BRAIN PRINCIPLES AND MODELING ABSTRACTIONS

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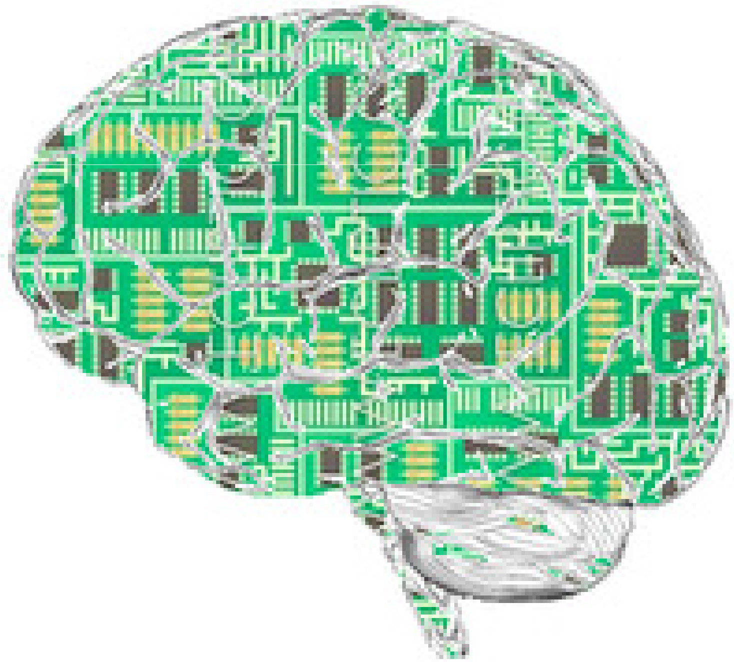
National Academy of Engineering Grand Challenge Reverse-Engineering the Brain

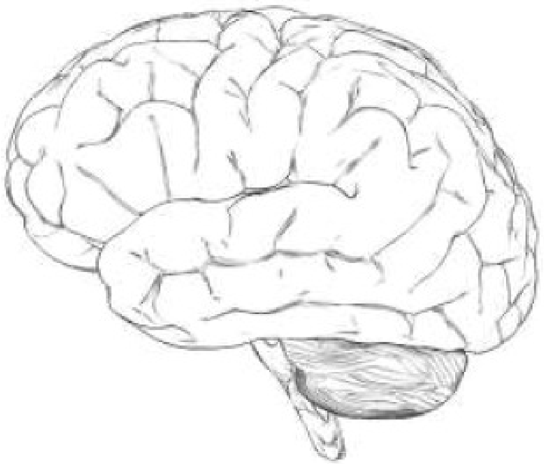
- Determine how it performs its magic.
- Should offer the benefits of:
  - Helping treat diseases.
  - Providing clues for new approaches to computerized artificial intelligence.
- Understanding its methods will enable engineers to simulate its activities, leading to deeper insights about how and why the brain works and fails.

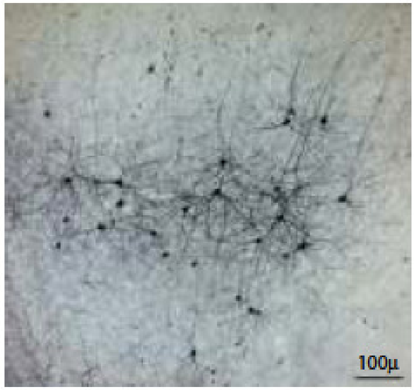
Neuromorphic Engineering

- Building Hardware and Applications Based on the Brain's Structure and Dynamics

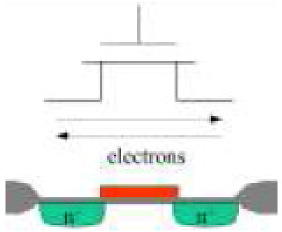


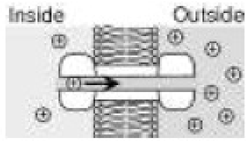
Neuromorphic Engineering





[Nuno da Costa, INI, 2008]





Main characteristics:

- Exploits the physics of silicon to reproduce the *bio*-physics of neural systems, using subthreshold analog VLSI circuits.
- Develops multi-chip spike-based computing systems using asynchronous digital VLSI circuits to encode and transmit signals between computational nodes.
- Employs these technologies to understand neural computation and to build behaving systems able to carry out behavioral tasks in complex environments, in real–time.

Neuromorphic Engineering: a brief historical perspective

Late '80s Max Delbrück, Richard Feynman, John Hopfield, and Carver Mead at CALTECH started investigating the *Physics of Computation* in biological, physical, and electronic systems.

Early '90s Carver Mead coined the term *"neuromorphic"* in 1990.

90's and 2000's Mead, Mahowald, Douglas, and generations of PhD students and now professors developed hybrid analog/digital microelectronic models of biological systems ranging from single cells to full sensory-motor systems.

Today Attempting to move from sensory systems, to real-time behaving ones that can learn and express cognitive abilities.

C. Mead.
Neuromorphic electronic systems.
Proceedings of the IEEE, 78(10):1629–36, 1990.

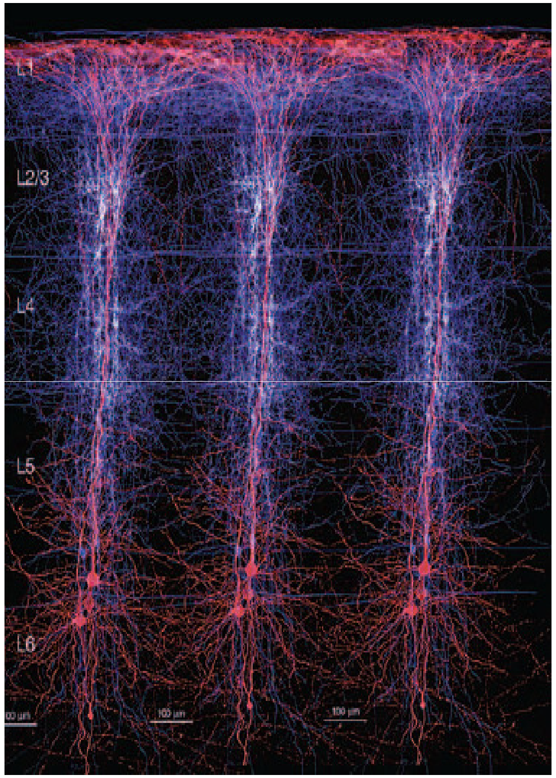
Giacomo Indiveri and Timothy K Horiuchi.
Frontiers in neuromorphic engineering.
Frontiers in Neuroscience, 5(118), 2011.

frontiers IN NEUROMORPHIC ENGINEERING

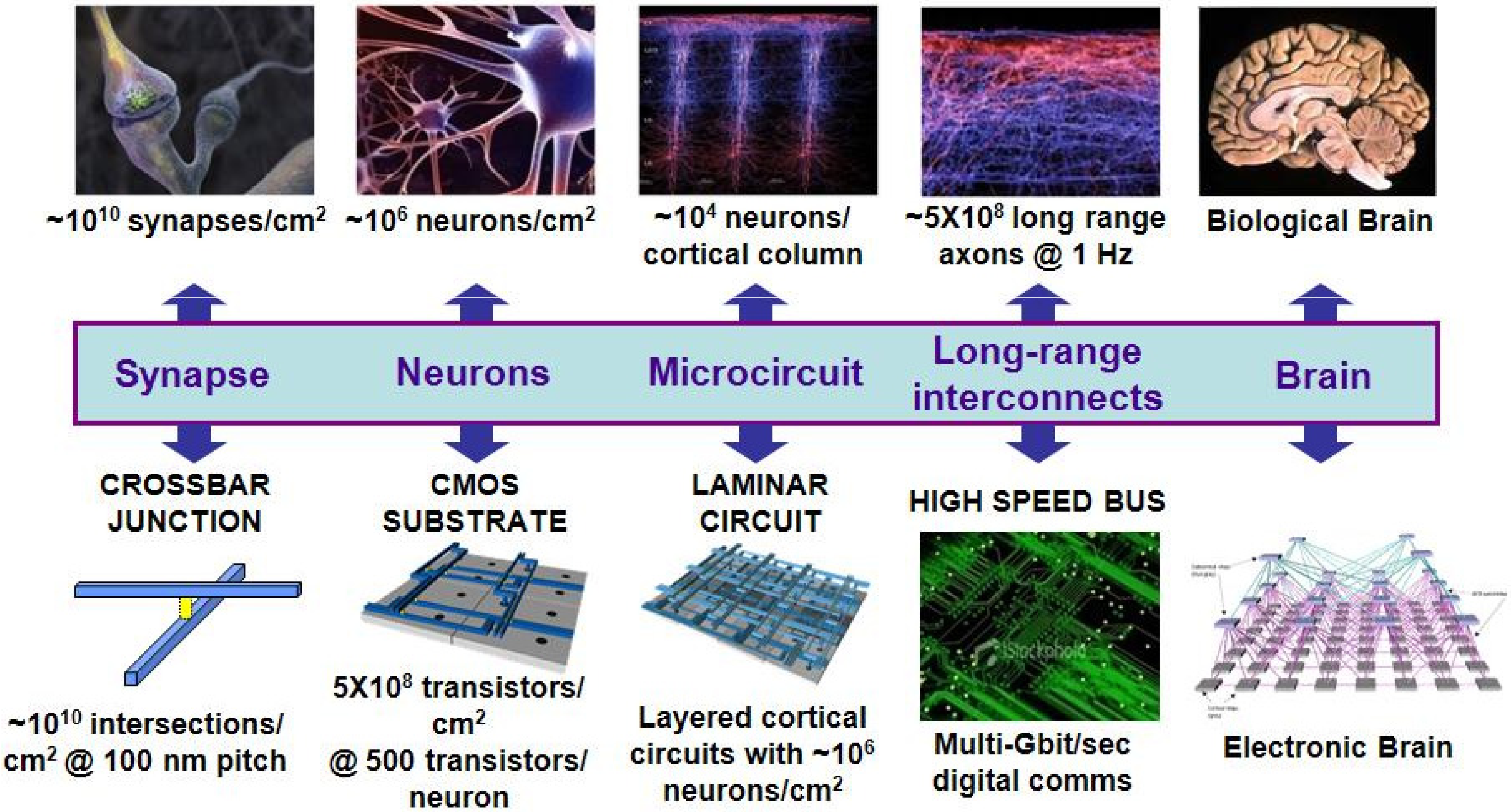
http://frontiersin.org/neuromorphic_engineering

