Indian Institute of Technology, Kanpur

Cognitive Science Course Project

Neural Prediction Challenge

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Contents

Abstract

Computational modelling of neuronal response supplements the understanding of the nature of processing in Human Brain. Various studies have looked at modelling the response of neurons from the visual motor cortex (V1) using synthetic data. In this project we try to model their response to natural movies shown to awake macquaes. The results of prediction using a Multi-Class adaboost classifier, Recurrent Neural Networks are presented. We also come up with a Spatio-Temporal filter for predicting the reponse of these neurons.

1 Introduction

Neural response is usually studied using techniques such as fMRI,EEG, MEG etc. An equally interesting approach is to look at the response of individual neurons.it has been hypothesized that the spike patterns of neurons encode information. There are many theories about how this information is encoded. (See [**?**]). One of them argues, that information is present in the spike rate of neural firing. Motivated by the same, in this project we try to explore the predicitive capability of this measure.

We obtained the spike rate data of 12 V1 neurons of awake Macqaues subject to viewing an image sequence of natural scenes. This data is available as part of the Neural Prediction Challenge [2]. Firstly, we use a conventional classification approach by implementing Adaboost. Such a technique doesnot incorporate any temporal information which is beleived to be very vital in studying neural reponse. Thus we get a base line measure of the accuracy we can hope for. Next, we try to incorporate temporal dynamics using Recurrent neural networks. Finally, we implement STRF filters based on studies by [3, 4] and evaluate their performance. Unfortunately, the movies presented to differet neurons are different thus chalking off the option of comparing response across neurons.

The report is organized as following: section 2 details the data we have got, section 3 talks about some characterstics of neurons, 4 talks about the various methods and the results and finally 5 is the conclusion.

2 Data

The details of the data is as following:

1. Each Movie typically is composed of 10000 frames.
2. The raw images are typicall of the size 120x120 pixels.
3. Images downsampled to 16*16 pixels have also been provided.
4. Each frame is presented for 16 ms in the video.
5. The count of spikes fired by the neuron in each time bin is given.

Some of the typical scene images have been shown in **??**.

3 Neuronal Characterstics

The firing of neurons is a chemical phenomena which involves the flow of ions. As a result, a neuron needs to charge up before it is able to fire. Consequently, their maximum fire rate is bounded. Some of the other interesting properties are presented in the following subsections.

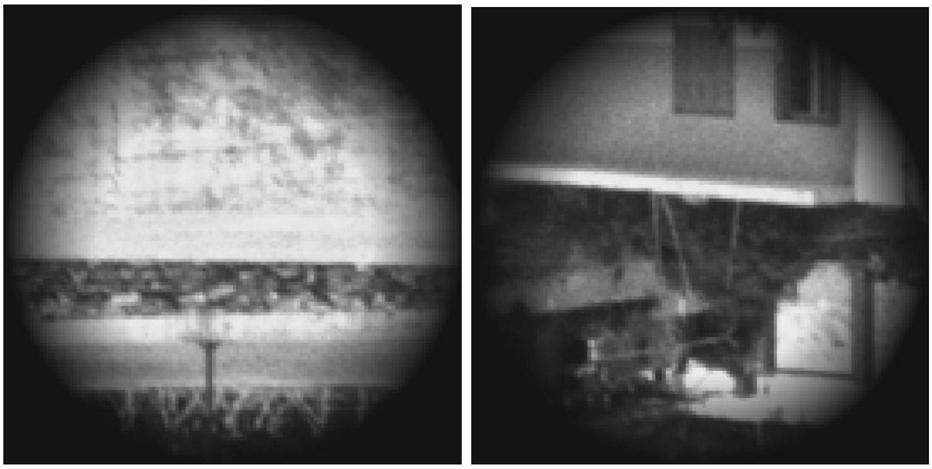

Figure 1: Typical Frames in the Dataset

3.1 Latency in Response

Neurons donot fire instantly. There is a lag between the onset of the stimulus and the time when we are able to see the response. The exact value of this lag is unknown for different neurons and is thus incorporated as a variable in our model.This lag is also reponsible in giving the temporal dimension to the response of neurons.

3.2 Receptive Field

The receptive field of a sensory neuron is a region of space in which the presence of a stimulus will alter the firing of that neuron [7]. Also, the neuron is illicited by a neuron after its lag interval. This lag may also depend on the stimuli. Thus the reponse varies in space and in time. In a nutshell, Spatio Temporal Field (STRF) of a neuron represents what types of stimuli inhibit/excite neurons. Also, if we assume linearity the neuron can be modelled as having a time-varying firing rate equal to the convolution of the stimulus with the STRF's [**?**].

