Thalamic Modulation of Memory in Recurrent Networks

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Abstract:
During delay tasks, some neurons in the murine thalamocortical system (Schmitt et al., 2017) and hippocampus (‘time cells’) (MacDonald et al., 2011) display transient spike responses with timing that is repeated reliably across trials. In higher mammals and primates, activity in some cells is consistently elevated. These transient responses during delays confer a short term memory of the stimulus. We wondered what neural network structures could facilitate the generation of such dynamic memory patterns. We show that in a simplified formalism of a dynamic recurrently-connected network (DRN), the number of unique dynamic patterns grows exponentially with network size. The DRN formalism emphasises the role in neural function of transient yet repeatable dynamics. Unlike reservoir networks, the connectivity matrix does not need to be finely tuned (random connectivity suffices), and the dynamics implement indefinite (not fading) memory. Gating of input patterns is assumed to be controlled by modulatory signals from the thalamus. In particular, recent experimental evidence suggests that inputs from the MD thalamus convey contextual information and can modulate cortical synaptic strengths. We show in a spiking neural network model that MD modulation of synaptic strength can indeed stabilize dynamic patterns of activity and hence short term memories.

Keywords: thalamus; short term memory; context; dynamics

Methods

Using the reduced model, we first investigated networks of between 5 and 500 neurons, with between 0.1% and 5% synaptic sparsity, with between 0.01% and 5% inhibitory connections. The activity vector is updated with the next iteration follows.

\[
1 \times n \text{ activity vector} \times \frac{\text{n x n weight matrix}}{} = 1 \times n \text{ result}
\]

\[
\text{Max( Limited to top k activities )}
\]

Results

Reduced Model

Fig 1. Activity update loop. The activity vector is multiplied by the weight matrix to obtain the 1 x n result. The activity vector represents all the neurons that just spiked as 1’s and the remainder as 0’s. The result is limited to the top k activities in a random selection of k neurons. We used a reduced network that iterated activity through a random matrix (Fig 2).

The top excitatory neurons are deemed to emit a spike with the remainder assumed firing (I&F) spiking. We wondered how the lengths of the generated sequences of activity.

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10% of neurons active at each step (1 step was equivalent to once around the activity update loop depicted in Fig 1). For the results, the network connectivity was set to 100% (all-to-all).

The theoretical maximum number of unique activity patterns for any given network is $n\text{choose}k$ where $n$ is the number of neurons and $k$ is the number active at each step. For a network of $n=500$ neurons with 10% active (i.e. $k=50$) there are more than $10^{60}$ possible patterns. 10% activity equates to a 5 Hz average firing rate if we assume there are 50 steps each second. At this rate, even for such a relatively small network, it would take approximately $10^{40}$ universe lifetimes to discover all the patterns. However not all patterns are dynamically accessible; that is, they cannot all be reached by cycling through the weight matrix as in Fig 1. This is because the number of theoretically possible states grows combinatorially with the number of neurons, but the number of weights only grows quadratically, so the number of reachable states is significantly less than the naïve maximum, and the discrepancy is larger for larger networks. Additionally, states are not independent since all state transitions utilize the same weight matrix. To test these ideas, we generated all possible patterns for networks where the total number of possible patterns was $10^7$ or less, and iterated them through a random weight matrix to see how many of the transformed patterns were dynamically accessible. Fig 2 (top) displays this as a percentage of all possible patterns for each network. We can see that the percentage of all possible patterns that were dynamically accessible decreased for larger networks, but that the decrease was significantly slower for sparser activity patterns. Sparse activity patterns therefore more efficiently use the range of the dynamically accessible state space of recurrent networks. To the best of our knowledge, this is a previously unrecognised advantage of sparse activity in recurrent networks.

To test the length of the sequences that could be generated, for each reduced-model network we created 1000 random starting patterns, then iterated each pattern through a random weight matrix 100 times (to simulate 2 seconds of activity at 50 steps/sec). If a pattern was repeated during these iterations, this was deemed a conflict, the iteration was stopped and the length of the cycle up to the conflict was noted. Fig 2 (bottom) shows the minimum cycle length for each network over the 1000 starting patterns. To reliably retrieve memories from dynamic patterns of activity, it is important that no cycles intersect within the required memory storage time. We can see that a network of 500 neurons with 1% activity (i.e. $k=5$) had a minimum cycle length of only 100 steps (Fig 2 bottom, light orange markers). However, by extrapolation, simply doubling the number of neurons (i.e. to $n=1000$, $k=10$) increased the minimum cycle length to approximately $10^6$ (light orange fit line). Assuming 50 steps/sec, this equates to at least 5 hrs of continuous unique non-overlapping pattern generation using random synaptic weights. Extrapolating further, approximately only 1600 neurons would give a minimum pattern length of $10^{11}$, which is sufficient to produce 50 unique patterns every second for the average human lifespan of 75 years.

**Sparse Connectivity**
Noise and Thalamic Modulation

Sustained Activity and Thalamic Modulation

Conclusion
Acknowledgments

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References