Brain Computations

- Massive parallelism (10^{11} neurons)
- Massive connectivity (10^{15} synapses)
- Excellent power-efficiency
  - ~ 20 W for 10^{16} flops
- Low-performance components (~100 Hz)
  - Neuron fires an action potential → Digital signal
- Low-speed comm. (~meters/sec)
  - Axon → Cable that carries the signal
- Low-precision connections
  - Synapse → low probability of delivering message

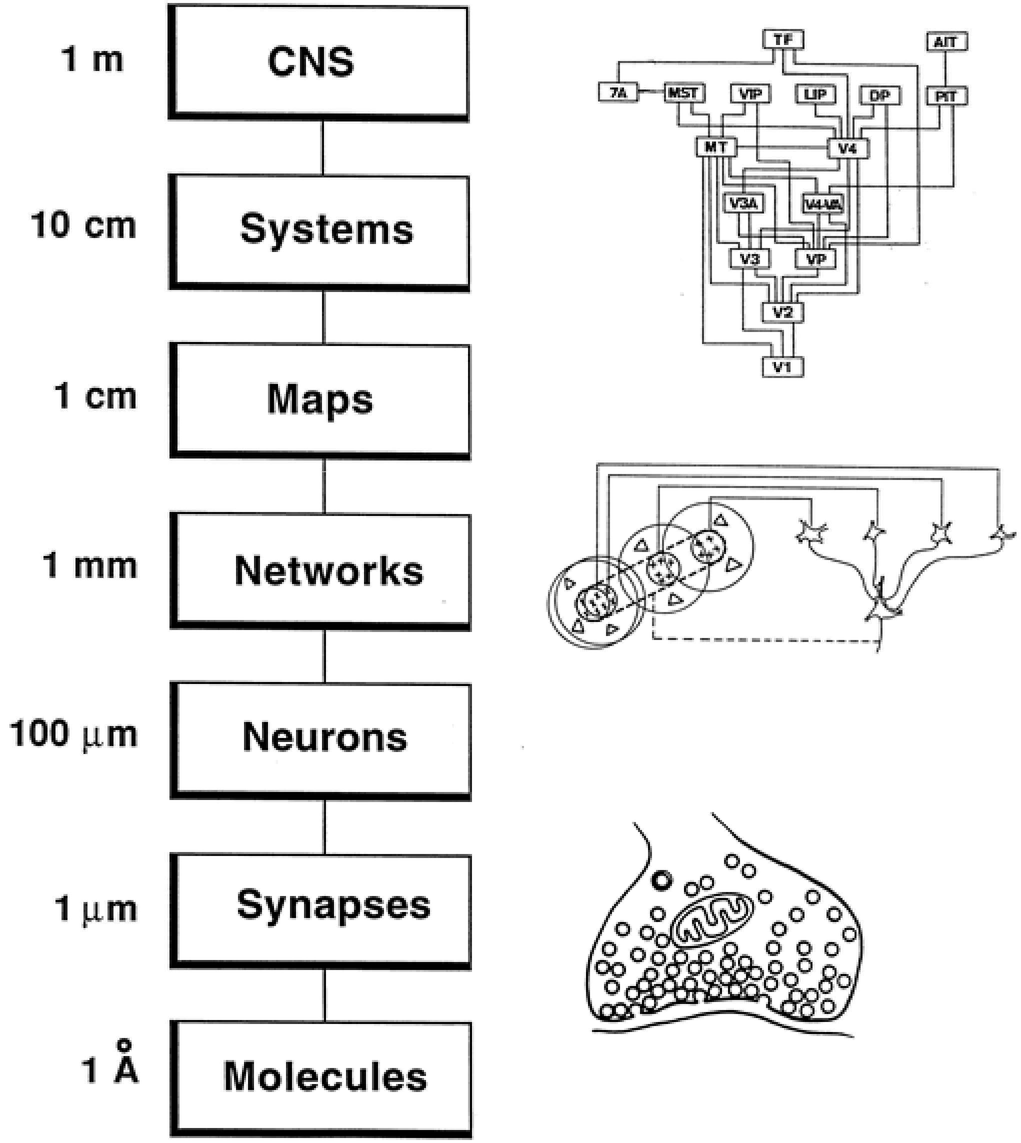


Converting Brain Circuitry to Electronic Circuitry



Brain principles and Modeling Abstractions

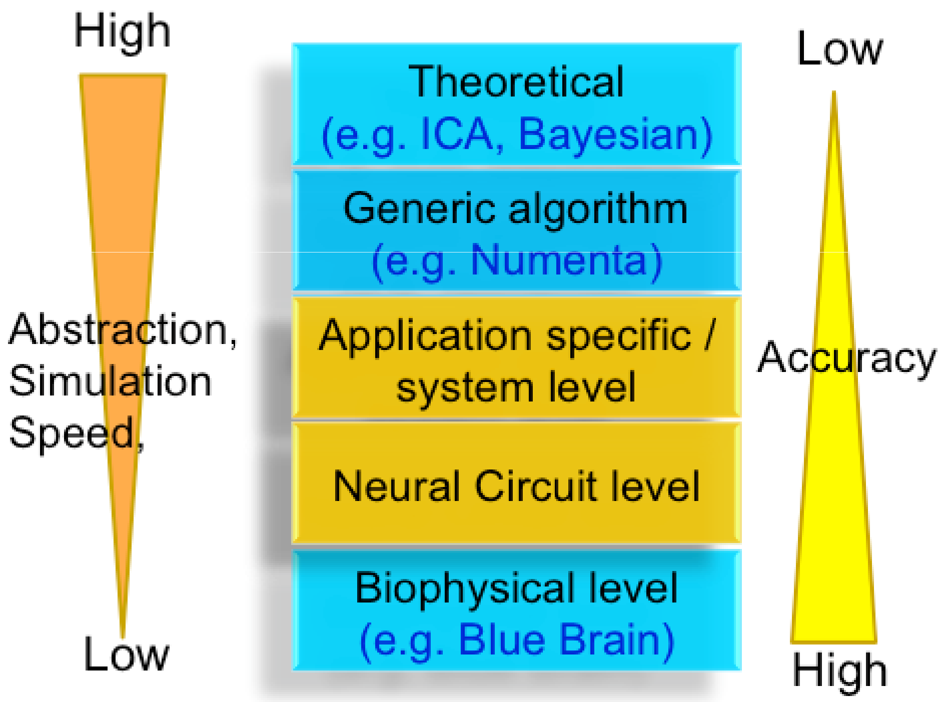
Levels of Investigation



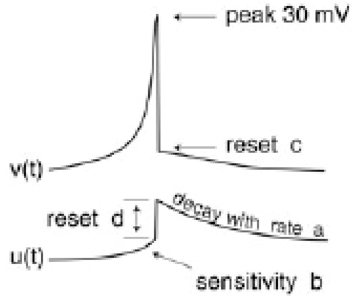
From Churchland & Sejnowski
“Compuational Brain”