3.3 Complex and Simple V1 Neurons

It is interesting to note that complex V1 neurons have phase invariant reponse as opposed to the reponse of simple V1 counterparts [3]. This is captured by taking the fourier transform of the stimulus in spatial dimensions and considering only the energt components.

4 Methods and Results

MultiClass Adaboost was used to perform a 10 fold Jack-Knife experiment on the given dataset. Such a blind experiment enabled to learn is there are any spatial patterns with predictive power. The results for neuron labelled as '$r0206_B$' are:

1. Accuracy: 0.344
2. Abolute value of Mean Correlation = 0.1543

This neuron had spike reponses from 0 to 6 spiked in a bin. Adaboost doesnot seem to be doing a good job over here. The code for binary adaboost if self implemented. Whule the code for the multi-class version

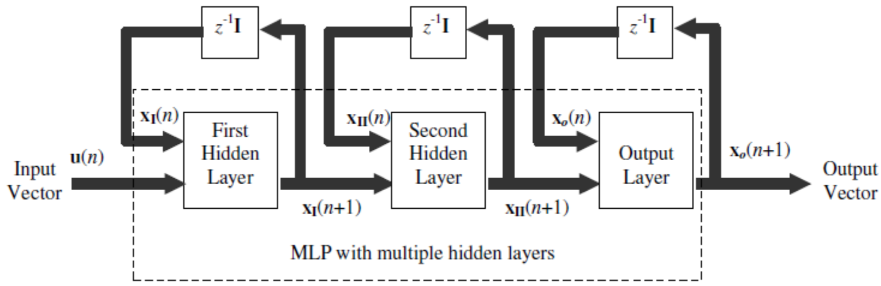

Figure 2: RMLP. Source: Xue et al. Development of a RNN Toolbox.

has been taken from [6].
The other 2 methods have been detailed below.

4.1 Recurrent Neural Networks

Recurrent neural networks are dynamic networks wherein the dynamic nature is caused because of the formation of a directed cycle by the connections between the neurons. Such networks, due to their ability to exhibit dynamic temporal behaviour, have found application in a lot of modern day problems like handwriting recognition etc. Because of their structure, these networks have a memory, which they can utilize to process seemingly arbitrary sequences of input [?].We now describe our use of such networks to solve the problem in hand - the Neural Prediction Challenge.

Recursive multilayer perceptrons are a type of RNN, which were initially developed by Puskorius et al. for the purpose of controling dynamic non-linear systems. Figure 2 shows the schematic of a typical RMLP with three layers.

As can be seen from the figure, the output from every layer is fed back to itself and if need be, to neurons of other layers too, to handle time-series data. For the shown network, the output will be given by:

$$X_I(n+1) = \varphi_I(w_I. \begin{bmatrix} x_I(n) \\ u(n) \end{bmatrix})$$

$$X_{II}(n+1) = \varphi_{II}(w_{II}. \begin{bmatrix} x_{II}(n) \\ x_I(n) \end{bmatrix})$$

$$X_0(n+1) = \varphi_0(w_0. \begin{bmatrix} x_0(n) \\ x_{II}(n) \end{bmatrix})$$

where, $X_0(n+1)$ is the output of the output layer and the other two are the output of the first and the second layer respectively. $\varphi_0(.,.), \varphi_I(.,.)$, and $\varphi_{II}(.,.)$ are the activation functions of the output, first and the second layer respectively.

Echo state netwroks are another type of RNN, wherein the hidden layer, called the reservoir is made up of a large number of sparsely and randomly connected neurons. Apparently, the idea was motivated by the results of a series of experiments done in neurophysiology and cognitive neuroscience. Once the connections in the reservoir have been chosen randomly, they are fixed and the neural network is trained with this sparsely connected kernel [?]. Figure 3 shows the schematic of an echo state network.

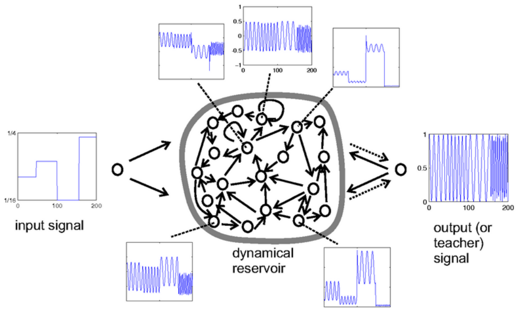

Figure 3: ESN. Source: http://www.scholarpedia.org/article/File:FreqGenSchema.png

