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NCS: A Large-Scale Brain Simulator

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WHAT IS NCS?

The NeoCortical Simulator (NCS) is a **free, open source, scalable, parallelizable, distributable, real-time** simulator for **large-scale neural networks and systems**, developed and maintained by the **UNR Brain Computation Laboratory**. It is also the one of the first simulators to support **real-time neurorobotics applications**. The current version of NCS, NCS6, uses **GPUs for parallel computation**. NCS6 is designed to create different types of neuron models: **leaky integrate-and-fire (LIF)** spiking neurons using a reordered form of the **Hodgkin-Huxley (HH)** equations and **Izhikevich** neurons using a dynamical system and **Izhikevich (IZH)** equations. Users also have an ability to design their own plug-in interface for different neuron types.

WHY USE NCS?

Interests/Reasons

- Biological brain models
- Real-time simulation
- Different levels of abstraction
- Several neuron models
- GPU computation

Advantages

- No programming language experience required
- Good for modeling networks and systems
- Real-time simulation for 500k neurons and 50M synapses
- Quasi real-time simulation for 1M neurons and 100M synapses

Disadvantages

- Lack of biophysical details
- No graphical user interface (GUI)
- No visualization

System Requirements

- Linux operating system
- NVIDIA graphical cards

PERFORMANCE

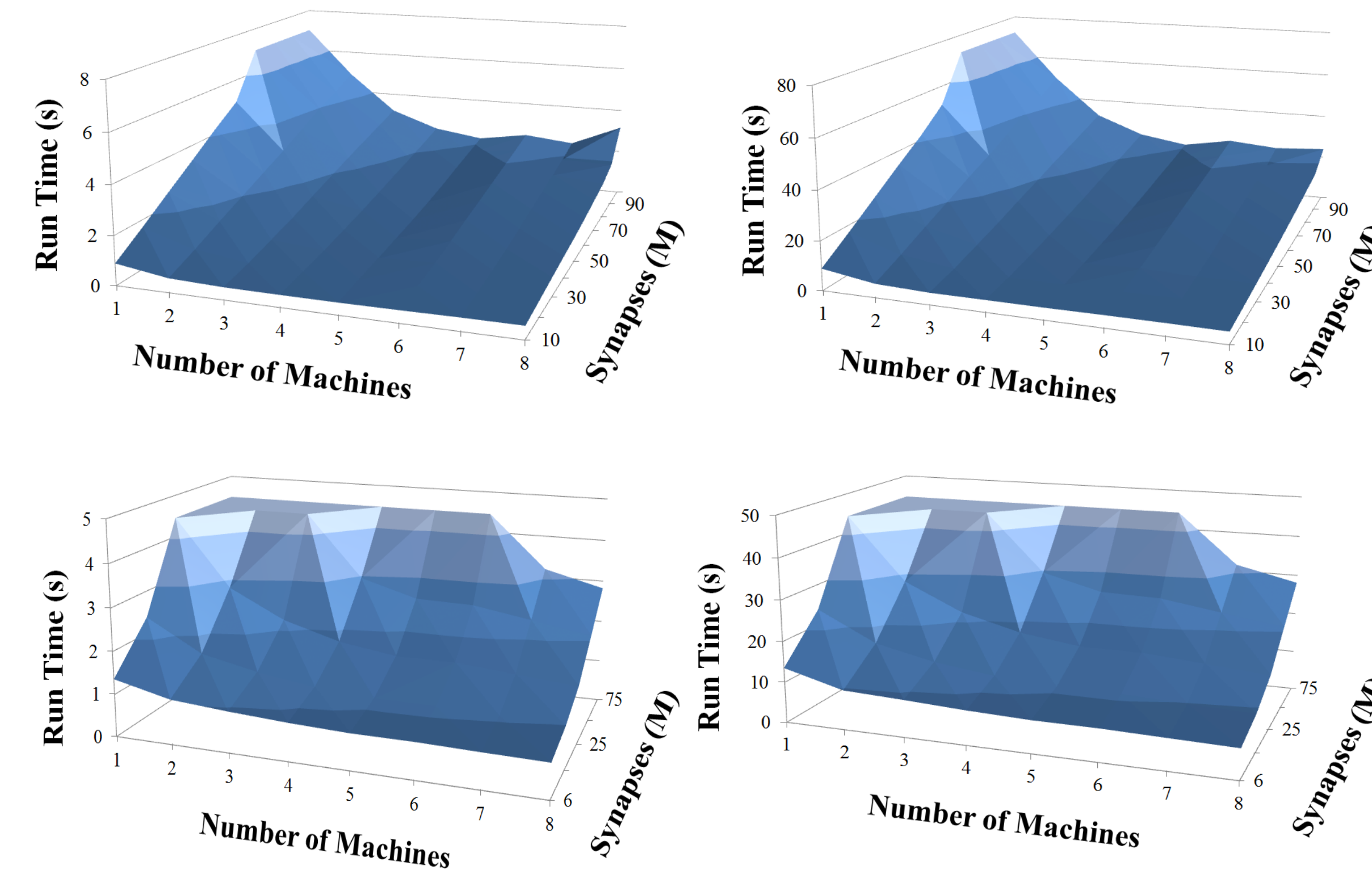


Figure 1: Performance Data (Top left: IZH 1s; top right: IZH 10s; bottom left: LIF 1s; bottom right: LIF 10s)