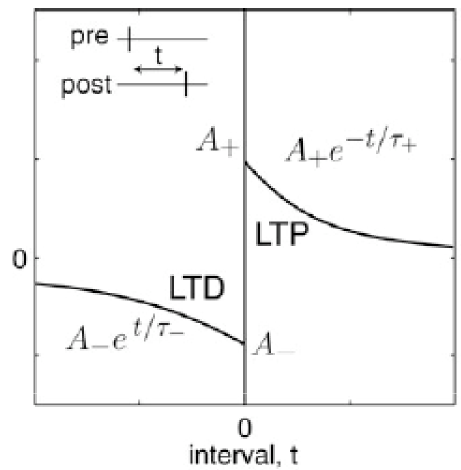
Neuromorphic Abstractions

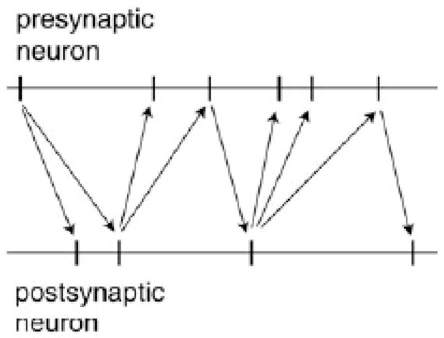
- Neural Circuit Models
  - Abstract away many molecular and cellular details.
  - Composed of:
    - Neurons for computation.
    - Synapses for learning and memory storage.
    - Axons for communication.
    - Neuromodulatory systems to control action selection and learning.
  - Still retain dynamics and structure.

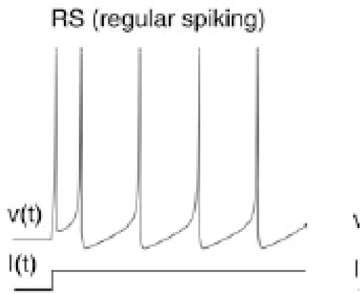


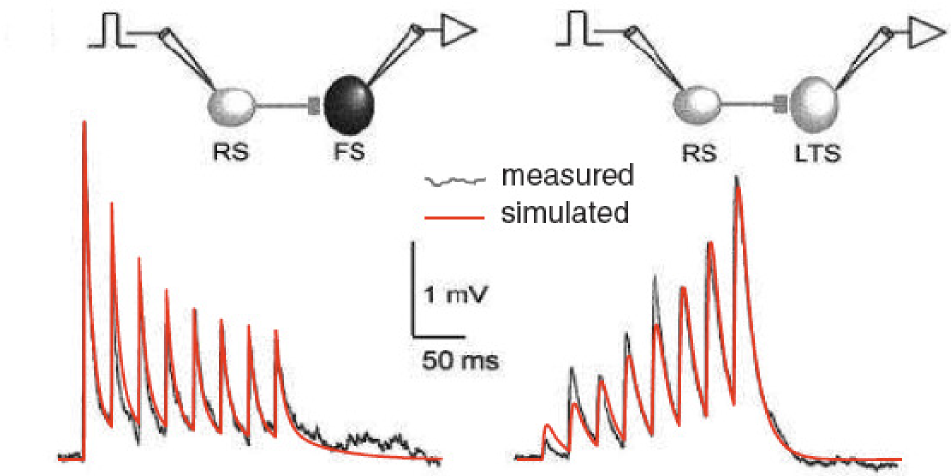
Large-Scale Modeling at the Neural Circuit Level

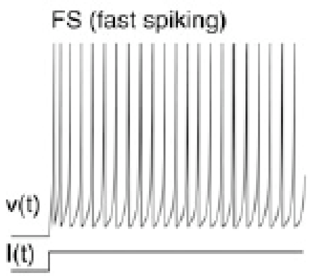








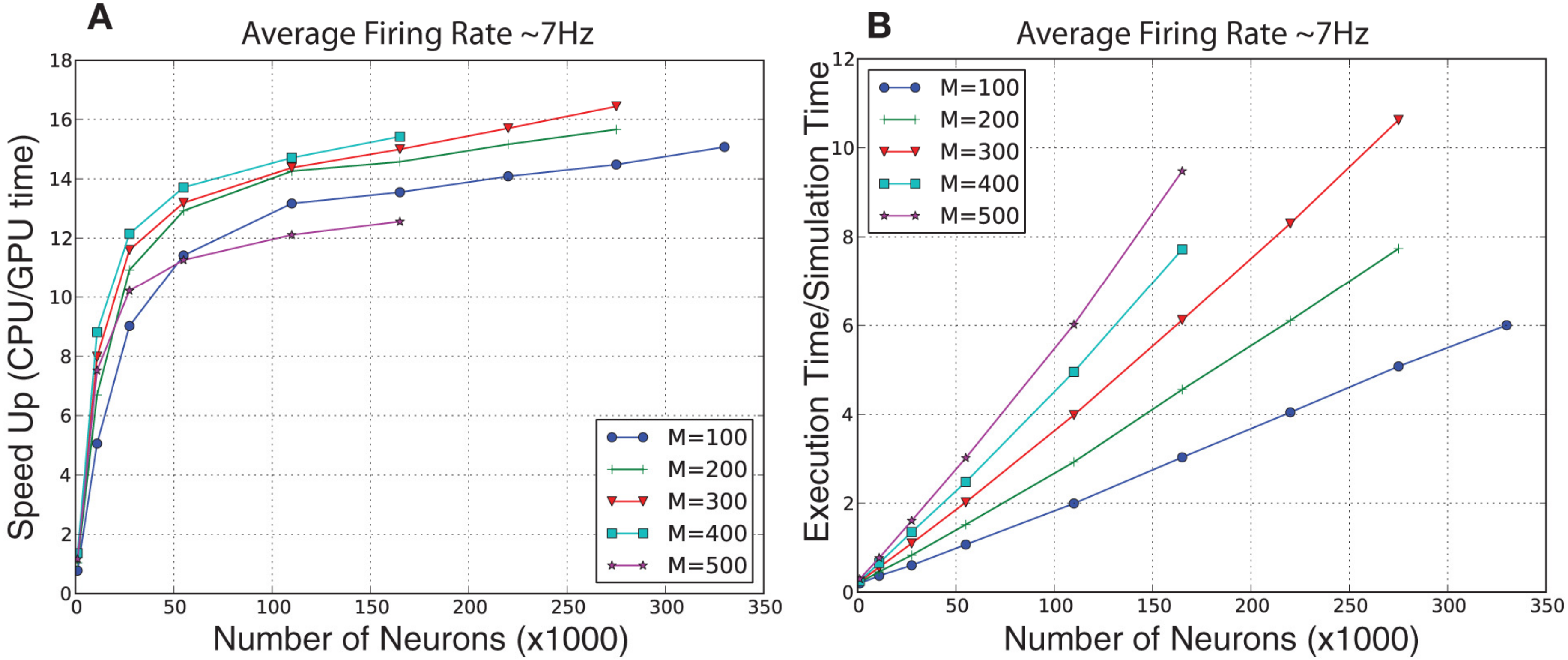




Hardware Architectures for Spike-Based Computations

- Low-cost, high-performance graphics architectures (e.g., NVIDIA GPUs) opens the door for large-scale SNN simulations on affordable, programmable platforms.
- GPUs have benefits and limitations
  - Large fine-grained parallelism.
  - Large off-chip memory bandwidth.
  - Special Function Units.
- Optimization techniques to effectively map SNNs on to GPUs:
  - Exploiting both neuronal and synaptic parallelism to maximize thread level parallelism.
  - Efficient representation of large-scale SNNs that improves the off-chip memory coalescing.
  - Minimizing thread divergence by delaying the execution of diverging conditions by buffering them and running them concurrently later.

Evaluation of Computational Performance in Randomly Connected Networks



Simulations run on a core i7 920 @2.67GHz and NVIDIA C1060

Nageswaran, et al (2009). A configurable simulation environment for the efficient simulation of large-scale spiking neural networks on graphics processors. Neural Networks *22*, 791-800.

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An efficient simulation environment for modeling large-scale cortical processing

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We have developed a spiking neural network simulator, which is both easy to use and computationally efficient, for the generation of large-scale computational neuroscience models. The simulator implements current or conductance based Izhikevich neuron networks, having spike-timing dependent plasticity and short-term plasticity. It uses a standard network construction interface. The simulator allows for execution on either GPUs or CPUs. The simulator, which is written in C/C++, allows for both fine grain and coarse grain specificity of a host of parameters. We demonstrate the ease of use and computational efficiency of this model by implementing a large-scale model of cortical areas V1, V4, and area MT. The complete model, which has 138,240 neurons and approximately 30 million synapses, runs in real-time on an off-the-shelf GPU. The simulator source code, as well as the source code for the cortical model examples is publicly available.

