


NCS: A Large-Scale Brain Simulator



Brain Computation Lab

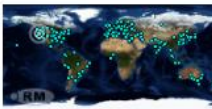
www.cse.unr.edu/brain



Brain Computation Lab

Navigation

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- Conferences
- Opportunities
- University of Nevada, Reno
- Department of Computer Science and Engineering
- School of Medicine
- Biomedical Engineering Program




Welcome to the Brain Laboratory!

Good Morning!

Founded in 2001, the brain lab is a joint research center between the departments of Computer Science & Engineering, Medicine, Physiology & Cell Biology, and the program of Biomedical Engineering. It also has neurobiological collaborations with the Brain Mind Institute at the EPFL (Switzerland), the University of Cergy Pontoise (France), and the University of Bonn (Germany).

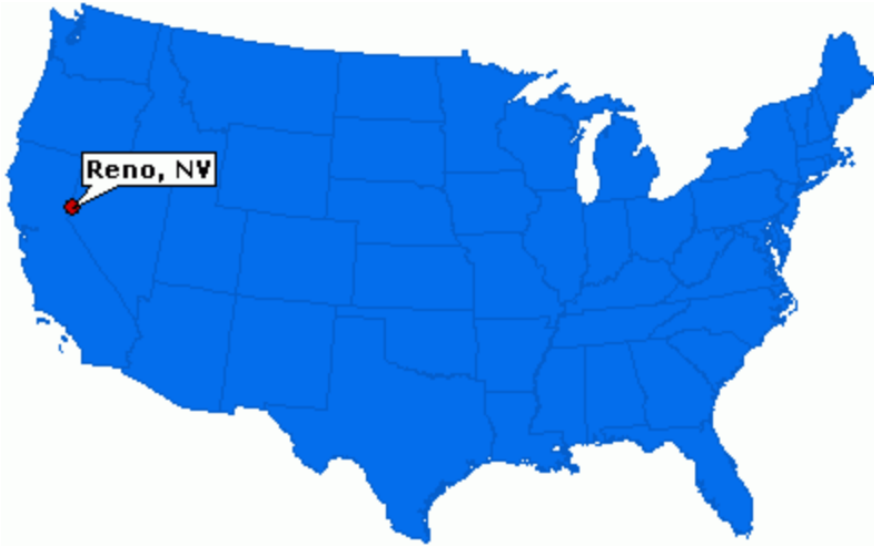
Our researchers consists primarily of undergraduate/graduate students and alumni of the University of Nevada, Reno. They are actively developing computational innovations to understand the physiological processes that give rise to neocortical memory, learning, and cognition. Our models and experiments help understand brain pathophysiology and create brain-like artificial intelligence and neural prosthetic devices.



New Publications

- Goal-related navigation of a neuromorphic virtual robot
- Brainlab: a Python toolkit to aid in the design, simulation, and analysis of spiking neural networks with the NeoCortical Simulator
- Design and Implementation of an NCS-NeuroML Translator
- Real-Time Human-Robot Interaction Underlying Neurorobotic Trust and Intent Recognition

Reno, Nevada



University of Nevada, Reno



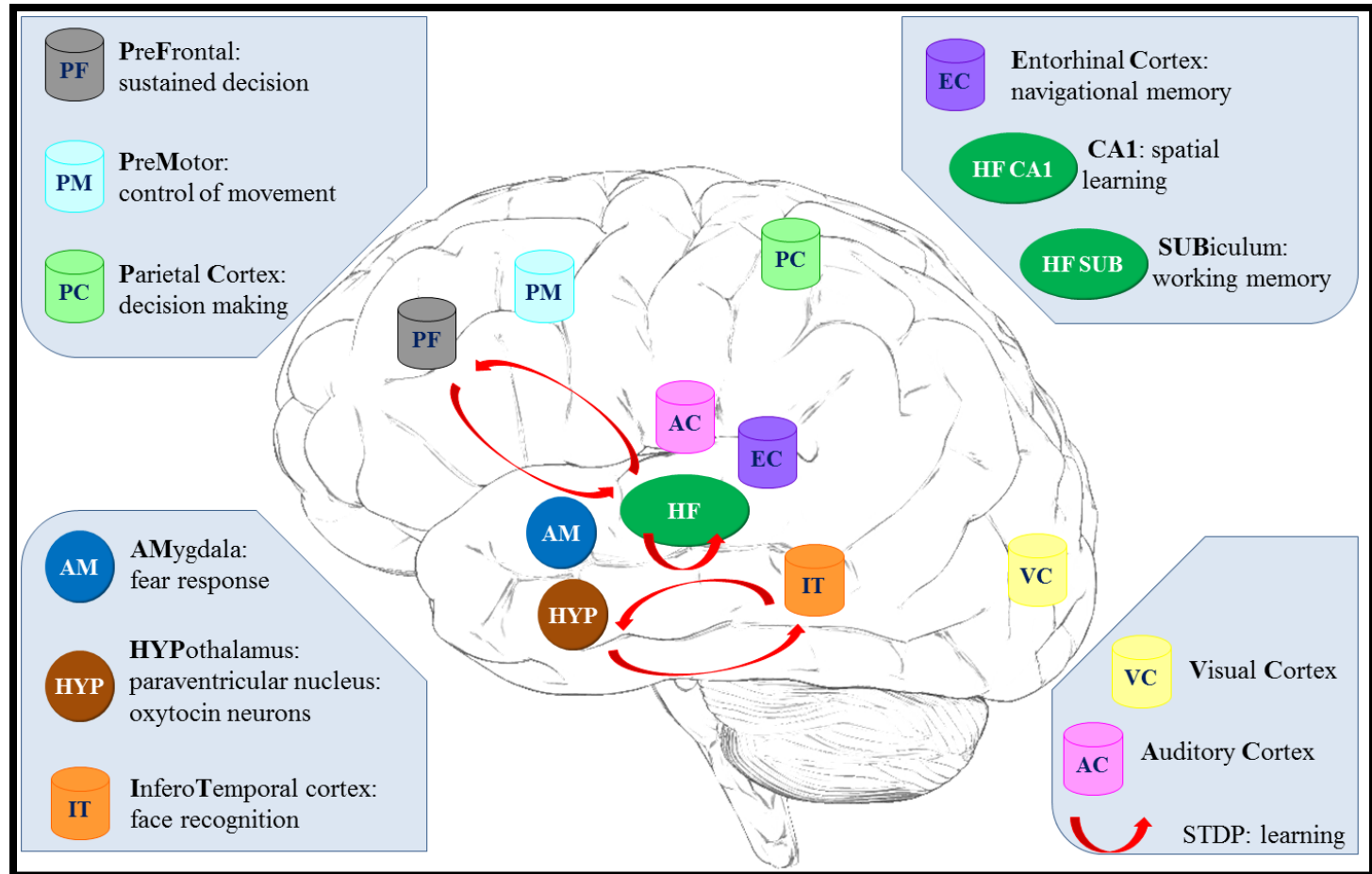
What is NCS?

- The NeoCortical Simulator (NCS) is designed for modeling large-scale neural networks and systems
- One of the first simulators to support neurorobotic applications
- Different types of neuron models available:
 - Leaky integrate-and-fire / Hodgkin-Huxley
 - Izhikevich
- Free and open source
- Developed and maintained by the UNR Brain Computation Laboratory

Why use NCS?

- Biological brain models
- Real-time Simulation
- Different levels of abstraction
- Several neuron models
- GPU computation
- No programming language experience required
- Good for modeling neural systems and networks
- Up to 1M neurons and 100M synapses in quasi real-time

Modeled Brain Regions Using NCS



History of NCS

- **Version 1:1999**
 - Matlab – Goodman, Markram, and McKenna
 - 160-cell, 2-column architecture
 - Each cell was modeled as a single integrative compartment (point neuron) with a spike mechanism,
 - calcium-dependent (AHP) channels, and
 - voltage-sensitive A and M (muscarinic) potassium channels

M.M. Kellog, H.R. Wills, and P.H. Goodman. "A biologically realistic computer model of neocortical associative learning for the study of aging and dementia." J. Investig. Med., 47(2), February 1999.

