Brain-Based Robots and Neuromorphic Engineering
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.
Neuroanatomy 101

Planning, make decision, long-term memory

Audition, language processing

Sensory integration

Visual perception
The Brain is Embodied and the Body is Embedded in the Environment
Neuromorphic and Brain-Based Robots
Design Principles

- Incorporate a simulated brain with detailed neuroanatomy and neural dynamics.
- Organize the unlabeled signals it receives from the environment into categories without a priori knowledge.
- Have a physical instantiation, which allows for active sensing and autonomous movement in the environment.
- Adapt behavior when an important environmental event occurs.
- Allow comparisons with experiments:
  - Behavioral data.
  - Physiological data.
Control architectures for robots based on some aspects of the nervous system:

- Embodied neural models may lead to a better understanding of brain and cognitive function.
- Neurobiology as inspiration for robotic control systems may lead to better robot designs.
Role of Neuromodulation
Exploit Environmental Events and Explore New Behaviors

Neuromodulation as a Robot Controller

Neuromodulation as a Robot Controller
The RatSLAM Project: Robot Spatial Navigation

Wyeth, Milford, Schulz, & Wiles in Neuromorphic and Brain-Based Robots, CUP, 2011, pp. 87-108.
Build a Cognitive Map of Environment

- Learn location of salient objects
  - E.g. Charging station, my office, my students, department chair
- Plan routes based on current needs
**Hawk-Dove Game**

- **Hawk**
  - Escalate a fight.
  - **Green** if CARL.
  - **Red** if Subject.

- **Dove**
  - Display one’s colors.
  - **Blue** for both CARL and Subject.

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**Hawk-Dove Model: Costs and Benefits of Fighting over Resources**

<table>
<thead>
<tr>
<th>Hawk-Dove Model: Costs and Benefits of Fighting over Resources</th>
<th>Hawk</th>
<th>Dove</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payoff^ to...</td>
<td>hawk</td>
<td>dove</td>
</tr>
<tr>
<td>...in fights against:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hawk wins 50% of fights; is injured in 50% of fights.</td>
<td>hawk</td>
<td>dove</td>
</tr>
<tr>
<td>Hawk always wins; dove flees.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Payoff: (V–D)/2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dove never wins; is never injured.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dove wins 50% of fights; is never injured; wastes time.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Payoff: V</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Payoff: 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Payoff: V/2–T</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

^V = fitness value of winning resources in fight  
D = fitness costs of injury  
T = fitness costs of wasting time

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Hawk-Dove game with CARL the Robot
Neural Model for Hawk-Dove Game

- **Neuromodulatory Neurons**
  - Raphe (Serotonergic)
  - VTA (Dopaminergic)

- **TOI-State Neurons**
  - Open
  - Escalate
  - Display

- **Action Neurons**
  - Escalate
  - Display
## Effects of Lesions on Model Performance

<table>
<thead>
<tr>
<th>PERCENTAGE OF ESCALATION FOR THE NEURAL AGENT</th>
<th>Control Agent</th>
<th>Raphe Lesion</th>
<th>VTA Lesion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safe</td>
<td>Safe</td>
<td>Safe</td>
<td>Safe</td>
</tr>
<tr>
<td>Safe</td>
<td>Safe</td>
<td>Safe</td>
<td>Safe</td>
</tr>
<tr>
<td>Harsh</td>
<td>Harsh</td>
<td>Harsh</td>
<td>Harsh</td>
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<tr>
<td>Harsh</td>
<td>Harsh</td>
<td>Harsh</td>
<td>Harsh</td>
</tr>
</tbody>
</table>

- **Raphe lesion** – lost ability to assess cost.
  - Led to risky, high reward behavior.
- **VTA lesion** – lost ability to assess reward.
  - Led to safe, low reward behavior.

| Statistical                   | 98%  | 10%  | 99%  | 93%  | 35%  | 7%  |
| Tit-for-Tat                   | 34%  | 14%  | 82%  | 82%  | 25%  | 13% |
| WSLS                          | 93%  | 9%   | 97%  | 97%  | 21%  | 8%  |
Acute Tryptophan Depletion Study
8 subjects (5 male, 3 female)

- Tryptophan is a precursor to serotonin.
- Low protein diet the day before the experiment.
- Drink amino-acid shake.
  - Without Tryptophan.
  - With Tryptophan.
- Normal tryptophan levels are 40-90 uMol/L.
  - Subjects with low tryptophan were < 20 uMol/L.
  - Subjects with high tryptophan were > 90 uMol/L.
- Neural model
  - Robotic and simulated versions of both games.
  - Control (intact) vs. Raphe lesion.
  - Friendly vs. harsh environment (25% vs. 75% chance serious injury).
Subjects Shifted Strategies Depending on the Type of Opponent they Played

- Switch from Win-Stay, Lose-Shift against an intact neural agent to Tit-For-Tat against a serotonin depleted neural agent.
  - Shift similar to the rejection of unfair offers in the Ultimatum Game.
  - Sends a message that the subject believes they are being treated unfairly.

