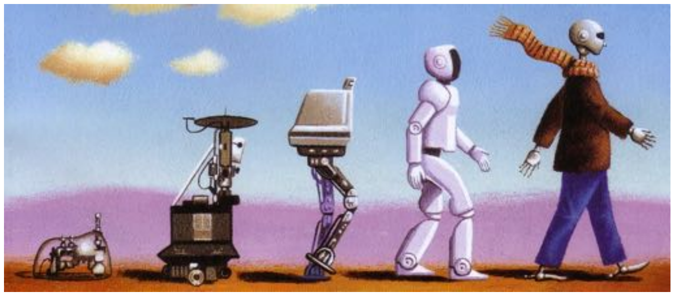
Cognitive Anteater Robotics Laboratory (CARL)

Jeff Krichmar
Department of Cognitive Sciences
Department of Computer Science

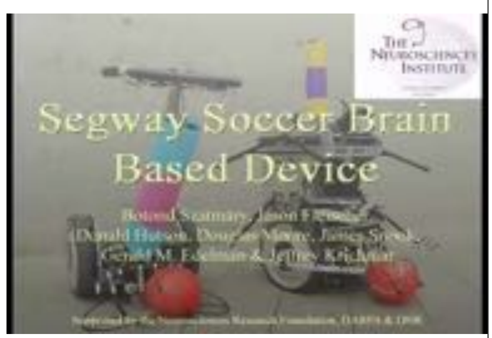
CARL Research and Related Coursework

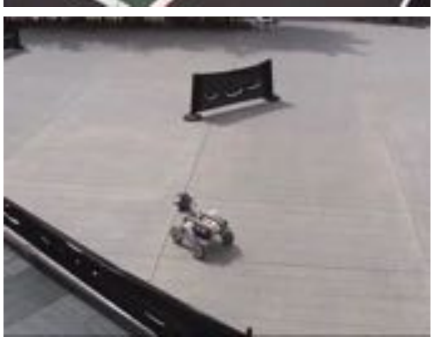
- Neurorobotics or Brain-Based Robotics
  - Neuromodulation as a robot controller
  - Socially Assistive Robot that focuses on touch
- Neuromorphic Computing
  - Spiking Neural Network of Motion Perception and Visual Navigation
- Courses
  - Cognitive Robotics
    - PSYCH 112R/LR
    - PSYCH 268R
  - Computational Neuroscience
    - PSYCH 268A

Goals of Neurorobotics



- Understanding through building
  - Building physical systems that demonstrate cognitive abilities could lead to a better understanding of the neural machinery that realizes cognitive function.
- Building more intelligent machines
  - Constructing physical systems could lead to a system that demonstrates capabilities commonly found in the animal kingdom, but rarely found in artificial systems.



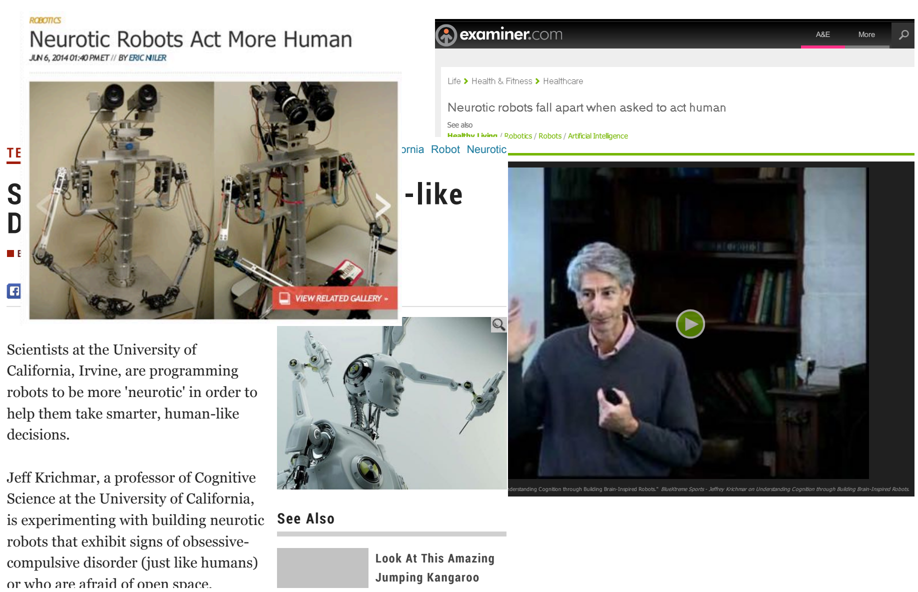


Design Principles for Neurorobots

- Engage in a behavioral task.
- Behavior controlled by a simulated nervous system that reflects the brain's architecture and dynamics.
- The world is an unlabelled place.
  - Organize the signals from the environment into categories without *a priori* knowledge or instruction.
- A value system that signals the salience of environmental cues to the robot's nervous system.
- Needs to be situated in the real world.
- Behavior and activity of its simulated nervous system must allow comparisons with empirical data.

Krichmar, J.L., and Edelman, G.M. (2005). *Artificial Life,* Vol. 11, 63-78.