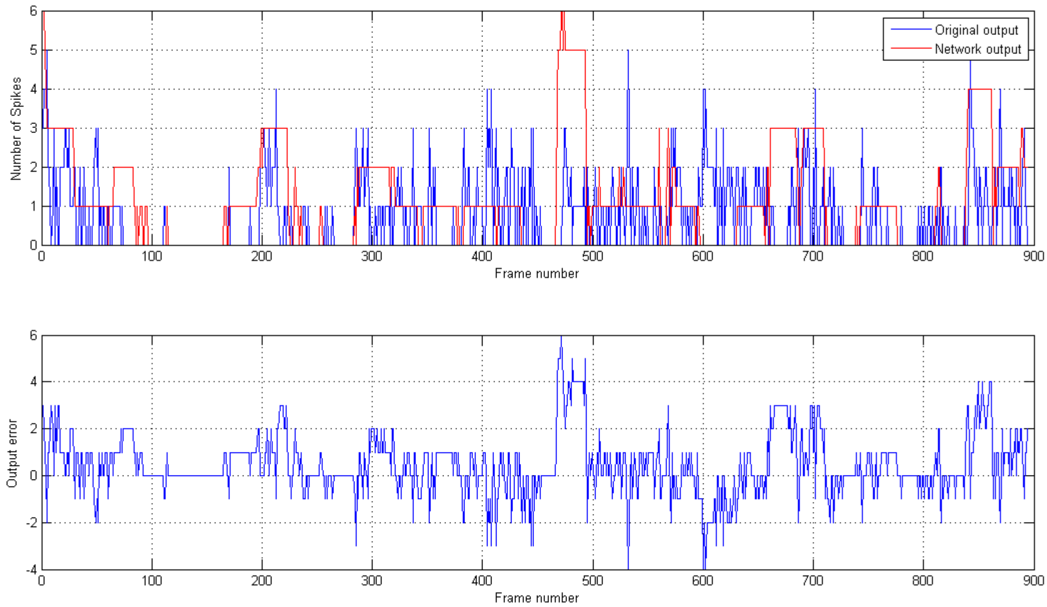

Figure 4: Network output of Neuron 1 vs. the actual output. Below: The error.

4.1.1 Code and results

A part of the code was taken from Development of a RNN Toolbox by Xue et al., and was modified to suit the requirements of the current problem. The network was trained on 90 % of the data from every V1 neuron and was tested on remaining 10 %. For some neurons, we got accuracy as high as 89 % and on average an accuracy of about 50 %, but in this case, the percent accuracy might not truly reflect the performace of the network. A more accurate measure of the correctness of the network output will be its correlation coefficient with the actual output.On an average, we got a correlation coefficient of 0.15. Figure 4 shows the output of neuron number 1 and contrasts it against the actual output. It also shows the error.

4.2 Using STRF

The estimation of STRF is based on the techniques proposed by [3]. The framework of the model is shown in 5.

The mathematics of estimation of the filter is shown above, where:

