UCI University of California, Irvine

# Attention and Navigation Strategies for Neurorobotics and Neuromorphic Applications

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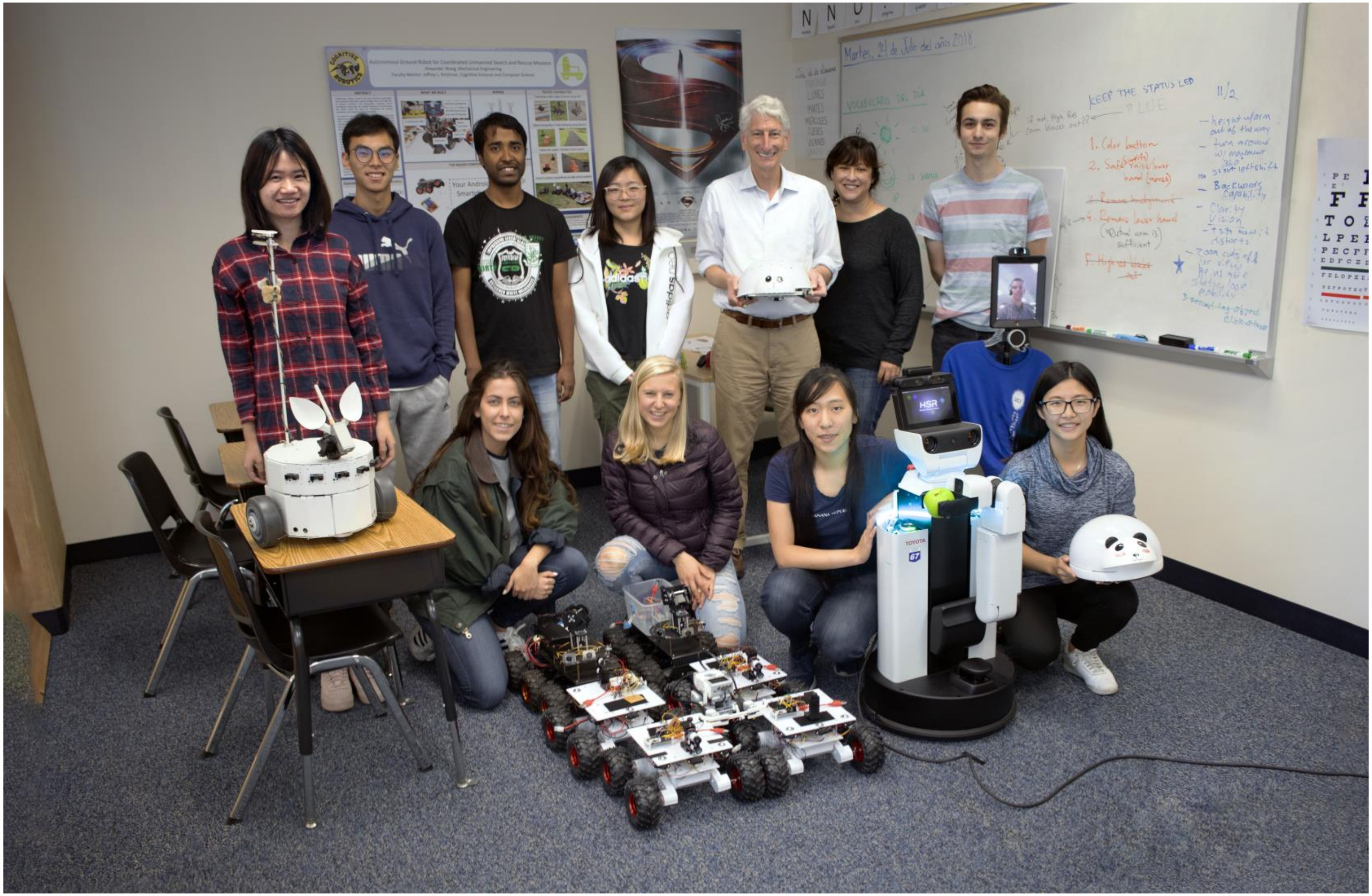
June 23, 2019

# Introduction

- In the Cognitive Anteater Robotics Laboratory (CARL) at UC Irvine, we develop neurorobots for studying cognition and building neuromorphic applications.
- The robot behavior is controlled by a simulated nervous system designed to reflect the brain's architecture and dynamics.
- Neurorobotics is a powerful tool for studying cognitive behavior and examining the artificial brain in detail.
- Neurorobotics is an ideal platform for the developing neuromorphic applications.

# CARL Family



Part I. Neuromorphic Navigation Strategies

Part II. Neuromodulated Goal-driven Perception in Uncertain Domains

Part I. Neuromorphic Navigation Strategies

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# PART I. Neuromorphic Navigation Strategies

## Outdoor Robotics Challenges

- Changes in lighting
- Different terrains
- Lack of continuous power

## Autonomous Navigation Implementation

- Long-term strategy
  - spike wavefront path planning
- Reactive strategies
  - terrain classification
  - road following
  - obstacle avoidance

## Complete Neuromorphic Solution

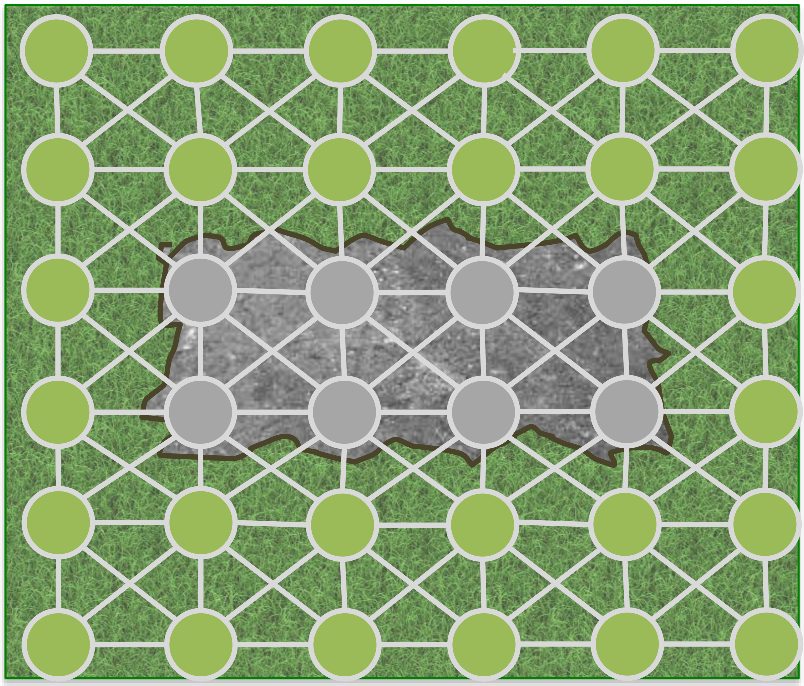
- Massively parallel
- Event-driven
- Energy-efficient

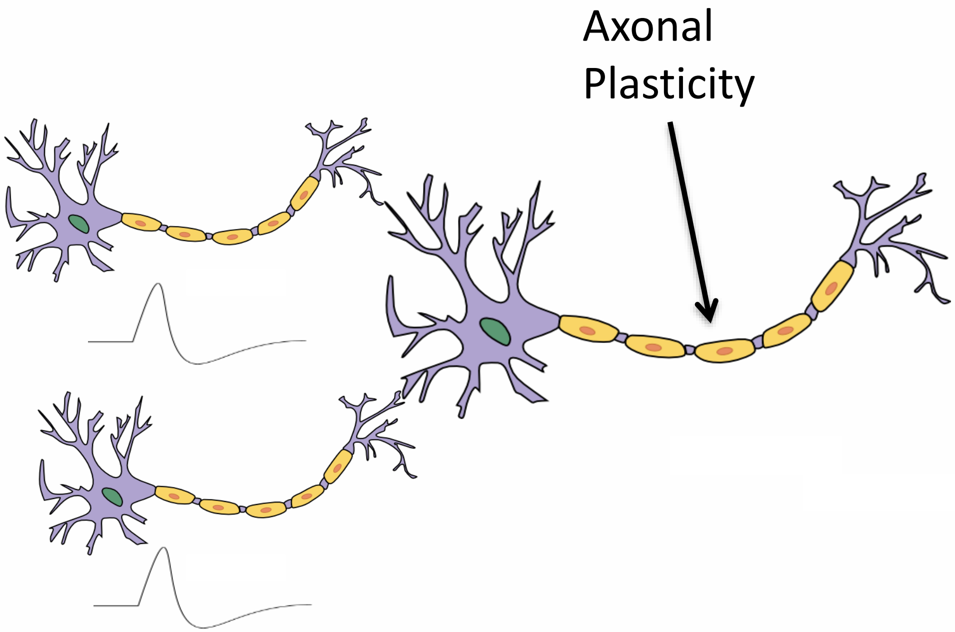
# Adaptive Path Planning

- Inspired by recent empirical findings supporting experience dependent plasticity of axonal conduction velocities.
- Cost of traversing through space is represented in the axonal delay between neurons.
- Spike propagation travels faster over lower cost paths.

T. Hwu, AY Wang, N. Oros, and JL. Krichmar, “Adaptive robot path planning using a spiking neuron algorithm with axonal delays,” IEEE TCDS, 2017.