History of NCS

- **Version 1b: 1999**
 - Direct translation to C from Matlab
 - 24 times faster.
 - tested on mixed excitatory-inhibitory networks of up to 1,000 cells

M.M. Kellog, H.R. Wills, and P.H. Goodman. "A biologically realistic computer model of neocortical associative learning for the study of aging and dementia." J. Investig. Med., 47(2), February 1999.

History of NCS

- **Version 2: 1999**

- code was then redesigned and rewritten for distributed processing on an existing 20-cpu cluster (Pentium II).
- Initial trials of this code were performed on cortical networks of 2 to 1,000 cells

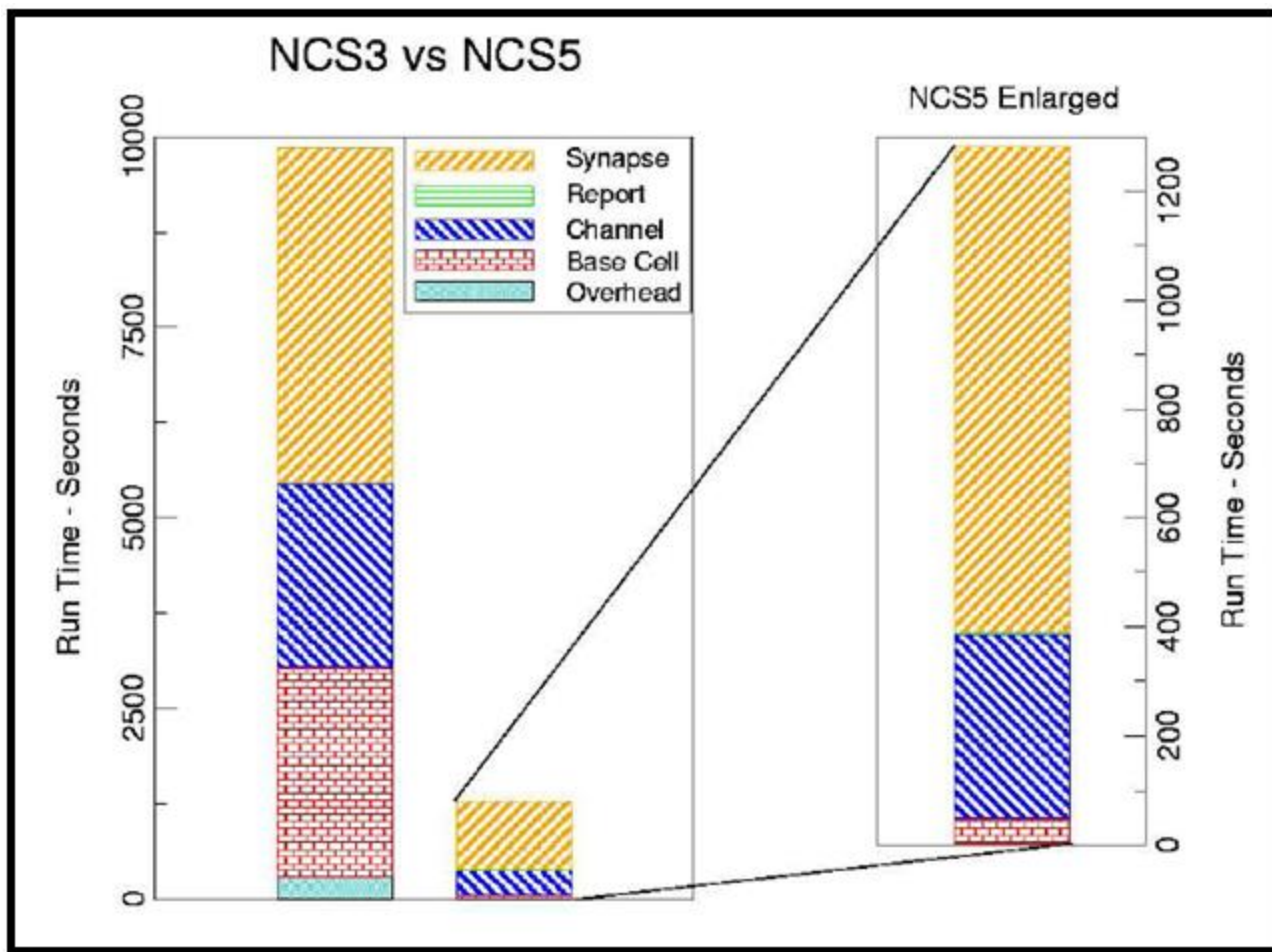
M.M. Kellog, H.R. Wills, and P.H. Goodman. "A biologically realistic computer model of neocortical associative learning for the study of aging and dementia." J. Investig. Med., 47(2), February 1999.

History of NCS

Item	NCS3	NCS5	Ratio
Overhead ^a	294.167	1.897	155.1
Base Cell/Cmp ^b	0.020	3.035	153.6
Channel ^b	0.152	0.398	2.6
Report ^c	0.017	4.113	239.4
Synapse, 0Hebb ^b	0.031	0.383	12.5
Synapse, +-Hebb ^b	0.020	0.368	18.1

a) Seconds.
b) Millions of Objects Processed per Second
c) Millions of Values Reported per Second

History of NCS



James Frye, James G. King, Christine J. Wilson, and Frederick C. Harris, Jr. "QQ: Nanoscale timing and profiling" In Proceedings of PME0-PDS, Denver, CO, April 3-8 2005.

NCS5 Hardware



2007

2008



**Sun v20z Oteron
(60 CPUs)**

ONR DURIP 2007:



**Sun 4600s and 4500s
16 core boxes with 200GB of RAM
connected by Infiniband
And several 24TB disk arrays**

ONR DURIP 2008:



Current NCS version 6 implementation

- GPU/CPU/cluster-based
 - Runs on CPUs and CUDA devices simultaneously
- Plugin interface for multiple model support
 - LIF/HH Neurons
 - Izhikevich Neurons
 - Ability to design your own
- Ability for multi-scale modeling

NCS 6 Software / Hardware

- Linux based operating system
- NVIDIA GPU (GeForce GTX 400 series or higher)

GeForce GTX 480 Fastest GPU in the World

Memory	1536MB / 384-bit GDDR5
Cores	480
Gfx / Proc / Mem Clock	700 / 1401 / 1848 MHz
Power Connectors	6-pin + 8-pin
Power	250W
SLI	3-way
Length	10.5 inches
Thermal	Dual Slot Fansink
Outputs	DL-DVI DL-DVI mini-HDMI



GeForce GTX 690 Specifications

CUDA Cores	3072
Base Clock	915 MHz
Boost Clock	1019 MHz
Memory Config	4GB / 512-bit GDDR5
Memory Speed	6.0 Gbps
Power Connectors	8-pin + 8-pin
TDP	300W
Outputs	3x DL-DVI Mini-Displayport 1.2
Bus Interface	PCI Express 3.0



Current Optimization

- C++ 11
- Heavily threaded
 - Latency hiding
 - Increased occupancy
- Modular message passing design
- GPU usage for parallel computation
- Load-balancing across heterogeneous clusters

Performance Data

Izhikevich

Izhikevich 1 second simulation			
Machines	# Neurons (k)	Synapses (M)	Time (s)
1	100	10	0.90
4	400	40	1.00
8	500	50	1.03
8	1000	100	3.16

