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Quantal synaptic failures improve performance in a sequence learning model of hippocampal CA3

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Abstract

Quantal synaptic failures are random, independent events in which the arrival of an action potential fails to release transmitter. Although quantal failures destroy information, there exist conditions where such failures enhance learning by a neural network model of the hippocampus. In particular, we show how the appropriate failure rate can allow the model to learn the hippocampally dependent task of transverse patterning. Usefully, since lowered activity levels produce higher memory capacity, synaptic failures lead to robust performance at lowered activity levels. Thus, the synaptic failure mechanism is another example of a random fluctuation that improves neural network computations.

Keywords: Neural network; Fluctuations; Noise; Configural learning; Transverse patterning

1. Introduction

Examined in isolation, a noisy communications channel is less efficient than noise-free communications channels, as it requires more energy to produce equivalent capacity. Although noisy communication is bad for the users of a single communication channel, it can have a positive effect on a postsynaptic neuron with many inputs [2] or a network of neurons. In two studies [5,6] a hippocampal model learning the transverse patterning (TP) problem was improved by adding a random component in a recurrently connected, Hebbian learning, neural network model of hippocampal CA3.

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This paper investigates the effects of introducing a biologically accurate, multiplicative form of noise, quantal synaptic failures, to the recurrent excitatory synapses of a hippocampal CA3 model. By adding the synaptic failure process, learning by the model is more robust, and TP can be learned at lower activity levels when a suitable synaptic failure rate is used.

2. Methods

Our model of hippocampal CA3 consists of a sparsely connected (10%) network of McCulloch-Pitts neurons. External inputs represent projections from the dentate gyrus and entorhinal cortex to CA3.

Previously a neuron's excitation was defined as the sum of the weights of its recurrent inputs that were active on time step $(t-1)$. However, with the addition of synaptic failures, a neuron's excitation is the sum of the weights of its active inputs that did not undergo synaptic failure. We model synaptic transmission at each synapse as independent random Bernoulli events. For $(y_j(t))$, the internal excitation of neuron j on time step t,

$$y_j(t) = \sum_{i=1}^{N} C_{ij} W_{ij}(t-1) Z_i(t-1) \Phi_{ij}(t),$$

where N is the total number of neurons. A synaptic connection from neuron i to neuron j is represented by C_{ij} (1 if a connection is present, 0 if a connection is not present). The weight of the synapse from neuron i to neuron j on time step t is represented by $W_{ij}(t)$. The variable $Z_i(t-1)$ represents the binary, $[Z_i(t-1) \in \{0,1\}]$, firing of neuron i on time step $(t-1)$. The binary variable $\Phi_{ij}(t)$ implements the random failure process at the synapse from neuron i to neuron j. All $\Phi_{ij}(t)$ are randomly and independently determined on each trial such that $\Phi_{ij}(t) = 1$ with probability $(1-f)$, where f is the probability of synaptic failure.

Once internal excitation has been calculated, a deterministic binary (0/1) output firing decision occurs, representing the absence or presence of an action potential respectively. Here this decision is determined according to a k-winners-take-all rule.

This model learns via locally controlled synaptic modification, using a minimally time-spanning associative synaptic modification rule [3,4]. On each time step of each training trial, the weight of every synapse in the network is updated according to the following equation:

$$W_{ij}(t) = W_{ij}(t-1) + \mu Z_j(t)(Z_i(t-1)\Phi_{ij}(t-1) - W_{ij}(t-1)),$$

where the synaptic modification rate, μ, is equal to 0.05. Synaptic modification occurs only if postsynaptic neuron j fires. At the beginning of a simulation, all weights have a value of 0.4.

Transverse patterning is a hippocampally dependent cognitive task that requires the subject to assign meaning to stimulus pairs that cannot be derived from the individual stimuli [1]. For a detailed description of how we simulate transverse patterning, see [5] or [7].

