
Learned Hippocampal Sequential Coding through Phase Precession

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Abstract

The hippocampal formation is necessary for spatial learning and memory in rats. One aspect of this cognitive function, the ability to remember path sequences, is thought to be achieved through phase precession. The two components of phase precession are a strong theta rhythm (8-12 Hz) in the local field potential and place-selective neurons, which fire selectively while the rat is in a particular area or “place field” of an enclosed arena. As a rat enters and leaves each place field, the respective neuron will fire most strongly in the center and less strongly in the periphery, but in addition to changing firing rate the cell will also fire at progressively earlier phases of the theta rhythm. This ultimately allows for the recent path of the rat to be represented by neuronal firing within one theta cycle, possibly reducing the time between place cell firing to allow for effective spike timing dependent plasticity. We test whether phase precession is required for sequence learning in a small recurrent network of Izhikevich neurons with place fields either around the circumference of a closed circular track or forming a grid across a closed square arena with synaptic weights updated according to a spike timing dependent plasticity rule. In either environment, we find that phase precession of place cell responses, as opposed to purely spatially tuned responses, is required for heteroassociative recall and spatial sequence learning.

1 Introduction

The hippocampus has been shown to be integral for episodic memory formation. The mechanisms behind this have been studied in rats through the context of spatial learning, due to the presence of spatially-selective neurons throughout the hippocampal formation [1]. Specifically, certain neurons known as “place cells” respond strongly to one area of a track or arena and decrease firing rate as the rat’s distance from the center of this “place field” increases. These cells provide a possible substrate for spatial memory, where experience could cause selective strengthening and weakening of synaptic connections in order to preserve path or location information. It is unclear however whether place cells and plasticity rules alone can generate sequential learning, which seems to be inherent in episodic memory in that memories are temporally unidirectional [2].

One of the defining characteristics of the rat hippocampus is the presence of a strong theta oscillation (7-10 Hz) in local field potential recordings [3]. This rhythm, which is thought to be generated by a pacemaker network in the medial septum, is propagated throughout the hippocampus by electrically-coupled interneurons. Each pyramidal neuron then receives the resulting theta inhibitory input in sync. The clock-like action of the theta rhythm possibly provides a temporal reference frame with which to coordinate sequential neuronal activity.

The key to sequential learning may involve making simultaneously active neurons fire in the temporal order in which they were first recruited. This phenomenon, which is observed *in vivo*, is known as “phase precession,” where co-active place cells fire through one cycle of theta in the order the rat ran entered their place fields. The causes and function of phase precession are currently a matter of debate, yet it is a prime subject for modeling because there are currently no experimental methods to eliminate phase precession while sparing the theta rhythm. Here, a simplistic model of neurons and spike-timing dependent plasticity in the CA3 region of the hippocampus is used while emulating or excluding phase precession to access its contribution to sequential learning.

2 Modeling methods

2.1 Neurons

100 neurons are modeled here using the Izhikevich spiking neural model [4]. This allows for computationally light simultaneous modeling of large numbers of neurons that show behavior similar to that observed in physiology. Each neuron is given dynamic variables V and u which respectively represent membrane voltage and recovery, in addition to four constant parameters a , b , c , and d . Following other similar models of CA3, we used initial values of

$$\begin{aligned} V &= -65 \\ u &= bV \\ a &= 0.02 \\ b &= 0.2 \\ c &= -65 \\ d &= 6 \end{aligned}$$

where the dynamic variables were governed by the equations

$$\begin{aligned} \frac{dV}{dt} &= 0.04V^2 + 5V + 140 - u + I \\ \frac{du}{dt} &= a(bV - u) \end{aligned}$$

and neurons which were driven past the threshold of 30 mv were considered to have spiked and pushed back to resting potential with a reset recovery variable such that

$$\text{if } V \geq 30 \text{ then } \begin{cases} V \rightarrow c \\ u \rightarrow u + d \end{cases}$$

The total current I for each neuron was a sum of synaptic current I_{ext} , a uniform random noise current I_n , and inhibitory current from the theta rhythm I_{LFP} .