Izhikevich 10 second simulation			
Machines	# Neurons (k)	Synapses (M)	Time (s)
1	100	10	8.98
4	400	40	9.89
8	500	50	10.13
8	1000	100	23.97

Performance Data

LIF

LIF 1 second simulation			
Machines	# Neurons (k)	Synapses (M)	Time (s)
1	25	6	1.36
4	50	12	1.18
8	50	12	0.99
8	300	75	2.82

LIF 10 second simulation			
Machines	# Neurons (k)	Synapses (M)	Time (s)
1	25	6	13.53
4	50	12	11.63
8	50	12	9.34
8	300	75	28.08

Leaky Integrate-and-Fire Model

Brain

- Define the simulation as a whole
- Preliminary outline of other structures
 - Anatomy
 - Stimuli
 - Reports
- Extrinsic connections
- Include files

Brain

```
BRAIN
  TYPE          Two_cell_MODEL_model
  JOB           Two_cell_MODEL_model
  FSV           1000
  DURATION      1
  SEED          -21
  DISTANCE      NO

##### COLUMN TYPE#####
  COLUMN_TYPE   TWO_CELL_MODEL_COLUMN

##### STIM INJECT#####
  STIMULUS_INJECT TWO_CELL_MODEL_STIM

#####

##### REPORTS #####
  REPORT        VOLTAGE_CELL_1
  REPORT        VOLTAGE_CELL_2

END_BRAIN
```

Anatomy

- Columns
- Layers
- Cells
- Compartments
- Channels

Anatomy

```
##### Define Column Shells #####
COLUMN_SHELL
  TYPE          TWO_CELL_MODEL_SHELL
  WIDTH         300
  HEIGHT        800
  LOCATION      0          800
END_COLUMN_SHELL

##### Fill Columns #####
COLUMN
  TYPE          TWO_CELL_MODEL_COLUMN
  COLUMN_SHELL  TWO_CELL_MODEL_SHELL
  LAYER_TYPE    layer_TWO_CELL_MODEL
END_COLUMN

##### Define Layer Shells #####
LAYER_SHELL
  TYPE          layer_TWO_CELL_MODEL_shell
  LOWER         0
  UPPER         49
END_LAYER_SHELL

##### Fill Layers #####
LAYER
  TYPE          layer_TWO_CELL_MODEL
  LAYER_SHELL   layer_TWO_CELL_MODEL_shell
  CELL_TYPE     TWO_CELL_MODEL_1    1
  CELL_TYPE     TWO_CELL_MODEL_2    1

#####
# ----- connections
#####
      |CONNECT
          TWO_CELL_MODEL_1    somaE
          TWO_CELL_MODEL_2    somaE
          synEE_TWO_CELL_MODEL 1    0
END_LAYER
```

Channels

- Km
 - Only has one activation particle (m). Inhibits its parent cell from reaching threshold
- Kahp
 - After Hyper Polarization Channels (Kahp) are voltage independent but Calcium dependent
- Ka
 - Helps the cell deal with background noise. It has both an activation (m) and inactivation (h) particle

Channel Km

```
CHANNEL Km
TYPE m
M_INITIAL 0.0 0.0
REVERSAL_POTENTIAL -80 0
M_POWER 1
E_HALF_MIN_M -44
SLOPE_FACTOR_M 40 20 8.8
TAU_SCALE_FACTOR_M 0.303
UNITARY_G 5
STRENGTH 0.00015
END_CHANNEL
```

Channel Kahp

```
CHANNEL Kahp
      TYPE                ahp1
      SEED                999999
      M_INITIAL          0.0          0.0
      REVERSAL_POTENTIAL -80          0
      M_POWER            2
      UNITARY_G          6
      STRENGTH           0.00015
      CA_SCALE_FACTOR    0.000125
      CA_EXP_FACTOR      2
      CA_HALF_MIN        2.5
      CA_TAU_SCALE_FACTOR 0.01
END_CHANNEL
```

Channel Ka

```
CHANNEL Ka
TYPE a
M_INITIAL 0.0 0.0
H_INITIAL 1.0 0.0
REVERSAL_POTENTIAL -80 0
M_POWER 1
H_POWER 1
E_HALF_MIN_M 11
E_HALF_MIN_H -56
SLOPE_FACTOR_M 18
SLOPE_FACTOR_H 18
UNITARY_G 0.12
STRENGTH 2.5
V_TAU_VALUE_M 0.0002 9999
V_TAU_VALUE_H 0.03 0.08 0.13 0.18 0.23
V_TAU_VOLTAGE_M 100
V_TAU_VOLTAGE_H -21 -1 10 21
END_CHANNEL
```

Stimulus

- External Stimulation (visual, audio...)
- Type of signals
 - Linear
 - Pulse
 - Noise
 - File-based
- Multiple times
- Different Destinations

Stimulus

```
##### STIMULUS INJECTS #####  
  
STIMULUS_INJECT  
  TYPE          TWO_CELL_MODEL_STIM  
  STIM_TYPE     realstim_TWO_CELL_MODEL  
  INJECT        TWO_CELL_MODEL_COLUMN      layer_TWO_CELL_MODEL      TWO_CELL_MODEL_1      somaE      1  
END_STIMULUS_INJECT  
  
#####define STIMULUS #####  
  
STIMULUS  
  TYPE          realstim_TWO_CELL_MODEL  
  MODE          CURRENT  
  PATTERN       PULSE  
  TIME_INCREMENT 0.1  
  FREQ_COLS     100  
  CELLS_PER_FREQ 1  
  DYN_RANGE     0      75  
  TIMING        EXACT  
  SAMESEED     NO  
  AMP_START     4  
  WIDTH         .010  
  TIME_START    0.500  
  TIME_END      0.600  
  #FREQ_START   99999  
END_STIMULUS
```

Connections

- Extrinsic and intrinsic connections
- Synapse connections
- From the source to the destination
- With or without decaying distance effects
- Recurrent connections

Connections

```
#####  
CONNECT  
      TWO_CELL_MODEL_1      somaE  
      TWO_CELL_MODEL_2      somaE  
      synEE_TWO_CELL_MODEL  1  0
```

Synapses

- Connections between other cells and their compartments
- Excitatory
- Inhibitory
- Synaptic Waveform
- Learning
 - Short term synaptic dynamics
 - Facilitation
 - Depression
 - Long term synaptic dynamics (Hebbian Learning)
 - STDP rule

Synapses

```
#####SYNAPSES TWO_CELL_MODEL_MODEL#####  
  
SYNAPSE  
  TYPE          synEE_TWO_CELL_MODEL  
  SFD_LABEL      NO_SFD  
  LEARN_LABEL    NO_STDP  
  SYN_PSG        PSGexcit  
  MAX_CONDUCT    0.004  
  DELAY          0.005  0.010  
  SYN_REVERSAL   0      0  
  ABSOLUTE_USE   0.25   0.1  
END_SYNAPSE  
  
##### NO SFD #####  
  
SYN_FACIL_DEPRESS  
  TYPE          NO_SFD  
  SFD           NONE  
  FACIL_TAU     0.0      0.0  
  DEPR_TAU     0.0      0.0  
END_SYN_FACIL_DEPRESS  
  
##### Long-term synaptic Dynamics #####  
  
SYN_LEARNING  
  TYPE          NO_STDP  
  LEARNING      NONE  
  LEARNING_SHAPE EXONENT  
  NEG_HEB_WINDOW 0.1      0.0  
  POS_HEB_WINDOW 0.05     0.0  
  POS_HEB_PEAK_DELTA_USE 0.02     0.0  
  NEG_HEB_PEAK_DELTA_USE 0.01     0.0  
  POS_HEB_PEAK_TIME 0.005    0.0  
  NEG_HEB_PEAK_TIME 0.005    0.0  
END_SYN_LEARNING  
  
##### synaptic CONDUCTANCE WAVEFORMS #####  
  
SYN_PSG  
  TYPE          PSGexcit  
  PSG_FILE      ./EPKG_Vogels_FSV1k_TAU05.inc  
END_SYN_PSG
```