It's called *Neurorobotic* not Neurotic



WCCI 2012 IEEE World Congress on Computational Intelligence
June, 10-15, 2012 - Brisbane, Australia IJCNN

A Biologically Inspired Action Selection Algorithm Based on Principles of Neuromodulation

frontiers in NEUROROBOTICS
ORIGINAL RESEARCH ARTICLE
published: 05 February 2013
doi: 10.3389/fnbot.2013.00001

A neurorobotic platform to test the influence of neuromodulatory signaling on anxious and curious behavior

Jeffrey L. Krichmar [1,2*]

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

Agent Design Principle: Value

- Intelligent agents are equipped with a value system that constitutes a basic assumption of what is good and bad for an agent.

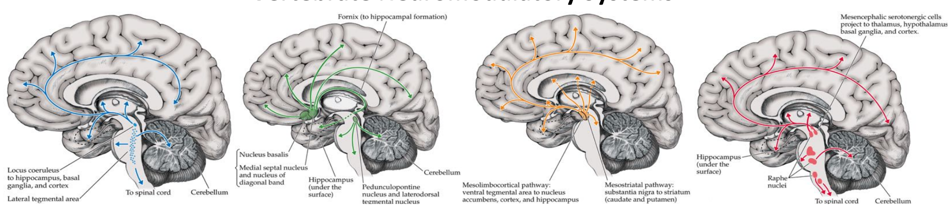
Pfeifer & Bongard, "How the body shapes the way we think." The MIT Press, 2007

UC Irvine 9

Organisms Adapt Their Behavior Through Value Systems

- Non-specific, modulatory signals to the rest of the brain.
- Biases the outcome of synaptic efficacy in the direction needed to satisfy global needs.

Vertebrate Neuromodulatory Systems



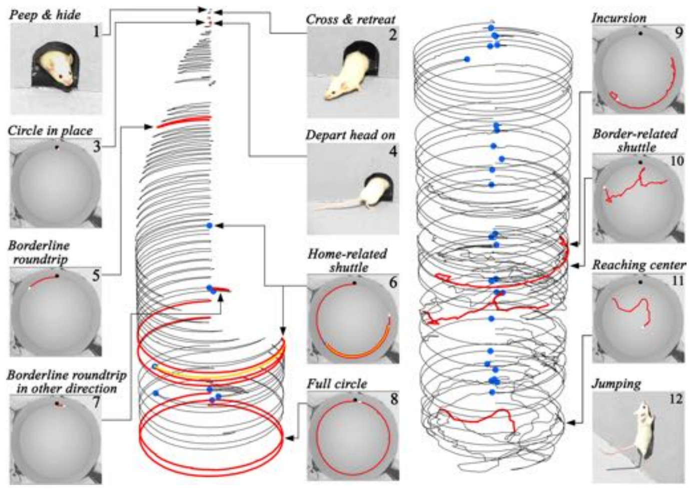
Noradrenergic | Cholinergic | Dopaminergic | Serotonergic

UC Irvine 10

Motivation

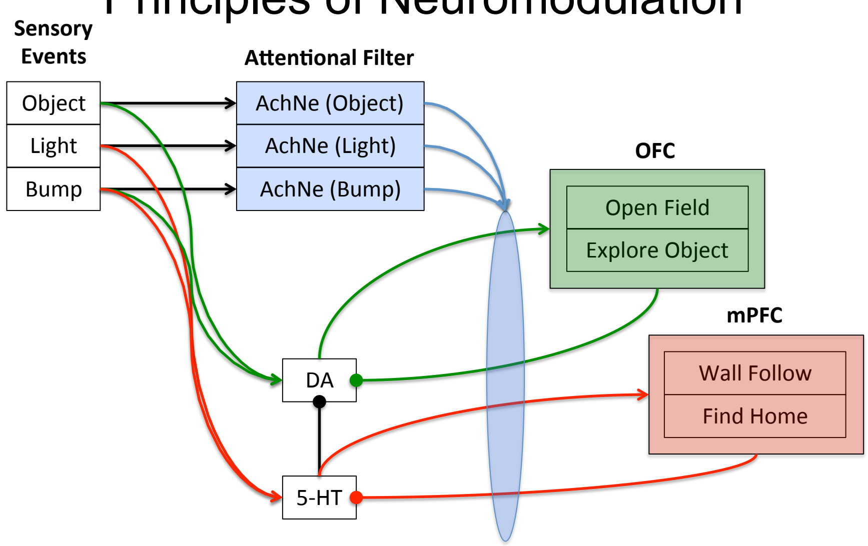
- Understand principles of the brain's neuromodulatory systems through building a ***neurorobotic*** system.
  - Neuromodulatory systems are present in all vertebrates and are critical for an animal to quickly assess the context of sensory input and take action.
  - Neuromodulators signal environmental changes to the nervous system and alter neuronal responses such that the organism can respond quickly and accurately to these changes.
- Present a minimal neural model that captures the aspects of neuromodulation with the goal of developing a biologically inspired controller for robots.
- Develop a model of social disorders and test the model in both an animal model and in human robot interaction experiments.