# Overview of Spiking Wavefront Planner

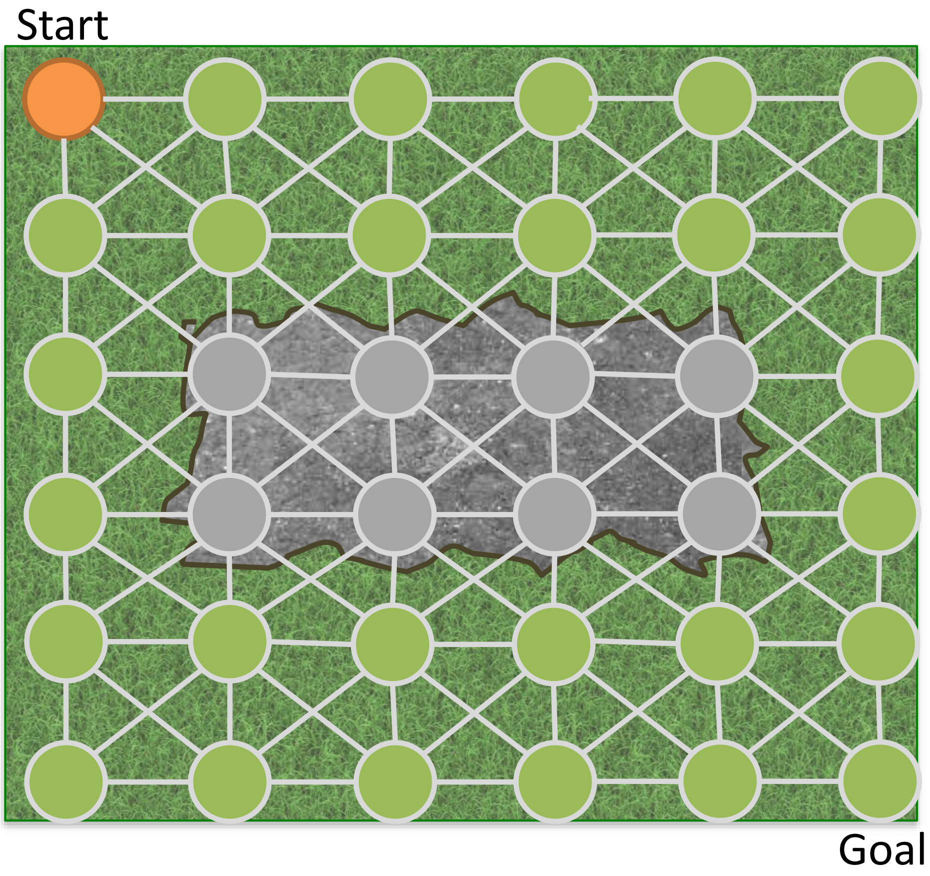




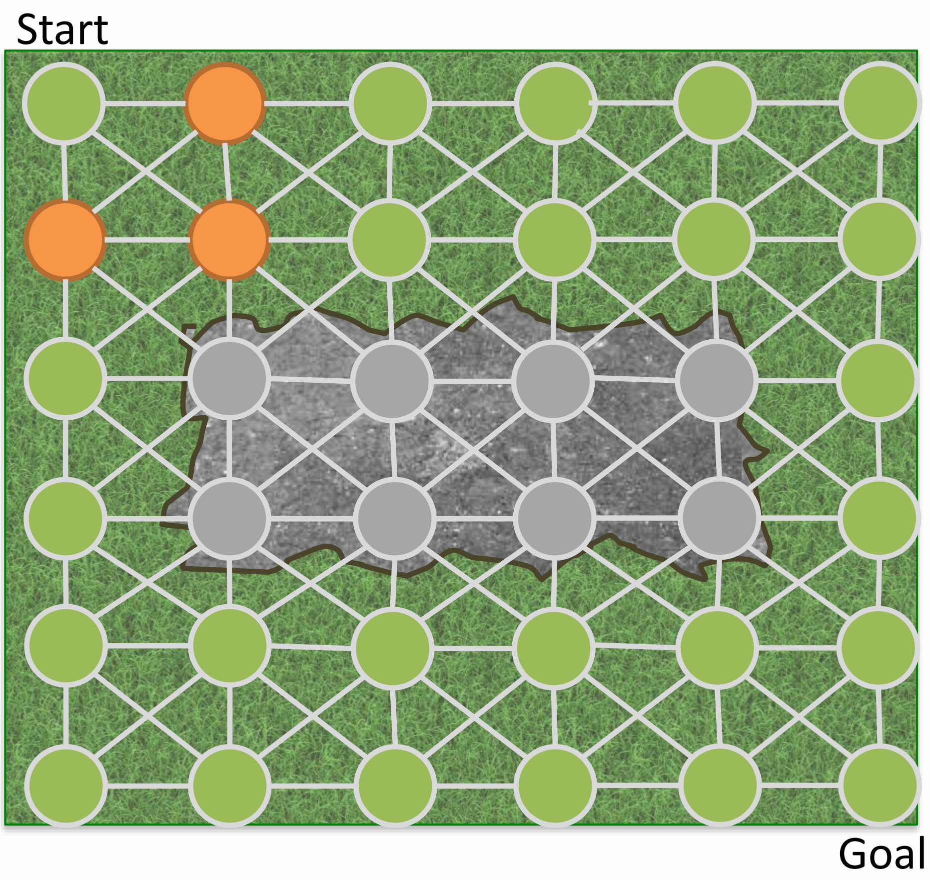

Overlay 2D Neuron Grid Over Physical Space

Code Obstacles and Environmental Costs Using Axonal Plasticity

# Spiking Wavefront Propagation



# Spiking Wavefront Propagation



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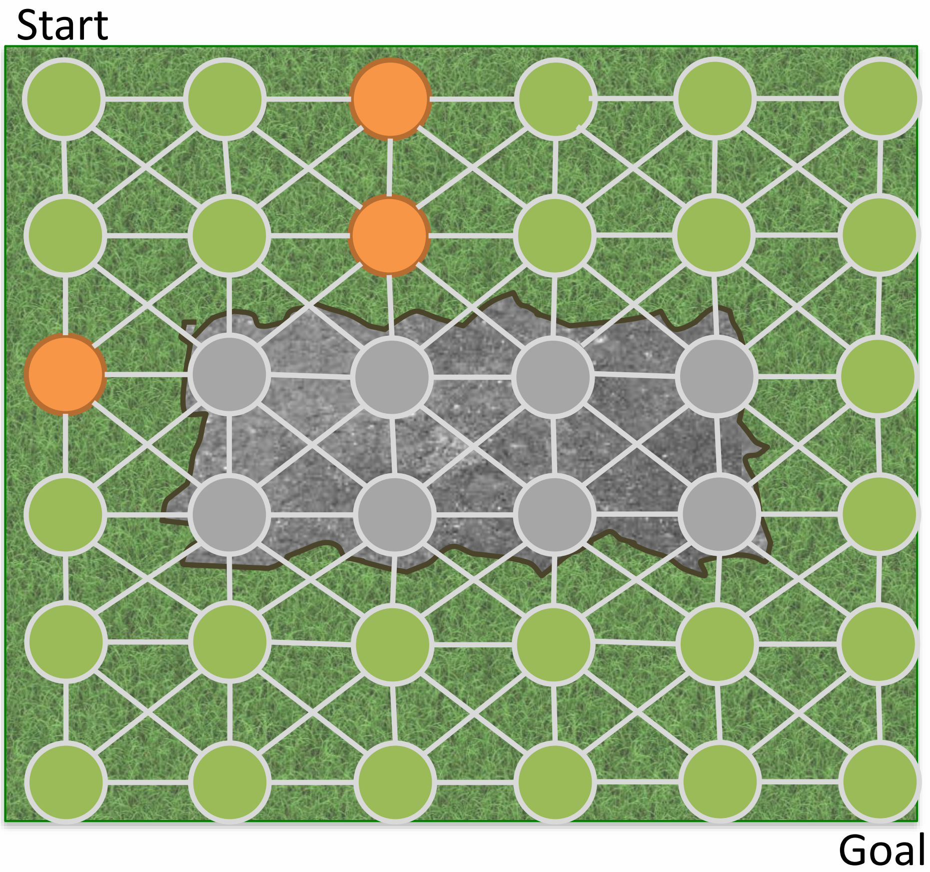

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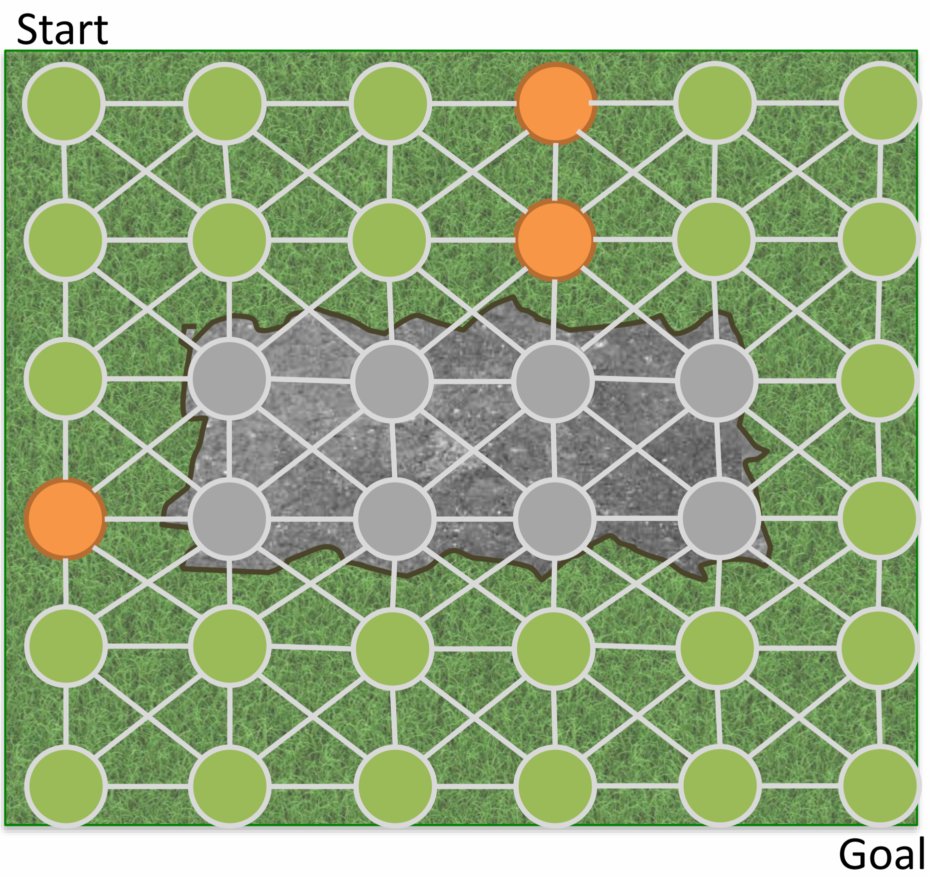