Reports

- Data about cells
- Report files:
 - Voltage
 - Current
 - Firecount
 - Channel
 - Synaptic strengths
- Automatically generated and saved

Reports

```
##### TWO_CELL_MODEL_MODEL REPORTS #####  
  
REPORT  
  TYPE          VOLTAGE_CELL_1  
  CELLS         TWO_CELL_MODEL_COLUMN layer_TWO_CELL_MODEL TWO_CELL_MODEL_1 somaE  
  PROB         1  
  REPORT_ON     VOLTAGE  
  FILENAME      TWO_CELL_MODEL_1_VOLTAGE_E.txt  
  ASCII  
  FREQUENCY     1  
  TIME_START    0  
  TIME_END      100  
END_REPORT  
  
REPORT  
  TYPE          VOLTAGE_CELL_2  
  CELLS         TWO_CELL_MODEL_COLUMN layer_TWO_CELL_MODEL TWO_CELL_MODEL_2 somaE  
  PROB         1  
  REPORT_ON     VOLTAGE  
  FILENAME      TWO_CELL_MODEL_2_VOLTAGE_E.txt  
  ASCII  
  FREQUENCY     1  
  TIME_START    0  
  TIME_END      100  
END_REPORT
```

Izhikevich Model

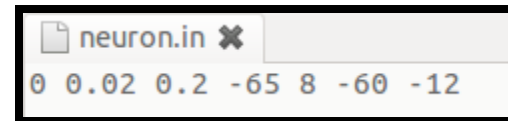
Files

- Neuron file
- Synapse file
- Current file

Neuron File

- Parameters
 - NeuronID
 - a
 - b
 - c
 - d
 - u
 - v

- Regular Spiking



```
neuron.in ✕  
0 0.02 0.2 -65 8 -60 -12
```

A screenshot of a text editor window titled "neuron.in" with a close button. The window contains a single line of text with seven numerical values: "0 0.02 0.2 -65 8 -60 -12".

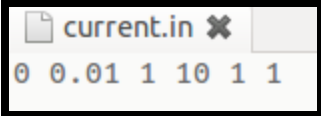
Synapse File

- Parameters
 - PreNeuron
 - PostNeuron
 - Delay
 - Weight
 - APlus
 - AMinus
 - TauPlus
 - TauMinus