Open Field Test
Typical Mouse Behavior when Free to Explore

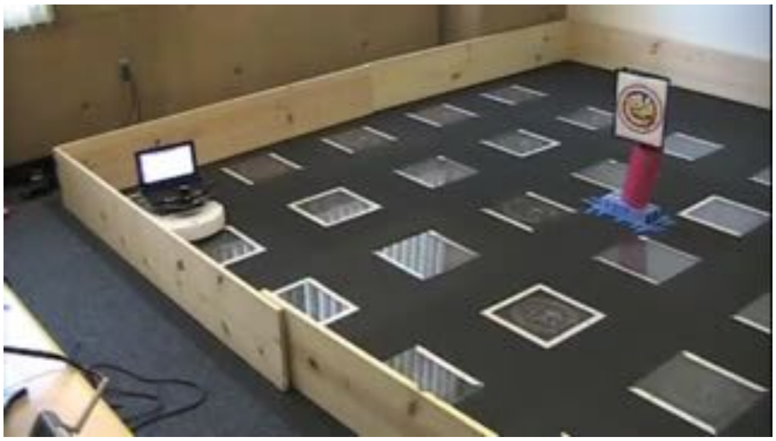


Fonio, E., Benjamini, Y., and Golani, I. (2009). Proc Natl Acad Sci *106*, 21335-21340.

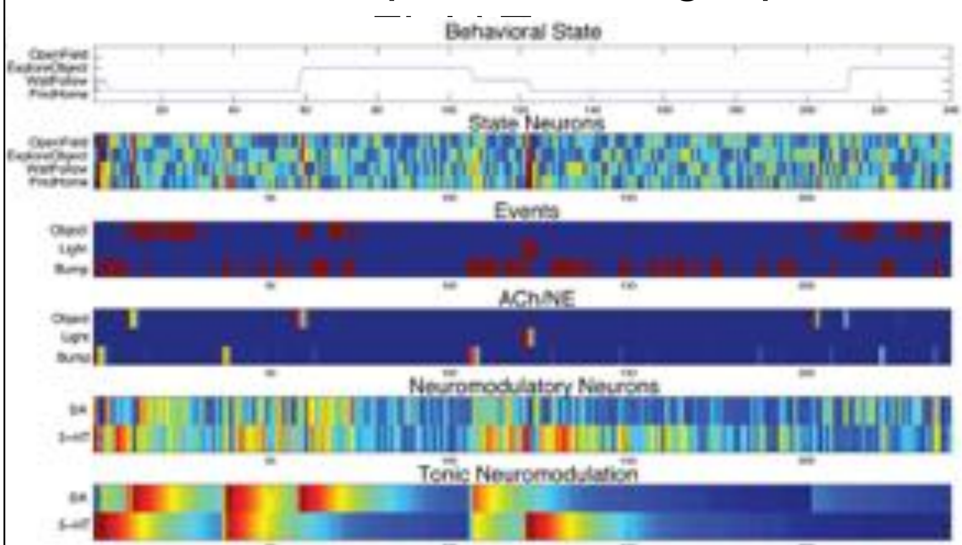
Model Architecture based on Principles of Neuromodulation