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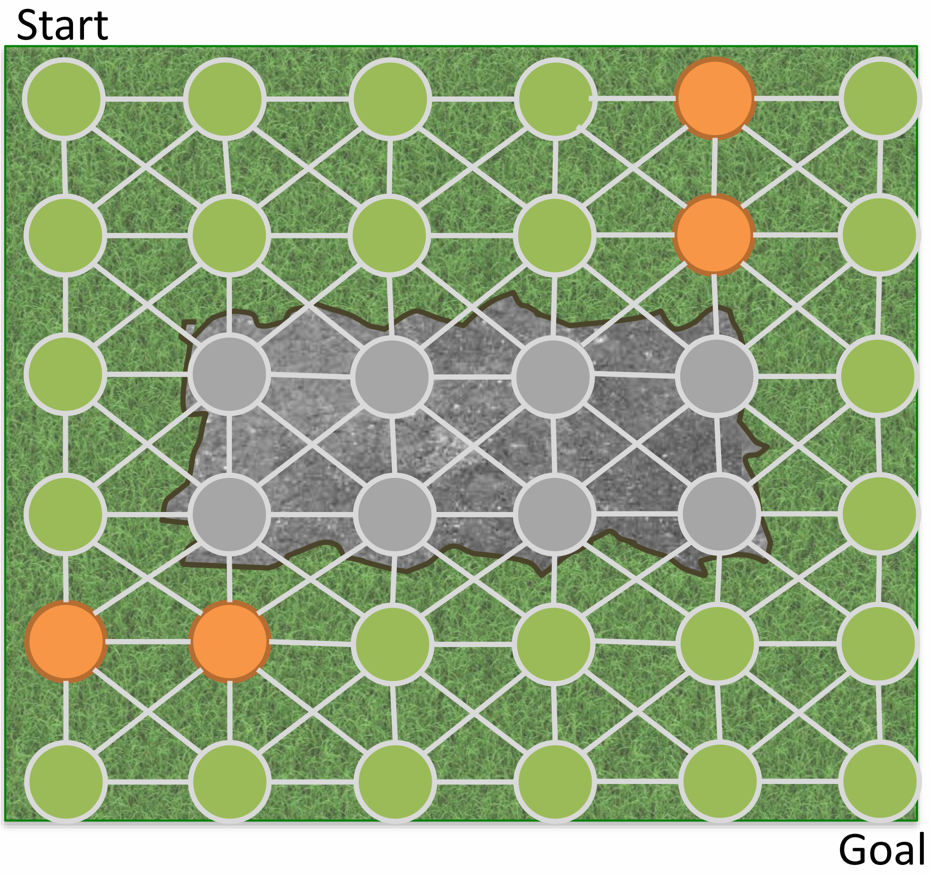

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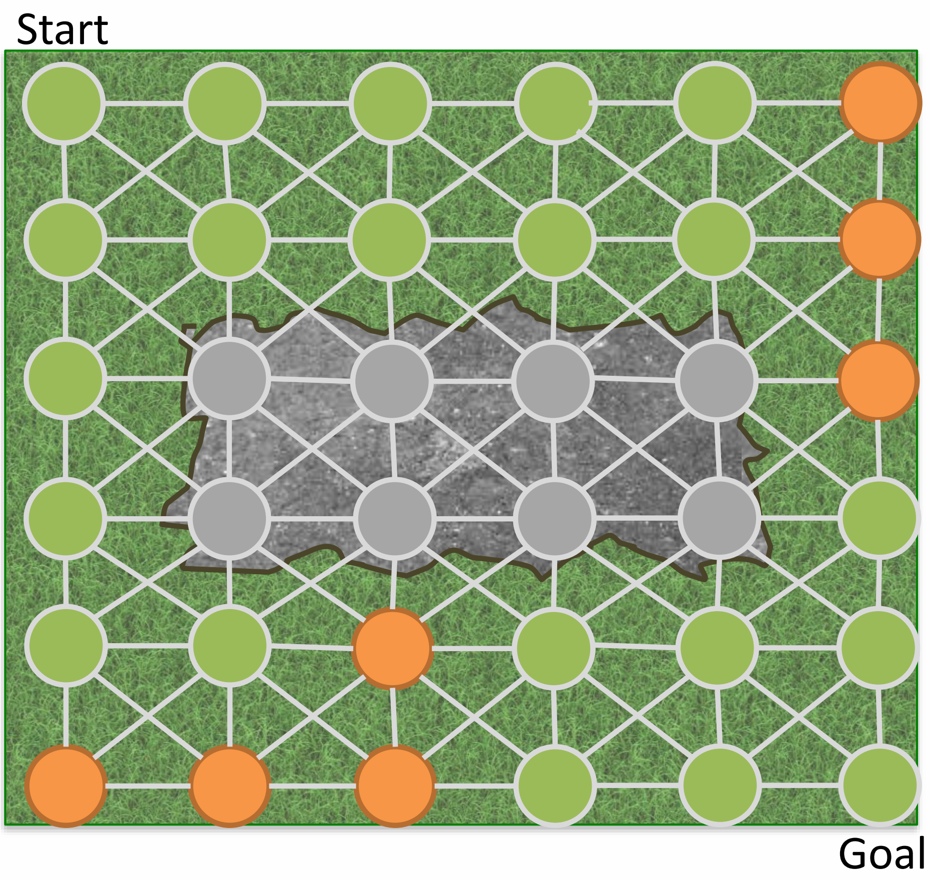

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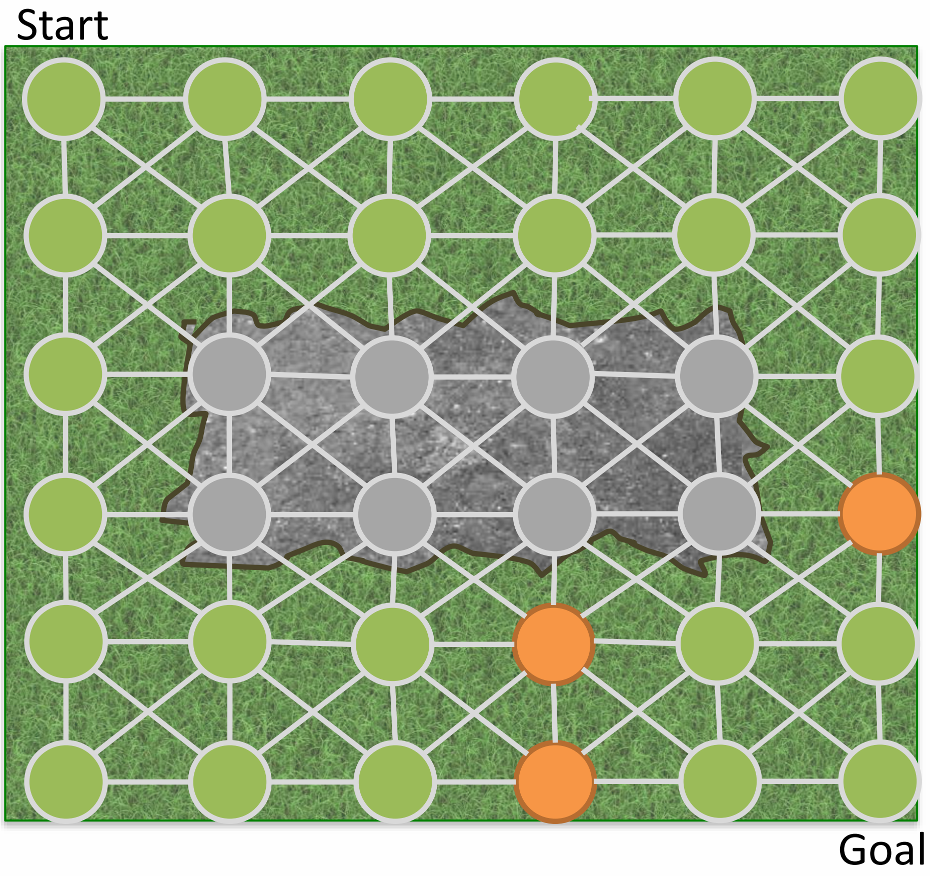

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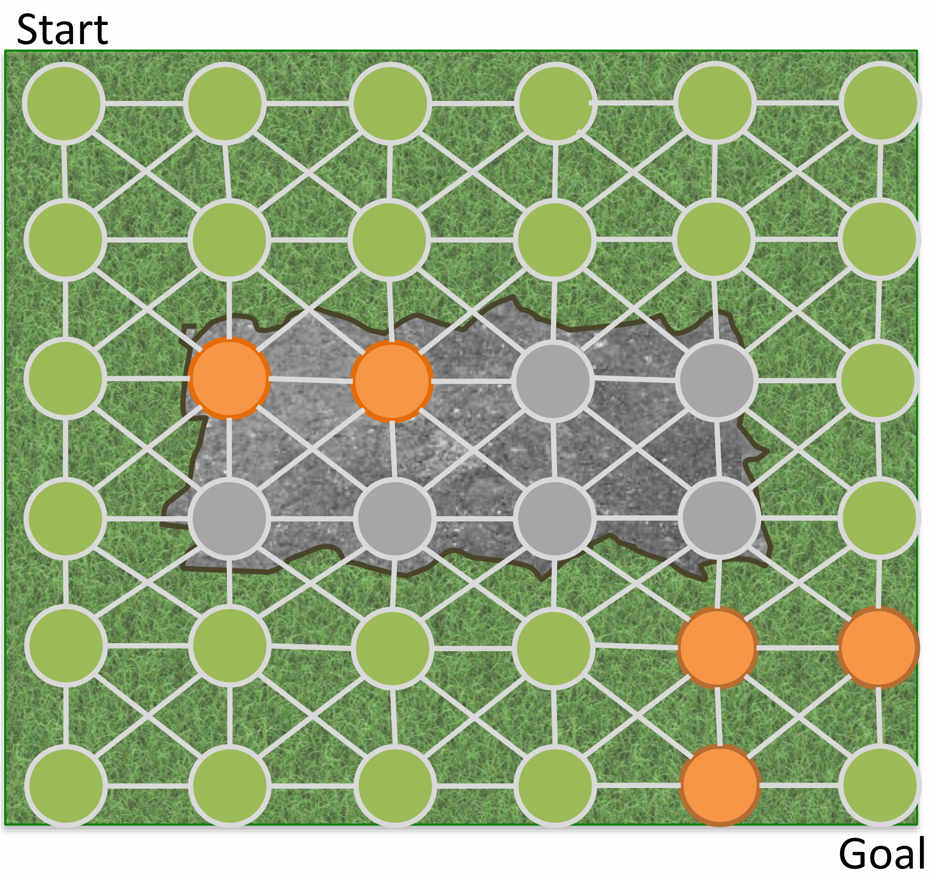