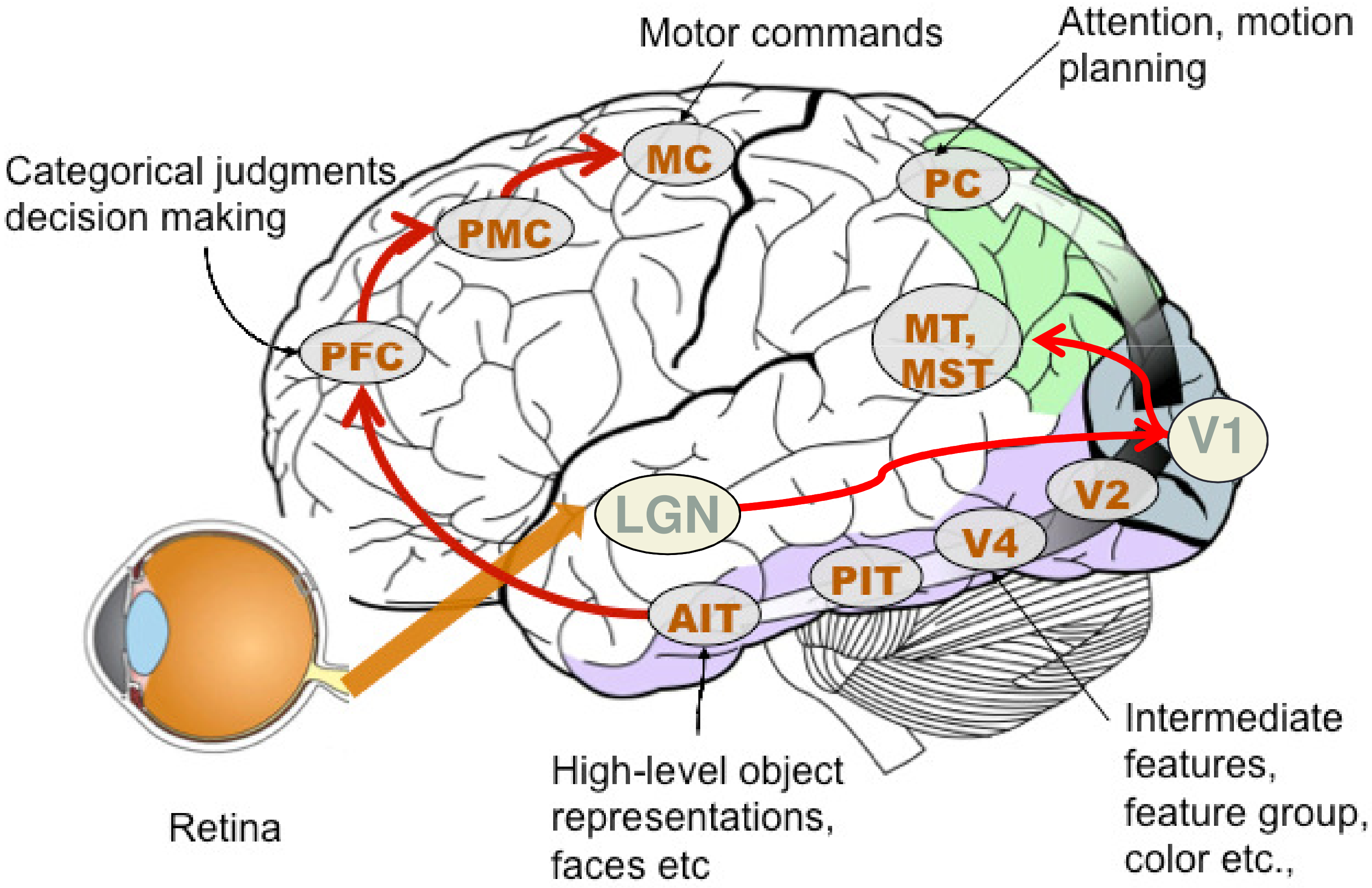
Keywords: visual cortex, spiking neurons, STDP, short-term plasticity, simulation, computational neuroscience, software, GPU

Code available at: http://www.socsci.uci.edu/~jkrichma/Richert-FrontNeuroinf-SourceCode.zip

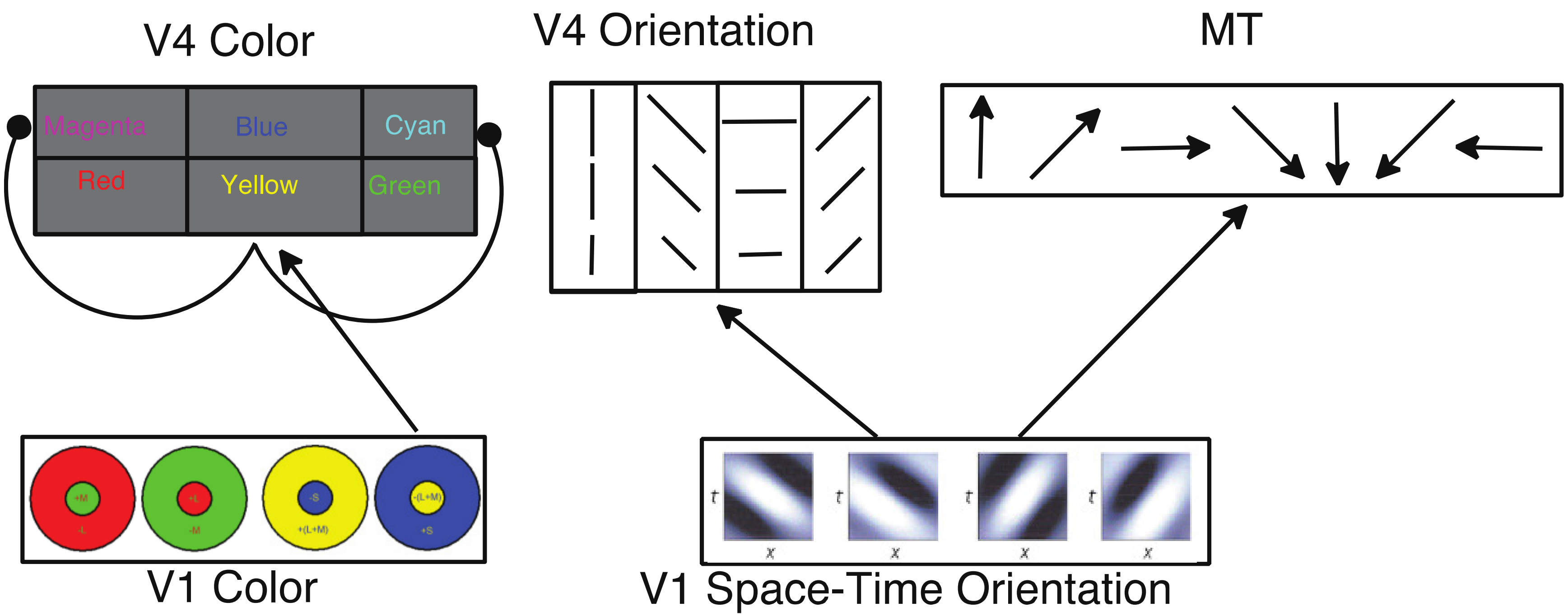
Functionality of our Simulation Environment

Functionality	Level of specificity	Notes
STDP enable/disable, parameters	Group	Defined Post-synaptically
STP enable/disable, parameters	Group	Defined Pre-synaptically
Plastic or not plastic synapses	Connection	
Izhikevich parameters	Group or Neuron	Uses a callback to specify per neuron
Synaptic weights	Group or Neuron Pair	Specified when making a connection
Maximum synaptic weight	Group or Neuron Pair	Specified when making a connection
Synaptic delays	Group or Neuron Pair	Specified when making a connection
Conductance time constants	Group	
Spike monitoring	Group	Specified per group but provides information per neuron
Spike injection	Neuron	Via a user-defined callback
Poisson rate	Neuron	
Maximum firing rate	Simulation	To determine a maximum buffer size

