Storing Associative Memories in Cell Assemblies of Neural Oscillators Bound by Gamma-Frequency Synchronization

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Abstract

Learning depends on the brain's ability to associate information from internal and external stimuli. Associating features of an environment allows an organism to learn from the past and predict the future. Binding cortical cell assemblies, each representing different stimuli, by gamma-frequency synchronization is thought to be a prominent method the brain uses to associate units of information. It has been shown that associated stimuli, each processed by an individual cell assembly, act as gamma-frequency oscillators and synchronize their oscillations in the gamma band. Spike-time dependent plasticity has been shown to synchronize cells oscillating at these frequencies. However, not much is known about the mechanisms by which whole cell assemblies transiently bind to and synchronize with each other. Another form of associative memory found in the brain is the storage of sequences of these synchronization groups. It is not known if and how coupled neural oscillator systems can accomplish this heteroassociative task. We explore past research on the autoassociative binding of cell assemblies which act as oscillators, and the heteroassociative recall of sequences of these patterns of activation. We also propose experiments to better understand the mechanisms behind these processes.

Introduction

One of the brain's key functions is to associate disparate information. This association allows an organism to learn from its environment, attend to features it has learned require attention, make inferences about its surroundings, and make predictions about the future. In order to accomplish the task of associating information, it must somehow represent relations between stimuli. However, the brain represents different types of stimuli in different ways and across different cortical areas. How can the brain associate sensory representations between cortical locations? Binding of cell assemblies by gamma-frequency synchronization is one theory for how this task is accomplished. It is hypothesized that synchronized groups have more power over their outputs than non-synchronized groups and therefore synchronization between groups representing the same object or concept can be used to associate them. However, the exact mechanisms behind binding are still unknown.

Binding of Cell Assemblies

Representations of information in the brain are thought to be processed by cell assemblies, which are groups of cells in a small area of cortex which process a specific unit of information. In order to associate stimuli, ideas, or information stored and processed by these assemblies, the brain "binds" the smaller assemblies together by synchronizing their oscillations in the gamma-frequency band (Gray et al., 1989; Singer and Gray, 1995; Eckhorn et al., 1988; Engel et al., 1992; Roelfsema et al., 1997). Stimuli and ideas are grouped in this way into frameworks, where more ideas can be incorporated into the model by synchronizing further cell assemblies (Engel et al., 2001). Synchronization between cell groups

