Neuromorphic Architecture for Robotic Spatial Navigation


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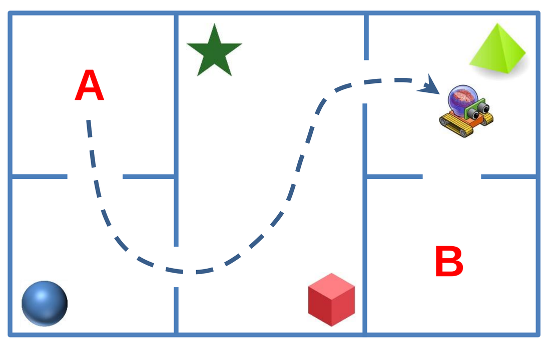
Introduction

Robotic systems can perform well-defined tasks with exquisite precision at high speeds, but they have much more difficulty when operating in unstructured environments.
With the discovery of place and grid cells in rats and humans, neuroscientists are starting to disclose the mechanisms underlying spatial navigation skills in these animals.
In this work we propose a neuromorphic architecture for robotic spatial navigation that aims at taking advantage of the flexibility and robustness of biological neural networks.



Our architecture runs on the neuromorphic hardware SpiNNaker, a massively-parallel computing architecture specifically designed to model large-scale spiking neural networks [2].
We take advantage of SpiNNaker's support for PyNN, a simulator-independent language for modeling spiking neural networks and we adapt existing models of grid and place cells based on recent experimental evidence [1].

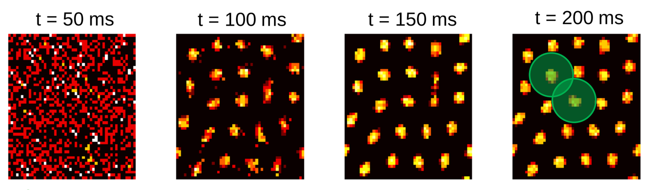
Our preliminary results show that it is possible to generate multi-scale grid maps adapting existing models of grid cells to spiking networks. In addition it is possible to realign the grids introducing sensory information via place cells.

Materials and Methods

Software

Continuous attractor model of grid cells

- Based on the model described in Couey et al. 2013 [1].
- 4 populations of 50x50 spiking neurons sensitive to different directions of the robot
- Each neuron:
  - inhibits its neighboring neurons
  - is injected with a velocity-dependent current



PyNN neural simulator

- Simulator-independent language for building spiking network models
- High-level interface for different simulators
- Support for neuromorphic hardware in development

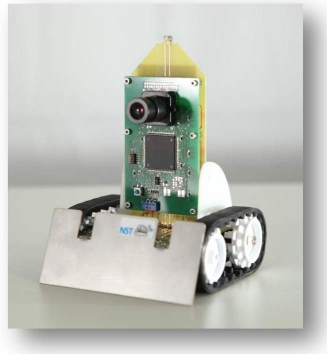
Hardware

SpiNNaker computer architecture

- multiple distributed units
- local computation and local memory
- fast asynchronous interconnections

Technical features:

- 48 chips, 864 cores / PCB
- 200 MHz clock frequency
- 96 KB RAM / core
- 128 MB RAM / chip
- 72 W power consumption
- 3.1 Gbps high speed asynchronous link



Mobile robot *Pushbot*

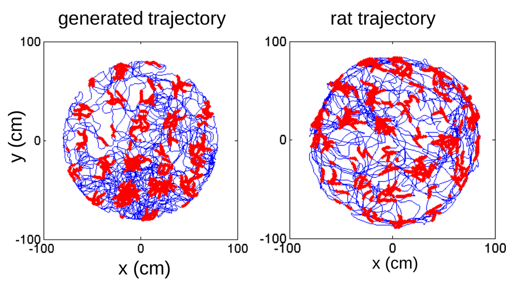
- Vision sensor
- Inertial Measurement Unit
- Wheel encoders
- Wireless interface

Results

Grid cell models with spiking networks

We successfully translated a continuous attractor model of grid cells [1] using leaky integrate and fire neurons and PyNN to configure and run the simulation.

We validated our grid cell networks using both a generated trajectory and an experimentally recorded trajectory of a rat freely moving in a circular arena.