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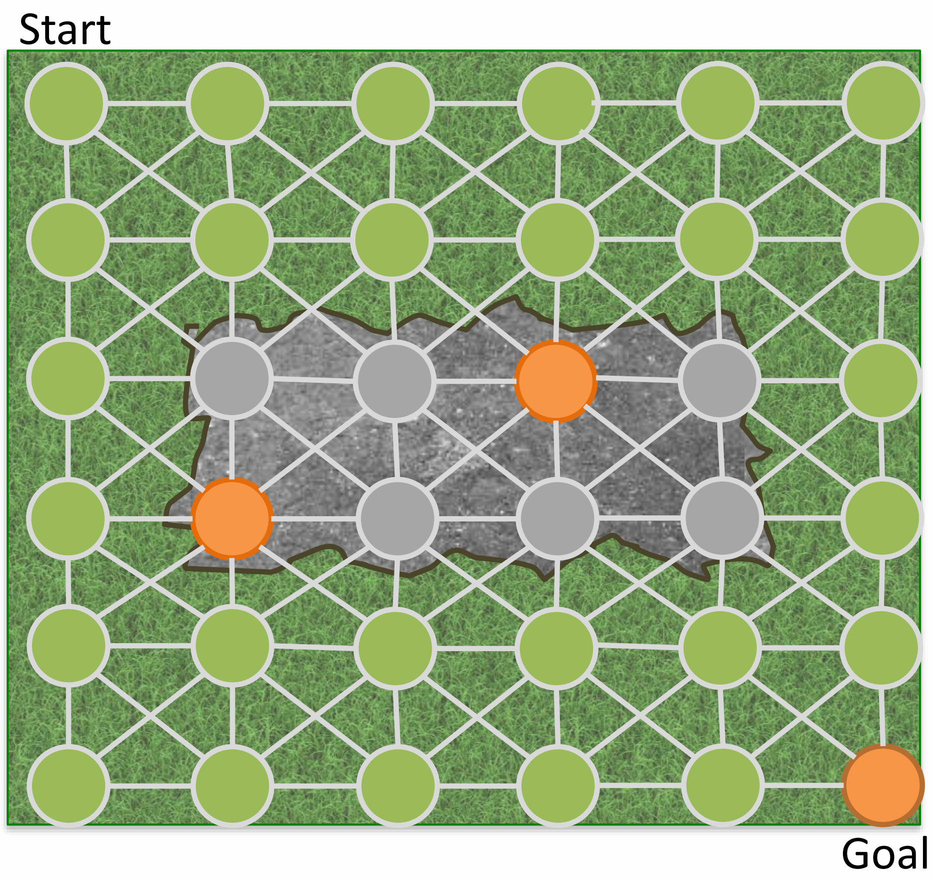

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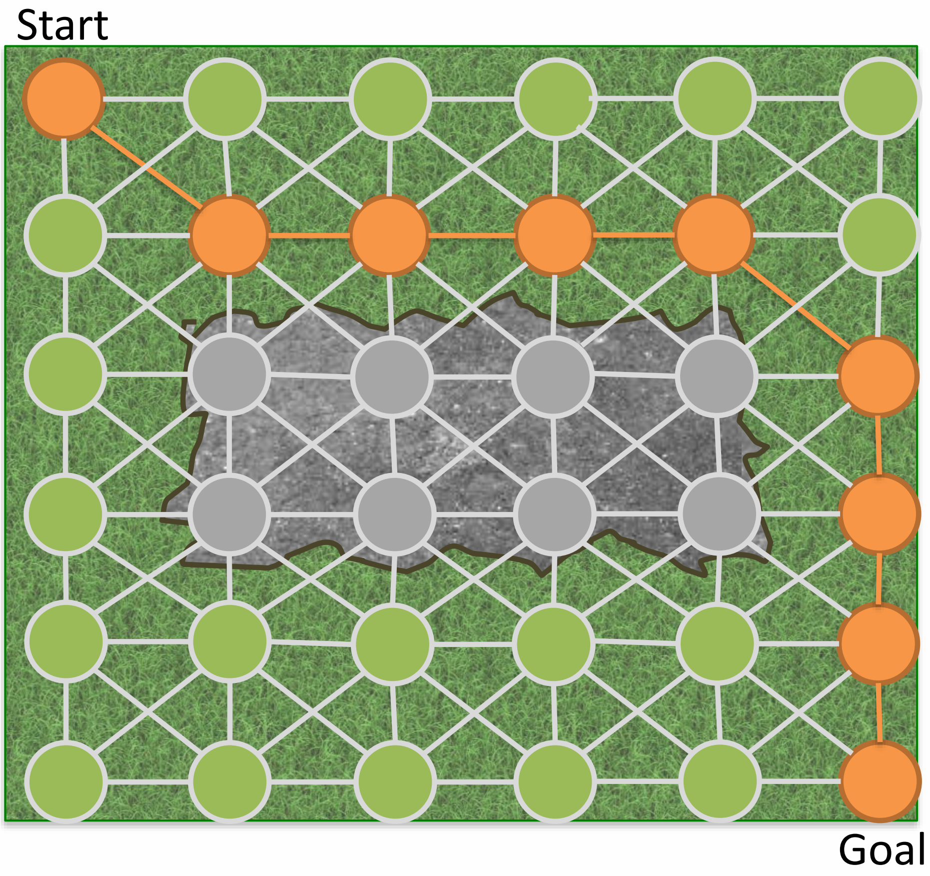
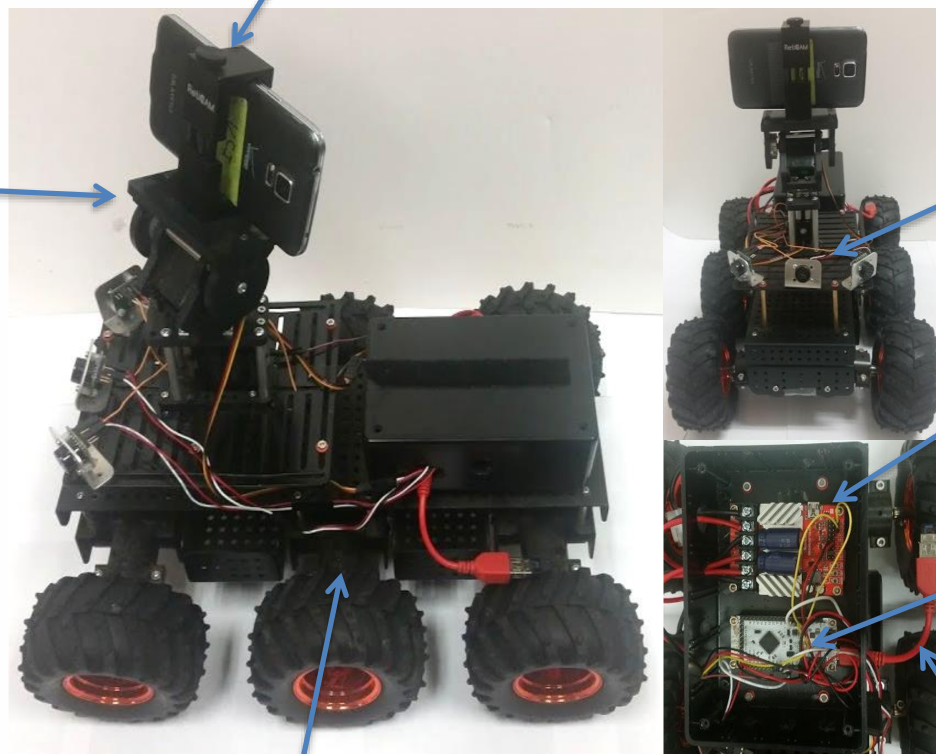


# Android-Based Robotics Platform

Android smartphone (GPS, Compass, Accelerometer, Gyroscope)

Pan/Tilt
SPT200



LV-MaxSonars

ION RoboClaw
Motor Controller

IOIO-OTG

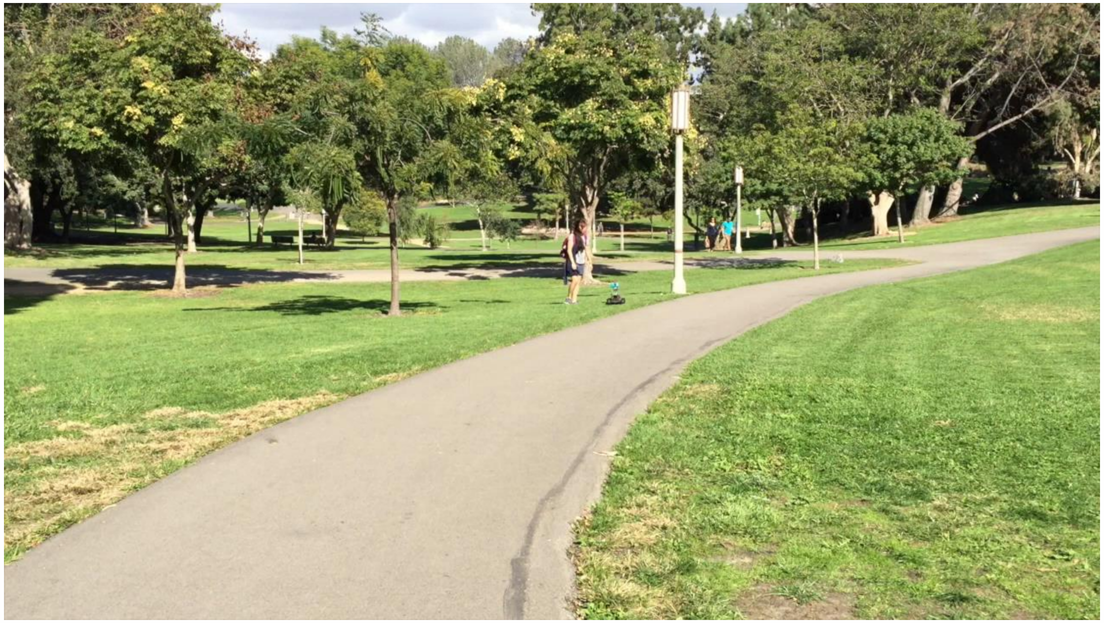
Bluetooth Dongle

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

Dagu Wild Thumper 6WD All-Terrain Chassis

- No Path Cost
  - take short cut


- Path Cost
  - follow road (not accurate based on GPS, so road following algorithm is later introduced)



# Spiking Wavefront Planner

- Spiking Wavefront Planner has lower cost and is more parallelizable than A*.
    - T. Hwu, AY Wang, N. Oros, and JL. Krichmar, “Adaptive robot path planning using a spiking neuron algorithm with axonal delays,” IEEE TCDS, 2017.
- Has been implemented in neuromorphic hardware.
    - IBM TrueNorth
        - KD Fischl, K Fair, W-Y Tsai, J. Sampson, and A. Andreou, “Path planning on the TrueNorth Neurosynaptic system,” in IEEE ISCAS 2017.
    - SpiNNaker
- Lightweight enough to run on smartphone.