Current File

- Parameters
 - Neuron ID
 - Time start
 - Time end
 - Amp
 - Width
 - Frequency

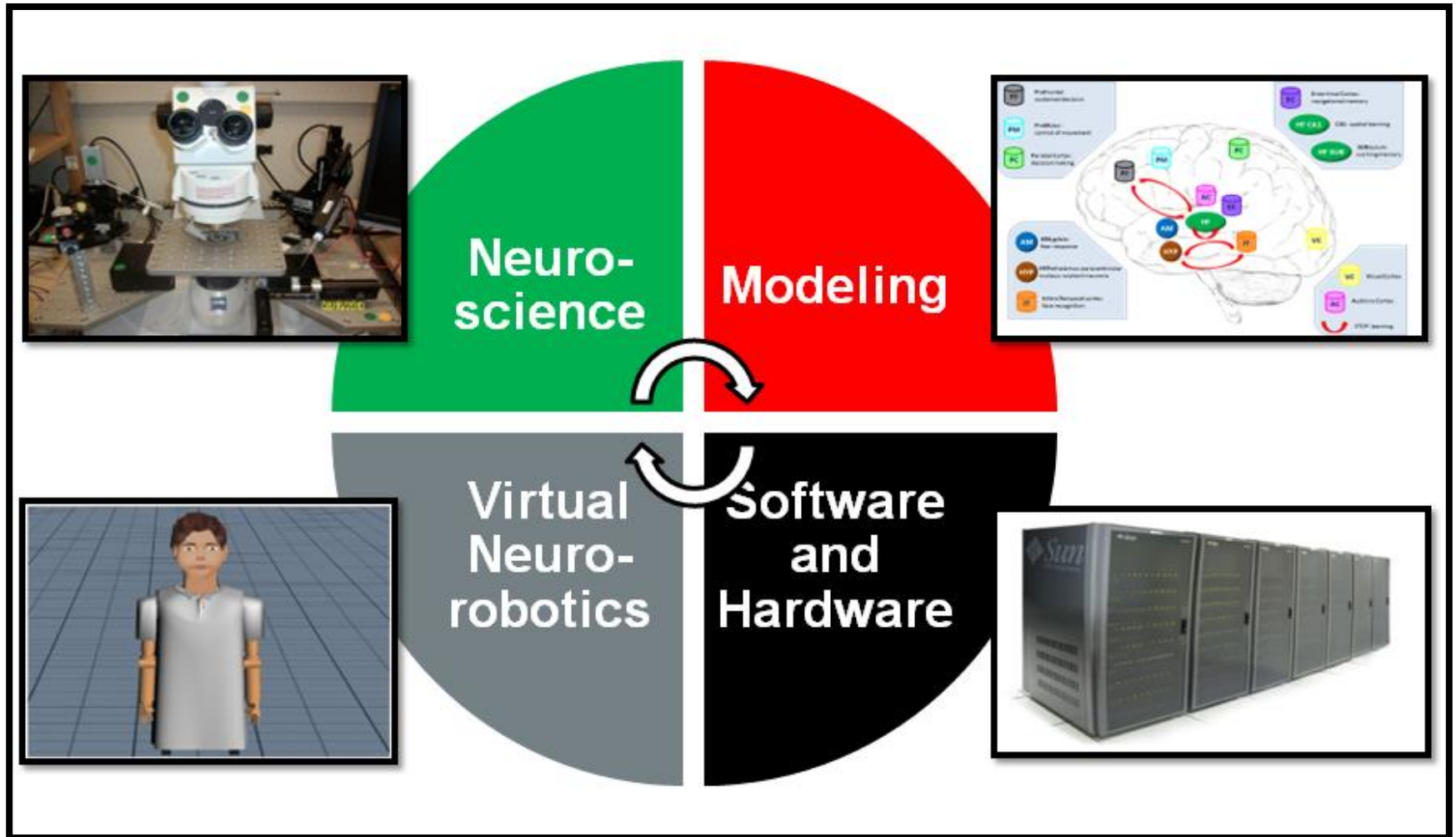
- Regular Spiking



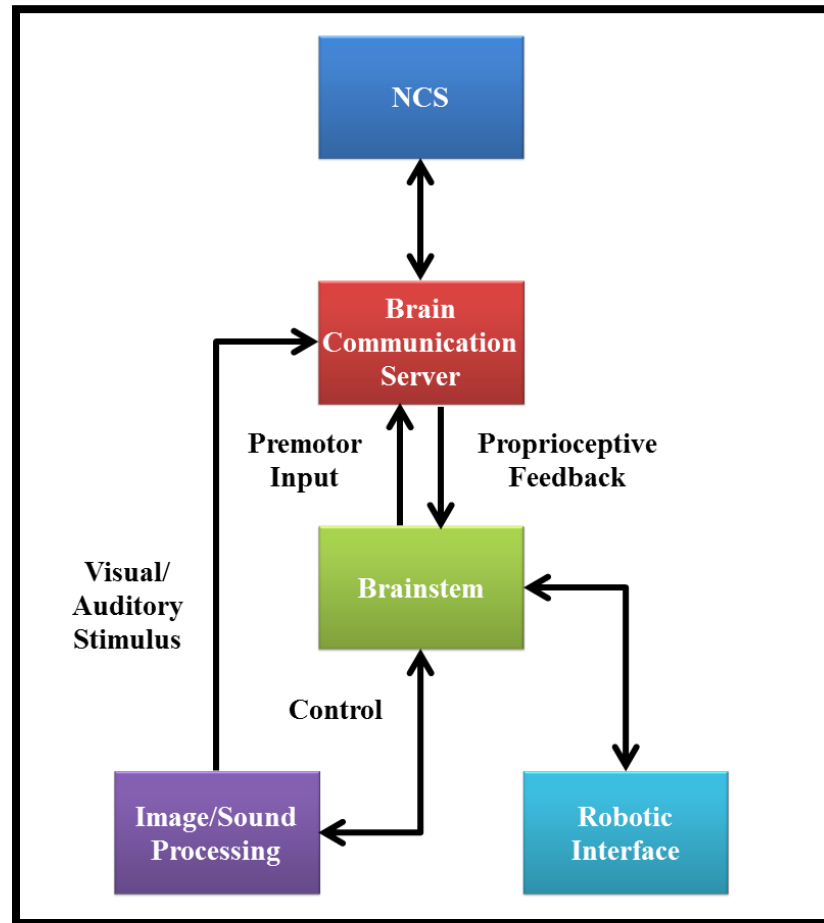
```
current.in ✕  
0 0.01 1 10 1 1
```


Robotic Applications with NCS

Technical Approach



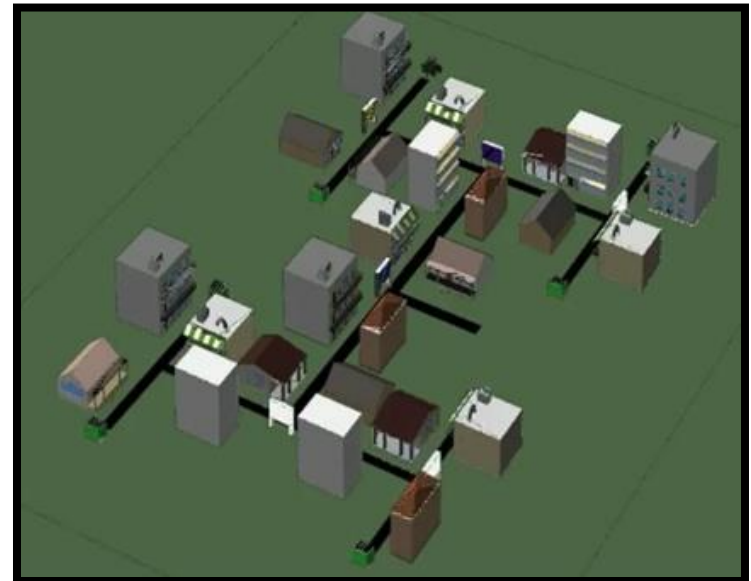
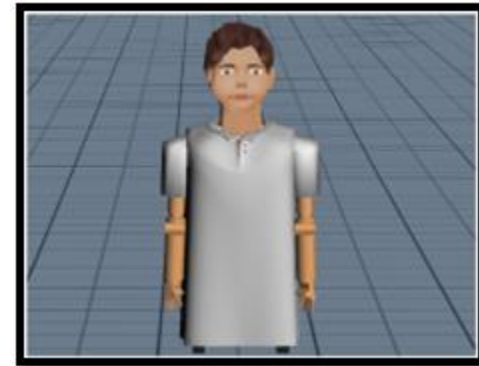
Virtual NeuroRobotic (VNR)



Laurence C. Jayet Bray, Sridhar R. Anumandla, Corey M. Thibeault, Roger V. Hoang, Philip H. Goodman, Sergiu M. Dascalu, Bobby D. Bryant, and Frederick C. Harris, Jr. "Real-time human-robot interaction underlying neurobotic trust and intent recognition" *Neural Networks*, 32:130-137, 2012.

Robotic Interface

- Constructed using Webots 5
- Motions were programmed in C++ using the provided interfaces and the communication was accomplished using the NCSTools C++ client



Trust

- Behavior between a humanoid neurorobot and human actor
 - Oxytocin release
 - Social reinforcement
 - Reduction of inhibition
- Experiment has two conceptual phases:
 - Learning
 - Challenge

Paradigm

Learning

Robot Initiates Action

1. Robot brain initiates arbitrary sequence of motions



Human Responds

2. Human moves object in either a similar ("match"), or different ("mismatch") pattern

Match: robot learns to trust



Mismatch: don't trust



Challenge (at any time)