Typical CARL-Roomba Behavior when Free to Explore

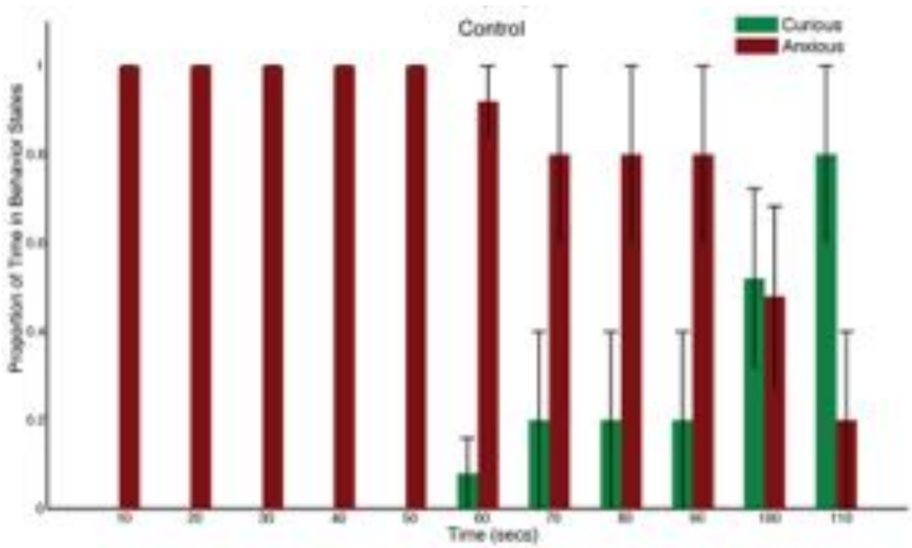


Neural Response During Open



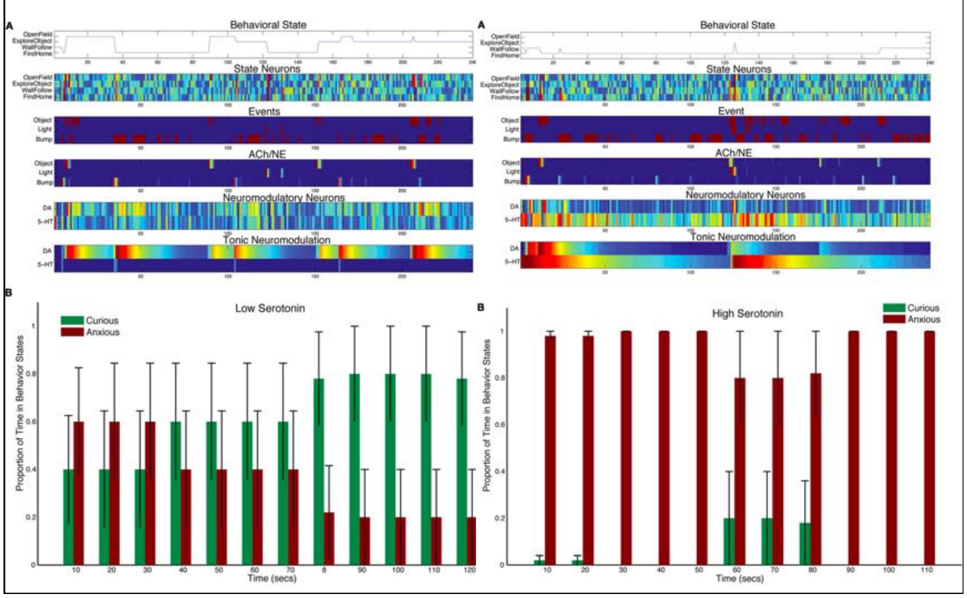
UC Irvine 15

Population Response to Light Flash



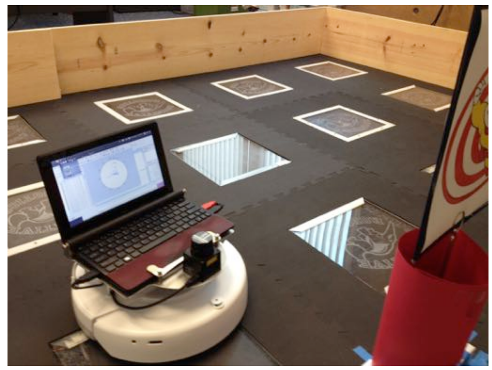
UC Irvine 16

Serotonin Levels Affect Risk-Taking



CARL Roomba and Cognitive Control

- Model for animal behavior and neurological diseases:
  - Anxious states, attention deficits, autism spectrum disorder
- Action selection module:
  - Fluidly switching between behavioral states.
  - Could be added onto conventional control systems.



Neuromorphic Engineering

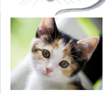
- Building Hardware and Applications Based on the Brain's Structure and Dynamics

Brains by the Numbers

Species	Neurons	Synapses
Nematode	302	10^3
Fruit Fly	100,000	10^7
Honeybee	960,000	10^9
Mouse	75,000,000	10^{11}
Cat	1,000,000,000	10^{13}
Human	85,000,000,000	10^{15}



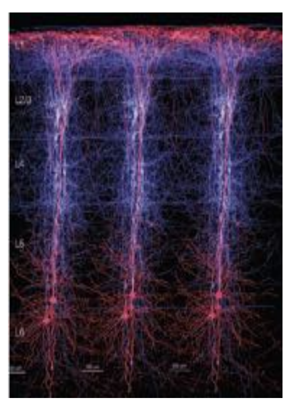





Source – http://en.wikipedia.org/wiki/List_of_animals_by_number_of_neurons

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)
- Low-speed comm. (~meters/sec)
- Low-precision synaptic connections
- Probabilistic responses and fault-tolerant
- Autonomous learning



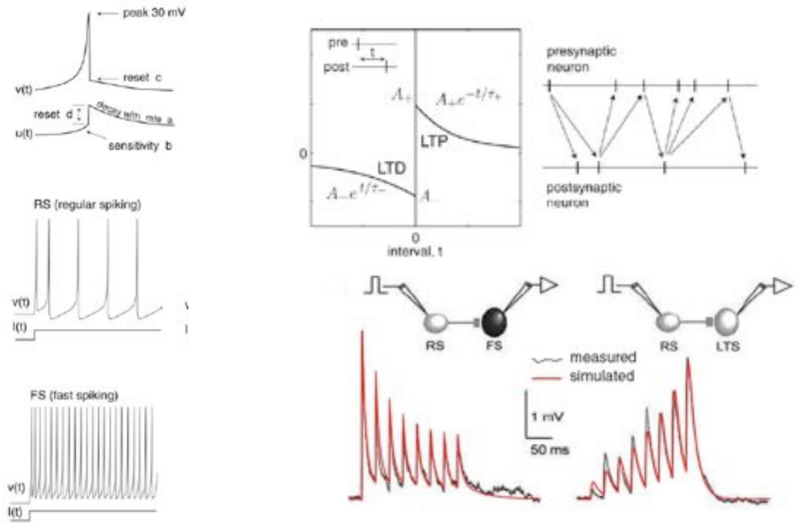
Examples of Neuromorphic Hardware Devices