2.2 Spike-Timing Dependent Plasticity

Each neuron in the model was synaptically connected to every other neuron excluding itself, and all synaptic weights were stored in a 100 by 100 connectivity matrix [5]. A basic spike-timing dependent plasticity model was used, where a postsynaptic neuron firing just after a presynaptic neuron strengthened the synapse, while the reverse order depressed the synapse. Five constants constrained this model, being A_+ , A_- , τ_+ , τ_- , and Δw_{max} , respectively representing the maximum change in synaptic weight Δw , the time constants of exponential decay for change in synaptic weight, and the maximum synaptic weight. In these variables, the subscript + applies to connectivity between presynaptic and postsynaptic neurons, and the subscript - applies to connectivity between postsynaptic and presynaptic neurons. These were applied to the equations for modifying synaptic weight

$$\begin{aligned} w_{\text{max}} &= 1 \\ A_+ &= 0.02w_{\text{max}} \\ A_- &= -0.01w_{\text{max}} \\ \tau_+ &= 20 \\ \tau_- &= 50 \end{aligned}$$

$s = \text{postsynaptic spike time} - \text{presynaptic spike time}$

$$\Delta w_+ = A_+ \left(1 - \left(\frac{1}{\tau_+} \right)^s \right)$$

$$\Delta w_- = A_- \left(1 - \left(\frac{1}{\tau_-} \right)^s \right)$$

2.3 Phase precession

Phase precession was modeled by delivering external input (from cells earlier in the pathway) to neurons at selective phases of theta, depending on whether the rat was entering or leaving the place field. As the rat entered a place field, synaptic current was given first at the peak of theta and progressed to later theta phases as the rat continued through the field. Separate place fields were assigned to each neuron and were spaced out evenly throughout the environment. This resulted in clusters of spikes when the animal was near the center of the place field and single spikes as it was entering or leaving the place field.

Lack of phase precession was modeled in the same way but excluding the theta phase-dependent excitatory input. In this way, neuronal excitation always occurred while the rat was in a given place field, with the center inducing the strongest input and the periphery inducing weaker input.

In both cases with and without phase precession, place fields were divided into eight subsections to determine both phase of theta to fire on and amplitude of excitatory input [5].

2.4 Circular track

For the circular track condition, a rat was simulated to run around 1000 cm circumference circle at 10 cm/s. Place fields from all 100 neurons were spaced out evenly in a linear fashion along the track with 80 cm diameters, and the rat was made to complete 1.5 runs through the track. Results do not vary if the animal runs more than 1.5 laps, so this duration of simulation was used for efficiency.

2.5 2-dimensional arena

For the 2-dimensional arena condition, a rat was simulated to run around a 1000 cm square area in a path determined by drawing a path through the arena. The rat would run at a constant predetermined speed through the given path, and once the path was complete the rat would run the same path again until the amount of total running time was equal to that as in the circular track. Place fields from all 100 neurons were spaced out evenly in a square grid arrangement throughout the arena. Place field diameter was set at 30 cm and the rat ran at 2 cm/s.

3 Results

3.1 Linear track

A demonstration of the phase precession model is shown below (figure 1). As the rat moves through a place field, the respective place cell fires bursts of action potentials at the center and fewer spikes in the periphery. Additionally, all neurons fire within one cycle of theta and fire progressively later in the cycle as the rat moves forward, maintaining a consistent order of neuronal firing throughout the run.

