NeuroNavigator: A Hippocampus-Inspired Cognitive Architecture for Spiking Network Implementation

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Abstract

Despite recent impressive progress in automated planning and navigation tools, artifacts still lack robustness and flexibility of biological systems. In order to mimic biology, it is necessary to use principles of dynamics and architecture found in the brain. Here we translate our biologically inspired model of spatial learning and navigation (Samsonovich and Ascoli, *L&M* 2005) into a model suitable for implementation in spiking networks with STDP synapses, based on soon to become available hardware. Simulation studies of the model prove its robustness and scalability. The approach naturally extends to various types of action planning beyond the spatial domain. The architecture can be used in autonomous intelligent agents of various nature.

Introduction

In recent years, considerable progress has been made in automated planning and mobile robotics, in particular, including low-level trajectory planning for mobile robots (e.g. Thrun et al. 2005) and high-level action planning based on efficient algorithms. At the same time, existing gaps and brittleness separate modern artificial tools from solutions found in biology.

Many attempts have been made to construct biologically inspired higher-level models intended to explain how the brain performs navigation (for a recent review, see e.g. Nehmzow 2006). In many cases these models are difficult to map onto the real brain; also, their practical usefulness for solving navigational problems is limited. In order to take practical advantage of the theoretically more robust and flexible solutions based on biological principles, it is necessary to implement them based on elements similar to those found in biology: specifically, STDP[1] synapses (Song et al. 2000) and spiking neurons. A substrate for implementation can be the hardware currently being developed and created based on spiking leaky integrate-and-fire neurons and STDP synapses (Mead, 1990).

A prototype for NeuroNavigator is the spiking network architecture that enables spatial learning and pathfinding (Ascoli and Samsonovich 2010). During exploration, synaptic weights are modified based on an exponential STDP rule (Song et al. 2000). The CA3-CA1 network in NeuroNavigator (Figure 1) is divided into submodules each corresponding to a particular abstract direction of motion: North, East, South, West, etc. Only two submodules are shown in Figure 1.

During exploration, only those synaptic weights are modified in DG-to-CA3 connections that correspond to the direction of the last move. At the same time, in CA3-to-CA1 connections, the rules are identical for all submodules and involve additive STDP with homeostatic plasticity.

During navigation, all imagined moves are performed in parallel, each in its own submodule. The imagined move that first causes a spike in a CA1 goal cell is selected and performed. As a result, the agent navigates toward the goal.

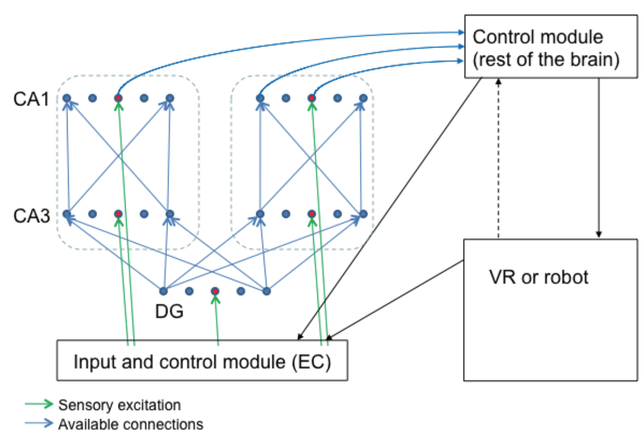

Figure 1. NeuroNavigator architecture design.

[1]STDP stands for spike-timing dependent plasticity.

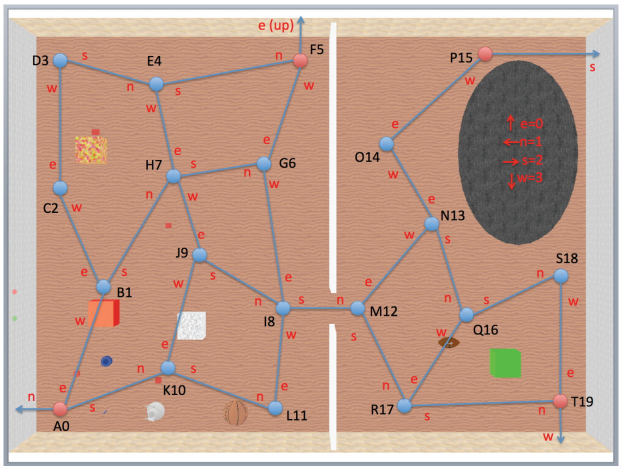

Figure 2. A virtual environment where the agent is embedded in CASTLE. Arrows represent the assigned entry-exit points. Nodes are numbered by letters and numbers from 0 to 19. Each node represents a domain in the room. The 4 directions are n, e, s, w.