# Road Following Algorithm

- Robot path planning algorithm relied on GPS and the phone's compass.
  - Low resolution of these sensors did not find the road.
- Developed vision-based road following algorithm
  - Finds paved paths.
  - Handles irregular paths, removes shadows, and avoids obstacles.
  - Uses smartphone's camera.
  - Determines the steering direction to center on road.

T. Hwu, JL. Krichmar, and X. Zou, "A complete neuromorphic solution to outdoor navigation and path planning," in IEEE ISCAS, 2017.

# Road Following Algorithm

Gaussian Blur + RGB2GRAY

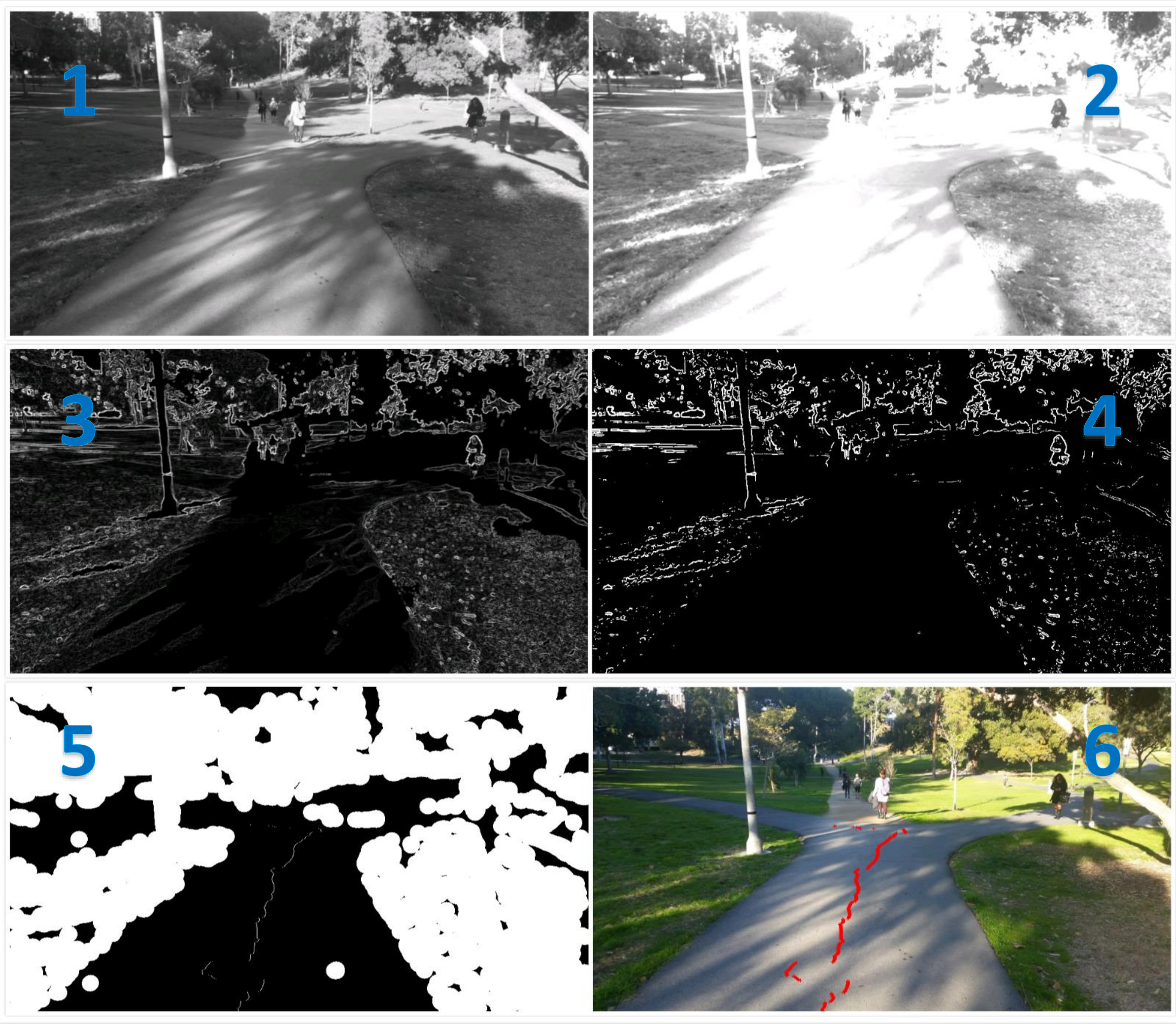
Contrast & Brightness Adjustment

Sobel Gradient Estimation

Binary Threshold

Dilation + Path Estimation

Path Labeling on RBG Frame




(T. Hwu, JL. Krichmar, and X. Zou, in IEEE ISCAS, 2017.)

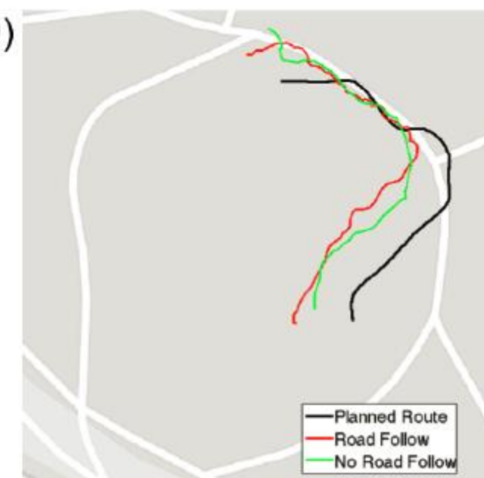
# Path Planning Results

| | Percent of route that the robot stayed on the road when it is supposed to | |
|---|---|---|
| | Original | Road Following Added |
| Starting off-road & Ending on-road | 51.2% | 63.2% |
| Starting on-road & Ending off-road | 41.2% | 87.3% |

B)


B) starting off-road and ending on-road.

D)

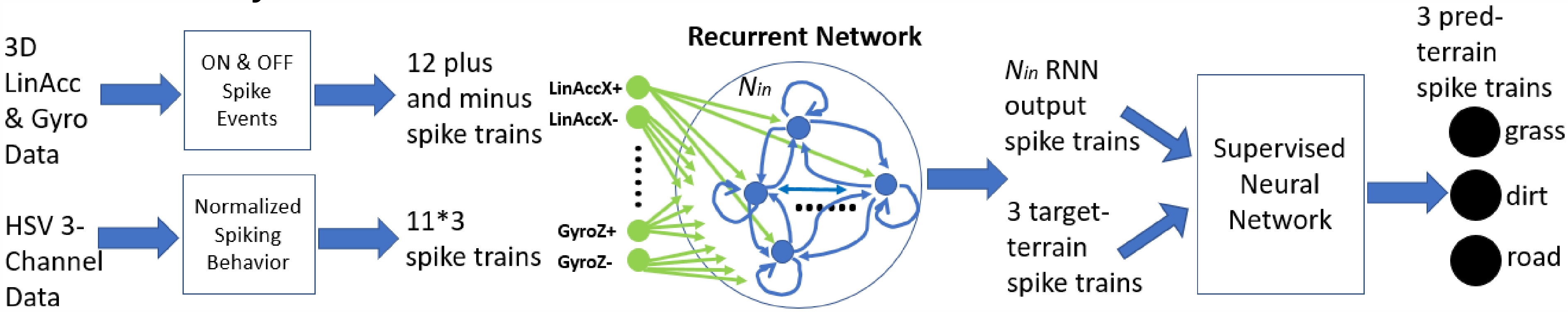



D) starting on-road and ending off-road.

(T. Hwu, JL. Krichmar, and X. Zou, in IEEE ISCAS, 2017.)

# Terrain Classification Algorithm

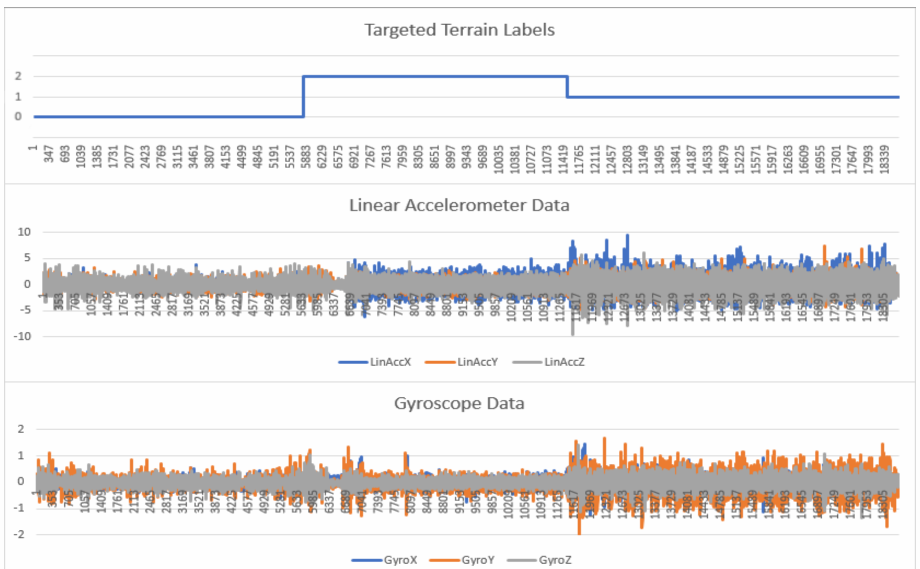
- Developed a biologically inspired, energy efficient algorithm for terrain classification.
- Collected terrain data on grass, dirt, road with an Android-Based Robot (ABR).
- Constructed a Reservoir-based Spiking Neural Network (r-SNN) to classify the terrains.