Human Acts

3. Human slowly reaches for an object on the table



Robot Reacts

4. Robot either "trusts", (assists/offers the object), or "distrusts", (retract the object).

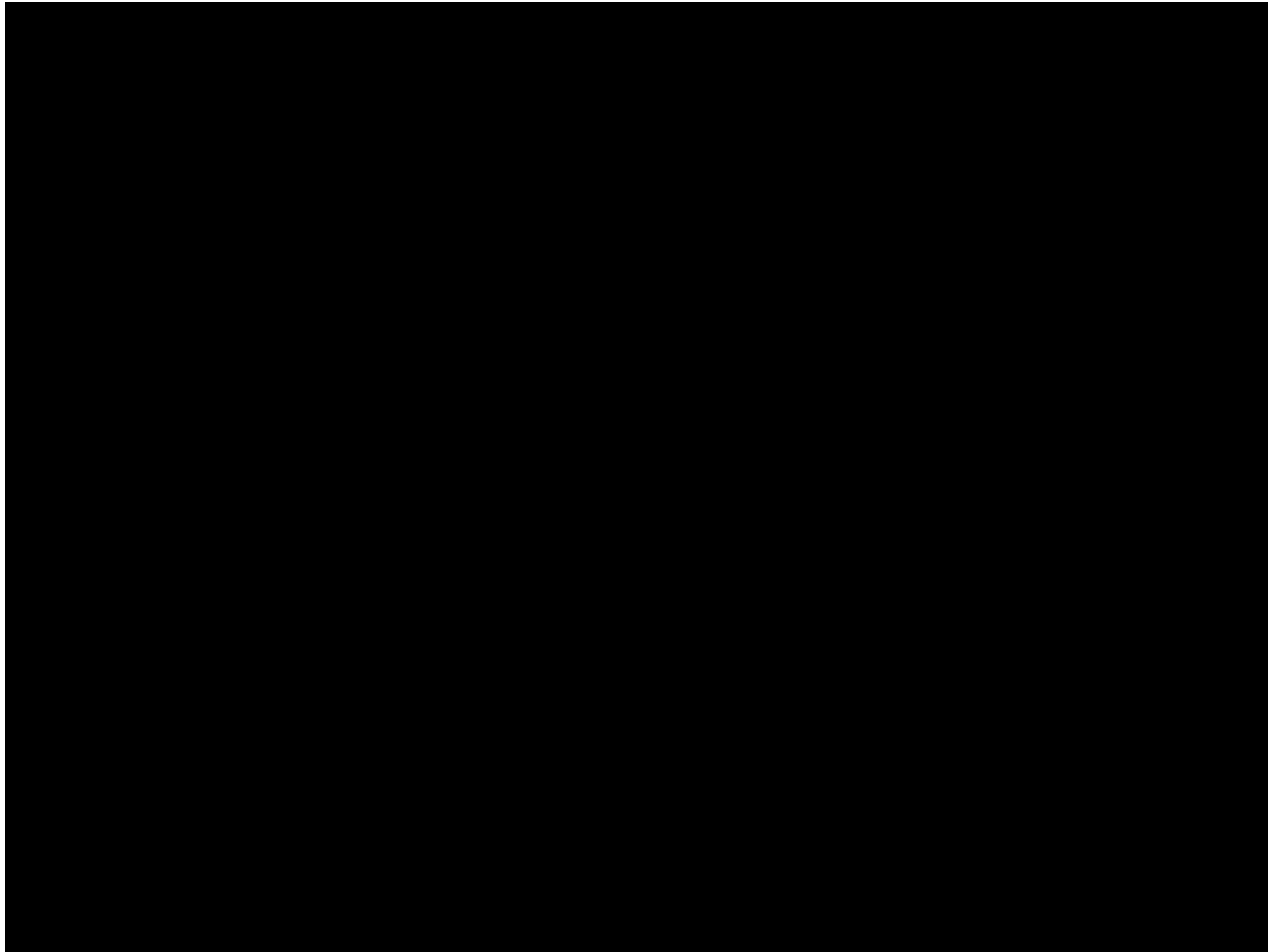
trusted



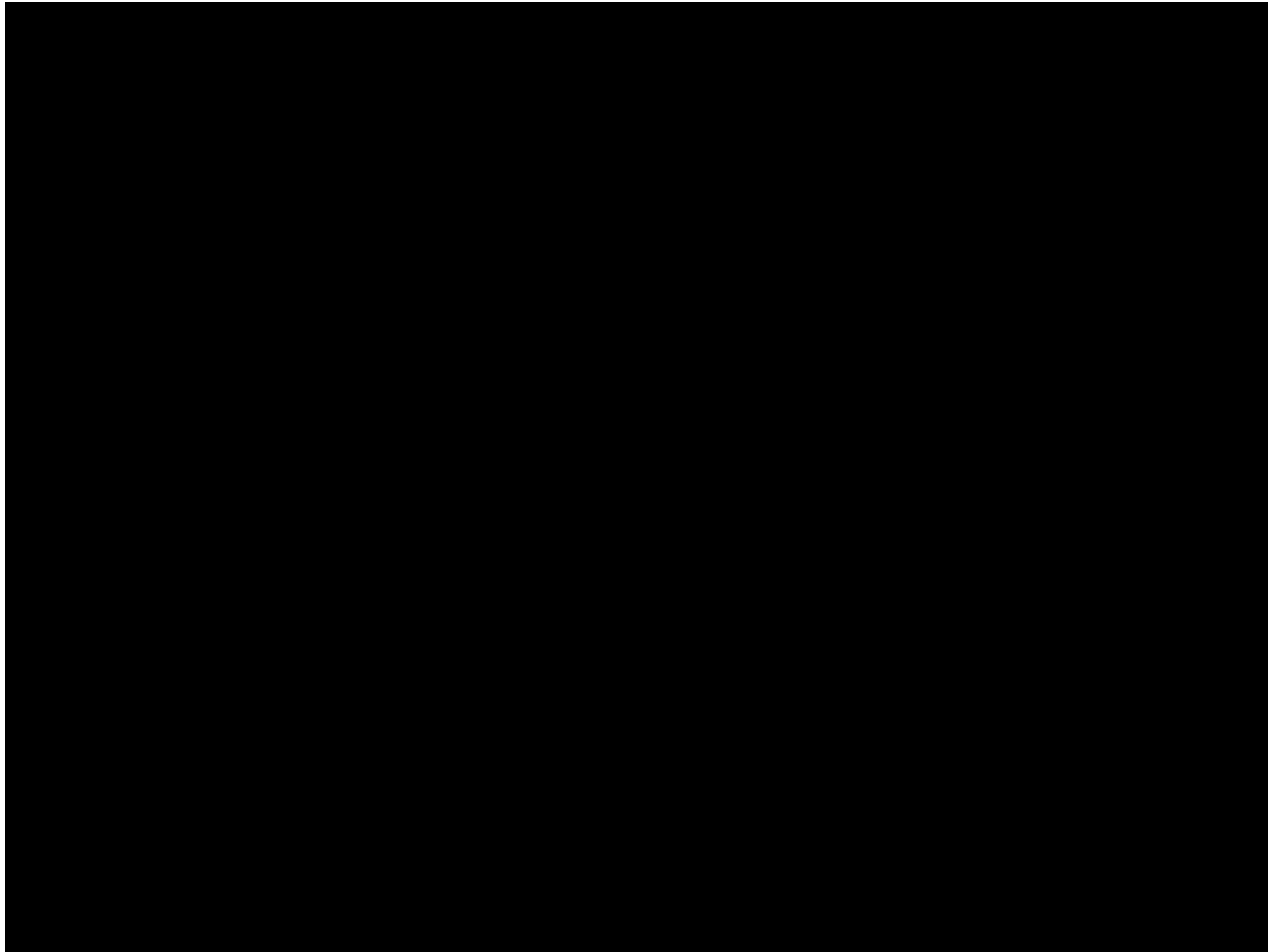
distrusted



Concordant Motions Video



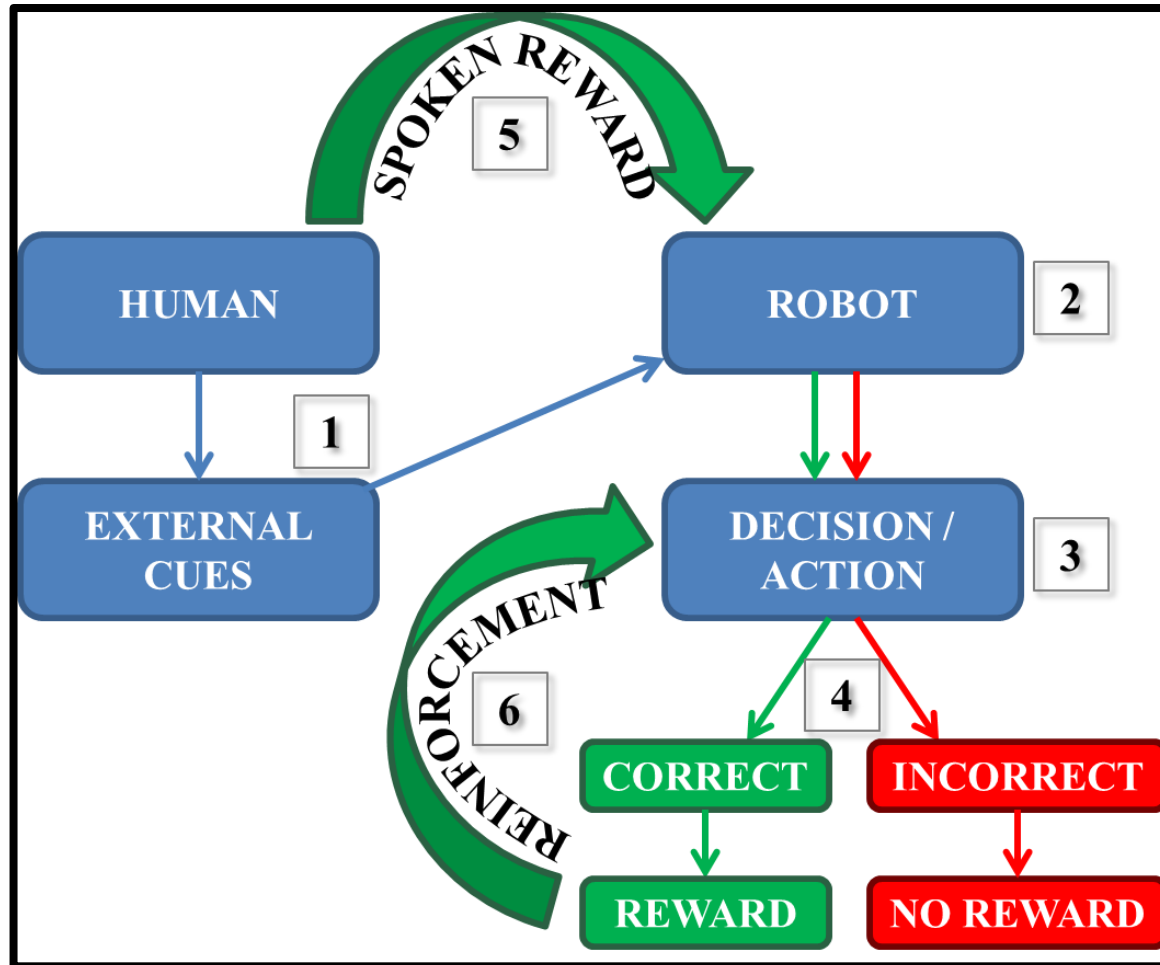
Discordant Motions Video



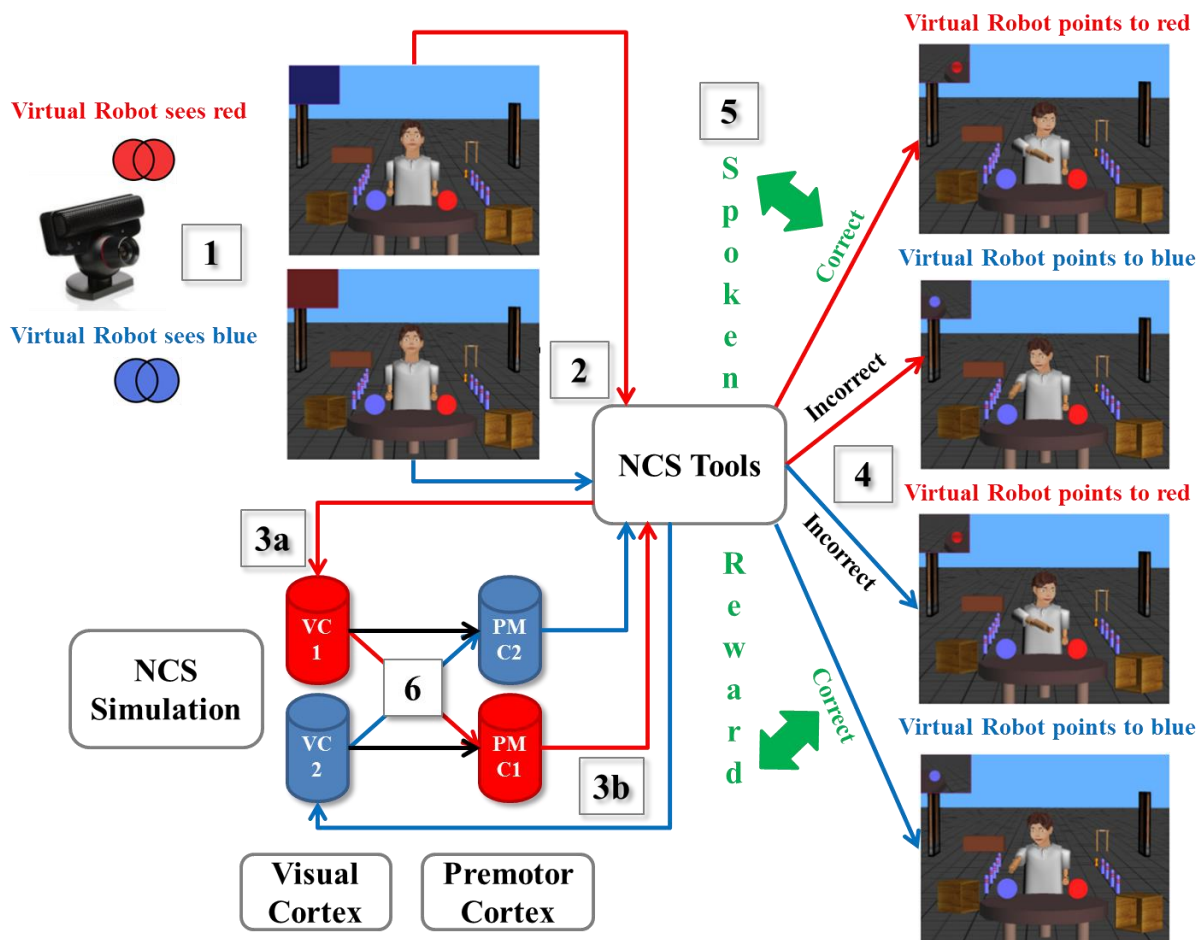
Emotional Speech

- Allows for more natural interaction between humans and robots
 - Determine the ideal behavior from a simple reward feedback
- Emotional Speech processor
 - Successfully distinguished “sad” and “happy” utterances
