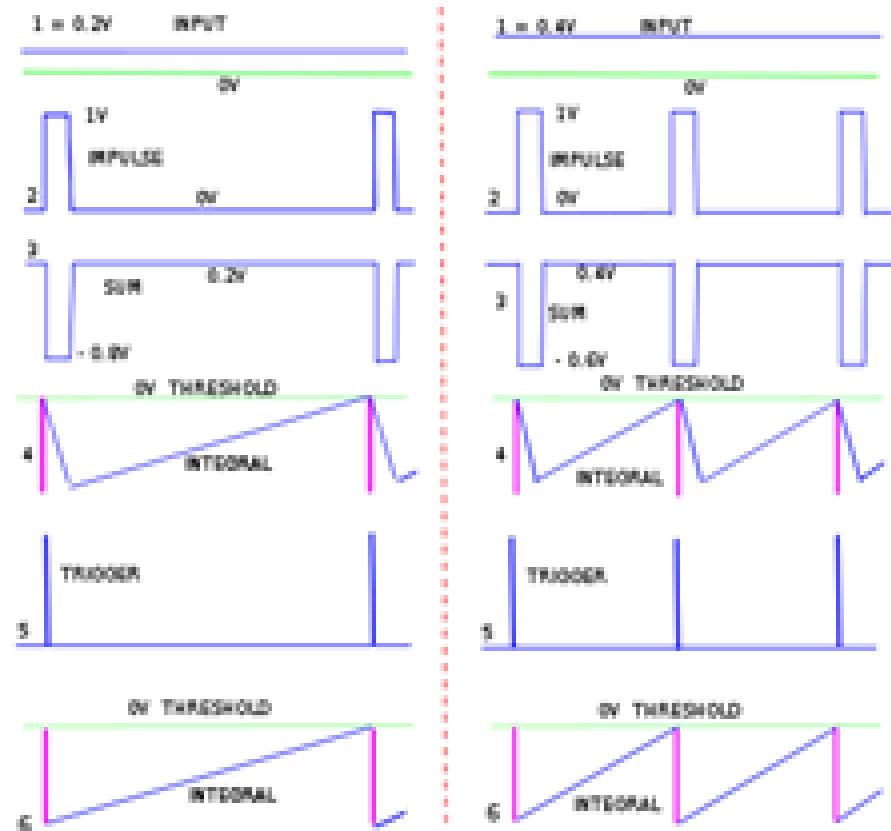
# Magnetic tunnel junction - MTJ



# Sigma-Delta modulator neuron



- Inputs and outputs: current spikes
- Similar to neuron
- Can be implemented with both conventional and nanoelectronic technologies



Typical Waveforms

# DARPA Synapse program

Hardware - Demonstrate an electronic synaptic component exhibiting Spike Timing Dependent Plasticity (STDP) with:

- Synaptic density scalable to  $> 10^{10}/\text{cm}^2$
- Operating speed  $> 10$  Hz
- Consumption  $< 10$ - $12$  Joules per synaptic operation at scale
- Dynamic range of synaptic conductance  $> 10$
- Synaptic conductance increase  $> 1\%$ /pulse for presynaptic spike applied somewhere within 80-1 msec before a postsynaptic spike
- Synaptic conductance decrease  $> 1\%$ /pulse for presynaptic spike applied somewhere within 1-80 msec after postsynaptic spike.
- 0%-0.02% conductance decrease if presynaptic spike applied  $> 100$  msec before or after postsynaptic spike
- Performance maintained over  $3 \times 10^8$  synaptic operations
- Awarded to group led by IBM

# NEURON MODEL: Izhikevich's Simple Spiking Neuron Model

## Key Features:

No fixed threshold value, computationally fast

Only two equations and four variables to change the type of neuron  
> 20 neuron types can be represented by the model