Large-Scale Simulation of Visual Cortex

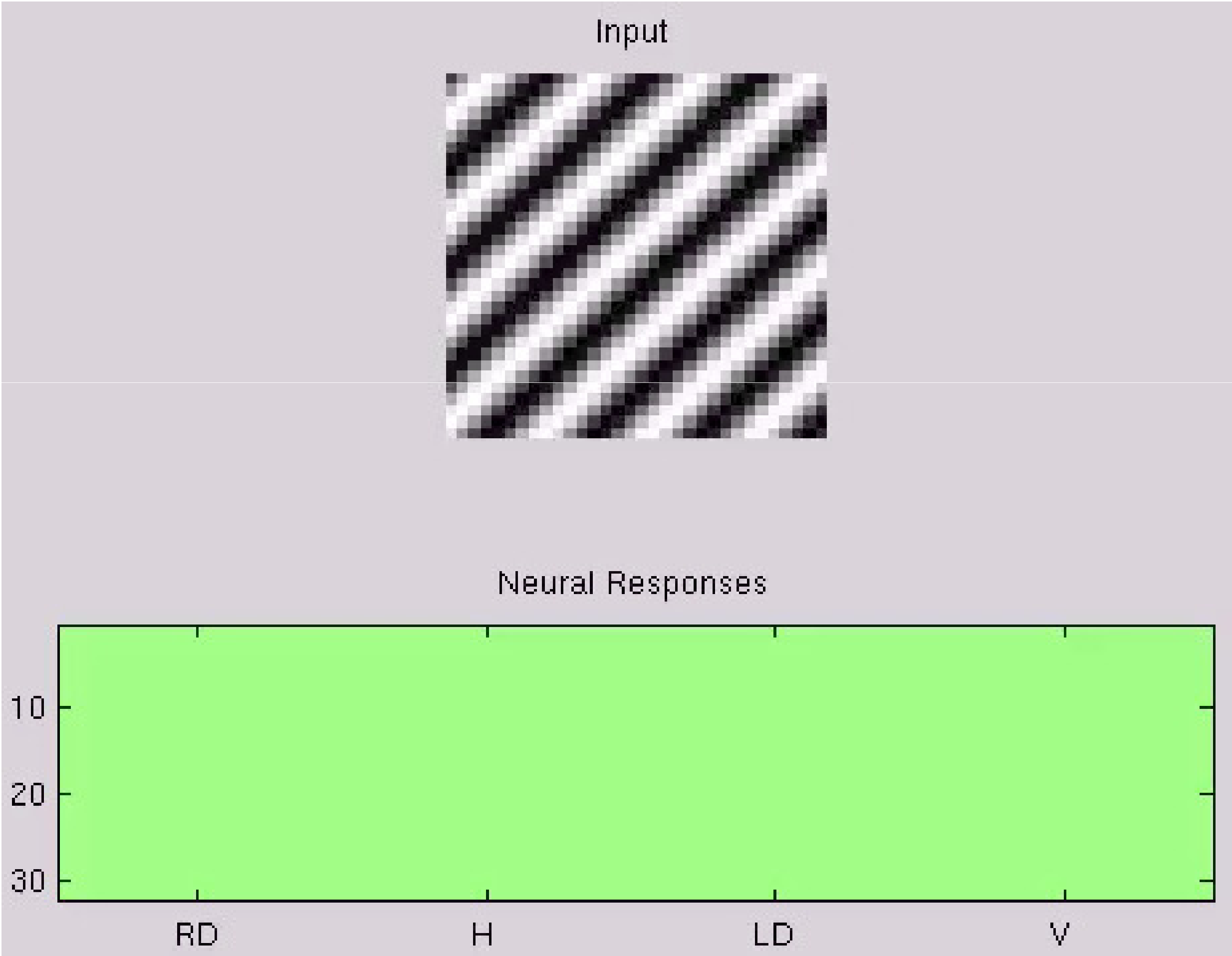


Large-Scale Model of Cortical Visual Processing



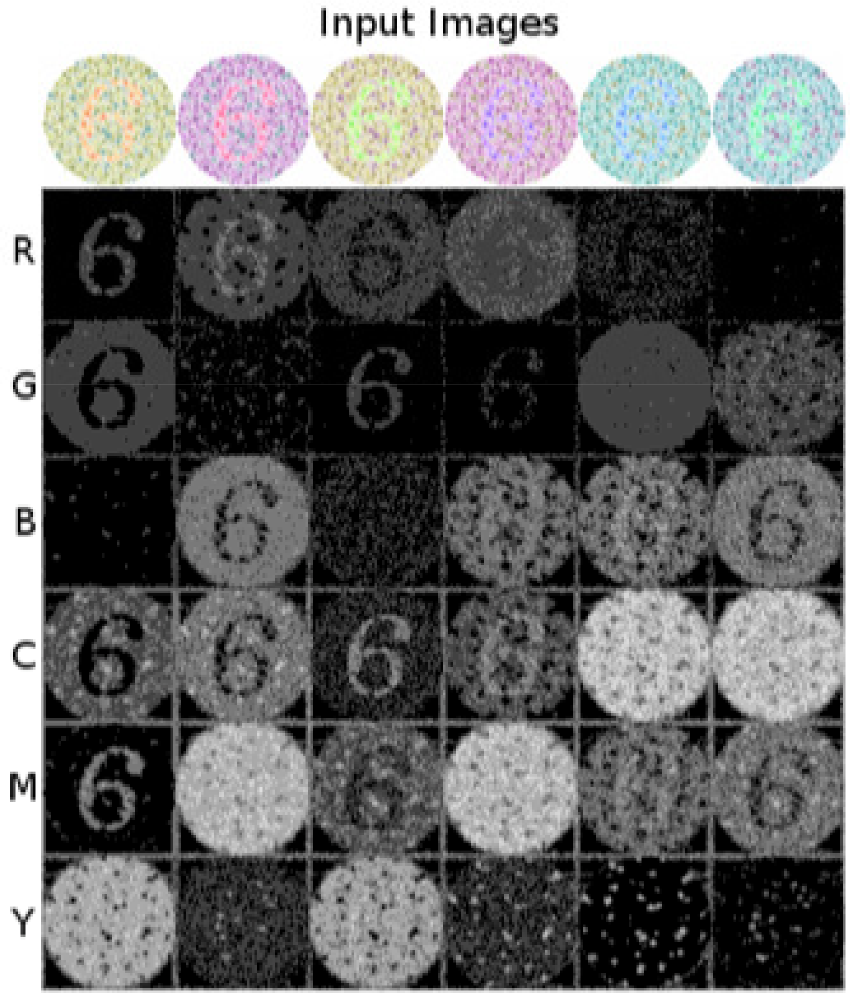
- 32x32 Resolution, 138,240 neurons; ~30 million synapses.
    - Running in real-time on single GPU card.
- 64x64 Resolution, 552,960; ~120 million synapses.
    - Running in real-time on GPU cluster.

V4 Orientation Responses

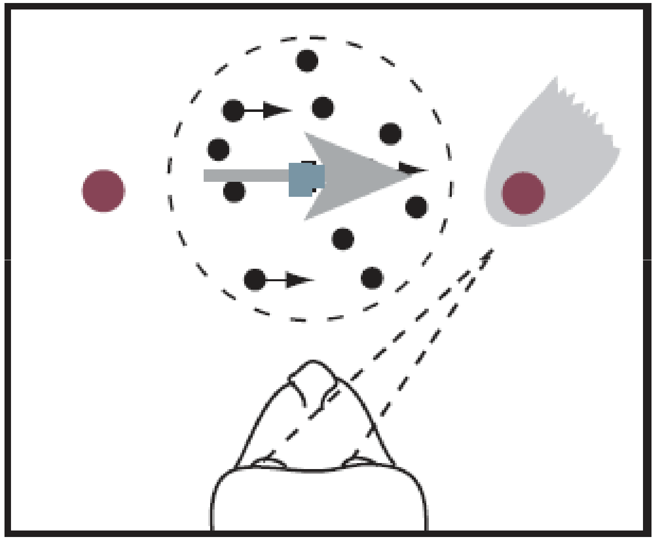


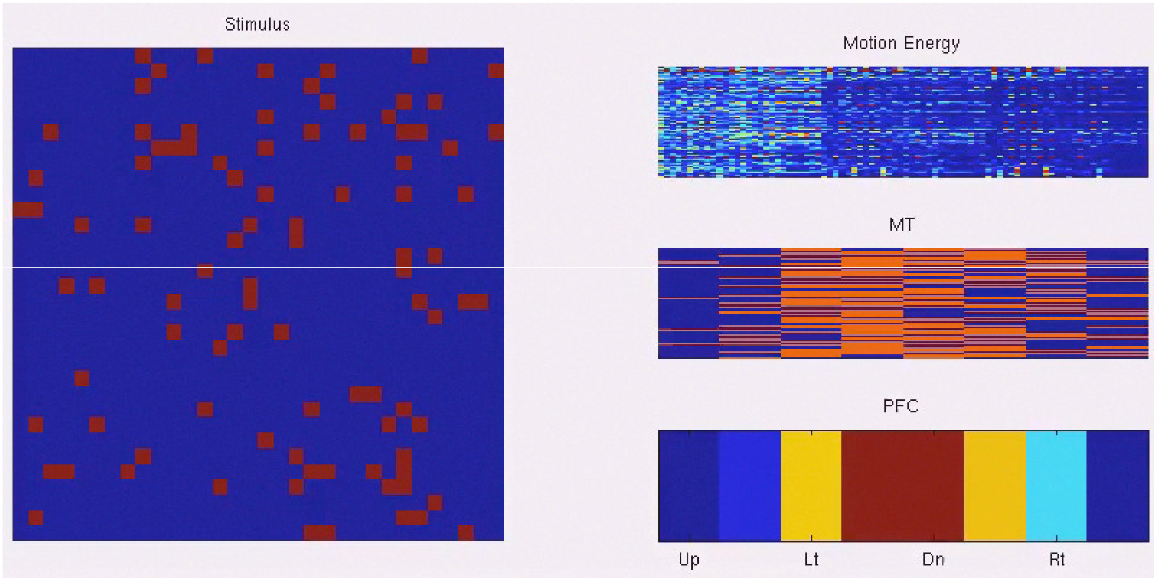
- V4 spiking neuron response to oriented gratings.