- Integrated into neurorobotic scenario
 - The robot received a spoken reward if the correct decision was made
- Step toward the combination of human emotions and virtual neurorobotics

Reward-based Learning Through ESP



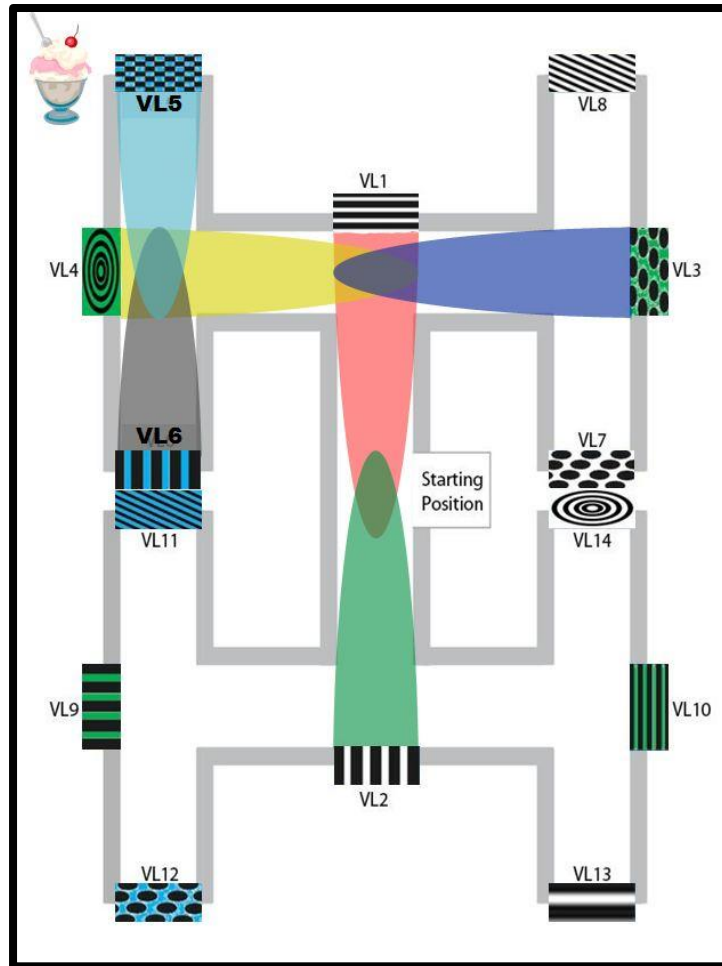
Reward-based Learning Through ESP



Navigation

- Navigate to familiar location
 - Prefrontal Cortex
 - Hippocampus (CA1 and Subiculum)
 - Entorhinal cortex
- Computational system representing a navigating rodent
- Reward at the end of a sequence of 3 turns
- Showed learning performance without biased decisions
- Short-term memory