Hardware Project: Hardware Group	Hardware Description	Neuron Models	Synaptic Plasticity	Max Neurons	Max Synapses
SpiNNaker: Industry and UK universities	- Completely digital - Consists of array of nodes - Each node has 18 ARM9 cores - Final goal: 1,036,800 cores	**Spiking: Izhikevich and non-spiking**	Yes: STDP	1,000 neurons per ARM9 core	10k synapses per ARM9 core
Neurogrid: Stanford University	- Analog/digital hybrid - Full board has 16 neurochips - Operates on only 5 W	**Spiking: Two-compartment neurons**	No	65,536 neurons per neurochip	375M synapses per neurochip
True North Cog. Architecture: IBM SyNAPSE Team	- Completely digital - Consists of hierarchical design - Neurosynaptic core is basic building block	**Spiking: many behaviors including LIF**	No	256 neurons per neuro-synaptic core	256K binary synapses per neuro-synaptic core
HRL neural chip: HRL Labs, SyNAPSE Team	- Analog/digital hybrid - Synaptic weights stored in memristors	**Spiking: Izhikevich**	Yes: STDP	576 neurons per chip	70k virtual synapses per chip
HiCANN: BrainScaleS Team	- Analog/digital hybrid - Each wafer has 384 chips - Neurons are analog - Synapses are digital	**Spiking: AdExp and I&F**	Yes: STDP	512 neurons per chip	16k synapses per chip

Spiking Neural Networks (SNNs)

- **What are SNNs?**
  - Neural Networks that model neuronal/synaptic temporal dynamics
  - Spike only when the membrane voltage exceeds a threshold
- **Why use SNNs?**
  - Spike events are rare: average brain activity 1-10 Hz
    - More energy efficient than sending an analog rate.
  - Event-driven nature of SNNs fits well with neuromorphic hardware
    - Use "**Address Event Representation**" (**AER**) to minimize communication.
    - Provides a common language for neuromorphic systems.
  - SNNs provide temporal coding but can still use rate coding
  - SNNs support biologically plausible learning rules
    - Spike Timing-Dependent Plasticity (STDP)
    - Short-term Plasticity.
    - Neuromodulation.

Components of a SNN



CARLsim

A User-Friendly and Highly Optimized Library for the Creation of Neurobiologically Detailed Spiking Neural Networks

- GPU-accelerated, user-friendly, well documented.
  - Runs on Linux, Mac OS, Windows systems with CUDA SDK.
- Capable of simulating biological detailed neural models.
  - Runs 10^4 to 10^5 neurons with ~10^7 plastic synapses in real-time on a single GPU card.
- Tactile Processing and Hedonic Touch in the Cortex
  - Chou, T.-S., Bucci, L.D., and Krichmar, J.L. (2015). Learning Touch Preferences with a Tactile Robot Using Dopamine Modulated STDP in a Model of Insular Cortex. Frontiers in Neurorobotics 9.
- Visual Cortical Processing
  - M. Beyeler, M. Richert, N. D. Dutt, J. L. Krichmar, Efficient Spiking Neural Network Model of Pattern Motion Selectivity in Visual Cortex. Neuroinformatics, 2014.
- Freely available at:
  - http://www.socsci.uci.edu/~jkrichma/CARLsim/

UCI University of California, Irvine

Learning Touch Preferences With A Tactile Robot Using Dopamine Modulated STDP In A Model Of Insular Cortex

Introduction

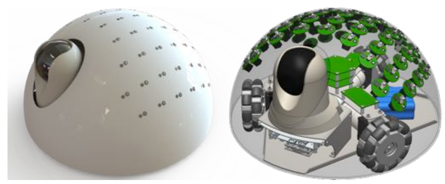
- Humans and other animals respond preferentially to different types of touches.
  - For example cats prefer to be petted from head to tail.
  - What neural areas respond to hedonic touch?
    - Insular cortex responds to hedonic touch.
    - Dopaminergic neurons respond to reward and pleasure.
- Designed a neurorobot that has a surface designed for petting.
  - Tactile sensors project to a model of somatosensory cortex and insular cortex.
  - Signals its preferences through coloration of its surface and auditory signals.
- Use this neurorobot and its simulated nervous system to explore learning preferences in uncertain, real-world environments.

UC Irvine 27

CARL-SJR

Cognitive Anteater Robotics Laboratory – Spike Judgment Robot

- Because hedonic touch requires a caresser and a caressee, we developed a human robot interaction study that required mutual reinforcement learning.
- To achieve these goals, we built a robot, named CARL-SJR, with a large tactile sensory area and a surface capable of displaying bright colors.

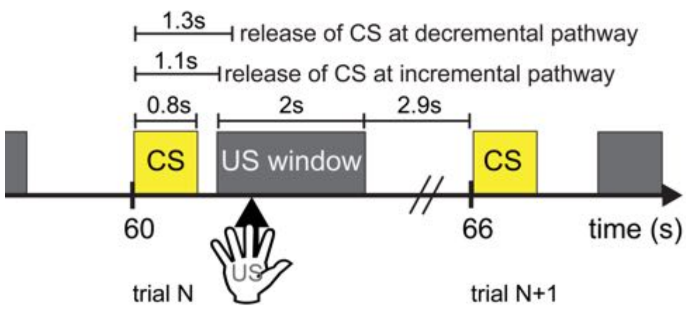


UC Irvine 28

Reinforcement Learning Paradigm

- The user has to learn how to reward CARL-SJR
  - CARL-SJR has innate tactile preferences.
  - CARL-SJR gives the user feedback in response to a touch.
- CARL-SJR can learn the user's preferences
  - Conditioning task: learn to associate conditioned stimulus (CS) and unconditioned stimulus (US).
    - CS is a color pattern and US is a touch.
    - Conditioned response (CR) is bright color.
    - Unconditioned response (UR) is a high tone.