Biologically plausible

$$v' = 0.04v(t)^2 + cv(t) + f - u(t) + I(t)$$

$$u' = a(bv(t) - u(t))$$

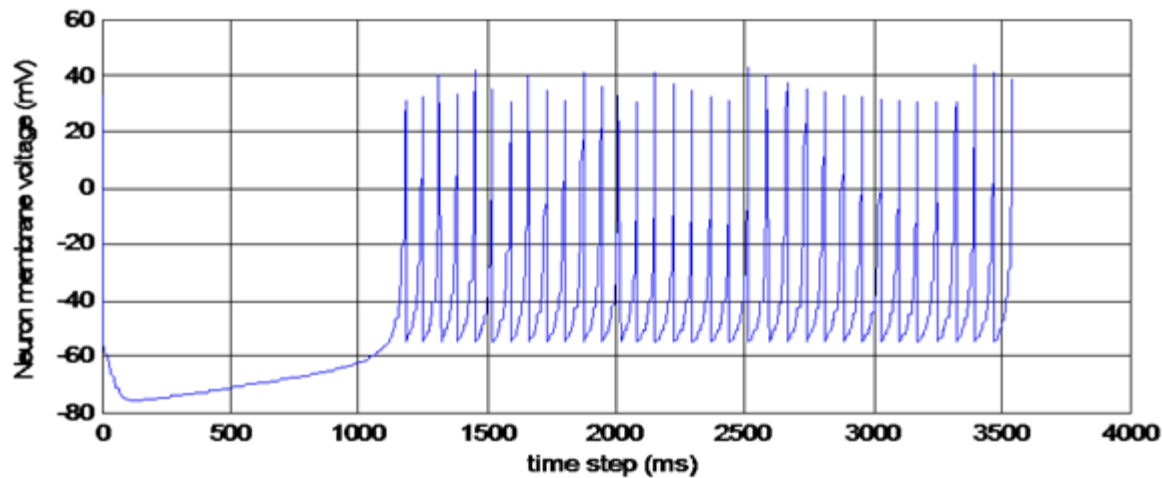
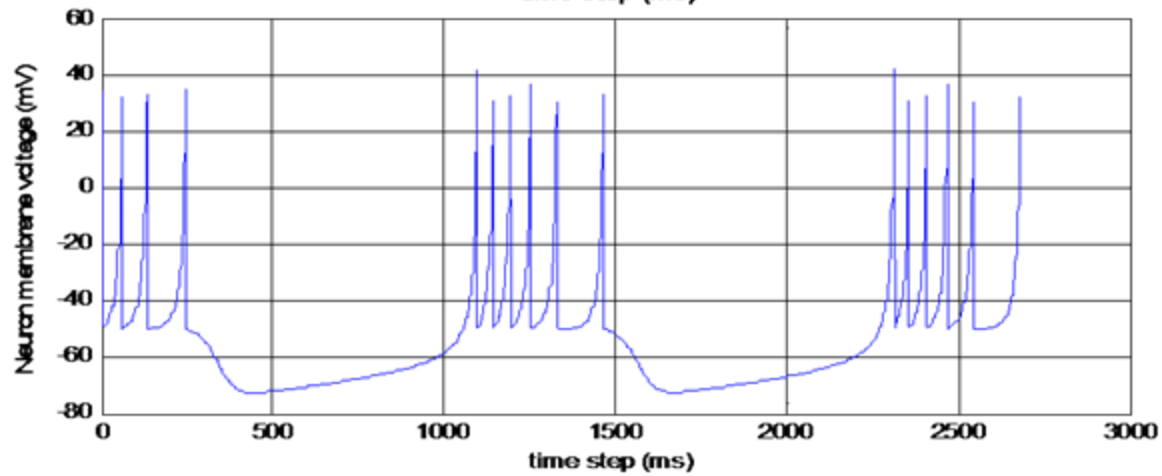
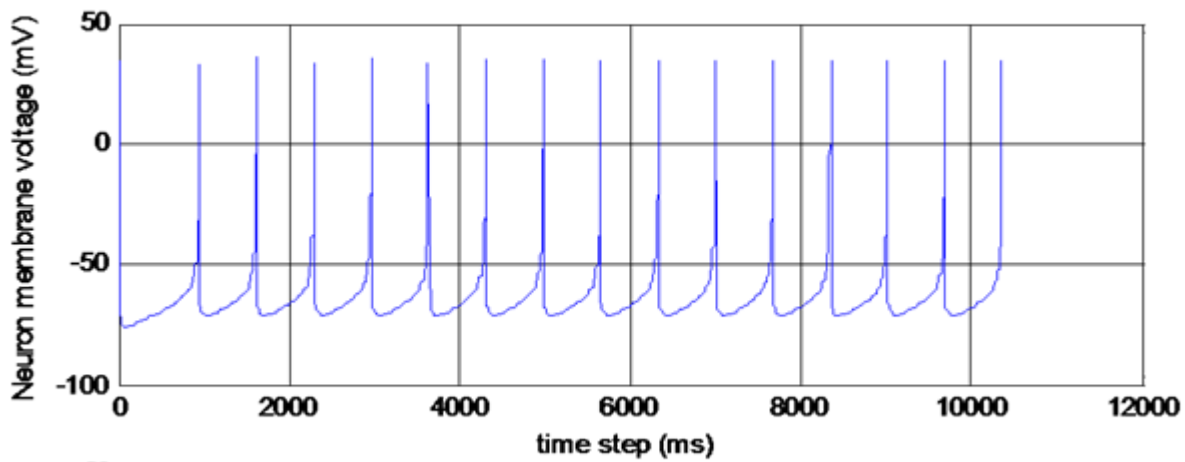
$v$ : membrane potential of the neuron  
 $u$ : membrane recovery variable  
 $a$ : time scale of the recovery variable  
 $b$ : sensitivity of the recovery variable  
 $c$ : after spike reset value of 'v'  
 $d$ : after spike reset value of 'u'  
 $I$ : synaptic input currents