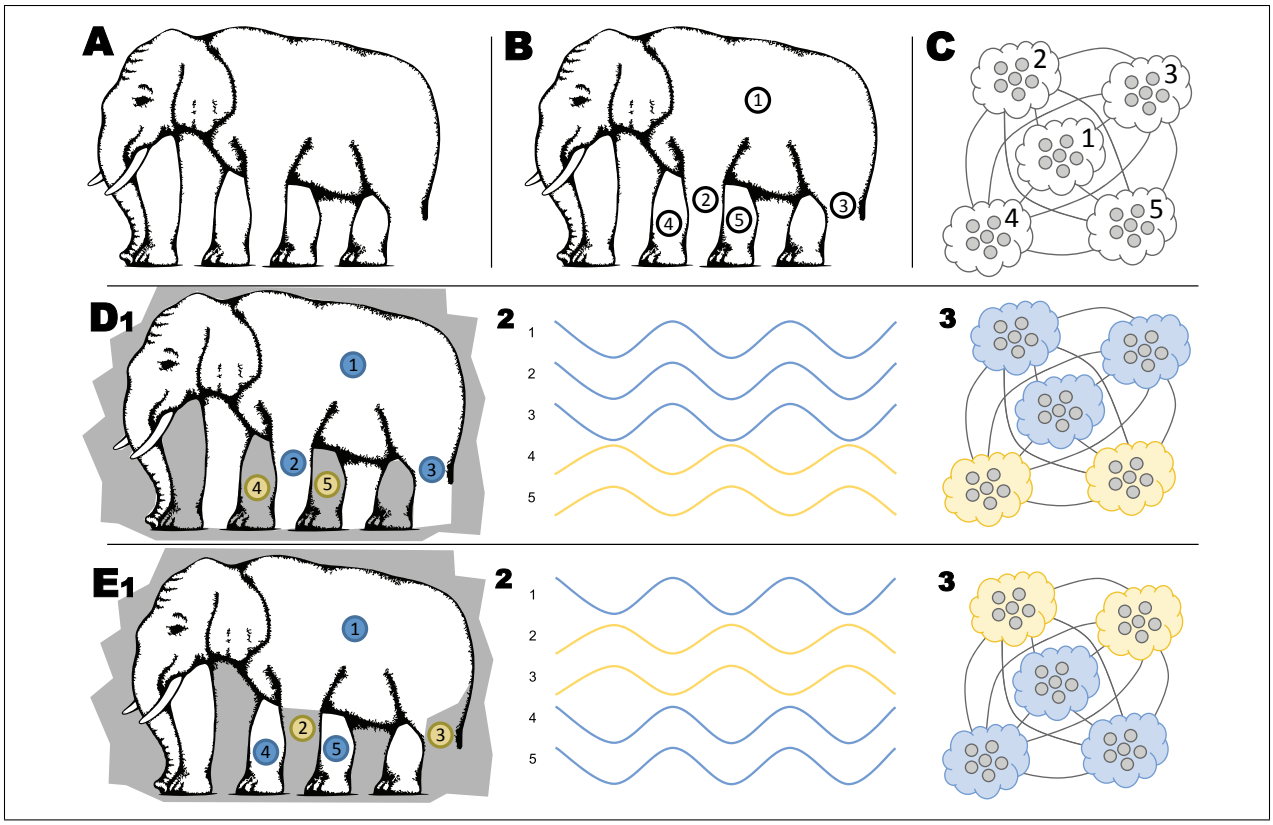


Figure 1: An example of binding between cell assemblies. **(A)** An image with multiple representations. The brain can group the sub parts of this image in different ways, depending on how the object is perceived. **(B)** The parts of the image which the brain can associate: the background, the body of the elephant (1), the legs (2,3), and the feet (4,5). Due to the incongruity in the image, the brain cannot easily associate all five objects into one larger object at the same time. **(C)** Cortical cell assemblies representing different objects in the visual scene. Assembly 1 represents the elephant's body, assemblies 2 and 3 represent the legs, and assemblies 4 and 5 represent the feet. **(D)** (1) When the body and legs are associated, (2,3) the assemblies representing the body and legs oscillate in-phase with each other, while the assemblies representing the feet do not. **(E)** (1) When the body and feet are associated, (2,3) the assemblies representing the body and feet oscillate in-phase with each other, while the assemblies representing the legs do not.

is thought to associate them because assemblies of neurons which are synchronized have a much higher probability of being processed together (Fries et al., 2001).

Binding of assemblies which process similar information has been observed between several cortical regions. In the visual cortex, binding occurred between neural assemblies processing similarly oriented bars moving in unison (Gray et al., 1989). This data suggests that the two bars of identical orientations, moving at the same speed and direction, are grouped by the brain into one object using this gamma-frequency synchronization between groups. Binding by gamma-band synchrony has also been observed between more distant cell assemblies. Cell assemblies in the visual cortex, parietal cortex, and the motor cortex have been found to synchronize when representing the same object (Roelfsema et al., 1997). Because of its prevalence, it seems likely that the binding of cell assemblies by gamma synchronization is a common method for associating information across cortical areas.

Local cell assemblies are usually groups of cells within a small area of cortex which oscillate with high coherence (Destexhe et al., 1999). Cells in the group do not have to be similar in their inputs; they can belong to different hierarchical levels of cortex (Gray, 1999). Therefore, a local cell assembly can be roughly thought of as a cortical column or a cluster of tightly connected cortical columns which processes closely related information (Varela et al., 2001). However, in cats, tight synchronization has been observed in cortical regions up to 5 mm apart (Destexhe et al., 1999). Synaptic delays within a local cell assembly

are nearly always less than 10ms, with the majority of delays being between 1.5 and 4ms for feedback, feedforward, and horizontal connections (Girard et al., 2001). These latencies are short enough to allow for gamma oscillations within the local group, as the 1.5-4 ms latencies are much shorter than 15-40 ms period of a gamma oscillation.

Neural Oscillators: The PING Model

Individual local cell assemblies which participate in binding can be thought of as gamma-frequency oscillators. There are various neural mechanisms capable of generating gamma-frequency oscillations in the brain. Some neurons generate gamma rhythms due to their unique electrophysiological properties. For example, chattering cells intrinsically oscillate at gamma frequencies, and are thought to serve as gamma rhythm generators (Gray and McCormick, 1996). Gap junctions can also play a role in generating gamma oscillations, both when they occur between dendrites of interneurons (Tamás et al., 2000; Traub et al., 2001), and between axons of pyramidal cells (Traub et al., 2000).

However, rare intrinsic electrophysiological characteristics are not required for a network to produce gamma rhythms. Simple networks of inhibitory and excitatory cells with no rare electrical capabilities can produce gamma rhythms in the form of interneuron gamma (ING) oscillators or Pyramidal-interneuron gamma (PING) oscillators. Pyramidal-interneuron gamma oscillators are particularly stable and are robust to heterogeneity in neuron connections and intrinsic parameters (Börgers and Kopell, 2005). They are also found in many areas of the brain. Most notably, PING circuits are found in the hippocampus (Fisahn et al., 1998) and also in cortex (Tiesinga and Sejnowski, 2009), where they are thought to be involved in the generation of cell assemblies (Whittington et al., 2000; Olufsen et al., 2003). As they are thought to play a role in the generation of cell assemblies, a core element of neural binding, we describe the mechanism of PING oscillation in detail.

A PING oscillator is a group of coupled inhibitory and excitatory neurons. The oscillatory effect caused by interacting excitatory and inhibitory cells is observed in a very wide range of network sizes, from single pairs of neurons (Börgers and Kopell, 2005; Lee et al., 2009), all the way up to hundreds or even thousands of cells (Börgers and Kopell, 2005; Izhikevich, 2003). Both the excitatory cell population ("E cells") and inhibitory cell population ("I cells") receive external input, and have cross and recurrent connections (Lee et al., 2009; Mazzoni et al., 2008). The external input causes the E cells to spike, and the E spikes cause the I cell population to spike. The I cells spike and inhibit the E cell population, and the E cells do not spike again until external input brings them back up to threshold, at which point the cycle repeats. These oscillations occur stably only in the gamma frequency range when there are biologically plausible cell parameters and slight heterogeneity in the network (Börgers and Kopell, 2005).

Such PING oscillations have been found to play a role in the generation of cell assemblies (Whittington et al., 2000; Olufsen et al., 2003), which are the local groups representing units of information associated to one another during binding. Each assembly acts as a PING oscillator, and multiple assemblies are associated through the gamma-rhythm synchronization of distant cortical areas (Fries, 2005).

