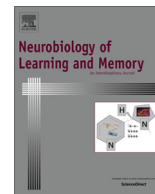




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## A hierarchical model of goal directed navigation selects trajectories in a visual environment

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## ABSTRACT

We have developed a Hierarchical Look-Ahead Trajectory Model (HiLAM) that incorporates the firing pattern of medial entorhinal grid cells in a planning circuit that includes interactions with hippocampus and prefrontal cortex. We show the model's flexibility in representing large real world environments using odometry information obtained from challenging video sequences. We acquire the visual data from a camera mounted on a small tele-operated vehicle. The camera has a panoramic field of view with its focal point approximately 5 cm above the ground level, similar to what would be expected from a rat's point of view. Using established algorithms for calculating perceptual speed from the apparent rate of visual change over time, we generate raw dead reckoning information which loses spatial fidelity over time due to error accumulation. We rectify the loss of fidelity by exploiting the loop-closure detection ability of a biologically inspired, robot navigation model termed RatSLAM. The rectified motion information serves as a velocity input to the HiLAM to encode the environment in the form of grid cell and place cell maps. Finally, we show goal directed path planning results of HiLAM in two different environments, an indoor square maze used in rodent experiments and an outdoor arena more than two orders of magnitude larger than the indoor maze. Together these results bridge for the first time the gap between higher fidelity bio-inspired navigation models (HiLAM) and more abstracted but highly functional bio-inspired robotic mapping systems (RatSLAM), and move from simulated environments into real-world studies in rodent-sized arenas and beyond.

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### 1. Introduction

The ability to successfully navigate to a predefined location is often a life crucial task for many higher order organisms. The goal location might be a food source, a temporary shelter, a nest, or some other desired location. Squirrels are effective at rediscovering their previously stashed food sources (Jacobs & Liman, 1991). Rats can learn to revisit or to avoid known food locations (Brown, 2011; Olton & Schlosberg, 1978). Mice learn to avoid an unpleasant environment, such as a water-maze, by finding an out-of-sight escape platform after only a handful of learning trials (Morris, Garrud, Rawlins, & O'Keefe, 1982; Redish & Touretzky, 1998; Steele & Morris, 1999). If a visible goal location is in the field-of-view of the agent, the navigation task becomes trivial: The agent proceeds towards the visible goal location avoiding potential obstacles on the way. However, if the goal location is out of visual range or hidden (as in the water-maze) then navigation mechanisms based

on cognitive capabilities that can exploit the previously encoded and currently out of view goal location become important to guide the agent to the goal. Such a navigation mechanism would not necessarily need to pinpoint the goal location. It would be sufficient to guide the agent to the general goal location neighborhood such that the goal is in the visual range of the agent. Consequently, the visually driven navigation system can take over to home the agent into the goal location, an approach that has been used successfully by the robotic mapping system used in this research (Milford & Wyeth, 2009).

There is compelling evidence gathered from physiological and behavioral data suggesting the existence of spatial cognitive mechanisms in the brain representing the agent's spatial environment and aiding it during goal-directed navigation experiments. The entorhinal cortex and hippocampus play a role in goal-directed behavior towards recently learned spatial locations in an environment. Rats show impairments in finding the spatial location of a hidden platform in the Morris water-maze after lesions of the hippocampus, postsubiculum, or entorhinal cortex (Morris, Garrud, Rawlins, & O'Keefe, 1982; Steele & Morris, 1999; Steffenach,

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Witter, Moser, & Moser, 2005; Taube, Kesslak, & Cotman, 1992). Recordings from several brain areas in behaving rats show neural spiking activity relevant to goal-directed spatial behavior, including grid cells in the entorhinal cortex that fire when the rat is in a repeating regular array of locations in the environment falling on the vertices of tightly packed equilateral triangles (Hafting, Fyhn, Molden, Moser, & Moser, 2005), place cells in the hippocampus that respond to mostly unique spatial locations (O'Keefe and Nadel, 1978), head direction cells in the postsubiculum that respond to narrow ranges of allocentric head direction (Taube, 2007), and cells that respond to translational speed of running (O'Keefe, Burgess, Donnett, Jeffery, & Maguire, 1998).

Some of the evidence related to the goal-directed navigation planning include forward sweeping events of spiking activity in rat place cell ensembles that have been observed during vicarious trial and error experiments (Johnson & Redish, 2007; Pfeiffer & Foster, 2013) and sharp wave ripple events during goal-directed spatial tasks (Davidson, Kloosterman, & Wilson, 2009; Foster & Wilson, 2006; Jadhav, Kemere, German, & Frank, 2012; Louie & Wilson, 2001). Furthermore, brief sequences of place cell ensemble activity encoding trajectories from an agent's current location have been observed to be strongly biased towards the agent's predicted goal location (Pfeiffer & Foster, 2013).

In this work we combine two biologically inspired models that generate and maintain representations of their environment as collections of simulated spatially tuned neurons such as grid cells and place cells.

The first one of these models is the RatSLAM model (Milford, Wyeth, & Prasser, 2004) which has been implemented on real robotic agents and has been shown to match or outperform the state of the art probabilistic robotic systems in encoding and navigating large environments over long periods of time (Milford & Wyeth, 2009; Prasser, Milford, & Wyeth, 2006). However, the current RatSLAM model is not easily scalable and its goal directed navigation module is less biologically plausible than its Simultaneous Localization and Mapping (SLAM) component.