1. S is the stimulus matrix
2. h is the filter

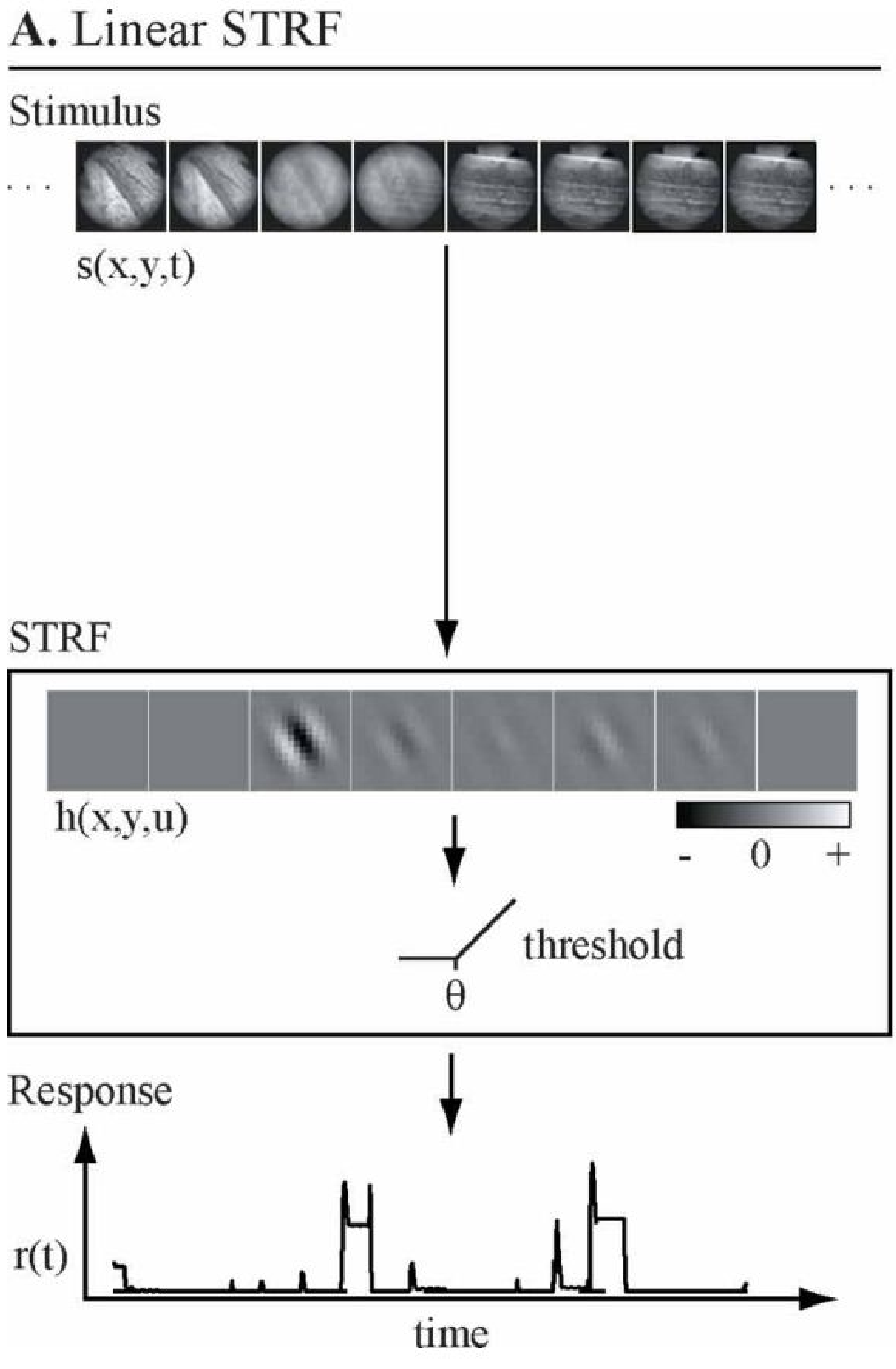

Figure 5: Filter Model taken from [3]

$$r(t) = \left| \sum_{i=1}^{N} \sum_{u=0}^{U} h(x_i, u) s(x_i, t-u) - \theta + \varepsilon(t) \right|^{+}$$

$$r = |Sh - \theta + \varepsilon|^{+}.$$

$$S_u = \begin{bmatrix} s(1, 1-u) & s(2, 1-u) & \cdots & s(N, 1-u) \\ s(1, 2-u) & s(2, 2-u) & & s(N, 2-u) \\ \vdots & & \ddots & \vdots \\ s(1, T-u) & s(2, T-u) & \cdots & s(N, T-u) \end{bmatrix}$$

$$S = [S_0 \quad S_1 \quad \cdots \quad S_U]$$

$$h = \frac{1}{T} C_{ss}^{-1} S^T r.$$

Figure 6: Mathematical Formulation

3. U is the lag
4. C_{ss} is the autocorrelation matrix

For the neuron labelled as 'r0206B' absolute mean correlation was 0.1526. This is the result for lag=4. Further we can prune the data for removing noise using Singular Vector Decomposition to remove the noisy components. The overall mean Correlation Co-efficient is 0.141 (as tested on NPC wesbite [2]).

5 Conclusion

Currently, our models are unable to predict neuronal responses very accurately. The accuracy could be improved by tuning the parameters like filter output thresholds. This leaves out tremendous scope for future research.

References

[1] Wikiepedia article on Neural Coding $http://en.wikipedia.org/wiki/Neural_coding$

[2] Neural Prediction Challenge *http://neuralprediction.berkeley.edu/*

[3] S. David,W. Vinje and J. Gallant, *Natural Stimulus Statistics Alter the Receptive Field Structure of V1 Neurons*, J. of Neuroscience, 2004

[4] S. David and J. Gallant, *Predicting neuronal responses during natural vision*, Computation in Neural Systems, 2005

[5] Wikipedia article on Receptive Field, $http://en.wikipedia.org/wiki/Receptive_field$

[6] Google Codes, *http://code.google.com/p/adaboostmatlab/*

[7] Wikipedia article on STRF, $http://en.wikipedia.org/wiki/Spatio_temporal_receptive_field$

[8] Scholarpedia article on Echo State Networks, $http://www.scholarpedia.org/article/Echo_state_network$

[9] Le Yang, Yanbo Xue $Development of A New Recurrent Neural Network Toolbox$. McMaster University, 2006.

[10] Don Hush , Chaouki Abdallah , Bill Horne. $The Recursive Neural Network.$, 1991.