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## Research article

## Robust path planning by propagating rhythmic spiking activity in a hippocampal network model

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## ABSTRACT

It is believed that humans and animals like rodents and bats navigate in a familiar environment using a cognitive map. Yet, how maps are previously learned when exploring a novel environment and then used to plan routes to specific goals remains unclear. We propose here a biologically inspired method, called *Multiwave*, with two main ingredients: (i) a symmetric spike-timing dependent plasticity rule that compels the connectivity to map the environment, and (ii) periodic wavefronts propagating through the network to direct the agent towards the goal and increase robustness to noise. The modeling involves a detailed neural network for biological plausibility and a simplified equivalent network, better suited for robotic implementation. Using both simulations and robotic experiments, we show the efficiency of *Multiwave* for path planning. *Multiwave* is relevant not only to neuroscience, as the detailed model is biologically grounded, but also to robotic applications, as the simplified model is suitable for analog implementation on neuromorphic hardware.

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## Introduction

One of the objectives in neuroscience is to make links between physiological recordings (single-cell activity) and higher cognitive functions (behavioral response). Such links have been studied in the context of spatial planning through behavioral experiments involving hippocampal structures. After the discovery of place cells in rodents (O'Keefe & Dostrovsky, 1971), which are neurons encoding for particular locations in the environment, it has been suggested that the hippocampus, and more specifically the CA3 area, is the neural site of a spatial representation system, the so-called cognitive map (Bush, Philippides, Husbands, & O'Shea, 2010; Muller & Stead, 1996). A cognitive map is believed to be a topographic map; that is, a mental representation of the environment whose connections between place cells represent feasible paths. Yet, how the map is built and used by animals to plan their routes to specific goals (food, water, mate...) is still unclear.

Neural network models of path planning have been proposed in the past. The earliest ones were based on graded Hopfield-like neurons (Glasius, Komoda, & Gielen, 1995; Grossberg, 1988; Weidong, Changhong, & Yugeng, 2003; Yang & Meng, 2000). The analog output of the goal neuron spreads through the network to create an intensity map whose stability is ensured via a Lyapunov function. This diffusion process enables to perform path planning by ascending the intensity gradient from the current location to the goal. Yet, directional information contained in the intensity gradient vanishes rapidly in large networks as the spreading of activation via diffusion decays exponentially with distance (Khajeh-Aliani, Urbanczik, & Senn, 2015).

To circumvent this drawback, recent models were based on a temporal gradient involving a single traveling wave of spiking activity. Two distinct neural mechanisms have been considered. One approach (Khajeh-Aliani et al., 2015) is based on weakly-coupled neural oscillators propagating firing phase information via the so-called phase response curve (Ermentrout, 1996). As distance-to-goal is encoded in the firing phase with respect to a global network oscillation, the smallest firing phase between neighboring neurons provides direction toward the goal. The other approach (Ponulak & Hopfield, 2013; Qu, Yang, Willms, & Yi, 2009) is based on strongly-coupled excitatory neurons propagating the

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activation wavefront emanating from the goal neuron. The direction from which the front hits the neurons indicates the shortest path to the goal. A prerequisite is that the wave propagates radially outward from the goal neuron without being back-propagated. This constraint has been satisfied by either increasing the activation threshold right after firing (Qu et al., 2009) or decreasing the synaptic weights after the wave passage (Ponulak & Hopfield, 2013).

Although classical single-wave models provide hypotheses on how path planning can be performed from spiking activity, it is still unclear how this is possible when noise is added to the neuronal processing. The presence of noise may trigger action potentials in normally silent neurons so that incorrect wavefront may originate elsewhere from the goal. With such incorrect wavefronts, directional information toward the goal is lost. It is therefore a risky strategy to plan the entire navigation to the goal based on a single wavefront. Instead, we suggest to use multiple wavefronts so that the agent can redirect to the goal after losing directional information. We propose here a neural model, called *Multiwave*, that perform robust path planning from periodic wavefronts. The modeling involves both a realistic neural network model of CA3 (with a conductance-based model of place cells and synaptic connectivity trained with spike-timing dependent plasticity) and a simplified equivalent network (with integrate-and-fire model neurons), better suited for robotic implementations. Using both simulations and experiments on a real robot, we show the robustness and efficiency of *Multiwave* for path planning.

