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Analysis of spectro-temporal receptive fields in an auditory neural network
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Abstract

Neural networks have been utilized for a vast range of applications, including computational biology. But the realism of these models remains in question. In the models of the auditory cortex, for example, the properties of neuronal populations are hard to fully characterize with traditional methods such as tuning curves. Spectro-temporal receptive fields (STRFs), which describe neurons in both the spectral and temporal domains, have been obtained in a variety of animals, but have not been adequately studied in computational models. The aim of this project is to address these issues by generating the spectro-temporal receptive fields on a basic, neural network model of the early auditory processing stages in the brain. As purposeful additions to the computational model are made, the new STRFs can be used to further analyze the changes to the properties of the neurons.

Keywords: neural network, auditory processing, spectro-temporal receptive field (STRF)

1 Introduction

Computational biology is a growing field of computer science made to better model the complexities of the brain and other biological organs. The visual domain has already been studied to a great depth, but the auditory domain is still relatively new territory for computer models. Although many models have been created for the auditory domain, the actual realism of these models is hard to judge.

One way to judge the realism of the models is to compare them to their biological counterparts. But how can one compare computer-generated neurons to the real ones? Spectro-temporal receptive fields (STRFs) have been used in many different animals including birds and ferrets. These receptive fields characterize the linear response properties of neurons in the spectral (frequency) and temporal (time) domains. In order to generate these STRFs, the responses of neurons to moving ripple stimuli are collected and transformed. The STRFs from the computational models can then be compared to STRFs from the literature, and can be quantitatively and qualitatively be analyzed.

In addition to analyzing the STRFs in a neural network, I also want to be able to generate a more realistic model of the early auditory processing pathways in the brain. A basic, linear transform neural network can be used in the initial analysis, but I also want to add some type of temporal coding and lateral inhibition. Temporal coding allows the neural network to respond to a stimulus over time, analogous to neurotransmitter reuptake. Inhibition models another class of neurotransmitters that inhibit the response of a neuron. Lateral inhibition is theorized to take place in almost all biological sensations, including hearing. With these two aspects in a neural network, the computational model will be able to more accurately mimic the complex biological processing.

Even as computational power exponentially increases, without the use of models and neural networks, the utility of that processing power goes to waste. With neural networks, computers will be able to perform many functions originally thought only humans can possess, such as pattern recognition and reasoning. Furthermore, neural networks of the brain will help scientists understand ourselves and our capabilities and aid doctors in complex medical pathologies.

2 Background

2.1 The Ear

The ear is the first step in a long, auditory processing chain. In the inner ear, mechanical signals are converted into electrical ones in a processing known as transduction. The cochlea is largely responsible for this process. In the cochlea, the coiled tubes respond to different frequencies of sound at different places. For instance, a frequency at 3 kHz will trigger different cells to respond than a frequency at 10 kHz. In computational biology, this phenomenon is represented through the use of spectrograms, frequency v. time distributions of sound stimuli. Although there are many ways to represent sound stimuli in the brain, spectrograms have been quite popular with many scientists.

2.2 Hebbian Learning

As neurons respond to stimuli, they communicate with other neurons using neurotransmitters. Dr. Hebb, a famous psychologist, hypothesized that two neurons that are simultaneously active, then the connection between the two neurons would be strengthened. This process is known as synaptic plasticity, and is also important in training neural networks of the brain [2].

2.3 STRFs

Scientists have a relatively clear idea on how some basic processing takes place in the brain. But scientists also want to know some specific properties of neurons. Receptive fields have been used quite extensively to determine those properties of the neurons. Spectro-temporal receptive fields (STRFs) are no new topic in the auditory biological systems. The STRFs have been analyzed in many types of animals, including ferrets and birds. The literature shows that STRFs plot not only the responsive areas of the sample neurons, but they also illustrate the interaction between excitatory and inhibitory processes [1].

3 Development

3.1 Neural network

The neural network is a two layer, linear transform model of the early auditory processing stages in the brain. The input to the neural network is a spectrogram, a representation of a sound stimulus in a frequency v. time plot. The neural network receives one timestep of the spectrogram at a time, which comprises of about 10 ms of auditory information. The input is then connected to the second layer through feed-forward weighted connections.

3.2 Training

The neural network will be trained on real-world, environmental stimuli from CDs and the Internet in order to make the weights in the network as realistic as possible. The neural network will be further improved with additions such as temporal coding and lateral inhibition as the year progresses. At each step of the way, the STRFs will be generated from the computational model in order to compare these to the hypothesized STRFs to the STRFs in literature. Both the weight vectors and the STRFs are the results of the program.

Currently, the training is done using Oja's Rule, a modified version of Hebbian learning. Oja's rule is a mathematical formula to update the weight values.

4 Results

The graph of the tuning curves show that the neurons perceive different sets of frequency ranges depending on which input units they are connected to. The Oja's Rule training has been successful. The weights also approach the first principal component of the data set, which can be found by get the eigenvector of the covariance matrix.

5 Conclusion

Neural networks are powerful approximations of the biological systems of human senses. Although the visual domain has been studied extensively, the auditory domain is less well-known. Models of the auditory processing in the brain remains unrealistic and hard to describe. Using STRFs, scientists can visualize the neuronal processing and therefore analyze the properties of the network.

The tuning curves represent the frequency selectivity of the auditory neurons. The neurons connected to lower frequency ranges are illustrated by the tuning curves to be connected to those lower frequency ranges. In the future, neural models like these can be used to analyze hearing loss in certain individuals. Music and other destructive noises can be fed into the model, and the weighted can be retrained to approach the principal component of the new set of data. The STRFs and tuning curves would be able to show which frequencies those sounds are targeting, and how to protect the ear against that kind of injury to prevent hearing loss.

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References

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