V4 Color Responses

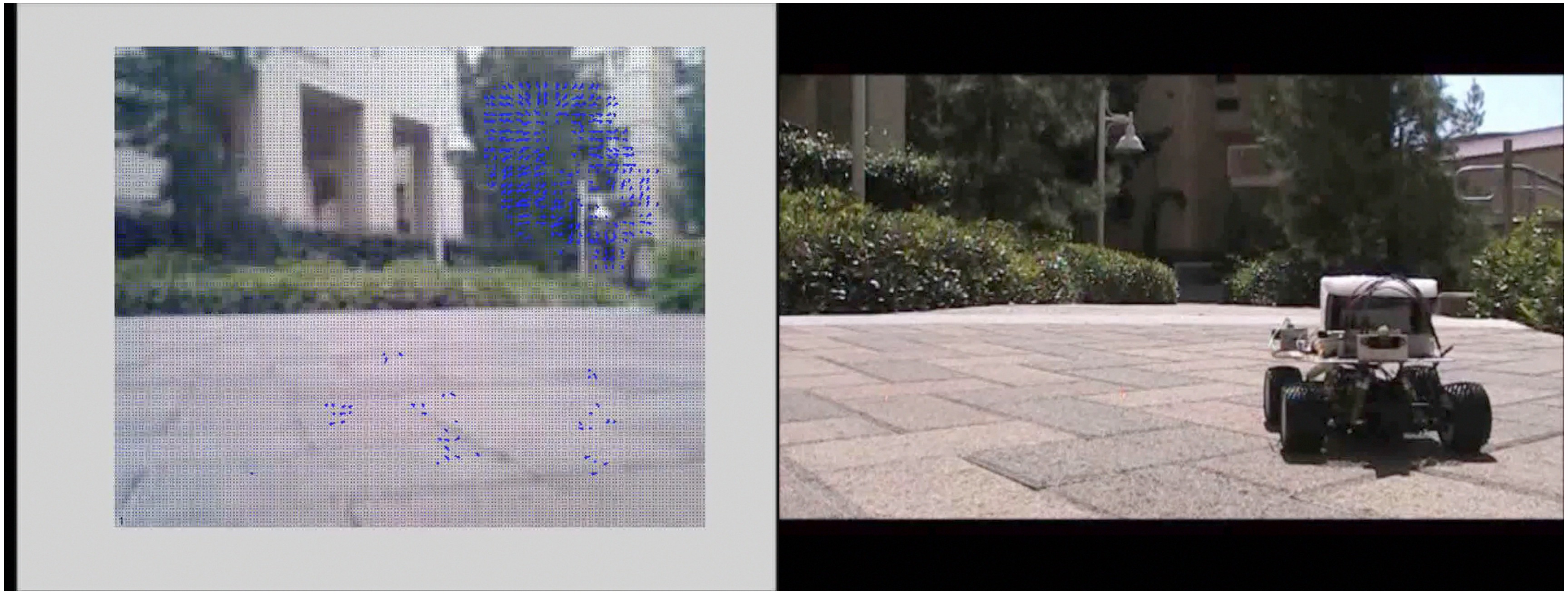


Random-Dot Kinematogram Test

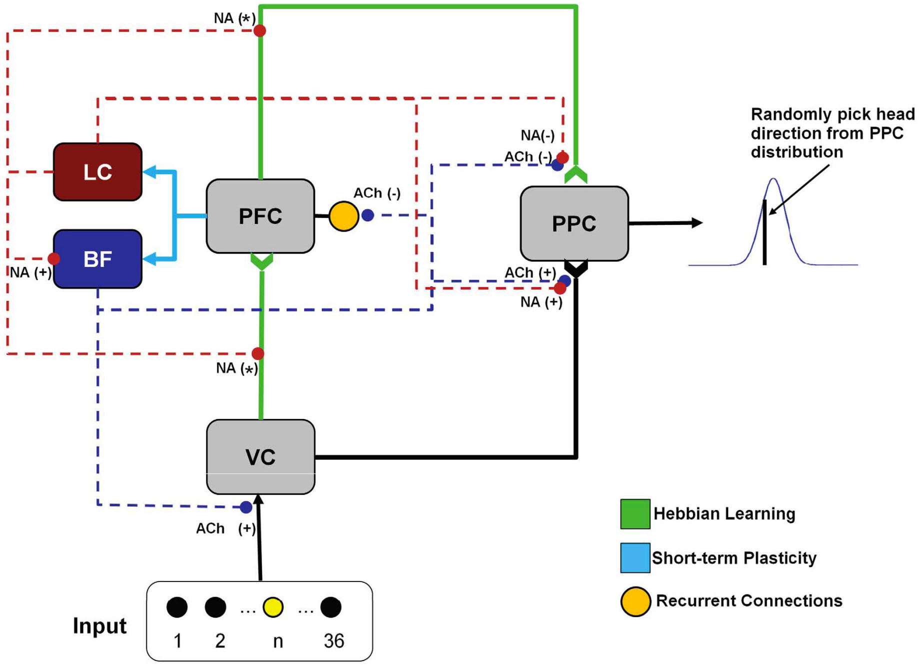




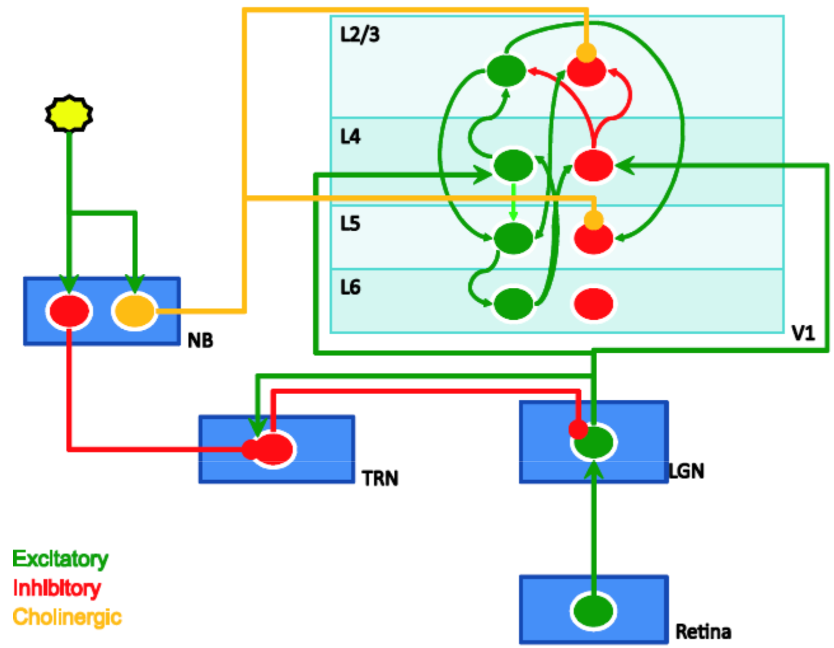
Motion Selectivity in Spiking Model of Area MT