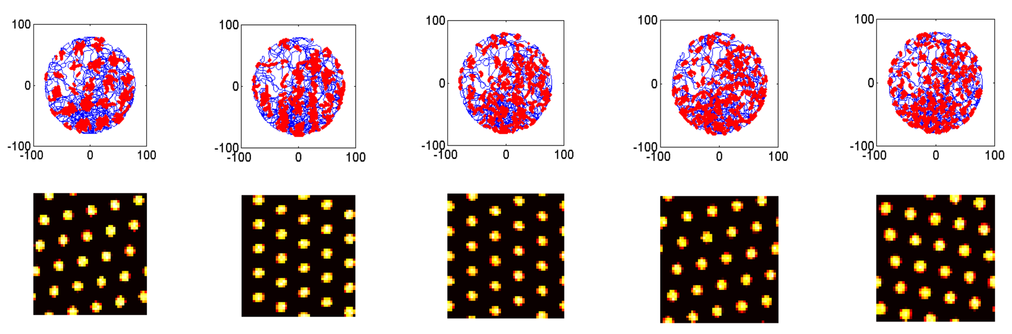


Generation of multi-scale grid maps

The correct working of the grid cell model require a fine balance between excitatory and inhibitory signals. In order to change the spatial scale of a grid map it is possible to appropriately modify the recurrent inhibitory connectivity. However, this solution involves time-consuming tuning of parameters for each desired spatial scale.
Alternatively, we found that varying the gain of input currents we can reuse the same network configuration to generate different spatial scales.

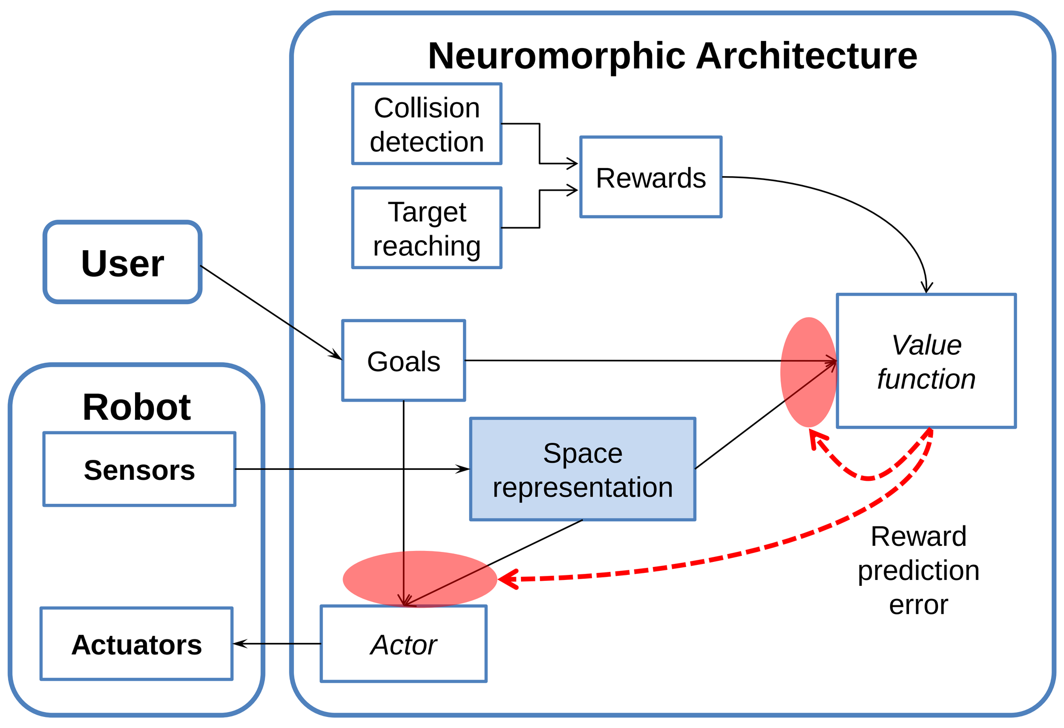
$$I_{injected}(t) = I_{baseline} + \boldsymbol{\alpha}\, v(t)\cos\big(\vartheta(t) - \vartheta_{preferred}\big)$$