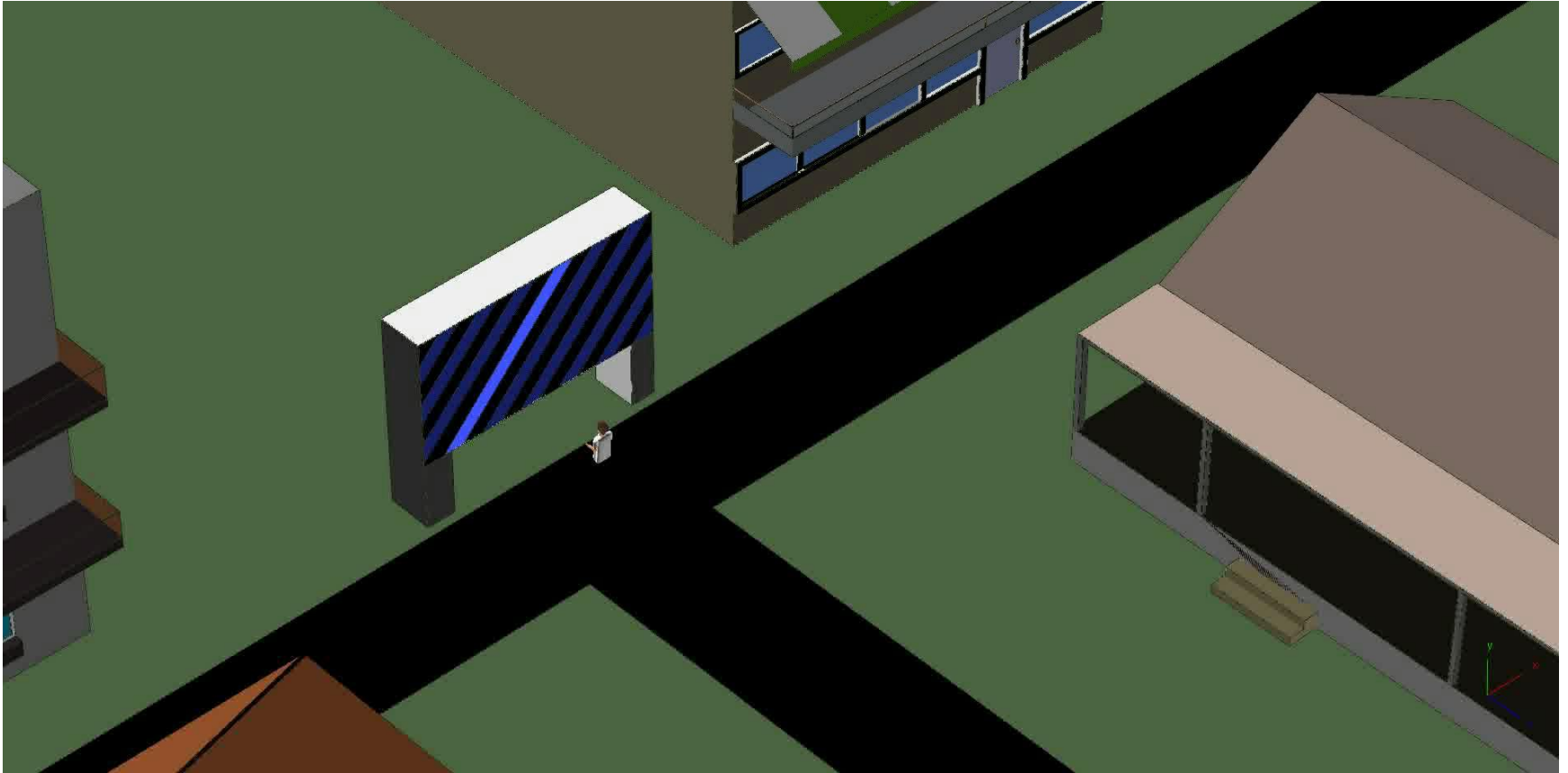
Paradigm



Jayet Bray L. A Circuit-Level Model of Hippocampal, Entorhinal and Prefrontal Dynamics Underlying Rodent Maze Navigational Learning. Ph.D. Dissertation. University of Nevada, Reno, 2010.

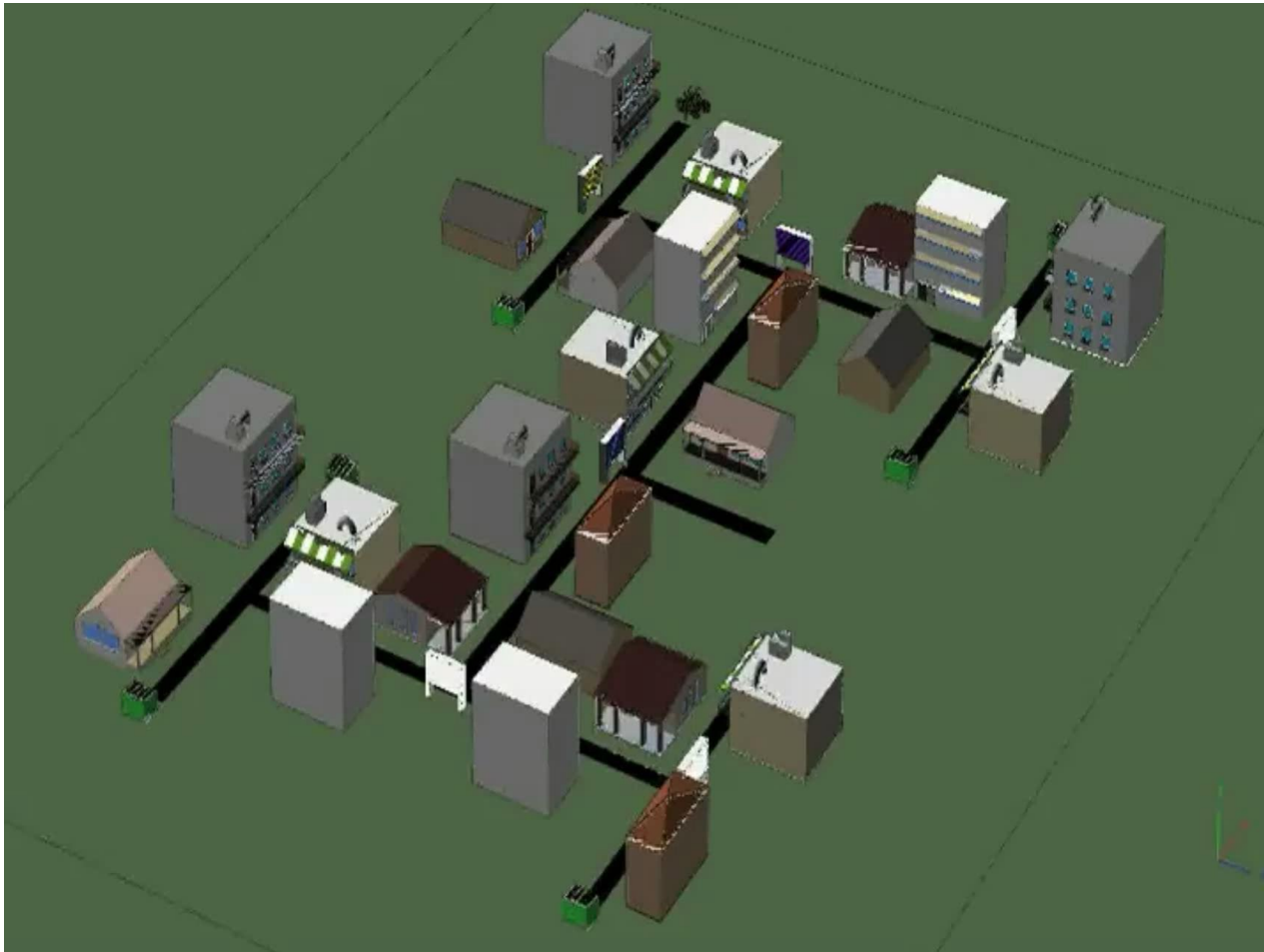
Navigation Video

Incorrect Choice



Navigation Video

Correct Choice



Future Directions

Simulator & Tools

- Near Term:
 - GUI-based brain model builder and visualizer
 - Multi-Scale modeling
 - Input language options
- Long Term:
 - Simulated fMRI data

Acknowledgments

- Office of Naval Research



- DARPA Synapse project and HRL