Experimental Paradigm



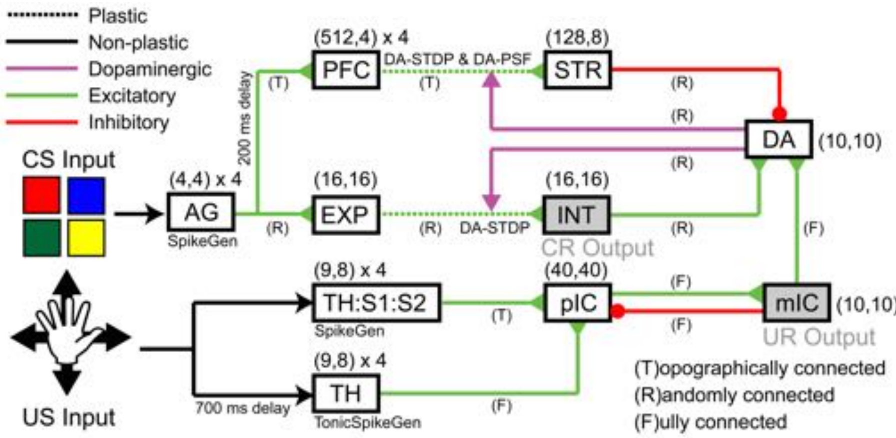
- CARL-SJR initiated a trial by displaying a color (CS).
- The user must choose to reward CARL-SJR with a touch pattern (US) within a 2 second window.

FeedMe

Learning CARL-SJR's Preferences

UC Irvine 31

SNN Network Architecture

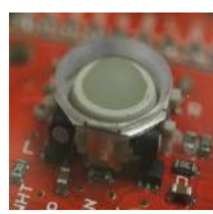


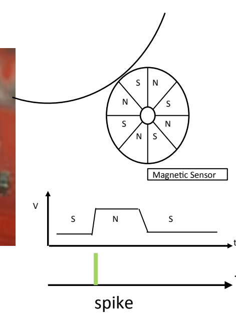
- The neural architecture based on the dual-pathway model:
  - CS input to both the decremental and incremental pathways.
  - US input to the incremental pathway.
  - Incremental and decremental pathways balance each other out when a reward predicted by the CS and arrives at the expected time of the US.

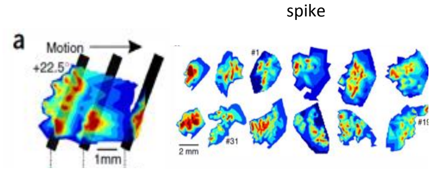
UC Irvine 32

Trackballs as a Biomimetic Tactile Sensor

- Generates spikes naturally:
  - Neuromorphic sensor
  - Directly compatible with simulated spiking neurons.
- Emulates first-order directionally tuned tactile neurons.



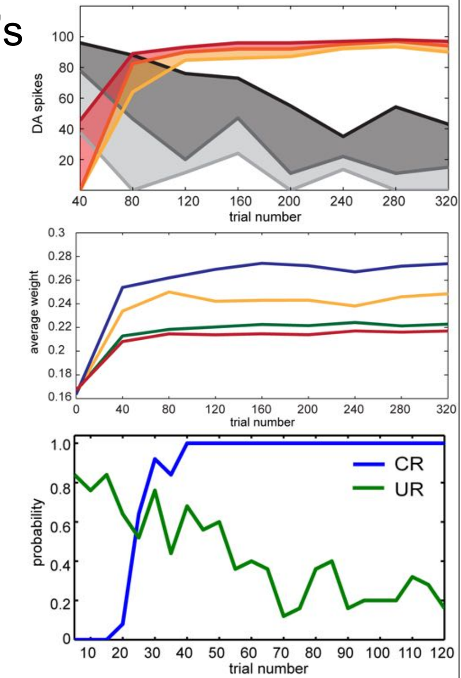




Pruszynski et al, (2014), Nature Neuronscience

CARL-SJR Learned User's Color Preference

- **Top:** DA response to the CS (colored lines) and US (gray lines).
- **Middle:** Synaptic weight changes during trials.
  - User reinforced Blue and Yellow.
- **Bottom:** Probability of CR and UR during trials.



Conclusions

- We demonstrated a neurorobot which was capable of:
  - Sensing noisy, real-world tactile inputs
  - Learning to associate user preferences with touch patterns.
- A detailed model cortical and subcortical brain areas controlled CARL-SJR's behavior.
- CARL-SJR may have applications as a tactile socially assistive robots with a long-term goal of standardizing and automating therapy for children with developmental disorders and adults with dementia.