α = 1.0 α = 1.2 α = 1.4 α = 1.6 α = 1.8



Spiking networks on SpiNNaker

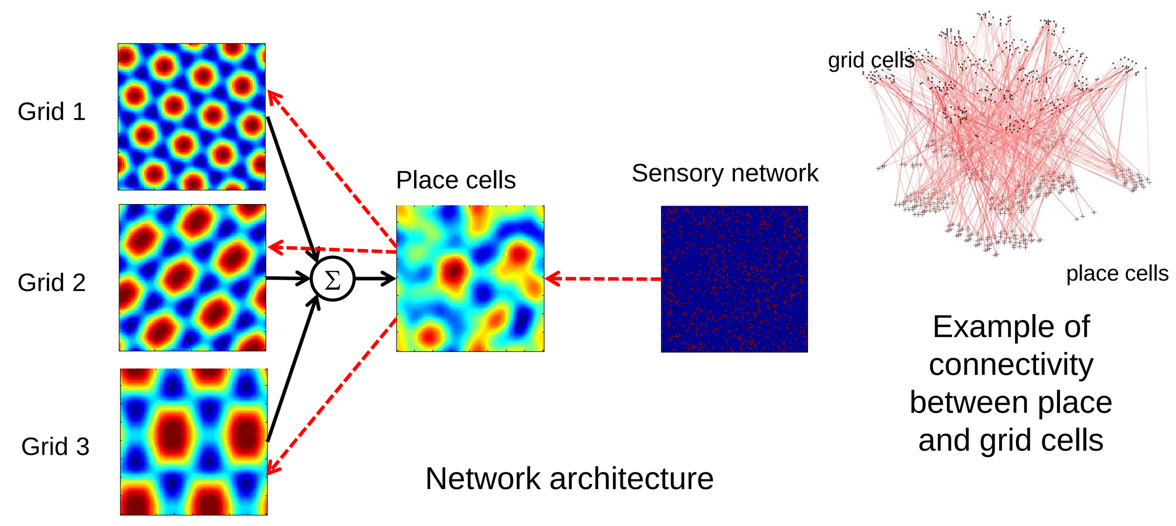
The massively parallel SpiNNaker computer architecture supports simulations of spiking neurons written in PyNN.
We tested our spiking models of grid cells on SpiNNaker in order to take advantage of its real-time computing capabilities suitable for robotic applications.
Unfortunately, the size of the simulated networks (~10^4 neurons) makes loading of the synaptic weights too long because of the limited speed of the Ethernet computer interface.



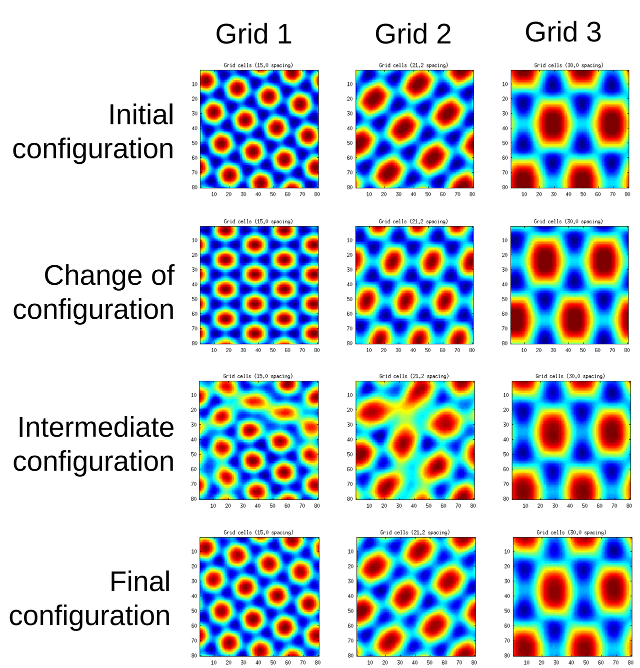
In order to avoid loading of synaptic weights we are currently translating our PyNN models into C. The configuration of the networks will be internally generated by SpiNNaker itself.
We think this will also make visualization more efficient because not anymore constrained by PyNN library functions.
The new implementation will integrate utility modules necessary to exploit the robust and flexible space representation of grid and place cells.

Grid realignment

The pattern of activation in the sensory network is dependent on the current sensory input. Learned connections between grid, place and sensory networks promote the reactivation of specific configurations of grid cells previously associated with specific places.



Example of connectivity between place and grid cells



In order to test our realignment algorithm we perturbed the system by abruptly changing the configuration of grid cell networks.
The continuous flow of excitatory signals from the sensory network pushes the place cell network towards its original configuration. In turn, the place cell network promote attractor states in grid cells that initially generated its configuration.

Conclusions and Future Works

We show our preliminary results for the implementation of a robotic spatial navigation system running on neuromorphic hardware. We believe that a deep understanding of the working principles of biology will ultimately allow us to endow mobile robots with animal-like navigation skills.
So far we focused on reproducing a biologically plausible representation of space. We implemented crucial parts that will be integrated into a fully functional system. In addition, our system lacks some important features. One of the next major steps is to enable goal-directed behaviors.

We think that the close integration of goals and sensory information could be instrumental to build robotic systems that can ultimately match human spatial navigation performance. In fact recent experimental results suggest that place cells might be closely involved in the representation of goals [4]. Moreover, in order to correctly realign grid cells it is necessary to integrate object recognition algorithms to detect landmarks in the surrounding environment.

References

[1] Couey, J.J. et al., 2013. Recurrent inhibitory circuitry as a mechanism for grid formation. *Nature neuroscience*, 16(3), pp.318–24

[2] Khan, M.M. et al., 2008. SpiNNaker : Mapping Neural Networks onto a Massively-Parallel Chip Multiprocessor. *IJCNN*, pp.0–7

[3] Solstad T, Moser EI, Einevoll GT. From grid cells to place cells: a mathematical model. In: Hippocampus. 2006;16(12):1026-31

[4] Pfeiffer, B.E. & Foster, D.J., 2013. Hippocampal place-cell sequences depict future paths to remembered goals. *Nature*, 497(7447)

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