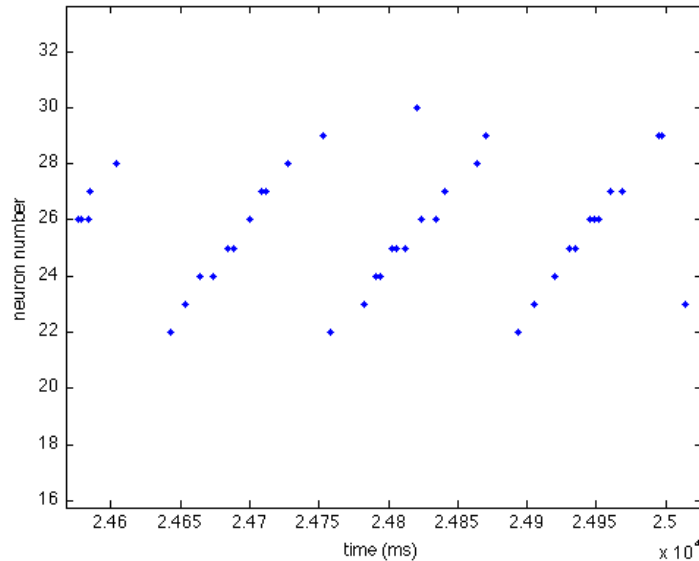


Figure 1: Raster plot of neuronal activity while the rat runs on a circular track. Neurons are connected in numerical order, such that successively higher number neurons respond to progressively farther areas on the track. Both rate changes with position in place field and phase precession are observed.

This was then examined in the context of spike timing dependent plasticity. As the rat ran around the track and phase precession was included, synaptic connections were strengthened unidirectionally for the order that the rat ran through the corresponding place fields (figure 2a). Alternatively, when phase precession was removed and only rate encoding was taking place, synaptic connections were strengthened bidirectionally for both the forward and backward order in which the rat ran through each place field (figure 2b). The orderly synaptic strengthening observed with phase precession depended on the size of the place field, where larger place fields increased the number of connections being simultaneously altered in addition to overall synaptic weight change (figure 2c). If the place field diameter was lowered enough, no substantial or meaningful synaptic weight changes occurred (figure 2d).