One may wonder how local cell assemblies can possibly encode information within themselves if the assembly is confined to firing at regular gamma frequencies in order to bind with other assemblies. There are several theories of ways a PING network processes information while still acting as a gamma oscillator. In order for gamma oscillations to occur in the local field potential, each cell in the PING network does not have to fire each gamma cycle. This allows cells to have independent rates, and they do not have to be constrained to gamma frequency firing (Mazzoni et al., 2008). It is thought that this also allows the neural ensemble to deal with different types of information in different frequency bands; the association by synchronization appears to occur in the gamma frequency band, while other information transfer occurs in other frequency bands.(Mazzoni et al., 2011; Magri et al., 2012). If these ensembles indeed process information independently in different frequency bands, it may be possible to safely abstract away non-gamma frequency bands and think of each ensemble as a PING oscillator in order to study how neural ensembles bind together at gamma frequencies.

Spike-time dependent plasticity (STDP) has been studied to a limited extent in PING networks. However, it has been found that STDP can strengthen connections between oscillators in both directions, weaken them, or strengthen connections in one direction but weaken in the other, and is therefore able to selectively synchronize oscillators.

When two oscillators are coupled and the connec-

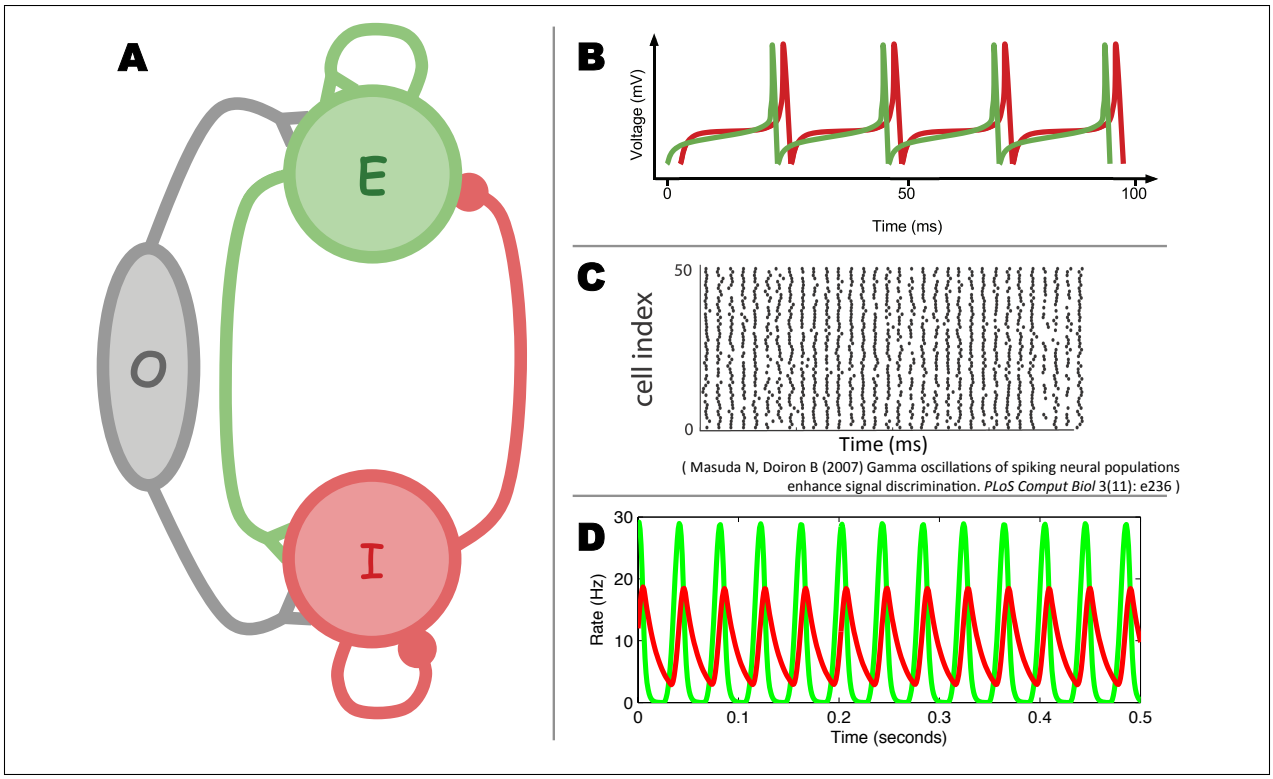


Figure 2: PING oscillators. **(A)** Wiring diagram for a PING oscillator. A population of excitatory pyramidal cells (group E) have recurrent output, and output to inhibitory interneurons (group I). The interneurons have inhibitory recurrent connections, and inhibit the pyramidal cell population. Both populations receive outside excitatory input (group O) from thalamus or other cortical areas. **(B,C,D)** The PING mechanism is robust over large population size ranges and levels of biophysical realism. **(B)** Detailed conductance-based simulations of a single pair of Pyramidal cell and interneuron display gamma-frequency spiking by the PING mechanism. **(C)** Less detailed spiking models with larger population sizes also display gamma oscillations. **(D)** Rate models, representing yet larger population sizes, also produce gamma oscillations by the PING mechanism.

tion strength between the two is allowed to change according to a STDP rule, the connection between the oscillators can either increase or decrease, depending on the respective rates of each oscillator (Lee et al., 2009). The change in synaptic weight can be symmetric but does not have to be. For example, if oscillator A fires at 40 Hz, and oscillator B oscillates at just under 50 Hz, the connection from B to A will become weaker, while the connection from A to B will become stronger (Lee et al., 2009, Fig. 3). However, depending on the STDP rule used, connections in both directions can both potentiate or both depress (Lee et al., 2009, Fig. 13,14).