X. Zou, T. Hwu, E. Neftci, and JL. Krichmar, "Terrain classification with a reservoir-based network of spiking neurons", spotlight talk and poster presented in Southern California Robotics Symposium, Caltech, 2019.

- Camera Screenshots Examples


- Gyroscope and Linear Accelerometer Data



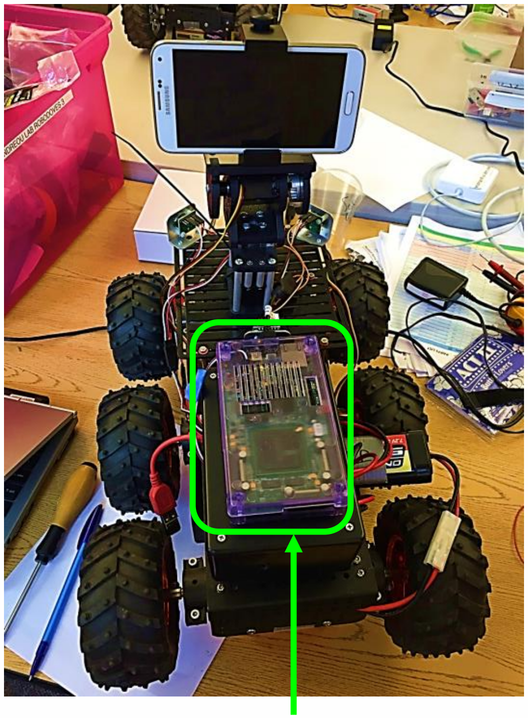

(X. Zou, T. Hwu, E. Neftci, and JL. Krichmar, presented in SCR, Caltech, 2019.)

- r-SNN Test Prediction Error (Compared w/ SVM and 3-L Logistic Regression)

| | r-SNN | SVM | 3L Logistic Regression | |
|---|---|---|---|---|
| | | | mse | xent |
| **Images only** | **5.2%** | 13.9% | 11.5% | 16.2% |
| **Sensors only** | **8.1%** | 14.5% | 13.7% | 59.6% |
| **Images + Sensors** | **3.5%** | 8.8% | 10.2% | 34.3% |

- The r-SNN was the most efficient method
  - only 70 RNN internal neurons
  - adaptation of only RNN-to-output weights
  - no need of splitting data into time chunks.
- Learning rule modified from SuperSpike
- r-SNN is compatible with event-driven neuromorphic hardware for a low-power autonomous navigation system.

# Self-Driving with Neuromorphic Implementation



NS1e with IBM TrueNorth

T. Hwu, J. Isbell, N. Oros, and J. L. Krichmar, *IEEE IJCNN*, 2017.

Part I. Neuromorphic Navigation Strategies

Part II. Neuromodulated Goal-driven Perception in Uncertain Domains

# Part II. Neuromodulated Goal-driven Perception in Uncertain Domains

**Biological Systems**

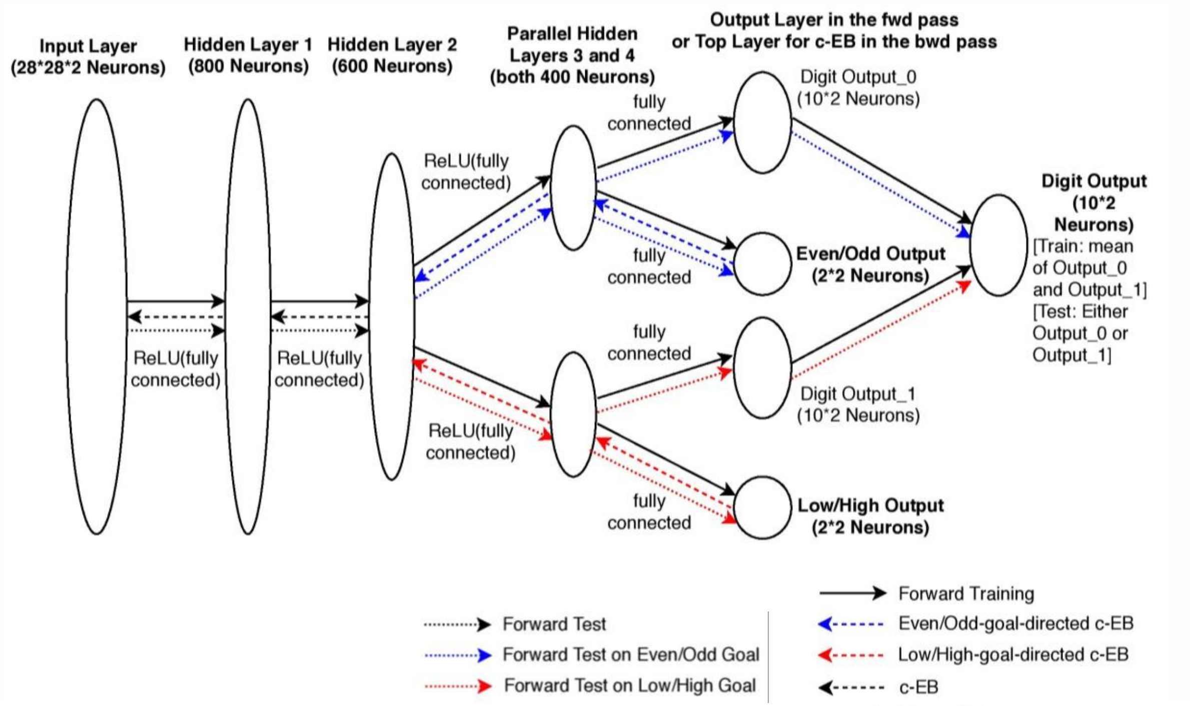
guide behavior with relevant info
+ rapidly adapt to unforeseen environment

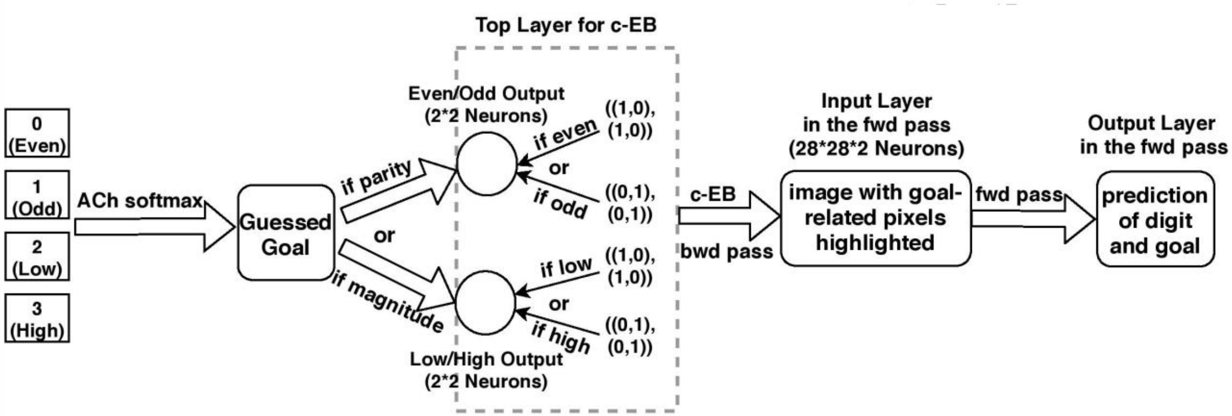
**Goal-Driven Perception**

focus on critical stimuli that need quick response

**Our Neuromodulated Goal-Driven Perception Model**

regulate goal selection with ACh&NE
+ highlight goals and ignore distractors in noisy & dynamic scenarios




X. Zou, S. Kolouri, PK. Pilly, and JL. Krichmar, “Neuromodulated goal-driven perception in uncertain domains,” arXiv preprint arXiv:1903.00068, 2019.

# Modified Contrastive Excitation Backprop (c-EB)

- Modified from Zhang et al. (2018)
- Cued from even, odd, low- or high-value
- Backpropagated contrastive signals for one layer
- Performed EB over remaining layers
- Highlighted only goal pixels by
  - cancelling out common winner neurons
  - amplifying discriminative neurons

(X. Zou, S. Kolouri, PK. Pilly, and JL. Krichmar, arXiv preprint arXiv:1903.00068, 2019.)

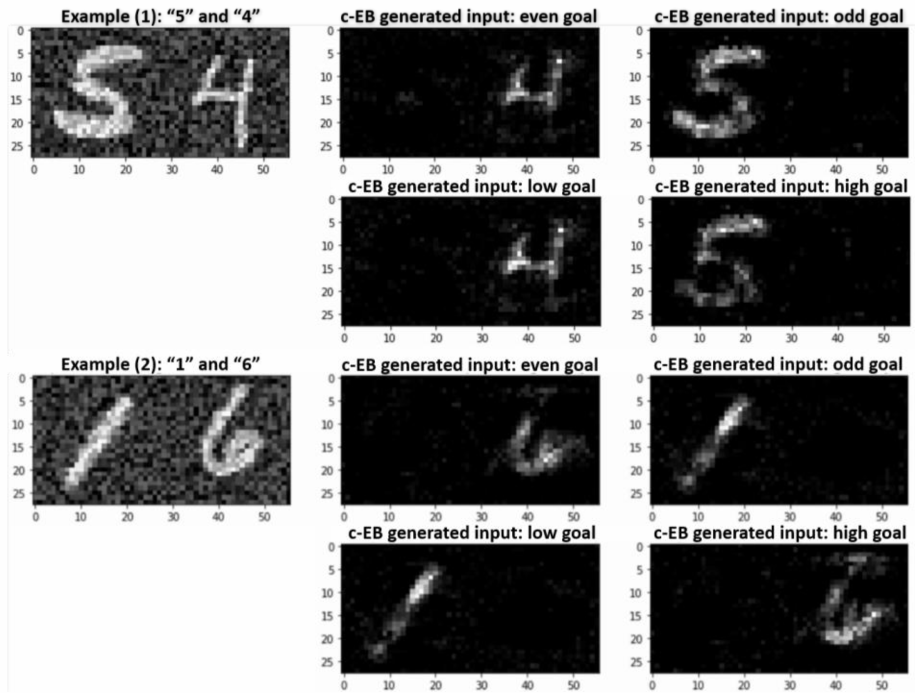



**Table 1. c-EB Prediction Accuracy for 10,000 test pairs of noisy MNIST digits**

| Goal Task | % Correct Digit Prediction | % Correct Goal Prediction |
|---|---|---|
| Even | 92.03 | 99.50 |
| Odd | 91.15 | 99.75 |
| Low | 95.39 | 99.54 |
| High | 87.46 | 98.22 |