NCS6 is capable of running large-scale neural models (100,000 - 1,000,000 neurons) faster than any other simulators by distributing data **across multiple GPUs**. Considering a **synapse to neuron ratio of 100** (e.g. 500,000 neurons and 50 million synapses), NCS runs any models up to **1 million neurons in quasi real-time**, for **1s and 10s simulations**, as presented in Figures 1 and Table 1 for the **LIF/HH and IZH neurons**, respectively. In the NCS performance figures, up to eight machines were used with each having two video cards (mostly **NVIDIA GTX 480**). From one to hundred-second simulations, NCS has shown minimal loss of performance over time.

Machines	# Neurons (k)	Synapses (M)	Time (s)
Izhikevich 1 second simulation			
1	100	10	0.90
4	400	40	1.00
8	500	50	1.03
8	1000	100	3.16
Izhikevich 10 second simulation			
1	100	10	8.98
4	400	40	9.89
8	500	50	10.13
8	1000	100	23.97
LIF 1 second simulation			
1	25	6	1.36
4	50	12	1.18
8	50	12	0.99
8	300	75	2.82
LIF 10 second simulation			
1	25	6	13.53
4	50	12	11.63
8	50	12	9.34
8	300	75	28.08

Table 1: Performance Data

ROBOTICS

Our **virtual neurorobotic (VNR)** system aims to develop combinations of **biological neural simulations with robotic agents** and human participants in closed-loop configurations. VNR is defined as a **computer-facilitated loop to study high-level behavioral systems**. As shown in Figure 2, VNR is composed of supporting tools that include the **Brain Communication Server**, which manages real-time input/output for a running simulation; **Brainstem**, which serves as a preprocessor for digital audio, visual, and tactile inputs and an **interpreter of motor-control outputs**, as required by our neurorobotics applications; and a **robotic interface**, which represents behavioral scenarios and higher-level behavioral outcomes.