Other work has shown that this increase in synaptic efficacy between oscillating neurons due to STDP encourages synchronization (Cassenaer and Laurent, 2007), and therefore it is thought that STDP between oscillators will synchronize them (Benchenane et al., 2011). However, this synaptic efficacy change depends on the nonsymmetry of the hebbian learning rule (Lee et al., 2009), and synchronization will only occur when the hebbian learning rule is asymmetric (Suri and Sejnowski, 2002). Given the proper STDP rules, oscillatory neurons can synchronize quickly, and this synchronization is robust to noise (Zhigulin et al., 2003). Specifically, there are three general rules for STDP in order to achieve synchronization between distant cortical cells (directly from Knoblauch et al., 2012):

1. Synaptic potentiation must be significantly stronger than synaptic depression for small (positive or negative) time lags between presynaptic and postsynaptic spikes.

2. Spike synchronization must be sufficiently imprecise, for example, within a time window of

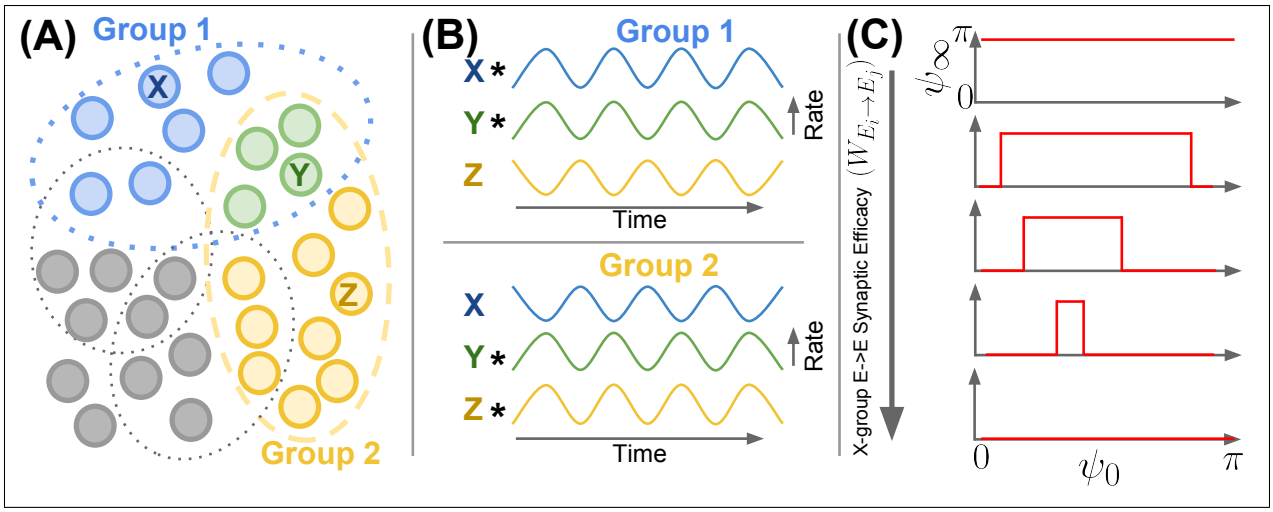


Figure 3: Phase difference bistability requirement and attractor/repellors. **(A)** Two overlapping groups, Group 1 and Group 2, contain oscillators X, Y, and Z, where X is in Group 1 but not 2, Z is in Group 2 but not 1, and Y is in both Group 1 and 2. **(B)** When Group 1 is activated but not Group 2, X and Y synchronize, but not Z. When Group 2 is activated but not Group 1, Z and Y synchronize, but not X. Therefore, it is necessary that there be synaptic connections between X and Y (or Y and Z) which allow for them to synchronize when stimulated simultaneously, and not synchronize when they are stimulated disparately. This is the phase difference bistability requirement. **(C)** Attractor and repellor states: steady state phase difference as a function of the initial phase difference. The strength of the attractors and repellors can be controlled by the strength of the cross-group excitatory to excitatory synaptic strength. The stronger the E→E synaptic strength, the larger the attractor basin, and the lower the E→E strength, the smaller the attractor basin.

5-10ms instead of 1ms.

3. Axonal propagation delays should not be much larger than dendritic delays.

If these STDP rules are not applied, the neurons may in fact *de*-couple due to STDP (Knoblauch et al., 2012).

The fact that STDP can encourage oscillator synchronization and increase synaptic efficacy between oscillators suggests that it should be possible for two coupled PING oscillators to synchronize when simulated simultaneously. If this is the case, then cell assemblies, acting as PING oscillators, should not only be able to synchronize and bind to each other at gamma rhythms, but also learn which assemblies they are most often associated with by the strengthening of connections between frequently simultaneously stimulated groups. In theory, this should allow for a network of cell assemblies to act as an attractor, where stimulating part of a pattern of oscillators will induce the whole pattern to synchronize their oscillations. However, it has not yet been shown whether this behavior is possible.

Recalling Cell Assembly Associations

It is not known if cell assemblies are capable of storing associative memories. Cortical cell assemblies may remember what groups they synchronize with most often, acting as an attractor network. This would be useful in cortex, since it would allow the brain to infer what to expect by the immediate activation of representations of concepts which are associated with currently observed concepts.

