

Thesis Proposal: Separating Cyclostationary Signals using the Nonlinear Dynamics of Continuous-Time Recurrent Networks

Vince Baker

May 19, 2017

1 Introduction

The human brain hosts advanced cognitive processes that remain only partially understood. Computational neuroscience seeks to understand brain functions through modeling at several levels of physical fidelity. “Biologically inspired” computation models are used in machine learning to solve a variety of problems that are intractable with conventional approaches. Computational biophysics provides insight into the lowest levels of neural functions while nonlinear dynamics provides tools for understanding some aspects of cognition. This research will examine the reservoir computing machine learning paradigm as the basis for a biologically plausible computational model for recognizing stationary and cyclostationary time series.

The reservoir computing computational model uses a nonlinear recurrent network as a reservoir of chaotic dynamics. Inputs to the reservoir evoke complex states with memory. Readouts from the reservoir can then be trained to use the reservoir to separate complex temporal inputs.

Reservoir computing has branches in both computational neuroscience (liquid state machines) and machine learning (echo state networks). The approaches are similar in that they invoke an untrained, high-dimensional reservoir with a trained readout. The types of networks used are different: echo state networks are typically discrete networks with random sparse connections while liquid state machines are continuous-time networks with biologically inspired connections. Recently, new echo state network models have been created using a few very fast photonic nodes and space-time coding to mimic a large spatial network. This work will focus on both approaches to continuous-time networks.

The key research problem will be to separate time series signals using a

recurrent continuous-time network. Test signals will include sine waves of different frequencies, modulated sine waves, and chaotic signals such as Mackey-Glass.

2 Background

Echo state network dynamics include (untrained) input weights W_{in} , sparse network weight W_x , and trained readout weight W_{out} . The internal network state x_n is driven by both the recurrent connections and the input signal. The time-dependent output y_n of an echo state network can be defined with the recurrence relation:

$$x_{n+1} = f(W_x \times x_n + W_{in} \times u_n) \quad (2.1)$$

$$y_n = W_{out} \times x_n \quad (2.2)$$

Where $f()$ is a nonlinear activation function, typically $\tanh()$ (also called a sigmoid activation). Training of the dense readout layer is accomplished with a simple technique such as linear regression.

Liquid state machines are described in terms of a continuous filter L^M on a continuous input $u(t)$:

$$x^M(t) = (L^M u)(t) \quad (2.3)$$

$$y(t) = f^M(x^M(t)) \quad (2.4)$$

The readout map f^M is trained using a biologically plausible mechanism such as the modified perceptron learning rule.

3 Approach

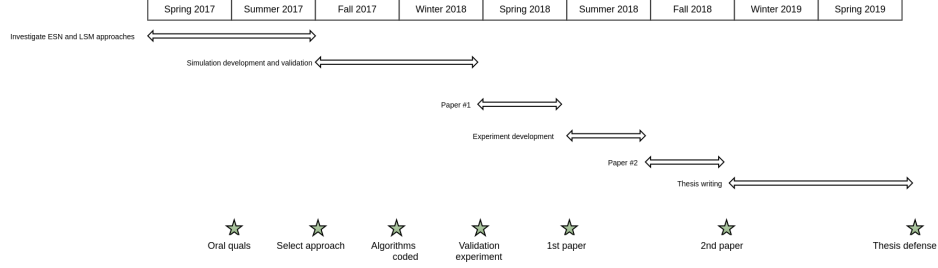
Use a recurrent network of nodes with a range of time scales as a near-chaotic reservoir. Model the networks using appropriate tools (NEURON, MATLAB ODE, Keras). Investigate biologically plausible connectivities and determine the onset of the chaotic regime. Train the readout to recognize cyclostationary signals using a biologically plausible mechanism such as spike-time-dependent plasticity.

4 Preliminary results

5 Work plan

The approach to the problem includes milestones at every quarter and several decision points. The first phase (two quarters) is an application of current echo state networks and liquid state machines to signals of interest to

Figure 1: Schedule



identify their strengths and weaknesses and understand the problem space. The chosen approach is then developed in the second phase (two quarters) through basic simulation. One quarter is reserved to refine the work into a paper for publication. The next stage may be an experimental study of nonlinear photonic delay systems OR a high-fidelity simulation using a tool such as NEURON. One quarter is reserved to refine the experiment or high-fidelity simulation for publication. The last two quarters are reserved for writing the thesis.

6 Implications of research

7 References