# ACh and NE Neuromodulation

- Extended Yu and Dayan's ACh-NE model (2005)
- 4 **ACh neurons** => **expected uncertainties**
  - drove attention toward a goal digit, and divert attention from distractors
  - ACh[guess] ↑ if pred's correct; vice versa
- 1 **NE neuron** => **unexpected uncertainties**
  - responded phasically when a goal identity change was detected
  - NE ↓ if pred's correct; vice versa

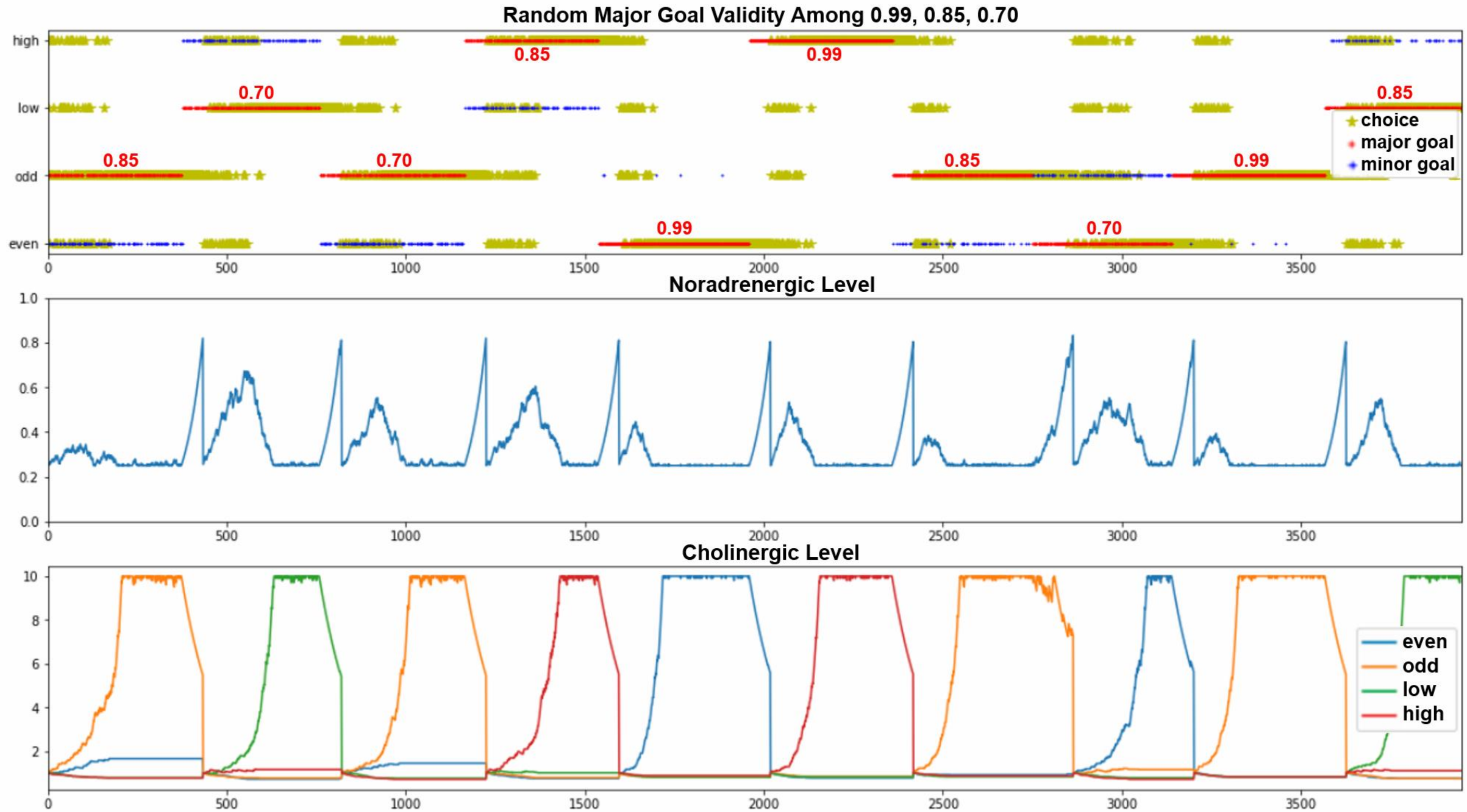
| NE Ablation | ACh Ablation | NE&ACh Ablation |
|---|---|---|
| no reset,<br>longer lag | rand guess,<br>high NE level | rand guess,<br>no ACh/NE firing |

(X. Zou, S. Kolouri, PK. Pilly, and JL. Krichmar, arXiv preprint arXiv:1903.00068, 2019.)

## Table 2. Average neuromodulation performance over 10 runs for each of the four goal validity settings.

(X. Zou, S. Kolouri, PK. Pilly, and JL. Krichmar, arXiv preprint arXiv:1903.00068, 2019.)

| Major Goal Validity | Minor Goal Validity | % Correct Major Goal | % Correct Minor Goal | % Incorrect ACh Softmax Prediction | % Incorrect c-EB Prediction |
|---|---|---|---|---|---|
| 0.99 | 0.01 | 67.0 | 0.1 | 26.0 | 6.9 |
| 0.85 | 0.15 | 54.0 | 1.3 | 38.9 | 5.8 |
| 0.70 | 0.30 | 37.4 | 4.8 | 53.3 | 4.5 |
| P_VALID | 1-P_VALID | 49.5 | 12.4 | 31.7 | 6.4 |



# Neuromodulated Goal-Driven Perception

- **Extended neuroscience model to support goal-driven perception**
- **Compatible w/ many attention mechanisms**
  - c-EB was chosen, similar to ACh system
- **Evaluated probability matching behavior**
  - Explored options ✓
    always choosing the most likely goal ✗
  - Underselected the most rewarding, similar to human behavior
  - Uncertainty seeking strategies governed by ACh systems can inspire AI
- **The system can be more scalable**
  - to learn goals online using a pool of ACh neurons without *a priori* assumptions
  - to work on more complex datasets (e.g. Microsoft COCO, ImageNet)

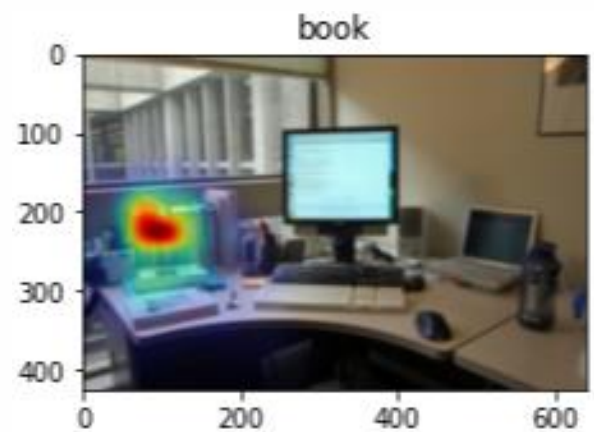
# Action-Based Goal-Driven Perception

- **Desired actions can drive attention in humans**
  - Neuromodulatory systems operate on a modified contrastive excitation backprop (c-EB) attention method.
  - Predicts the current desired action and increases attention to related objects.
  - The HSR will carry out the desired action on the attended object.

"I guess he wants to drink"

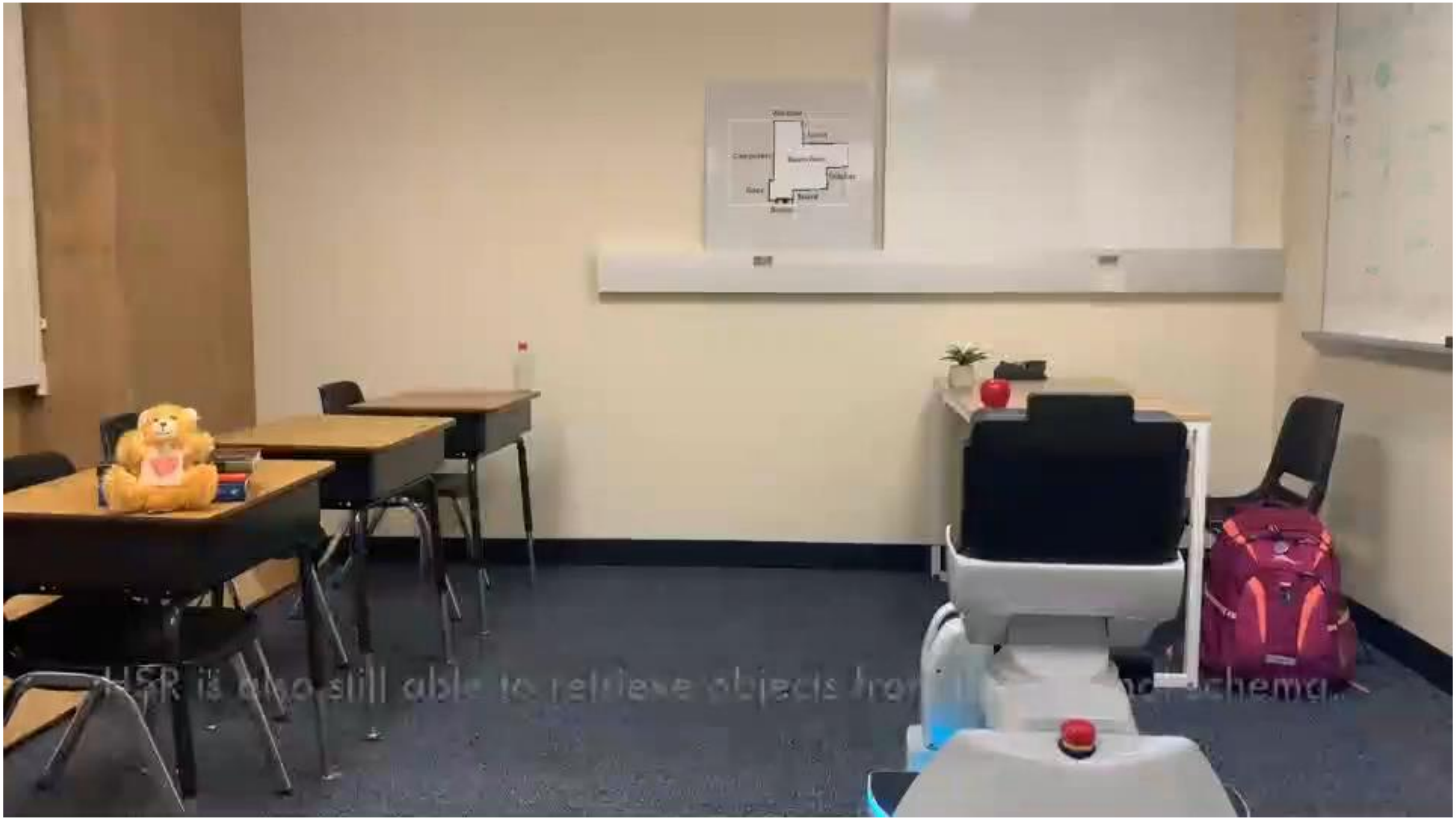
Toyota HSR

Action = "read"