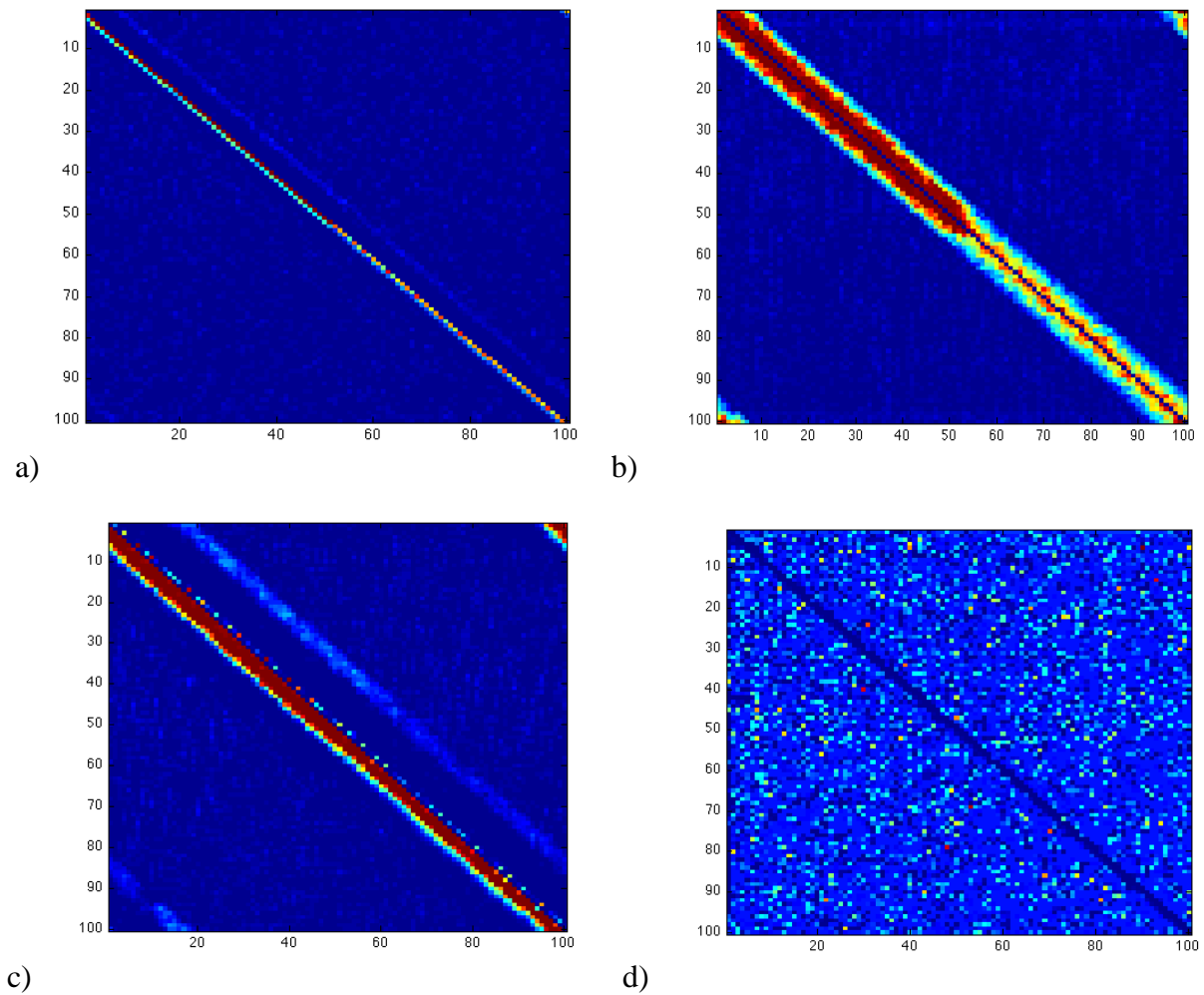
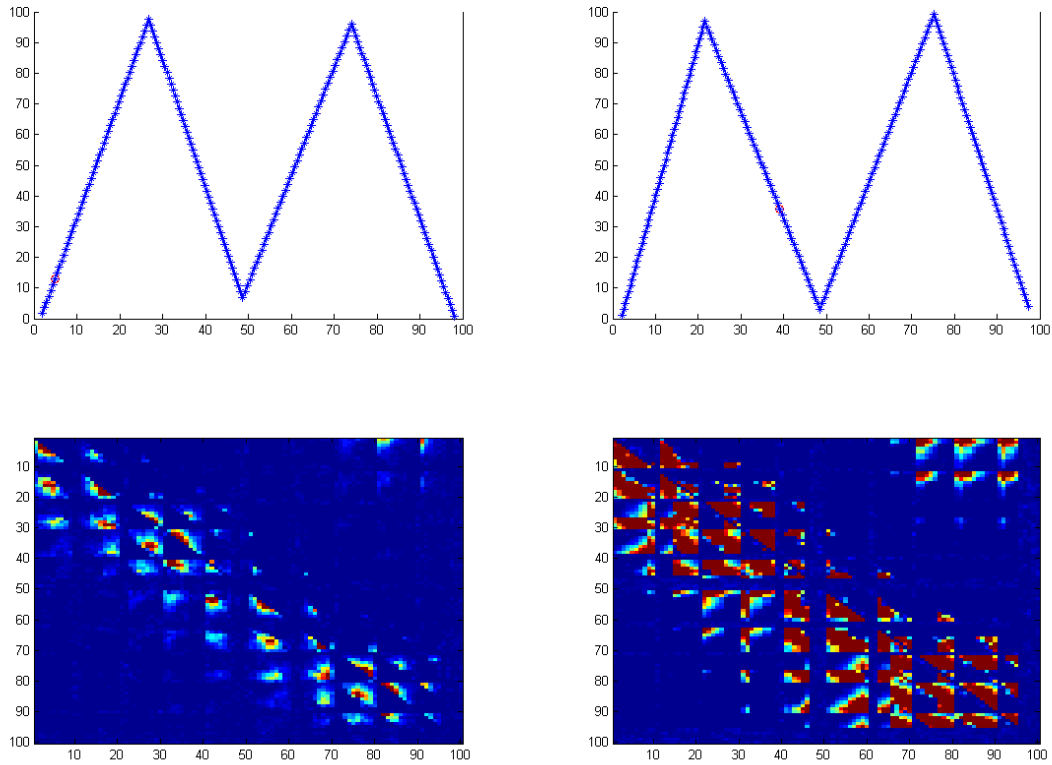


Figure 2: Synaptic weight change with experience. All plots give independently scaled synaptic weights between neurons, where increasing neuron number represents neurons with place fields progressively farther along the circular track. Identity line shows no connectivity between neurons and themselves, below the identity line represents connections between neurons with place fields following each other, and above the identity line represents connections between neurons with place fields preceding each other. a) With phase precession, b) without phase precession, c) 200 cm diameter place field with phase precession, d) 20 cm diameter place field with phase precession.