![Subjects' Usage of WSLS in Hawk-Dove](image1)

![Subjects' Usage of T4T in Hawk-Dove](image2)

- p < 0.05
- p < 0.001
Categorization of Subject Variation using Bayesian Graphical Models

Subjects responded strongly, but idiosyncratically to the effects of:

- Serotonin levels & Embodiment

In collaboration with Shunan Zhang & Michael Lee
The brain is embodied and the body is embedded in the environment.
- Cognition and intelligence require a close coupling between brain, body, and environment.

Intelligent, brainy robots of the future will one day, very soon, be interacting and cooperating with human society.

Neurorobot research approach will advance science and society in positive and prosperous ways that we can only now imagine.
Neuromorphic Engineering

- Building Hardware Based on the Brain’s Structure and Dynamics
Brain Computations

- Massive parallelism ($10^{11}$ neurons)
- Massive connectivity ($10^{15}$ synapses)
- Excellent power-efficiency
  - $\sim 20$ W for $10^{16}$ flops
- Low-performance components ($\sim 100$ Hz)
- Low-speed comm. ($\sim$ meters/sec)
- Low-precision synaptic connections
- Probabilistic responses and fault-tolerant
- Autonomous learning
The DARPA SyNAPSE Project is focused on developing a brain-like computer that can process information in a manner similar to the human brain. The project aims to create a system that can mimic the biological brain's ability to learn and adapt to new situations.

The diagram illustrates the progression from synapses to the brain, highlighting key characteristics at each level:

- **Synapses**: ~$10^{10}$ synapses/cm²
- **Neurons**: ~$10^{6}$ neurons/cm², ~$10^{4}$ neurons/cortical column
- **Microcircuits**: ~$5 \times 10^{8}$ long range axons @ 1 Hz
- **Long-range Interconnects**: Biological Brain

The diagram also shows the electrical and physical components at each level:

- **Synapse**: Crossbar Junction, ~$10^{10}$ intersections/cm² @ 100 nm pitch
- **Neurons**: CMOS Substrate, 5X10^8 transistors/cm² @ 500 transistors/neuron
- **Microcircuits**: Laminar Circuit, Layered cortical circuits with ~$10^{8}$ neurons/cm²
- **Long-range Interconnects**: High Speed Bus, Multi-Gbit/sec digital comms

The ultimate goal is to create an electronic brain that can function as efficiently as the biological brain.
Neural Modeling 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

![Diagram showing levels of abstraction from biophysical to theoretical, indicating accuracy and speed](image)
Spiking Neural Network (SNN) Primitives

- Peak voltage: 30 mV
- Reset: c
- Decay with rate: a
- Sensitivity: b
- RS (regular spiking):
- FS (fast spiking):

Graph showing pre- and postsynaptic neuron activity with LTP and LTD curves.

- Measured vs. simulated data:
  - RS
  - FS
  - LTS

Graph with measured and simulated data, showing voltage and time scales.
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.
Evaluation of Computational Performance in Randomly Connected Networks

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

80% excitatory neurons, 20% inhibitory neurons
An efficient simulation environment for modeling large-scale cortical processing

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¹ Department of Cognitive Sciences, University of California, Irvine, CA, USA
² Department of Computer Science, University of California, Irvine, CA, USA

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

# Functionality of our Simulation Environment

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

- Motor commands
- Attention, motion planning
- Categorical judgments, decision making
- High-level object representations, faces etc.
- Intermediate features, feature group, color etc.
Large-Scale Model of Cortical Visual Processing

- 32x32 Resolution, 138,240 neurons; ~30 million synapses.
- 64x64 Resolution, 552,960; ~120 million synapses.
V4 Orientation Responses

- V4 spiking neuron response to oriented gratings.
Response of V4 Neurons to Hues
V4 Response – 64x64 pixels
Random-Dot Kinematogram Test
Tuning Approaches

• **Ad-hoc approach by skilled Scientist**
  - Most common, certainly not optimal.

• **Parameter sweep**
  - Exhaustive search with every parameter set.
  - Cons: tedious and slow process.
    - 5 parameters with 10 values each needs $10^5$ simulations
    - Time: ~15 days for 1K network with 5 parameters

• **Optimized Parameter Search**
  - Automated pruning of search space.
  - Stochastic search: evolutionary algorithms, simulated annealing, etc.
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.

Brain-based robots and neuromorphic engineering will move us closer to meeting the grand challenge of reverse-engineering the brain.

- [Website](http://www.socsci.uci.edu/~jkrichma/)