The second model we use in our work is the HiLAM (Erdem & Hasselmo, 2013), a biologically inspired goal-directed navigation model based on look-ahead trajectories in a hierarchical collection of simulated grid cells and place cells. While HiLAM is highly capable in simulating behavioral goal-directed navigation experiments, it is prone to failure in the presence of noisy and degraded input, since it does not have mechanisms in place to detect and to correct for the stochastic loss of fidelity in its state representation. Consequently, like many other high fidelity computational models, the HiLAM has not been previously tested on real life data.

In this work we combine the RatSLAM model and the HiLAM such that their individual fortes complement each other in generating and maintaining stable spatial maps using real life visual data (RatSLAM) and in using the generated maps for goal-directed path planning in a biologically plausible manner (HiLAM).

## 2. Material and methods

The framework presented in this work shows collaboration between two previously developed computational models for spatial mapping and navigation. While the RatSLAM model generates rectified odometry data, the Hierarchical Look-Ahead Trajectory Model (HiLAM) provides a mechanism for goal directed navigation. We also show the scalability of the HiLAM using odometry data extracted from noisy real-life visual information collected from a small remote controlled vehicle referred to as the "agent". Using ground truth extracted from external cameras, we show the goal directed navigation accuracy in two environments, a small open-field square indoor maze and an outdoor area that is larger

than the indoor maze by two orders of magnitude. We first extract the unrectified odometry data from the optic flow information implicit in the camera's field of view. Then, we rectify the raw odometry data by detecting loop-closure points in time and space using the RatSLAM model. Finally, we form spatial representations using grid cells and place cells in the HiLAM and select trajectories to goal locations using hierarchical linear look-ahead probes in this model.

### 2.1. Hierarchical Look-Ahead Trajectory Model (HiLAM)

In the HiLAM, head direction cells modulated by proprioceptive velocity data provide inputs to downstream grid cells driven by a *phase interference model* (Blair, Gupta, & Zhang, 2008; Burgess, 2008; Burgess, Barry, & O'Keefe, 2007; Hasselmo, 2008). Several grid cells with different scales and field spacings converge to form a single place cell. Each place cell also provides downstream spiking input to a single reward cell proposed to represent prefrontal cortex mechanisms, i.e., place cells and reward cells have a bijective topology (Fig. 1).

A head direction cell is a neuron that significantly increases its firing rate when the rat's allocentric head orientation in the world horizontal plane, i.e., the head azimuth, approaches a specific angle which is referred to as its *preferred direction* (Sargolini et al., 2006; Taube, Muller, & Ranck, 1990). The head direction cell's preferred direction depends on the environmental cues and proprioceptive inputs. The head direction cells simulated in the HiLAM are cosine tuned and velocity modulated. Given the agent's instantaneous velocity vector  $\mathbf{v}(t)$  and the preferred direction  $\theta_i$  of a simulated head direction cell  $i$  its output  $d_i$  can be given as:

$$d_i(t) = \mathbf{v}(t) \cdot \begin{bmatrix} \cos(\theta_i) \\ \sin(\theta_i) \end{bmatrix} \quad (1)$$

A grid cell is a neuron type which increases its firing rate significantly when the animal traverses a regular array of periodic locations in the environment. The collection of locations where an individual grid cell fires, i.e., the grid cell's firing fields, forms a two dimensional periodic pattern with regular inter-field intervals and similar field areas. More specifically, the firing fields of a single grid cell tile the infinite two dimensional plane as the vertices of equilateral triangles. Extensive experimental data show the existence of grid cells with different inter-field spacing and field areas along the dorsal to ventral axis of the medial entorhinal cortex (Barry & Burgess, 2007; Hafting et al., 2005; Stensola et al., 2012). In a single rat, grid cells in the medial entorhinal cortex are organized in anatomically overlapping modules with distinct firing field orientation and discrete scales (Stensola et al., 2012). The simulated grid cells found in the HiLAM use a variant of the persistent spiking model (Hasselmo, 2008) which belongs to the class of phase interference models (Burgess, Barry, & O'Keefe, 2007) for grid cells. The spiking output of the  $j$ th grid cell  $g_j$  can be defined as:

$$\begin{aligned} \phi_{(ij)}(t) &= 2\pi \left( ft + b_j \int_0^t d_i(\tau) d\tau \right) \\ s_{(ij)}(t) &= H \left( \cos(\phi_{(ij)}(t) + \psi_{(ij)}) - s_{thr} \right) \\ g_j(t) &= \prod_{s \in S_j} s(t) \end{aligned} \quad (2)$$

where  $\phi_{(ij)}$  is the phase of the persistent spiking cell modulated by the  $i$ th head direction cell,  $f$  is the frequency,  $b_j$  is the scaling factor for all persistent spiking cells projecting to the  $j$ th grid cell,  $s_{(ij)}$  is the persistent spiking cell signal,  $\psi$  is the phase offset,  $s_{thr}$  is the action potential threshold,  $H$  is the Heaviside function satisfying  $H(0) = 0$ , and  $S_j$  is the set of persistent spiking

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