E. M. Izhikevich, *Simple Model of Spiking Neurons*, IEEE Trans. Neural Networks

14 (2003) 1569-1572



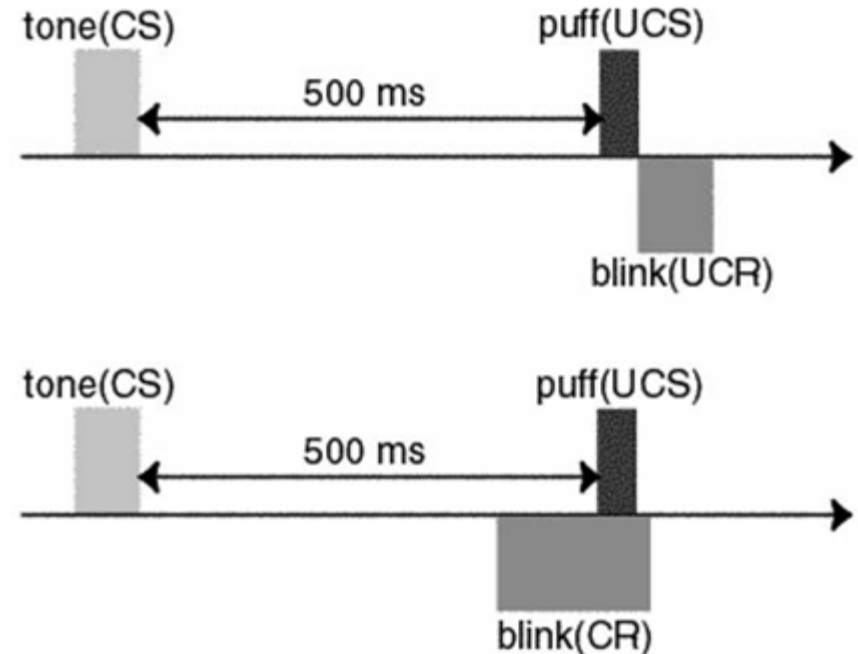
# Examples



# NETWORK MODEL: Levy's Minimal Hippocampal Model

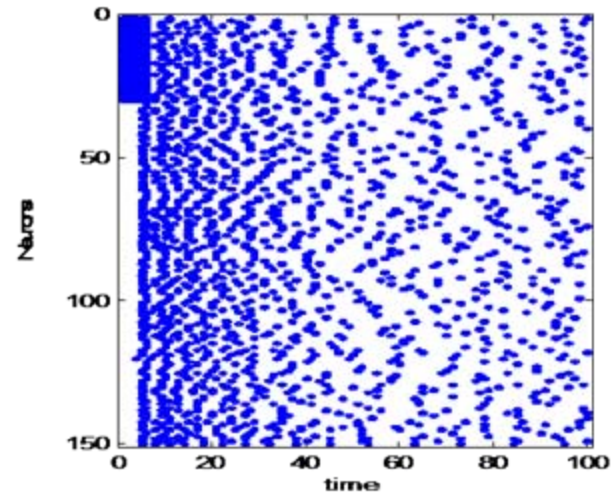
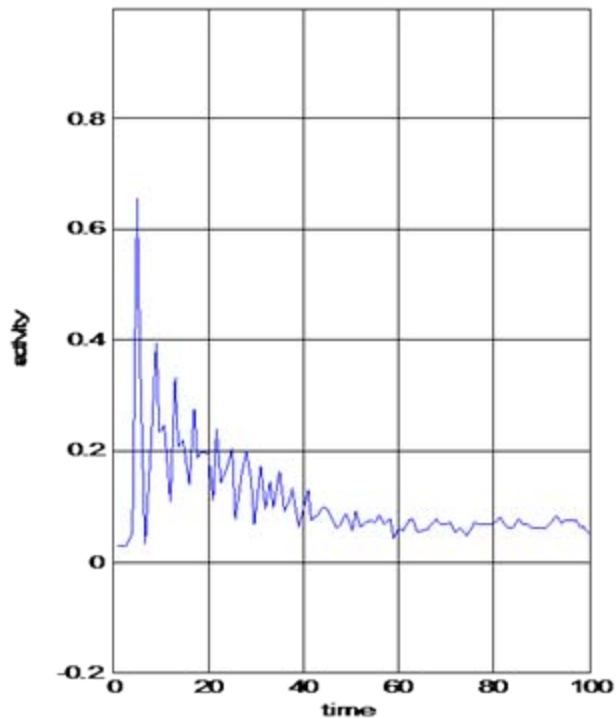
**Hippocampus:** Long term memory and  
spatial navigation