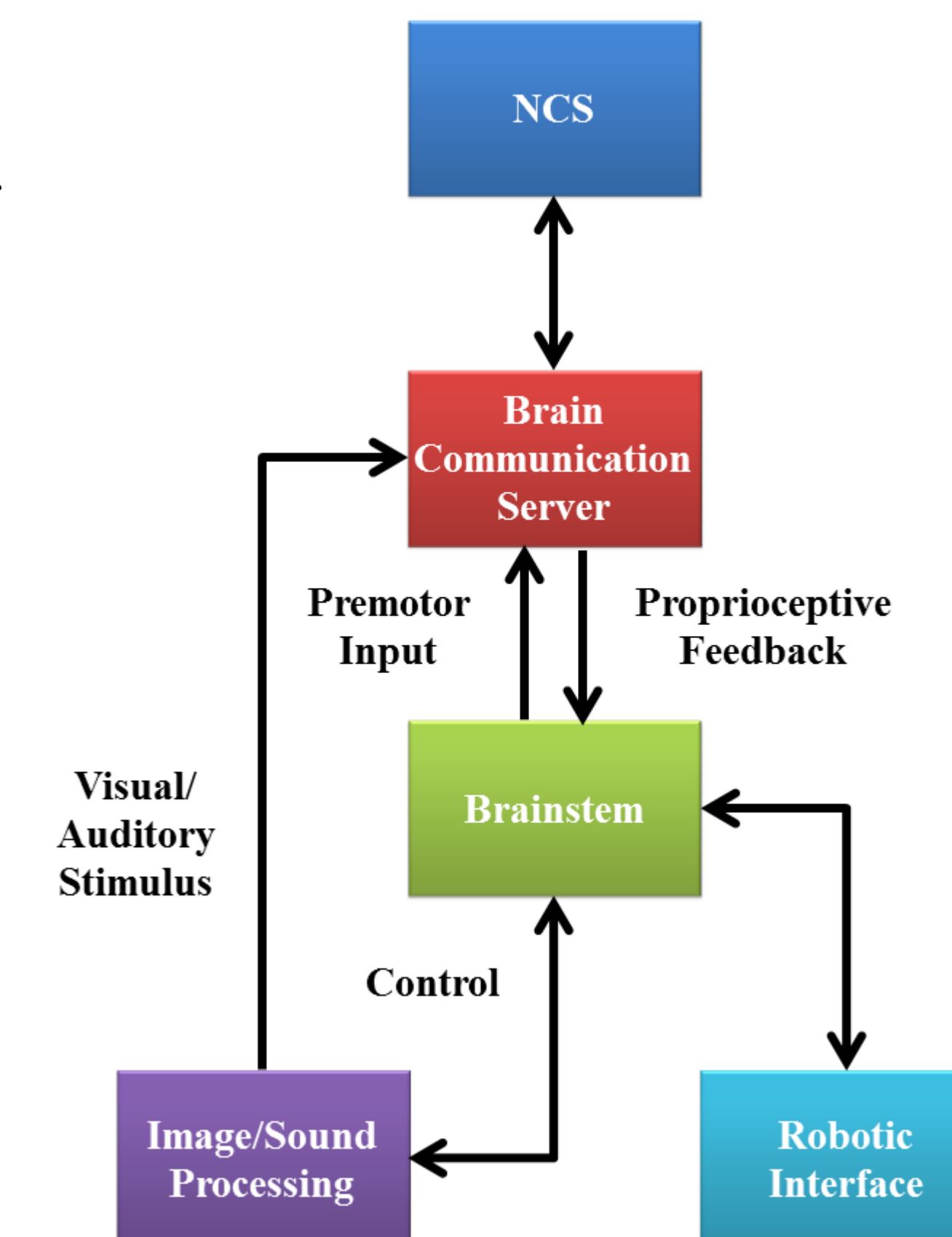


Figure 2: VNR

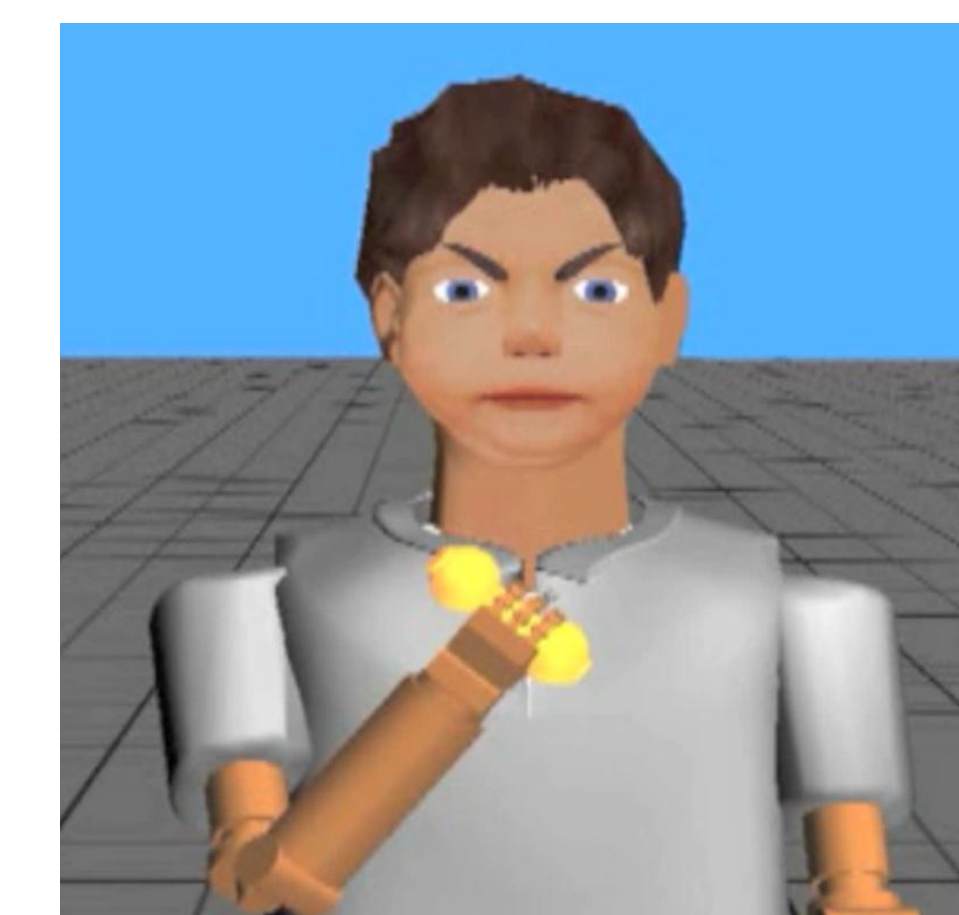


Figure 3: Virtual Robot

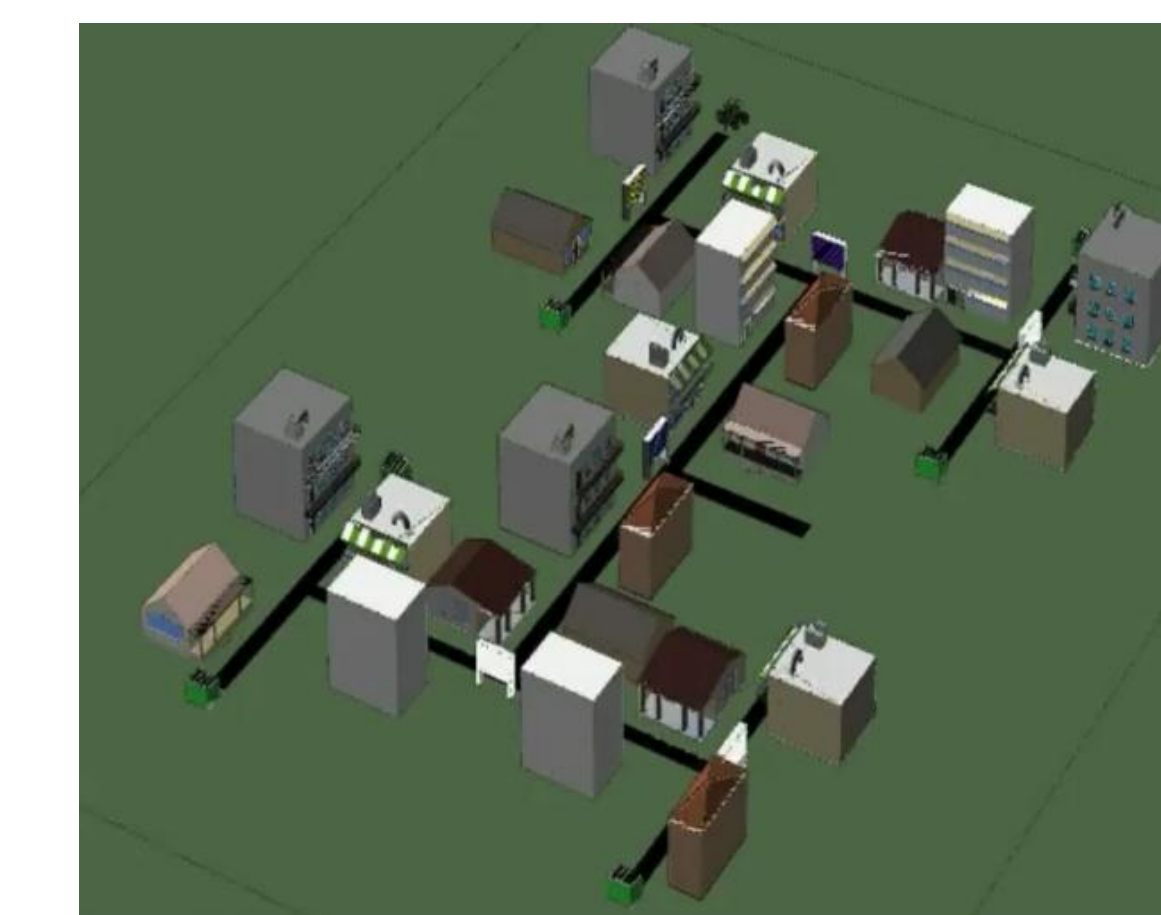


Figure 4: Virtual Environment

Our existing models and robotic applications consist of replicating **trust and intent recognition and spatial navigation**. In the **first** project, we offer a model of a mechanism for trust-building between our virtual neurorobot (Figure 3) and a human participant where imitation of behavior can result in an **increase in trust**. In this model, we try to replicate the trusting role of hypothalamic oxytocin cells and the suppressing functions of the amygdala. In the **second** project, we use a virtual city-like maze (Figure 4) to examine the formation of **short-term memory, decision making, and reward-based learning** during the exploration of a three-binary-decision maze to reach a goal. In this model, we try to replicate the dynamics of mammalian hippocampal-prefrontal loop circuitry during sequential learning.