If such an autoassociative system of oscillators is possible, it is necessary that synaptic connectivity schemes exist which allow two oscillators to end up in-phase when stimulated simultaneously or started in-phase, but end up out-of-phase when stimulated disparately or started out-of-phase.

This is required because a robust autoassociative network is made up of many overlapping groups (fig. 3a). Therefore, there are nodes which are part of two (or more) groups. If some node (say, node X) is stimulated at the same time as one group (say, group A), then it should synchronize with that group. If the node is stimulated at the same time as another group (say, group B), then it should synchronize with *that* group (fig. 3b). So, when stimulated with group A,

the node will synchronize with some other node in group A (say, node Y). Suppose node Y is in group A, but not in group B. When node X is stimulated along with group B and synchronizes with group B, then nodes X and Y should not synchronize. So, there has to be some synaptic connectivity between X and Y such that when stimulated together, they synchronize, but when stimulated disparately, they do not synchronize. This phase difference bistability is required for a robust autoassociative network.

Preliminary results (fig. 3c) suggest that there are connectivity parameters resulting in phase difference bistablilty. These results also show that the system can act as an attractor or a repellor, where each group can repel the other group, resulting in an out-of-phase relationship, or attract the other group, resulting in an in-phase relationship. The strength of the repulsion or attraction is determined by the strength of the inter-group excitatory to excitatory connection.

These preliminary results suggest that the system should be able to act as an attractor and be able to store autoassociative memories. This is because the individual units can act as attractors and repellors. If each member of a group has attracting relations with members of the same group but, on average, repelling relations with out-of-group members, then the in-group oscilators will synchronize, and the out-of-group oscillators will not synchronize with the activated group.

The system should be able to *learn* associations, because the size of the attractor basin increases with larger cross-group excitatory to excitatory connection strength (fig. 3c). This strength increases due to STDP during synchronization (Lee et al., 2009), so the more often two groups are bound, the stronger their attraction to each other becomes, and the more likely they are to synchronize. By this process oscillators should be able to learn to synchronize with oscillators they are frequently synchronized with.

Sequence Recall

In addition to remembering spatial patterns of activation, it is thought that circuits in the brain are able to recall sequences of these patterns of activation. Direct evidence of this sequence recall can be found in the replay of location representation processions in the hippocampus. Cells in the hippocampus have been shown to represent certain locations by selectively firing only when the organism is in or thinking about a specific area (O'Keefe and Dostrovsky, 1971; O'Keefe and Nadel, 1978; Leutgeb et al., 2005a).

Theta rhythms are observed in hippocampal EEG recordings (O'Keefe and Recce, 1993; Skaggs et al., 1996). During path-running experiments, CA3 hippocampal cells encoding place location have been found to spike at progressively earlier times in the theta cycle as the animal approaches the location for which the cell encodes (O'Keefe and Recce, 1993). Cells representing further points along the track spike subsequently, in order, along the theta cycle (Skaggs et al., 1996). This suggests the hippocampal cells are remembering the procession of locations experienced in the past. Procession of place cell firing within the theta cycle has also been observed to encode predictions of paths (Johnson and Redish, 2007). These findings show that networks in the hippocampus are able to recall sequences of activation.

However, the representation of location in the hippocampus is not as simple as one-cell location codes. Activity in the hippocampus is actually better characterized by a map of activation, where the subset of cells that are active encode the location, and the rate of those cells encode sensory information about that location (Leutgeb et al., 2005a,b). These maps are thought to be part of an autoassociative network, with each map being an attractor state, such that the organism can determine its environment even with slightly corrupted location information (Jensen et al., 1996).

It is thought that sequences of these map-attractor representations are encoded by hippocampal cells. Specifically, it is thought that this occurs in the dentate-CA3 circuit (Lisman, 1999). The recall of place representations occurs at gamma frequency, and the recall of one sequence occurs each theta cycle (Skaggs et al., 1996; Jensen and Lisman, 1996a; Lisman, 1999). One location representation activates another location representation that the organism has learned proceeds the first. This second representation activates a third, and so on. This cycle continues until the end of the theta cycle, at which point the system "resets" and a new procession occurs (usually starting at a later point than the procession of the preceding theta cycle (Skaggs et al., 1996)). Usually around seven gamma-frequency representations can fit into a single theta cycle, and it is thought that this limitation is the cause for the similar number of representations that will fit into working memory (Jensen and Lisman, 1996a).

Recalling sequences may not be a simple enough task to be performed by a single, uniform recurrent