UCI University of California, Irvine

A Cortical Neural Network Model For Visually Guided Robot Navigation

Navigating a Cluttered Scene Using Vision

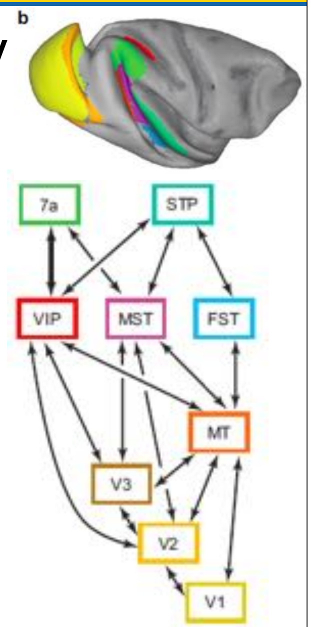
Crossing a busy intersection in Ethiopia

https://www.youtube.com/watch?v=UEln8GJIg0E

Walking through a crowd at the San Diego County Fair

Visual Motion Pathway

Dorsal Stream (Macaque)
Spatial Localization and Action

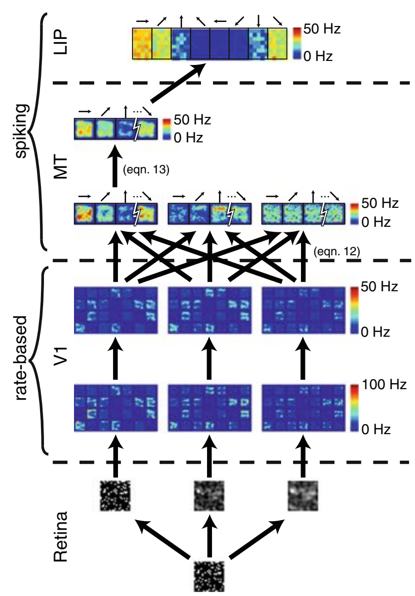


- Primary visual cortex (V1)
  - Tuned to simple attributes of shape, motion, color, texture, depth.
- Middle temporal (MT) area
  - Tuned to coherent local motion (retinal flow)
- Medial Superior Temporal (MST) area and Ventral Intra-Parietal (VIP)
  - Tuned to global, complex motion.
  - Self-motion and object motion.
  - Multimodal.

(Britten, 2008)

V1 and MT Model

- Spatiotemporal-energy model of V1
  - Bank of linear space-time oriented filters (rate-based).
    - Adapted from Simoncelli & Heeger, 1998.
  - Direction-selective cells.
  - Fully realized in CUDA.
- Two-stage spiking model of MT
  - Izhikevich spiking neurons: regular-spiking / fast-spiking
    - 153,216 neurons.
    - ~40 million synapses.
    - Runs in real-time with video.
  - Component Direction Selective cells.
  - Pattern Direction Selective cells:
    - Direction pooling + opponent inhibition.
    - Signals the global pattern of motion.
    - Solves the aperture problem