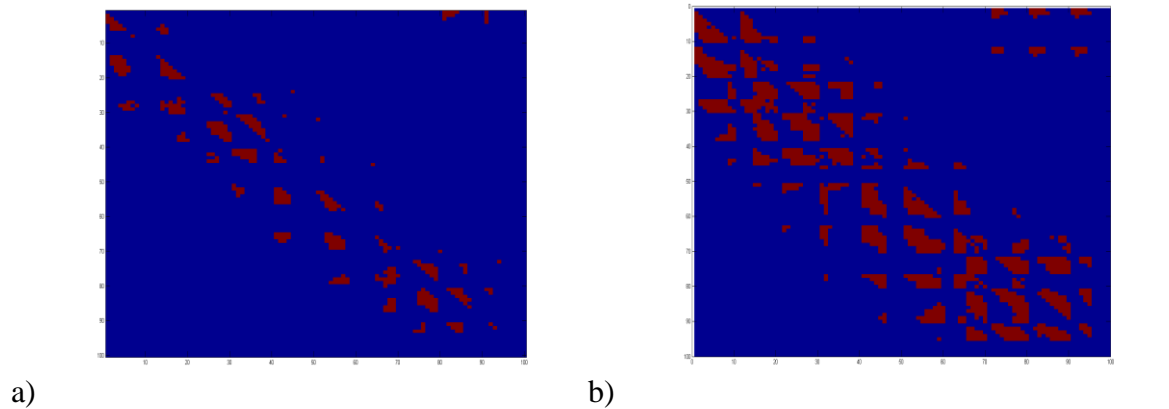
3.2 2-dimensional arena

The expanded model simulated a rat running in a pre-determined path through a 2-dimensional arena (figure 3). The phase precession model gave results qualitatively similar to those from the 1-dimensional track (figure 3a), and likewise omitting phase precession gave stronger and more symmetrical connections also seen in the 1-dimensional track (figure 3b).



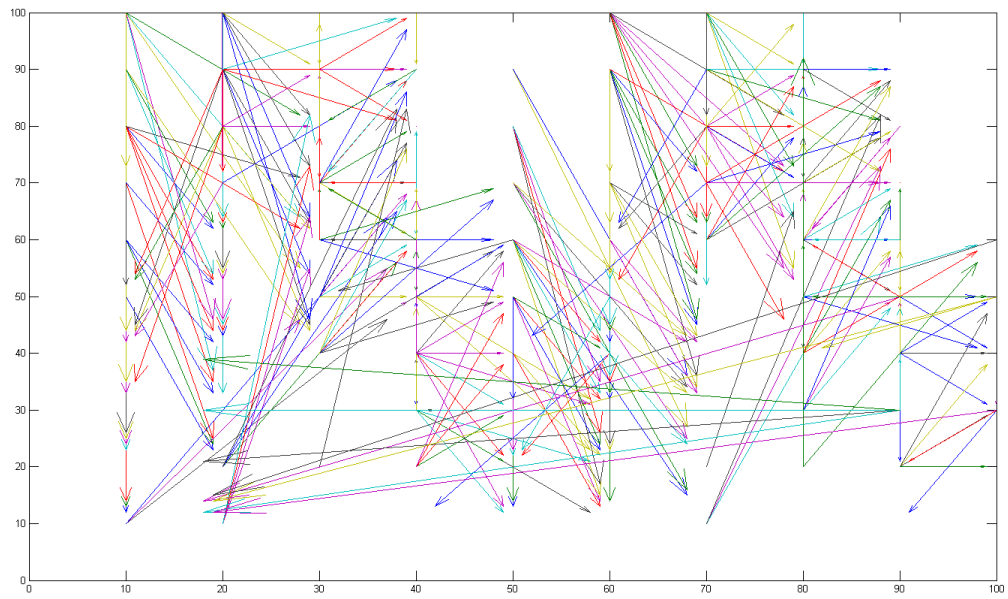
a) b)
Figure 3: Upper panels show pre-drawn path for rat, lower panels show synaptic weights after running for the same duration of time as in the 1-dimensional track. a) With phase precession, b) without phase precession, parameters for both cases are identical.