3. Results

Fig. 1 demonstrates the model's sensitivity, at a particular set of parameters, to the rate of synaptic failure. As rate of synaptic failure is increased from 0% to 10%, TP learning increases from 0% to 80% of the simulations. For a wider range of failure rates, 30–70%, five out of five simulations successfully learn TP. However, when synaptic failure rates exceed 70%, performance drops abruptly. Thus, very small differences in synaptic failure rate can lead to very large differences in TP performance rate.

Synaptic failure rate interacts with the other simulation parameters, such as number of neurons, activity level, learning rate, initial weight, and size of the input code. The range of synaptic failure rates that are beneficial changes according to the other parameters. The number of neurons in the network is especially important. Although synaptic failures do not benefit networks smaller than 2000 neurons, the effects of synaptic failures become more robust as network size increases. This effect is likely due to an insufficient number of active connections per neuron in the smaller networks.

The interaction of synaptic failure rate with lowered activity levels is, perhaps surprisingly, beneficial. Although one might expect that lowered activity together with synaptic failures would lead to too few active inputs per neuron (and this can happen when failure rate is too high and activity level is too low), it is not always so. Fig. 2 shows TP performance rates for simulations run at four activity levels and two synaptic failure rates. Without synaptic failures, simulations require activity levels of 10% in order to achieve good ($>80\%$) TP performance. But when synaptic failures are present (here, set to 70%), simulations can learn TP with 100% success at each of the four activity levels plotted.

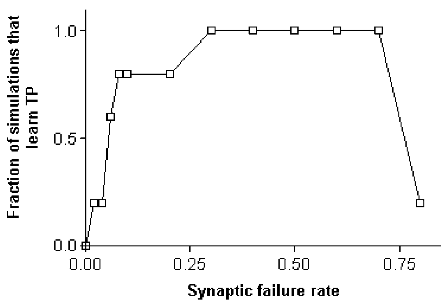

Fig. 1. Synaptic failure improves TP performance. Running at a relatively low activity level (7%), simulations are incapable of successfully completing the TP problem without synaptic failures. However, as the probability of synaptic failures is increased, TP performance rate rises quickly. While simulations display robust performance when synapses fail between 30% and 70% of the time, a synaptic failure rate that is too high ($>80\%$) destroys performance. Simulation parameters: $N = 8192$, Activity $= 0.07$, number of external inputs $= 172$, and $\mu = 0.05$.

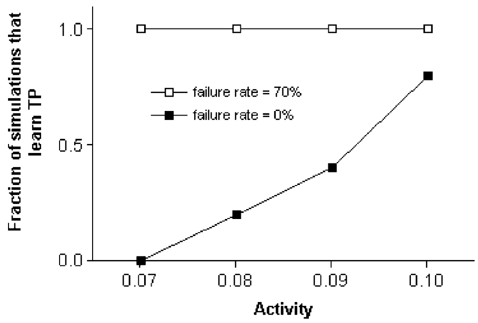

Fig. 2. Synaptic failures allow better TP performance, with the greatest improvement found at lower activity levels. When synaptic failure rate is set to zero, performance at 7%, 8%, and 9% activity is poor, with less than three out of five simulations successfully completing the TP task. However, when the probability of synaptic failure is set to 70%, five out of five simulations at each of the activity levels plotted learned TP. Each point is the average success rate of five simulations, each simulation using a different random connectivity matrix. For each simulated activity level, the external input comprises 30% of the active neurons. Simulation parameters: $N = 8192$, $\mu = 0.05$.

4. Discussion

Synaptic failures can benefit computation via greater memory capacity and more robust performance. Apparently, the rate of synaptic failure is a powerful parameter that can have profound effects on the model's ability to learn transverse patterning. Specifically, the simulations here, with low activity levels, can learn TP only if synaptic failures are present in the model. While information is lost—individually—at each failing synapse, the overall computation is more robust. This is in line with the conclusion of [2] that there is more than enough information going into a neuron even when connections are relatively few (low hundreds). Future studies will investigate the basis of this effect, but the idea developed and quantified in [5] concerning fluctuation driven code search during training seems to be a good candidate.

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