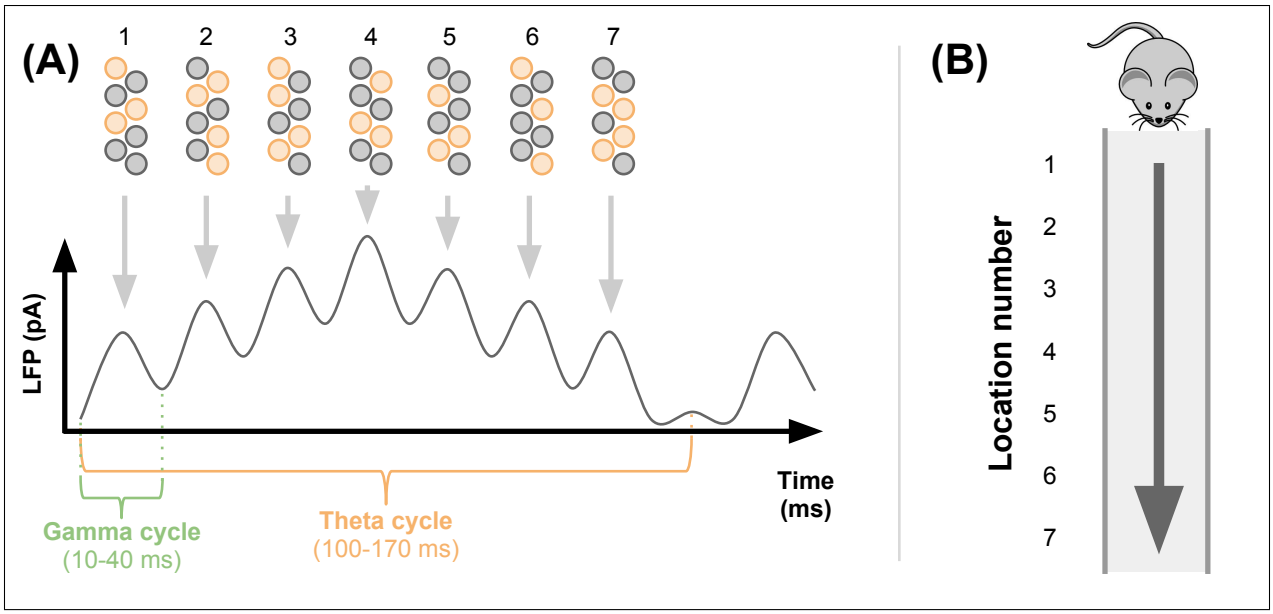


Figure 4: Sequence recall by groups of neurons in the hippocampus. **(A)** The subset of cells which fire together in a gamma cycle encode a location. A location is represented at each gamma cycle. The LFP shows theta-modulated gamma rhythms in the cell population, where each theta period corresponds to the recall of a single sequence. At the end of each theta phase, the system "resets," and a new sequence is recalled the next theta phase. **(B)** The recall of sequences of progressive location representations in mice remembered from moving along a track has been seen in hippocampal CA1 and CA3 cells (Skaggs et al., 1996; Johnson and Redish, 2007).

network. It is thought that shorter timescales in the autoassociative synapses and longer time constants in the heteroassociative synapses are required for reliable sequence recall (Jensen and Lisman, 1996b). This allows the system to perform pattern completion and separation at the autoassociative synapses, and then use this "de-corrupted" pattern to recall the next pattern in the sequence through the heteroassociative synapses (Lisman et al., 2005). It is not clear if this dual system of heteroassociatively coupled autoassociators is necessary for sequence recall, or if a single system of heteroassociatively coupled oscillators can accomplish the task. We hope to also answer this question in our proposed research.

Methods (proposed)

We use a rate model to simulate neural oscillator cell assemblies, and we use a spiking model to verify the biological plausibility of the results obtained using the rate mode.

Rate Model

To simulate neural oscillators, we use a simple rate model. Each population's average rate is defined by

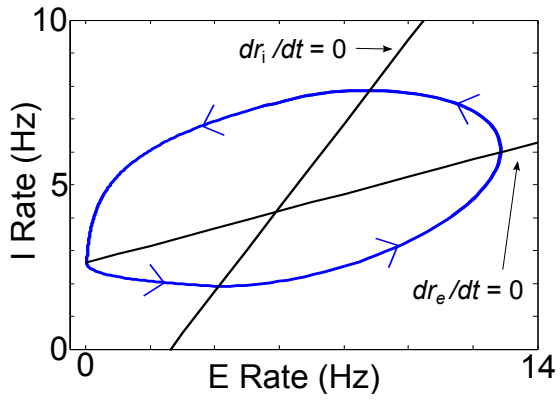
$$\tau_i \frac{dr_i}{dt} = -r_i + [\sum_{j=1}^{n}(W_{ji} r_j) + \gamma_i]_+ \qquad (1)$$

where

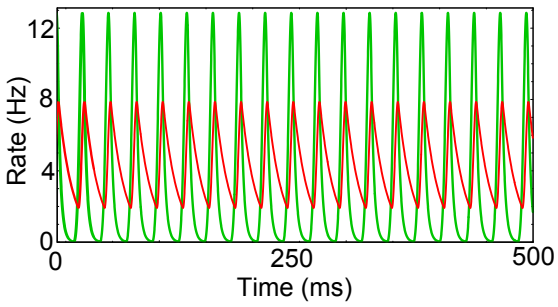
- W_{ji} is the synaptic efficacy from presynaptic cell population j to postsynaptic cell population i,
- τ_i is the membrane time constant for neuron population i,
- r_i is the average rate of cell population i, and
- γ_i is the constant input to the cell population x (or threshold for activity if γ_i is negative).

Constructing a PING oscillator

To construct a PING oscillator, we couple two of the rate models described above (Equation 1). One is an



(a) The phase-plane of the coupled oscillator described by equations 2 and 3. The blue curve is the stable oscillation cycle, and the black lines are the nullclines.



(b) Time domain for a rate model of a PING network oscillating at 40 Hz, with parameters $\gamma_E = 10$ Hz, $\gamma_I = -10$ Hz, $\tau_E = 3$ ms, $\tau_I = 15$ ms, $W_{EE} = 2$, $W_{II} = -2$, $W_{EI} = 3.817$, and $W_{IE} = -3.817$. The green line is the excitatory population rate, and the red line is the inhibitory population rate.