Trace conditioning



# INTEGRATED MODEL

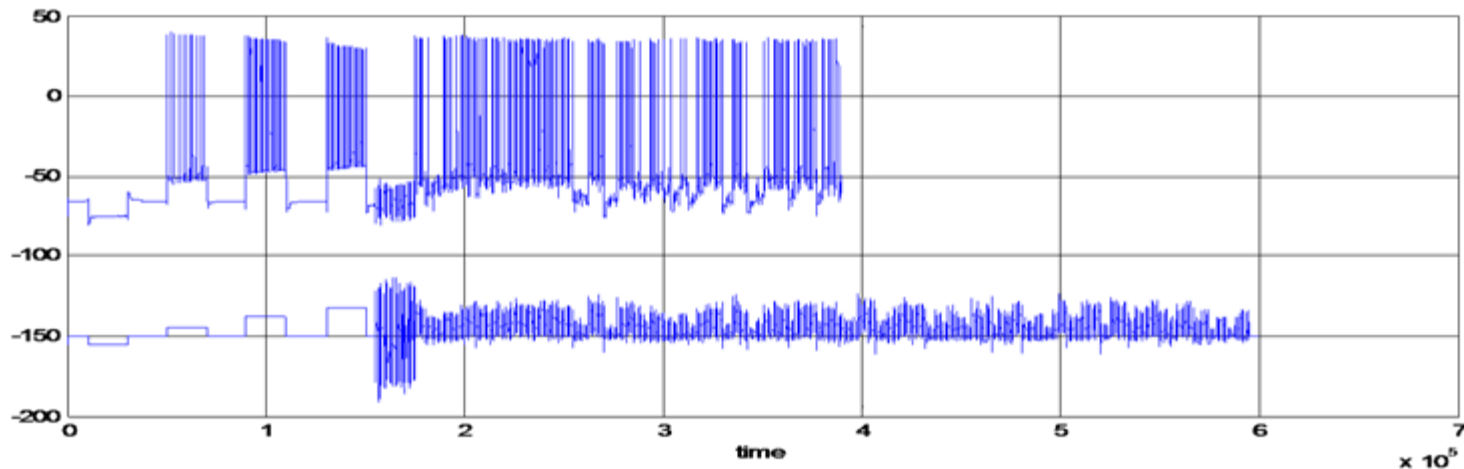
Number of Neurons: 1000  
Desired network activity: 0.1 (%10)  
Network connectivity: 0.3 (%30)