Result of top-down attention

# Object Grabbing by Toyota HSR



Hwu, Kashyap & Krichmar, "Applying a Neurobiological Model of Schemas and Memory Consolidation to Contextual Awareness in Robotics", IROS 2019, under review.

# CONCLUSIONS

- Attention and navigation algorithms are developed to work in noisy and unpredictable environments.
- Android-Based Robot platform allows mapping, localization, path planning, and reactive controls to be implemented with traditional or neuromorphic methods.
- Neuromodulated goal-driven perception extends neuroscience ideas, and can inspire AI and neuroscience reciprocally.
- Neurorobotics will serve as an important platform for cognitive systems that can be generalized across multiple task domains and over longer time frames.

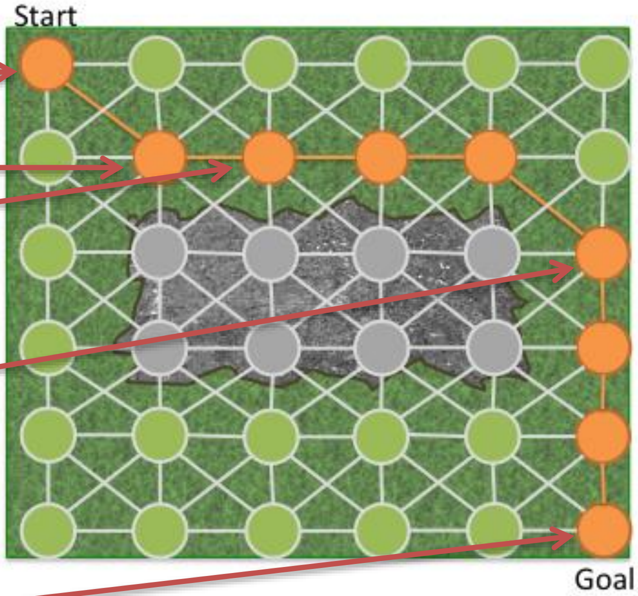
# Thank You!

- UCI CARL Lab Publications
  - http://www.socsci.uci.edu/~jkrichma/publications.html
- Android™ Based Robotics
  - http://www.socsci.uci.edu/~jkrichma/ABR/
  - https://github.com/UCI-ABR
- Contact us
  - Xinyun Zou xinyunz5@uci.edu
  - Jeffrey L. Krichmar jkrichma@uci.edu

# Path Readout

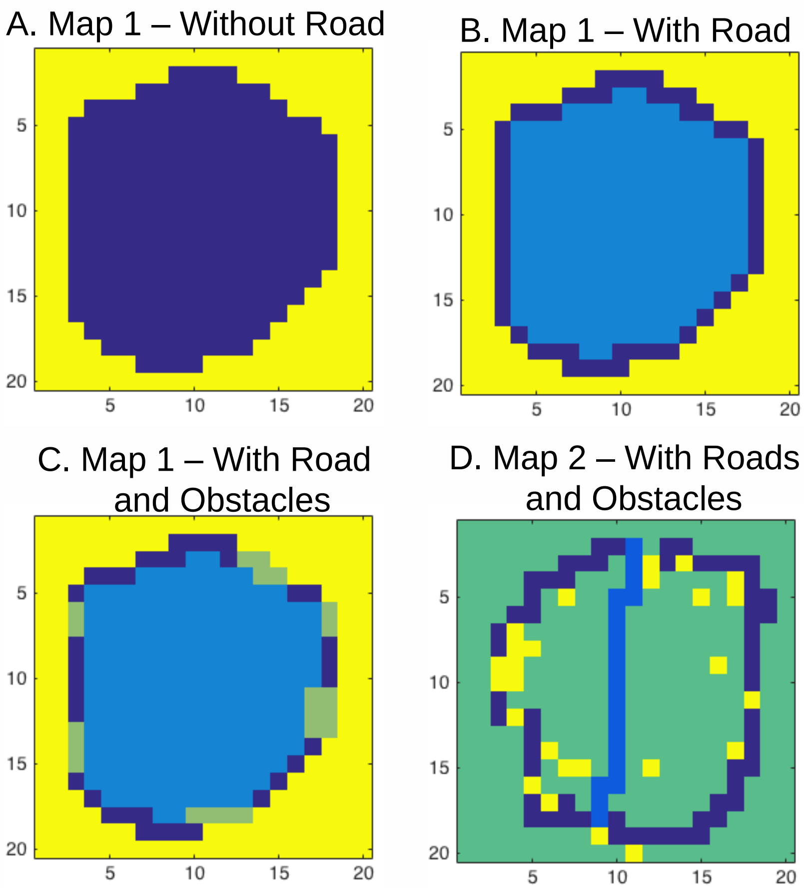
Address Event Representation (AER)

| Time | Neuron ID (r,c) |
|---|---|
| 1 | (1,1) |
| 2 | (1,2),(2,1),(2,2) |
| 3 | (1,3),(2,3),(3,1) |
| … | … |
| 6 | …(3,6),(5,3),… |
| … | … |
| 9 | (3,4),(4,2),(6,6) |




T. Hwu, AY Wang, N. Oros, and JL. Krichmar, "Adaptive robot path planning using a spiking neuron algorithm with axonal delays," IEEE TCDS, 2017.

# Map of Testing Environment


T. Hwu, A. Y. Wang, N. Oros, and J. L. Krichmar, "Adaptive robot path planning using a spiking neuron algorithm with axonal delays," *IEEE TCDS*, 2017.

# r-SNN Terrain Classification Algorithm

## A. Spiking Neuron Model

- Leaky integrate-and-fire (LIF) neurons.
- Synaptic current ($i_{syn}$) jumps upon spike arrival from presynaptic neurons.
- Postsynaptic membrane potential ($U_i$) is updated w.r.t. $i_{syn}$, membrane time constant, and resting potential.
- If $U_i$ > threshold, a spike is triggered. A refractory period follows.

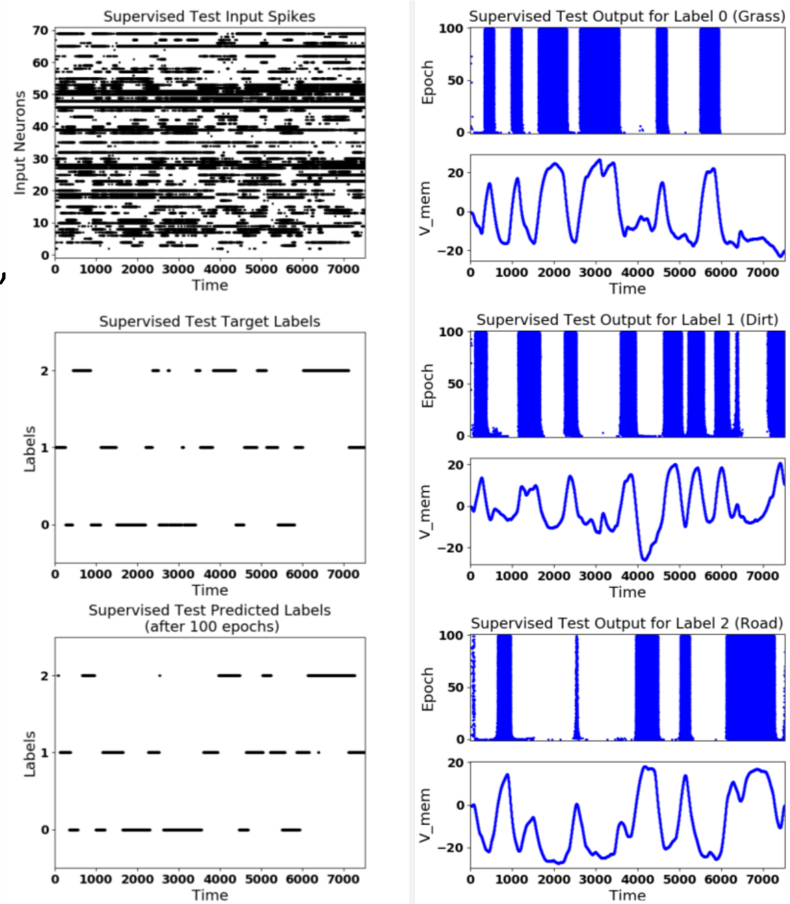
## B. Learning Rule

- Inspired from SuperSpike, RNN-to-output $w_{ij}$ changes according to a nonlinear Hebbian rule with individual synaptic eligibility traces

$$\Delta w_{ij} = \eta \cdot \left[\epsilon \otimes \left(\widehat{S_i} - \sigma(U_i)\right)\right] \cdot \sigma(U_i) \cdot \left(1 - \sigma(U_i)\right)$$

- $\eta$: learning rate, $\widehat{S_i}$: target postsyn spike pattern,
- $\epsilon$ jumps with presynaptic spikes.

- r-SNN Test Prediction Results




(X. Zou, T. Hwu, E. Neftci, and JL. Krichmar, presented in SCR, Caltech, 2019.)