Figure 5: Simulated rate model

inhibitory cell population and the other is excititory:

$$\tau_E \frac{dr_E}{dt} = -r_E + [W_{EE} r_E + W_{IE} r_I + \gamma_E]_+ \quad (2)$$

$$\tau_I \frac{dr_I}{dt} = -r_I + [W_{EI} r_E + W_{II} r_I + \gamma_I]_+ \quad (3)$$

This system will only oscillate with specific parameter choices. We choose parameters such that the system oscillates intrinsically at gamma frequency (we use 40 Hz).

We choose excitatory decay times corresponding to decay times of excitatory AMPA synapses (Börgers and Kopell, 2005),

$$\tau_E = 2 \text{ ms} \quad (4)$$

and inhibitory decay times corresponding to decay times of inhibitory GABA_A synapses (Börgers and Kopell, 2005),

$$\tau_I = 10 \text{ ms} \quad (5)$$

To determine what connectivity parameters will give oscillations with a frequency of 40 Hz, we find the eigenvalues of the stability matrix, whose real parts determine the oscillatory nature of the system, and whose imaginary parts determine its oscillation frequency (Dayan and Abbott, 2001).

We find the nullclines for the derivatives of the excitatory and inhibitory firing rate models (Equations 2 and 3), which, respectively, are

$$\frac{dr_E}{dt} = 0, r_E = \frac{W_{IE} r_I + \gamma_E}{1 - W_{EE}} \quad (6)$$

and

$$\frac{dr_I}{dt} = 0, r_I = \frac{W_{EI} r_E + \gamma_I}{1 - W_{II}} \quad (7)$$

To find the stability matrix, we evaluate the derivatives of the rate models (Equations 2 and 3) at the values of r_E and r_I which correspond to the fixed point. Using this method, we can compute four combinations of derivatives and arrange them into the stability matrix for the system,

$$\begin{pmatrix} (W_{EE} - 1)/\tau_E & W_{IE}/\tau_E \\ W_{EI}/\tau_I & (W_{II} - 1)/\tau_I \end{pmatrix} \quad (8)$$

We find the eigenvalues, λ, of this matrix,

$$\lambda = \frac{1}{2}\left(\frac{W_{EE} - 1}{\tau_E} + \frac{W_{II} - 1}{\tau_I} \pm \cdots \right.$$
$$\left. \cdots \sqrt{\left(\frac{W_{EE} - 1}{\tau_E} - \frac{W_{II} - 1}{\tau_I} \right)^2 + \frac{4 W_{IE} W_{EI}}{\tau_E \tau_I}} \right) \quad (9)$$

We set $W_{EE} = -W_{II}$ and define

$$x \equiv W_{EE} = -W_{II} \ , \quad (10)$$

and set $W_{EI} = -W_{IE}$ and define

$$y \equiv W_{EI} = -W_{IE} \ . \tag{11}$$

The system is only oscillatory when the real solution to the eigenvector is greater than zero, $Re\{\lambda\} > 0\ \mathrm{s}^{-1}$. Therefore the weight parameters W_{EE} and W_{II} are constrained to

$$W_{II} < -\frac{\tau_I}{\tau_E} W_{EE} + \frac{\tau_I}{\tau_E} + 1 \tag{12}$$

and assuming $W_{EE} = -W_{II}$ (Eq. 10), $\tau_E = 2$ ms (Eq. 4), and $\tau_I = 10$ ms (Eq. 5), the weight parameter x is constrained to

$$x > \frac{-\tau_E - \tau_I}{\tau_E - \tau_I} = \frac{3}{2} \tag{13}$$

When the systems is oscillatory, the oscillation frequency, f is given by the imaginary solution to the eigenvector (Equation 9) divided by 2π, $Im\{\lambda\}/2\pi = f\mathrm{Hz}, Im\{\lambda\} < 0$. Therefore, the solution for the weight parameters x and y with oscillation frequency f becomes the hyperbola,

$$(8\pi f)^2 = \frac{4y^2}{\tau_E \tau_I} - \left(\frac{x-1}{\tau_E} + \frac{x+1}{\tau_I} \right)^2 \tag{14}$$

Our solution space for x and y becomes

$$(8\pi f)^2 = \frac{4y^2}{\tau_E \tau_I} - \left(\frac{x-1}{\tau_E} + \frac{x+1}{\tau_I} \right)^2, x > \frac{3}{2} \tag{15}$$

We take

$$x \equiv 2 \tag{16}$$

and solve for y, getting

$$y \approx 2.873 \tag{17}$$

Our final parameter choices for the PING system (Equations 2 and 3) which result in an oscillatory system with a frequency of 40 Hz are

$$\begin{array}{lcl} \gamma_E & = & 10 \text{ Hz} \\ \gamma_I & = & -10 \text{ Hz} \\ \tau_E & = & 2 \text{ ms} \\ \tau_I & = & 10 \text{ ms} \\ W_{EE} & = & 2 \\ W_{II} & = & -2 \\ W_{EI} & = & 2.873 \\ W_{IE} & = & -2.873 \end{array} \tag{18}$$

The system with these parameters result in stable oscillations at 40 Hz, which we confirm by simulation (Figures 5b and 5a).

Spiking Model

For each sucessful result of the rate model, we will run a simulation of noisy, heterogenic spiking neurons to determine if we can get the same results with a more biologically plausible system.

