

Think of a title later

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December 12, 2015

**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 was based off of the same equations as used in [1]. There are  $N$  neurons connected in an all-to-all environment. Each neuron  $i$  bursts when its membrane potential,  $V_i$ , hits the threshold  $V_\theta$ . 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:

$$\tau_V \frac{dV_i}{dt} = -g^L(V - V^L) - g^E(V - V^E) - g^I(V - V^I) \quad (1)$$

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

### 2.2 Learning

Introduction to what we did.

#### 2.2.1 STDP Learning

Talk about STDP learning in this implementation.

#### 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  $r_{in}$ ,  $\eta$  and  $\epsilon$ . 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  $r_{in}$ .

../Code/LOTS/Firing\_Rate\_Binsize\_80ms-eps-converted-to.pdf

- 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.