MODELS

As shown in Figure 5, key interacting brain regions have been modeled (PF-PreFrontal, PM-PreMotor, PC-Parietal Cortex, AM-Amygdala, HF-Hippocampal Formation, EC-Entorhinal Cortex, HYP-Hypothalamus, IT-Infero-Temporal, VC-Visual Cortex, Red Arrows-Learning: STDP rule)

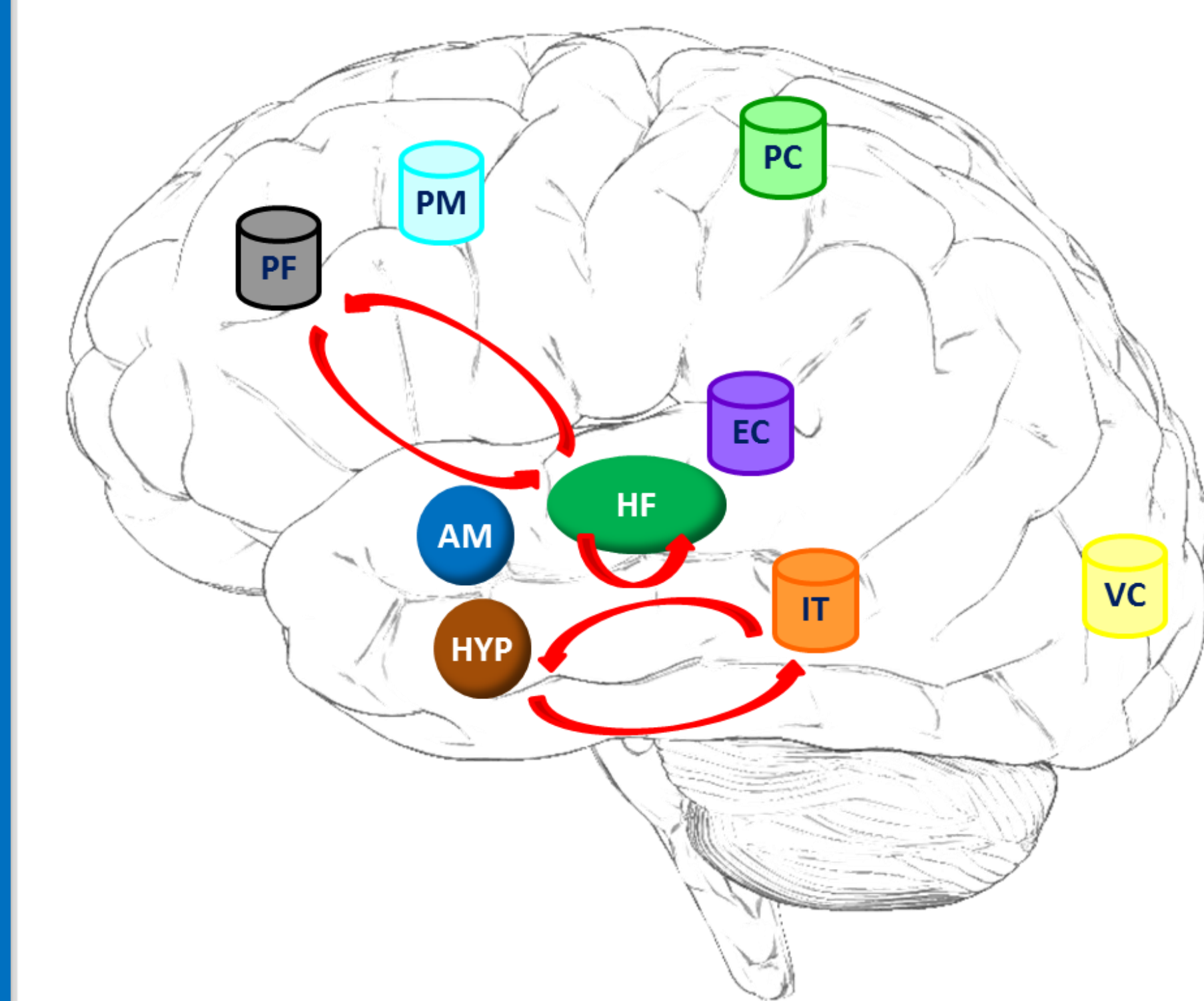


Figure 5: Modeled Brain Regions

FUTURE DIRECTIONS

Simulator & Tools

Near Term:

- Input language options
- GUI-based Brain Model Builder and Visualizer
- Multi-Scale Modeling

Long Term:

- Simulated fMRI data

Modeling & Simulation

Near Term:

- Higher-level behavior
- Expanded and more detailed models

Long Term:

- Disorders and interventions
- Drug interactions

Supported by a grant from the U.S. Office of Naval Research (N000140110014)