Attentional Modulation of Visual Cortex

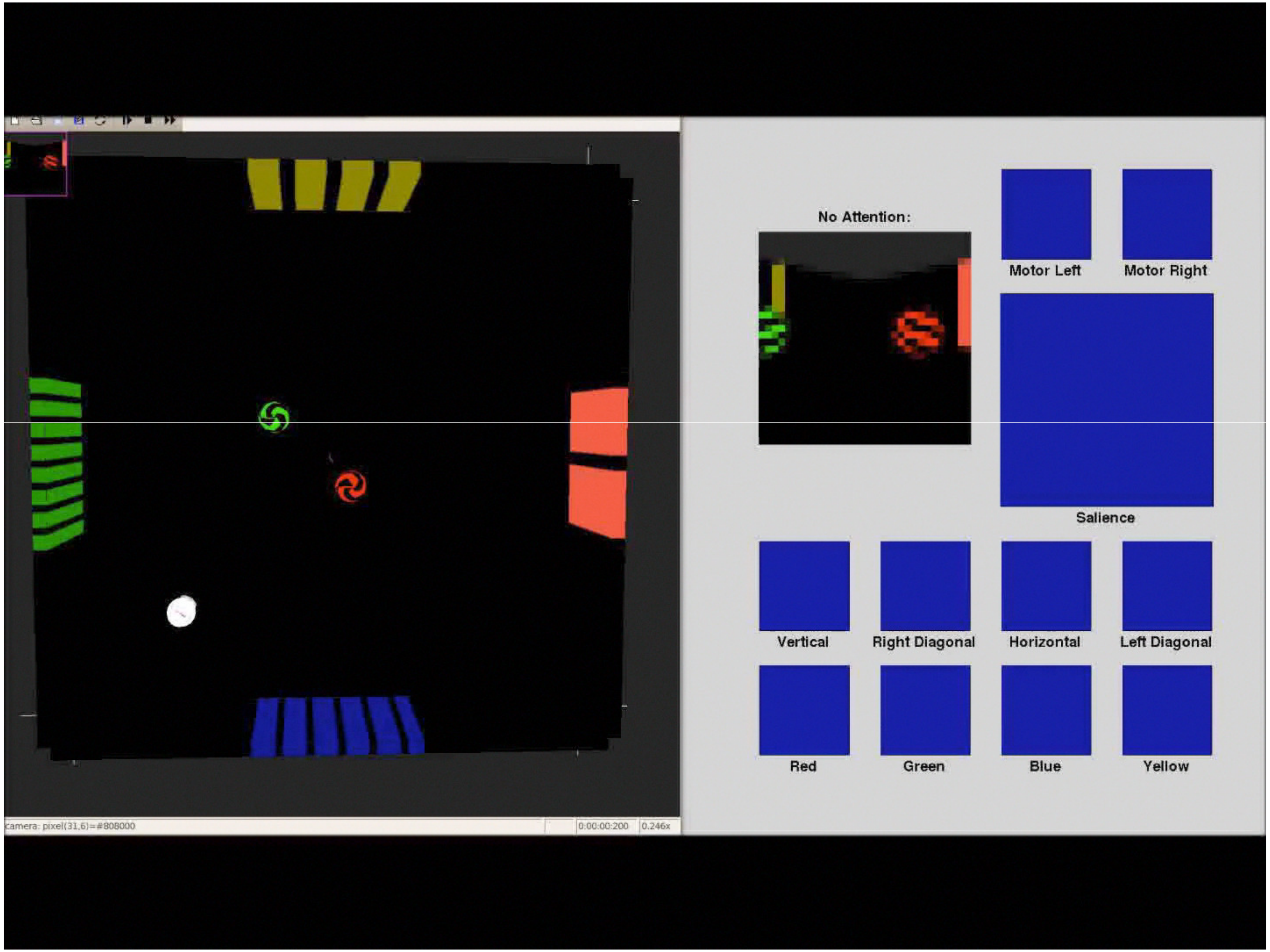


- Balance between goal-directed and sensory driven attention.
- Avery, Nitz, Chiba, & Krichmar, (2012). Simulation of Cholinergic and Noradrenergic Modulation of Behavior in Uncertain Environments. *Frontiers in Computational Neuroscience*.



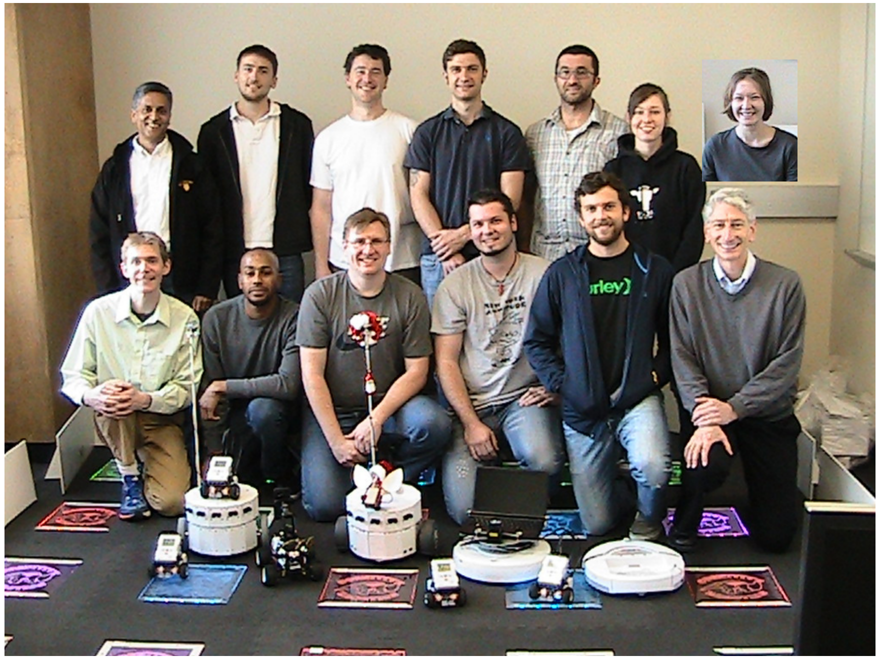
- Increase reliability of neurons.
- Decorrelate noise between neurons.
- Avery, Krichmar, & Dutt (2012). Spiking Neuron Model of Basal Forebrain Enhancement of Visual Attention. *IJCNN.*

Attentional Modulation in an Easter Egg Hunt



Thanks to…

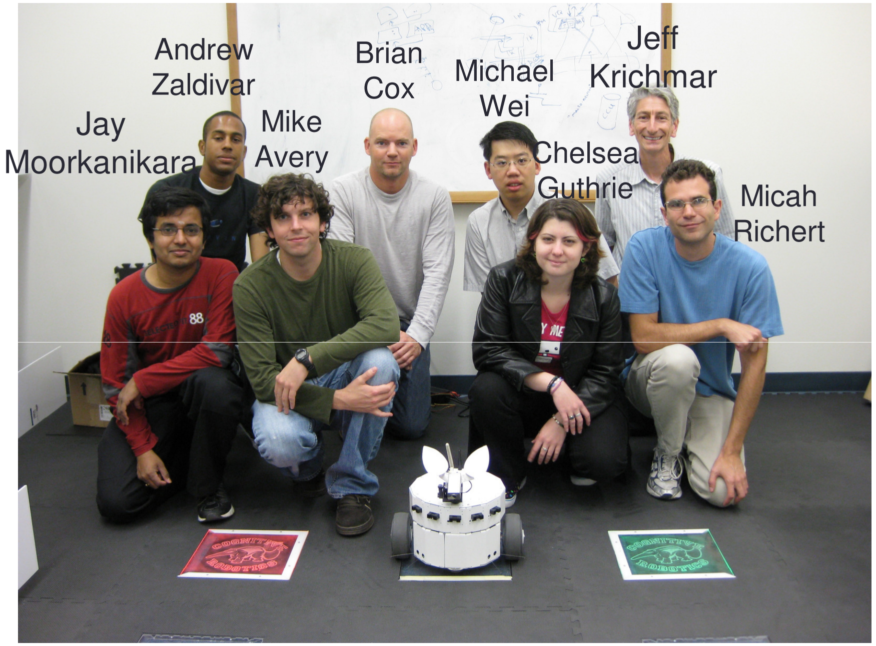
Team CARL Now – UC Irvine



Front row – Brent Miller, Andrew Zaldivar, Kris Carlson, Michael Beyeler, Mike Avery, Jeff Krichmar

Back row – Nikil Dutt, Nicolas Oros, Derrik Asher, Liam Bucci, Wess Gates, Alexis Craig, Emily Rounds

Team CARL Then – UC Irvine



Front row – Jay Nageswaran Moorikanikara, Mike Avery, Chelsea Guthrie, Micah Richert

