Think of a title later

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Abstract

Abstract goes here.

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1 Introduction

Write an introduction here.

2 Methods

In this paper, we used the simulated Integrate and Burst model introduced in [1]. We then implemented STDP learning and Hebbian learning.

2.1 Integrate and Burst Model

Our integrate and burst model is an implementation of equations described in [1]. For convenience, we also provide a detailed description of these equations here. There are N neurons connected in an all-to-all environment. Each neuron i bursts when its membrane potential, V_i, hits the threshold V_θ. We assume that every neuron bursts for T_{burst} time. While bursting, each neuron fires four times uniformly over the burst interval before resetting to V_{reset}.

When a neuron is not bursting, its potential is governed by a typical conductance based leaky integrate and fire model with built-in inhibition:

$$\tau_V \frac{\mathrm{d}V_i}{\mathrm{d}t} = -g^L(V - V^L) - g_i^E(V - V^E) - g_i^I(V - V^I) \tag{1}$$

The leak conductance, g^L, is assumed to be a homogeneous constant input, as is the leak potential V^L. Notice that in the absence of excitatory or inhibitory conductance, neuron i will tend to V^L. Therefore we can say that the leak potential is also equal to the rest potential.

The excitation potential, V^E, and the inhibition potential, V^I, act as upper and lower bounds on untethered (What was the word for IF potential plots without a firing threshold?) potential respectively.

The excitation conductance, g^L, is defined by the activity in neighboring neurons as well by external random stimulation:

$$g^L = Ws + W_0 b$$

Where W_{ij} is the strength of the synapse from neuron j to neuron i, W_0 is the conductance strength of external synapses and b is a Poisson random variable with frequency r_{in}. s_i is the activation of neuron i. It is incremented each time neuron i fires, and it decays by

$$\frac{\mathrm{d}s}{\mathrm{d}t} = -\tau s$$

The inhibitory conductance, g^I, is defined as the sum of the adaptation inhibition, g^I_{ada}, and the global inhibition, g^I_{glob}. The adaptation inhibition is the internal inhibition generated by activation of a neuron. It is defined by the same equations as s_i, but with a constant multiplier A_a and a slower time-constant τ_{ada}.

2.2 Learning

The purpose of this paper is to replicate and test some of the claims made in [1]. One of the claims made is that the model used by [1] demonstrates how STDP can contribute to the synchronous regular synfiring chains exhibited in Zebra Finch (Where? Maybe cite second paper here?).

2.2.1 STDP Learning

We followed [1] in our implementation of Learning. Define

$$K(t) = \begin{cases} e^{-t/\tau_{STDP}} & \text{if } t \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

as the STDP kernel. Let $\rho(t) = \sum_k \delta(t - t_k)$

2.2.2 Hebbian Learning

Talk about Hebbian learning here.

2.3 Parameter Choices

Talk about how we chose parameters here.

3 Results

Introduce the big idea and what we got.

3.1 Parameter Tuning

- 4000 Hz doesn't work! (Burst Plot)
- Mention annealing and our choice of r_{in}, η and ϵ. Name the two data sets we refer to for the remainder of the paper. (Scatter Error Function)
- Setting w_{max}. (Burst History)

3.2 Convergence and Stability

- Demonstrate the stability of our IB model by showing the firing rate plot and how it splits according to r_{in}.

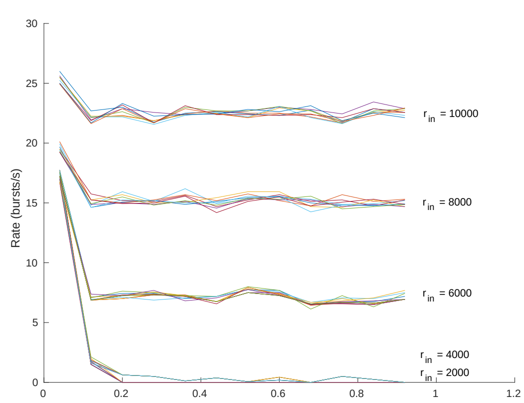

Figure 1: Caption will go here

- Plot Weight and WW^T for 4000 and 6000 Hz to show some level of convergence.
- Plot error function over time from normal and from permutation matrix
- Describe why the error function converges away from 0.

3.3 Hebbian Learning versus STDP

- Introduce the idea of the refutation.
- Give a theoretical description why the type of learning should be relatively unimportant.
- Compare plots (WW^T, Error vs Time, Burst History).

4 Discussion

Further improvements that could be made to our model and where this research could be taken.

5 Summary

Quick summary of our results and everything.

References

[1] Ila R. Fiete, Walter Senn, Claude Z.H. Wang, and Richard H.R. Hahnloser. Spike-time-dependent plasticity and heterosynaptic competition organize networks to produce long scale-free sequences of neural activity. Neuron, 65(4):563 – 576, 2010.