Paradigm and Implementation

In our study, a large environment is represented by a set of small graphs connected together into a tree. A node of a tree corresponds to a graph, and the graph corresponds to a discretization (e.g., Voronoi tessellation in our case) of an environment fragment taken at a certain scale: a room, a street, a highway network, etc. Figure 2 shows a virtual indoor environment implemented in CASTLE (Pope and Langley 2008) together with its discrete model.

The general paradigm is the following. First, the robot explores the hierarchical environment and learns its topology and geometry. Then it is asked to navigate to a specific goal location.

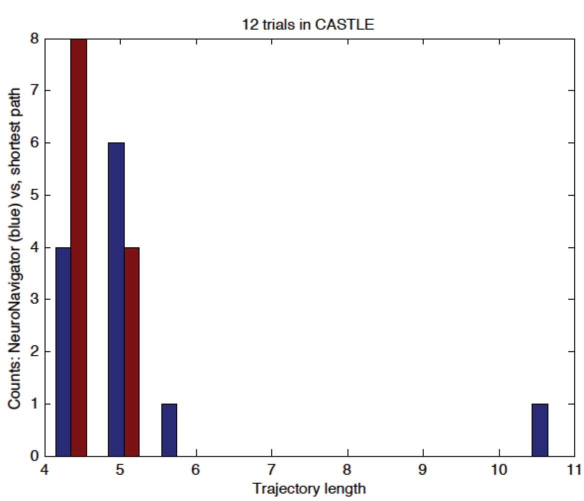

Figure 3. Histograms of path lengths computed over 12 trials. Red: shortest path length, blue: NeuroNavigator path length.

The developed architecture was implemented in C++ on a MacBook Pro. NeuroNavigator interacts with CASTLE that provides a virtual embodiment for the architecture, and with Matlab to perform on-line data analysis and visualization. The implementation easily scales from tens and hundreds up to millions of neurons: this is done by alteration of a single numerical constant in the code.

Results and Discussion

Each node of the hierarchy (a 4-level ternary tree, not shown) was associated with a small CASTLE environment of a fixed geometry shown in Figure 2. The agent reached an arbitrarily set goal in every simulated session. Over 12 trials, the trajectory toward the goal was always the shortest path in the hierarchy and always close to a shortest path (if not a shortest path) in the graph. Histograms of trajectory lengths are represented in Figure 3.

In summary, results presented above demonstrate the existence of a highly scalable, biologically-plausible solution of the navigation challenge based on a network of spiking neurons and STDP synapses. The scalability of this approach up to networks of a million of neurons was tested computationally. The selected strategy based on a hierarchical approach to exploration and navigation will be further developed elsewhere.

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References

Ascoli, G. A., and Samsonovich, A. V. 2010. NeuroNavigator: A biologically inspired universal cognitive microcircuit. In Samsonovich, A. V. et al., eds. *Biologically Inspired Cognitive Architectures 2010, FAIA* 221, pp.10-16. Amsterdam: IOS Press.

Mead, C. 1990. Neuromorphic electronic systems. *Proceedings of the IEEE* 78 (10): 1629-1636.

Nehmzow, U. 2006. *Scientific Methods in Mobile Robotics: Quantitative Analysis of Agent Behaviour.* Berlin: Springer.

Pope, A., and Langley, P. 2008. CASTLE: A framework for integrating cognitive models into virtual environments. In Samsonovich, A. V., ed. *Biologically Inspired Cognitive Architectures: Papers from the AAAI Fall Symposium. AAAI Technical Report* FS-08-04, p.152. Menlo Park, CA: AAAI Press.

Samsonovich, A. V., and Ascoli, G. A. 2005. A simple neural network model of the hippocampus suggesting its pathfinding role in episodic memory retrieval. *Learning & Memory* 12 (2): 193–208.

Song, S., Miller, K. D., and Abbott, L. F. 2000. Competitive Hebbian learning through spike-timing-dependent synaptic plasticity. *Nature Neuroscience* 3 (9): 919-926.

Thrun, S., Burgard, W., and Fox, D. 2005. *Probabilistic Robotics*. Cambridge, Mass.: MIT Press.