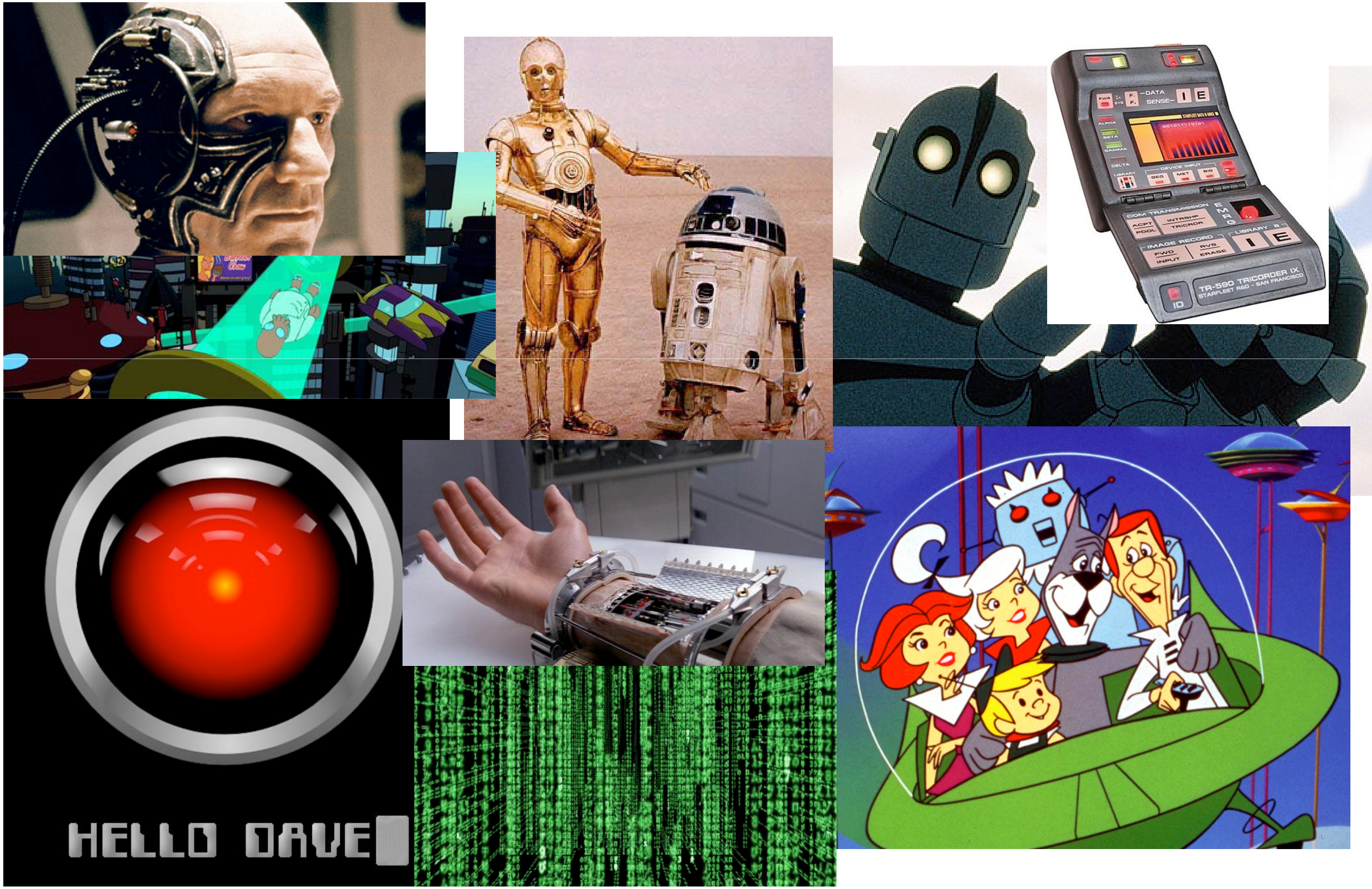
Back row – Andrew Zadivar, Brian Cox, Michael Wei, Jeff Krichmar

Supported by the National Science Foundation and the Defense Advanced Research Projects Agency.

Current Thinking

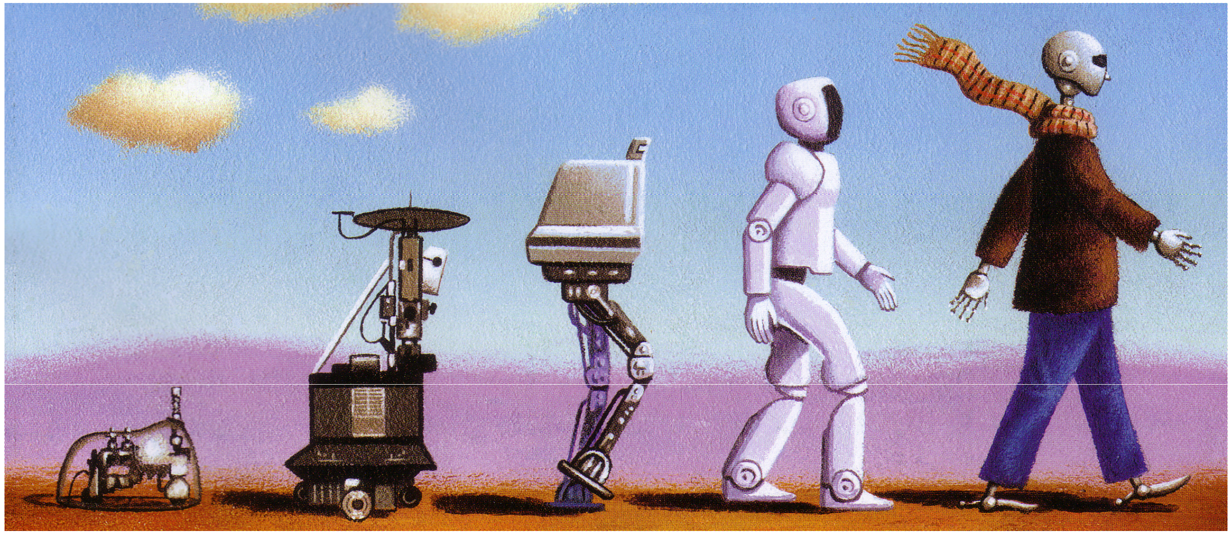
If you build it, they will come…

…still looking for the neuromorphic killer app

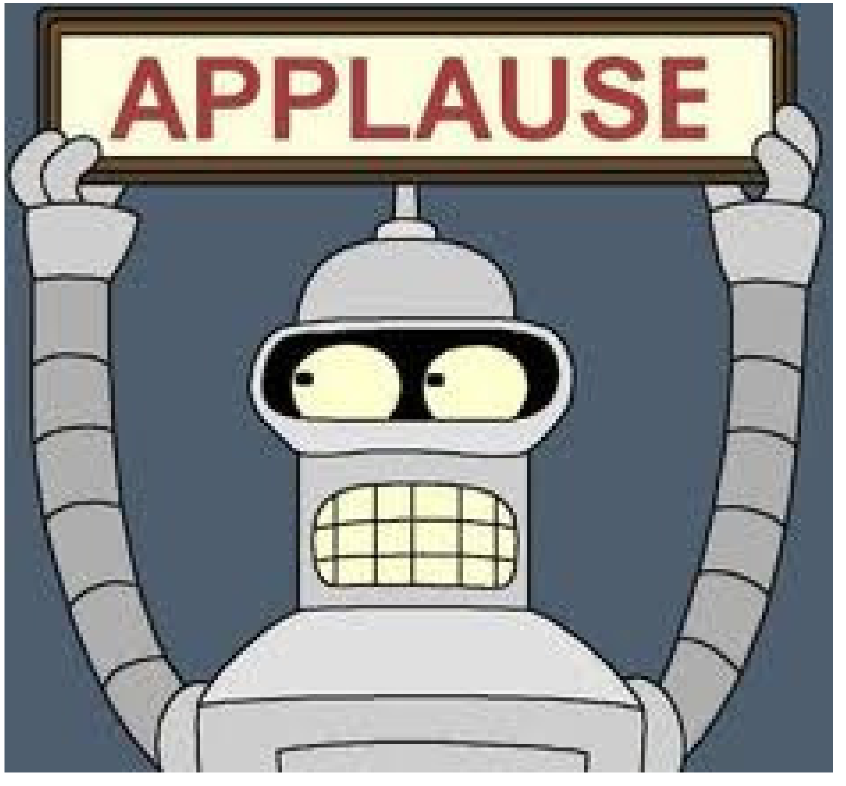


Understanding Through Building

Reverse Engineering the Brain through Neuromorphic Modeling



- The advent of new hardware, which resembles the brain's architecture, complexity and dynamics is necessary for:
  - True understanding of the brain and mind.
  - Construction of artificial brains that are truly intelligent.
- Need to think about what nervous systems (and us) are good at:
  - We are not good at mathematical algorithms, abstract thinking, and are unreliable.
  - We are exceptional at fluid behavior, adaptation, perception, and building predictions.
- Hardware and simulation tools will move us closer to meeting the grand challenge of reverse-engineering the brain.



- Questions or Comments???