To model more realistic networks of spiking neurons, we use the Izhikevich's simple model of spiking neurons (Izhikevich, 2003). In this model, the membrane potential, v, of each neuron is defined by:

$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I \tag{19}$$

where u is the recovery variable, a characterization of the negative feedback induced by the activation of K^+ and Na^+ currents, and is defined by

$$\frac{du}{dt} = a(bv - u) \tag{20}$$

where

- a determines the time scale of the recovery variable, u, where lower values of a result in slower recovery from a spike (slower spiking).
- b defines the sensitivity of the recovery variable u to subthreshold voltage fluctuations.
- I is the sum of the thalamic input and input to neuron i from all neurons j which spiked during the last timestep,

$$I_i = I_{thal \to i} + \sum_{j=1}^{n} w_{ji}(v_j \geq 30\mathrm{mV}) \tag{21}$$

where w_{ji} is the synaptic efficacy from neuron j to i.

The potential for a neuron is reset after it spikes according to

$$\text{if } v \geq 30\mathrm{mV}, \text{ then } \begin{cases} v = c \\ u = u + d \end{cases} \tag{22}$$

where

- c is the reset membrane potential value after a spike, and
- d is the increment value of the recovery variable u upon spike.

Experiments

Our two main research questions are:

1. Can oscillating cell assemblies remember what groups they are often synchronized with, acting as an autoassociative network?

2. Can oscillating cell assemblies recall sequences, acting as a heteroassociative network?

In the following two sections, we design experiments to determine the answers to these questions.

Autoassociative Group Recall

In order to determine if oscillators can autoassociatively synchronize with other oscillators they are frequently synchronized with, we need to ensure that there is phase-difference bistability, as discussed in the introduction.

Phase-difference bistablity is, more formally, when the initial phase difference between two oscillators, $\Delta\psi_0$, is zero, the steady-state phase difference, $\Delta\psi_\infty$, is zero:

$$\text{if } \Delta\psi_0 \approx 0, \text{ then } \Delta\psi_\infty \approx 0 \ , \tag{23}$$

and when the initial phase difference is out-of-phase, the steady-state phase difference is out of phase:

$$\text{if } \Delta\psi_0 \approx \pi, \text{ then } \Delta\psi_\infty \approx \pi \ . \tag{24}$$

Or generally, phase difference bistability occurs when

$$|\Delta\psi_{\infty,\Delta\psi_0\approx 0} - \Delta\psi_{\infty,\Delta\psi_0\approx\pi}| \approx \pi \ . \tag{25}$$

In order to test whether this condition can occur, we will couple two neural oscillators together, and vary the four inter-group synaptic strength parameters to find a region of 4 dimensional parameter space where phase difference bistability (Eq. 25) occurs.

If we find such parameters do exist, then we need to determine what subspace of these parameters give rise to attractor and repellor behavior as discussed in the introduction. That is, we need to find connectivity parameters between two groups that cause the groups to synchronize when started *close* to in-phase, and end up out-of-phase when started *close* to out-of-phase. We also need to find that connectivity parameters are able to change the size of these attraction basins, in order for the autoassociative network to function (as discussed in the introduction).

To determine if the system displays attractor and repellor behavior, we will find $\Delta\psi_\infty$ as a function of $\Delta\psi_0$ for areas of parameter space in the two coupled oscillator system which allowed for phase difference bistability.

Attractor and repellor behavior will be characterized by in-phase steady state phase differences for in-phase initial phase differences,

$$\Delta\psi_\infty \approx 0 \text{ when } \Delta\psi_0 \approx [-\frac{\pi}{2}, \frac{\pi}{2}] \ , \tag{26}$$

and out-of-phase steady state phase differences for out-of-phase initial phase differences,

$$\Delta\psi_\infty \approx \pi \text{ when } \Delta\psi_0 \approx [\frac{\pi}{2}, \frac{3\pi}{2}] \ . \tag{27}$$

We also look for areas of parameter space where changing connectivity strengths can change the width of these ranges (in Eqs. 26 and 27).

If we find connectivity parameters which give rise to this attractor/repellor behavior, then the next step is to see if the system can *learn* these parameters via STDP. We will couple two oscillators and allow the cross-group connectivity strengths to change according to STDP rules as we activate the two oscillators synchronously. We will vary STDP parameters to explore STDP rule parameter space, and determine what STDP rules result in the synaptic parameters which cause basins of attraction and repulsion when the two groups are often activated synchronously.

If STDP can allow oscillators to learn these connectivity schemes, we will try teaching small groups of oscillators patterns of activation by synchronizing groups. If small groups can learn patterns, we will teach larger groups of oscillators random patterns of activation. For the larger groups, we will characterize connection strength between groups as a function of their group relation, and analyze network capacity as a function of network size, group size, and STDP rules.

Heteroassociative Sequence Recall

We will also determine if the system is capable of recalling sequences. Previous studies have suggested that recalling sequences requires two different systems with different within- and cross-system time constants (Lisman et al., 2005). However, we will determine if the recall can be performed by a uniform system without heteroassociatively coupled autoassociators.

We will vary the STDP parameters to determine if there is a region of parameter space which allows

for the recall of sequences of spatial patterns of activation. For each parameter choice, we will activate sequential random groups at gamma frequency, and determine if the system can recall these presented sequences. We will analyze whether sequences can be stored at all, and if so, analyze average storable sequence length, and average storable item size as a function of the STDP parameters.

Regardless of our findings for a single-time constant system, we will also construct a system of heteroassociatively coupled autoassociators as in (Lisman et al., 2005), only using neural oscillators. We aim to determine whether neural oscillators can code items, instead of single neurons. We will couple two autoassociative systems described in the previous section, and determine the ability of the system to store sequences of spatial patterns of activation as a function of STDP parameters and time constants.

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