Model Response to Motion Patterns

Component and Pattern Selectivity

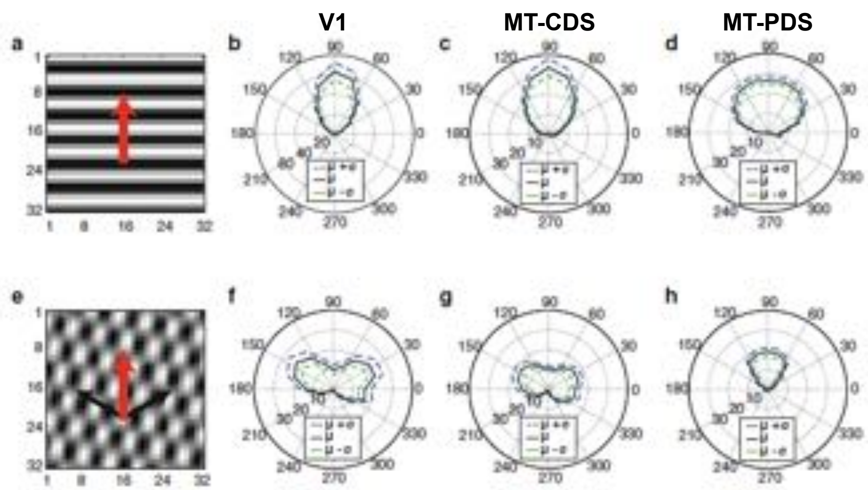
Component-direction-selective

Pattern-direction-selective

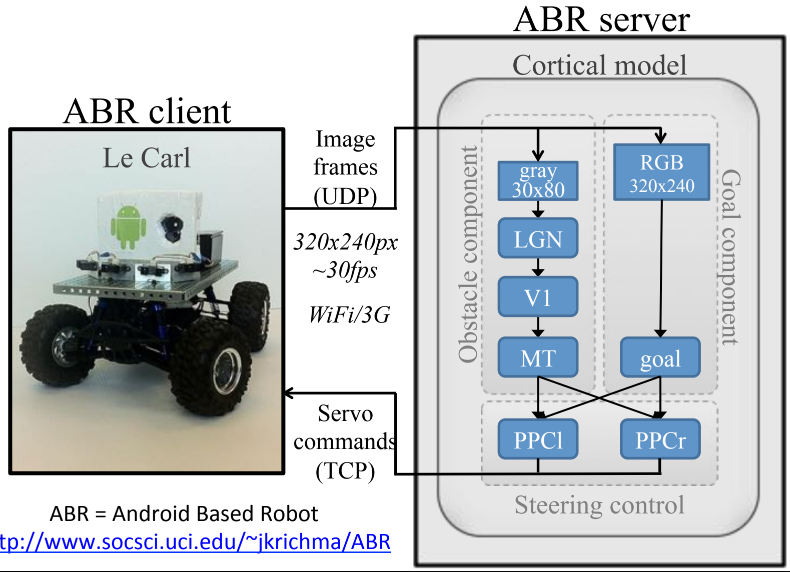
→ ↗ ↑ ↖ ← ↙ ↓ ↘

Model Response to Motion Patterns

Component and Pattern Selectivity



Visually Guided Robot Navigation
Architecture and I/O



ABR = Android Based Robot

http://www.socsci.uci.edu/~jkrichma/ABR

Android Based Robotics (LeCarl)

http://www.socsci.uci.edu/~jkrichma/ABR

UC Irvine 43

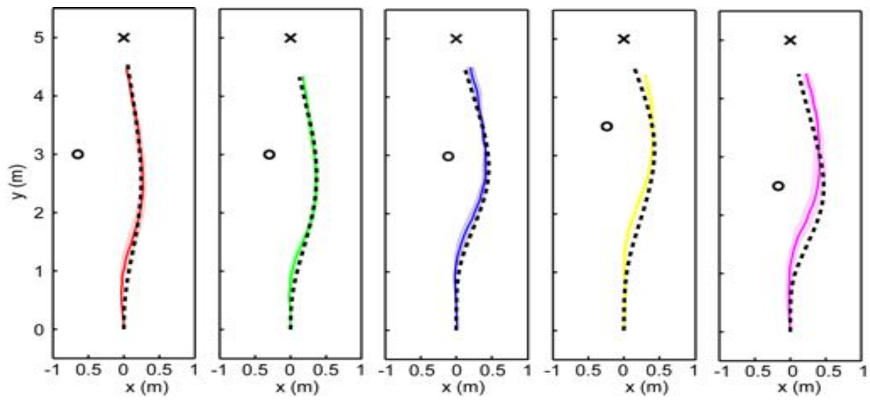
Visually Guided Robot Navigation
Server Control GUI and Results

UC Irvine 44

Visually Guided Robot Navigation
By a Spiking Neural Network of Visual Cortex

UC Irvine 45

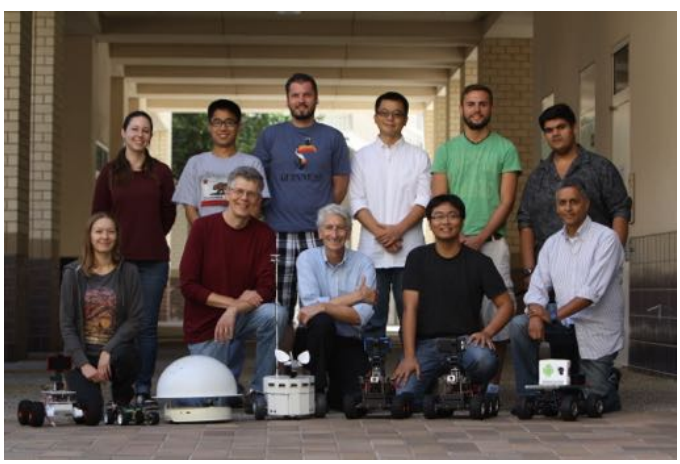
Comparison to Psychophysical Data



- Dotted lines are human trajectories
  - Replicated with dynamical system by Fajen & Warren, 2003; 2007.
  - Comparable to neural simulation by Browning, Grossberg & Mingolla.
- Colored lines are robot trajectories.

UC Irvine 46

Team CARL



Hirak Kashyap

Tiffany Hwu

Stas Listopad

Back row from left to right: Alexis Craig, Alex Wang, Michael Beyeler, Feng Rong, Timo Oess, Saideep Gupta.
Front row from left to right: Emily Rounds, Steve Doubleday, Jeffrey Krichmar, Ting-Shuo Chou, Nikil Dutt.

Neuromorphic Applications and Neurorobotics

- Large-scale, complex, realistic brain simulations are necessary:
  - For the field of neuromorphic engineering to produce results and applications of practical value.
  - To help computational neuroscientists develop new theories of neural function.
- Embodying neural algorithms on physical devices are necessary to:
  - Closely couple the brain, body and environment.
  - Critical for understanding cognition.
  - Develop truly cognitive machines.
- To address this challenge, our approach leverages:
  - Optimization capabilities of evolutionary computation.
  - Exploits graphical processing unit (GPU) parallelism.
  - Implementation is compatible with neuromorphic hardware.
- Simulation environment is publicly available:
  - http://www.socsci.uci.edu/~jkrichma/CARLsim

Thank You!!

- More information can be found at:
  - http://www.socsci.uci.edu/~jkrichma