Because the synaptic weight plots in the case of two dimensions are difficult to interpret alone, significant connections were first defined as a synaptic strength of two standard deviations of the mean (figure 4). Vector plots were then made where arrows pointed from the center place field of a presynaptic neuron to the center place field of its connected postsynaptic neuron (figure 5). The inferred strength and directionality differences from the phase precession and non-phase precession models are demonstrated spatially through the vector plots (figure 5a,b).



a) b)
Figure 4: Synaptic weights at or above two standard deviations of the mean from the plots in figure 3. a) With phase precession, b) without phase precession.

a)



b)

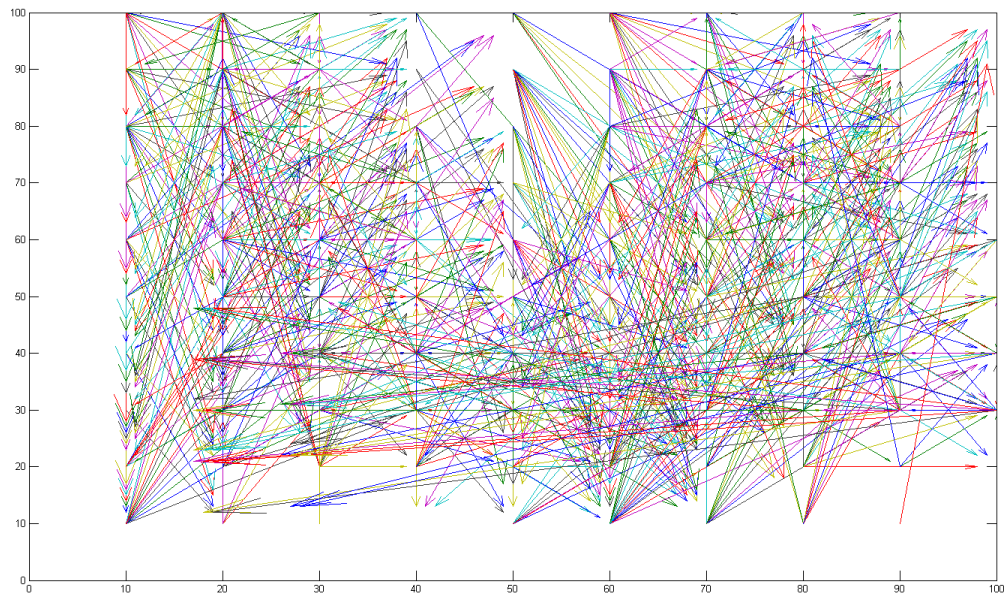


Figure 5: Connections between place cells based on increased synaptic weights from figure 4. Arrows are from the center of the place field of the presynaptic neuron to the center of the place field of the postsynaptic neuron. a) With phase precession, b) without phase precession.

4 Discussion

A computationally feasible but complexly behaving spiking model was used to simulate spatially-selective firing of neurons in the CA3 region of the hippocampus. Two conditions of 1-dimensional and 2-dimensional running areas were simulated while including or excluding phase precession of the place cells. As expected, phase precession in both conditions resulted in unidirectional and refined connections, while omitting phase precession resulted in bidirectional and broad connections. This provides a possible means for sequential coding, where phase precession restricts strong connections only to neurons which were activated in temporal order. Memories of spatial paths in this case are then more identical to the actual experience of the animal with phase precession than without. It is also possible that this mechanism allows for the temporal encoding of other hippocampus-mediated memories, such as sequential stimulus presentation.

5 References

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