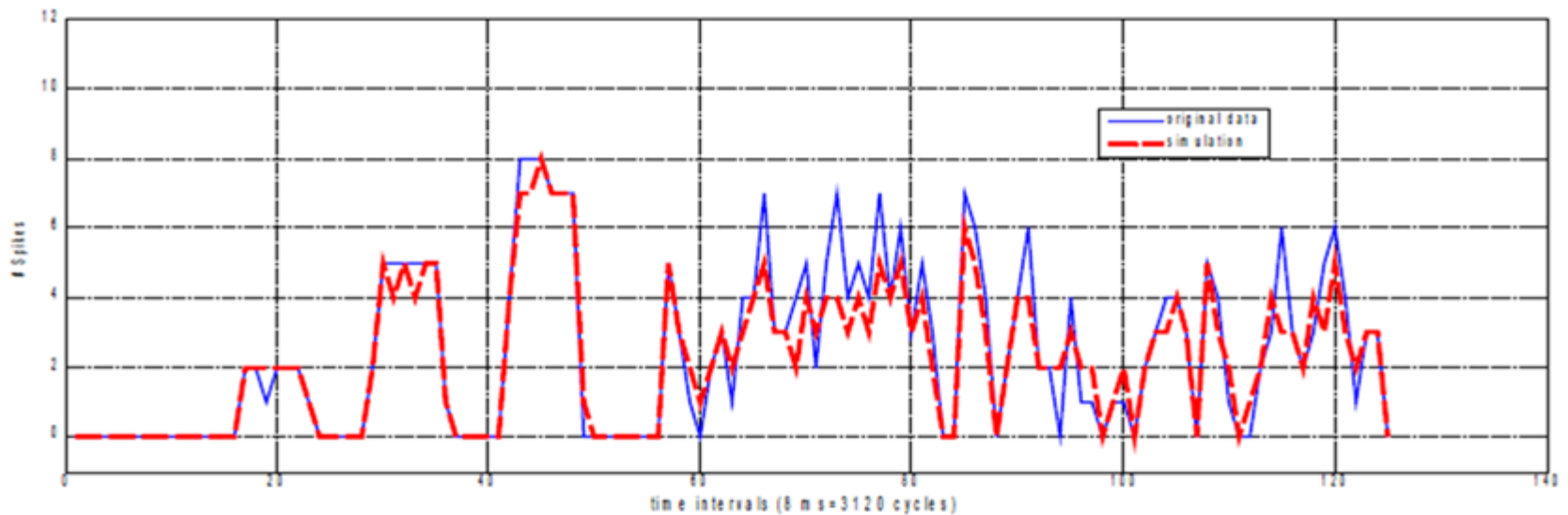
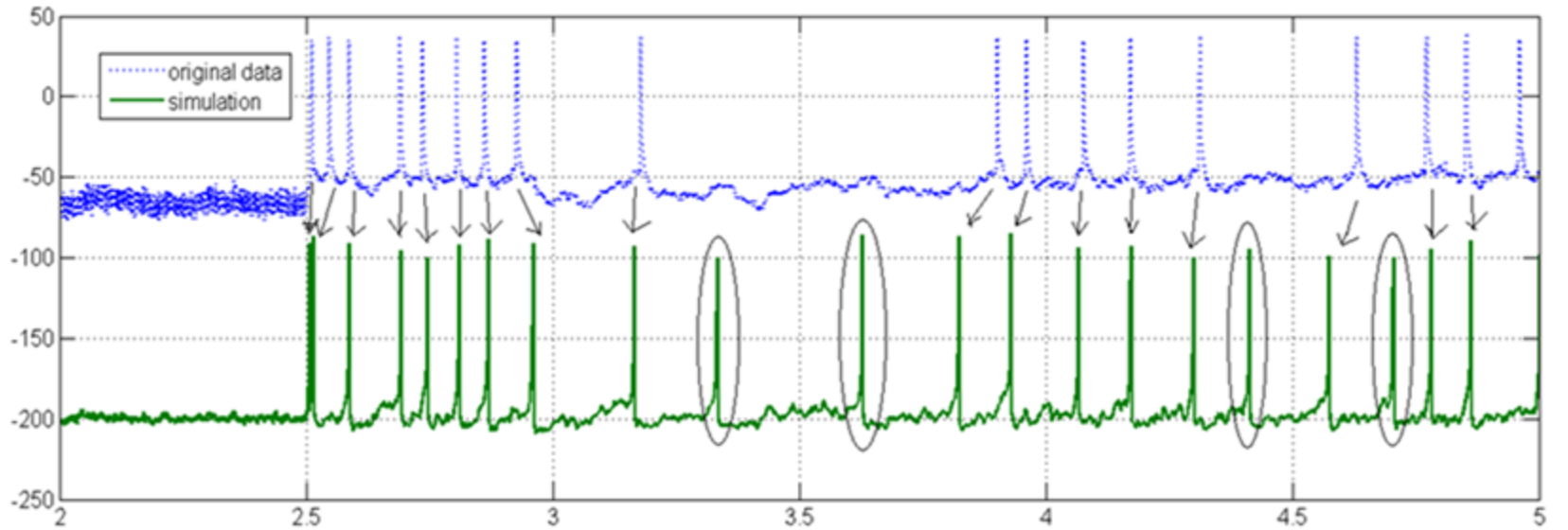
# VALIDATION of MODEL

## Quantitative Single-Neuron Modeling Competition

- **Goal:** Bridge the gap between experimentalists and modelers
- Predict the spike timing of a regular spiking L5 pyramidal cell responding to in-vivo-like current injection
- **Input Current:** First part is 17.5 seconds of 3 step current with a duration of 2 seconds and an inter-step rest time of 2 seconds followed by an injection of white noise of 2 seconds



# Preliminary results



# Conclusions and future work

- Opportunities: biologically inspired, low energy, potential to exploit novel technologies, electronic “brain”
- Challenges: heavily interdisciplinary, many possible points of failure
- Next: funding, refining of neuron model, realize a full neural network, physical implementation