## Results

### Neural path planning in 1 dimension and gambler's ruin problem

To outline the difference in path planning based on single and multiple waves let us first introduce a simple navigation task in the 1-dimensional case. Consider an agent (real or virtual robot) starting at position  $x = n/2$  that has to reach the goal at position

$x = 0$  without being trapped by an absorbing barrier at position  $x = n$ . The navigation problem is encoded in a linear chain of spiking neurons each one coding for a position  $x$  in the environment (Fig. 1A). Excitatory synaptic connections between adjacent neurons propagate an activation wavefront emanating from the goal neuron. The movement of the agent is then opposite to the wave propagation. Due to noise in the system, directional information is lost when an incorrect wavefront is produced elsewhere from the goal. We consider that an incorrect wavefront is produced with some probability  $p$  by the absorbing barrier at position  $x = n$ . As the entire path of the agent is planned from this unique wavefront (Fig. 1B), the probability of reaching the goal is given by  $1 - p$  and thus decreases linearly with  $p$  (Fig. 1D). It is therefore a risky strategy to plan the entire path of the agent based on a single wavefront. Instead, we consider periodic wavefronts. Correct and incorrect wavefronts are produced by the goal and the absorbing barrier with probability  $q = 1 - p$  and  $p$ , respectively. The path is now planned step by step after each wave passage (Fig. 1C). This situation can be seen as a special case of the Gambler's ruin problem (Feller, 2008) for which the success rate in reaching the goal is given by

$$\frac{(q/p)^{n/2} - (q/p)^n}{1 - (q/p)^n}$$

Fig. 1D indicates that the success rate in multiple-wave models is a sigmoid function of  $p$  which is more robust than the linear dependency obtained in classical single-wave models. The probability to reach the goal is almost one as long as  $p < 0.5$  and vanishes when  $p > 0.5$ . This trend is reminiscent of the gambler's ruin problem where the probability of going home a winner is almost one when the probability to lose each bet is lower than 0.5 (Feller, 2008). In the following we propose a hippocampal neural network model, called *Multiwave*, that allows for such robust path planning in 2-dimensional environments.

#### A. Traveling wave model in 1 dimension

##### Correct Wave propagation



#### B. Incorrect wave in single-wave model

##### Incorrect Wave propagation

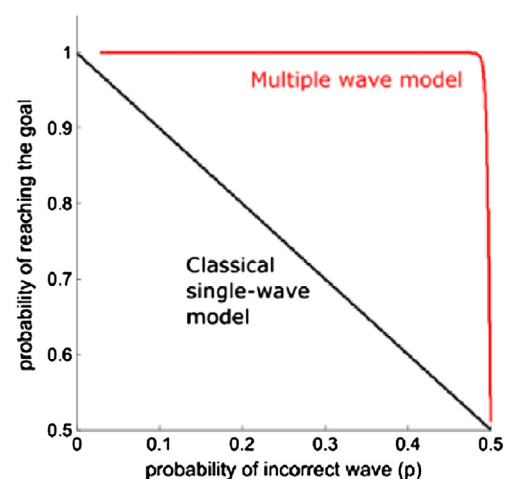


#### C. Incorrect wave in multi-wave model

##### Incorrect Wave propagation



#### D. Probability of reaching the goal vs. Probability of incorrect wave



**Fig. 1.** Illustration of robust path planning in 1 dimension. The movement of the agent is opposite to the propagation of a traveling wave in a linear chain of neurons with the goal at position  $x = 0$  and an absorbing barrier at  $x = n$  (A). Correct wavefronts originate from the goal with probability  $q = 1 - p$  whereas incorrect wavefronts are produced by the absorbing barrier with probability  $p$ . Following an incorrect wavefront in a single-wave model, the agent ends up to be trapped at  $x = n$  as the entire path is planned from this unique wave (B). In a multiple-wave model, the path is planned step by step after each wave passage (C). This results in a much more robust path planning strategy. Unlike for single-wave models, the success rate in reaching the goal does not decay gradually with the probability of incorrect waves (D).

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