DEMONSTRATION
Plasticity: A Synaptic Modification Simulation Environment

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Abstract

We present a simulation environment, *Plasticity*, which allows the user to perform a wide variety of simulations of rate-based neural networks. The package focuses on, but is not limited to, simulations of visual neurons and allows one to compare on equal footing many of the most common learning rules. This includes variants of Hebbian learning(Linsker, 1986; MacKay and Miller, 1994; Erwin and Miller, 1998), BCM(Bienenstock et al., 1982; Intrator and Cooper, 1992; Blais et al., 1999), and ICA(Hyvarinen and Oja, 1997; Blais et al., 1998). The goal of this package is consistent with the philosophy of reproducible research: providing a complete package which can fully reproduce any results or figures in publications.(Schwab et al., 2000). One aspect of this package which makes it different than other neural network packages is that it allows the user to explore environments from simplified low dimensional vectors(Clothiaux et al., 1991), to high dimensional correlation-based environments(Erwin and Miller, 1998) to natural images(Blais et al., 1998). The package is currently being extended to include spike-based learning.

1 Introduction

Scientific research requires the open exchange of ideas, making clear exactly how results were obtained and what assumptions are necessary.(Schwab et al., 2000) In the neural computation community there are many different approaches to explaining synaptic plasticity in the sensory systems. These differences often fall into three categories: differences in learning rules, input environments and architectures. We present here a software package written in MATLAB, called *Plasticity*, which allows the user to perform a wide variety of simulations of rate-based neural networks. The package allows one to vary one parameter at a time, e.g. compare different learning rules in the same environment and architecture or compare the same learning rule and architecture in different input environments.

*The package can be found at web.bryant.edu/~bblais/plasticity

One aspect of this package which makes it different than other neural network packages is that it allows the user to explore environments from simplified low dimensional vectors(Clothiaux et al., 1991), to high dimensional correlation-based environments(Erwin and Miller, 1995) to natural images(Blais et al., 1998). In addition, *Plasticity* allows one to easily compare results with a single cell to those of networks, in order to understand what *minimum* assumptions necessary for obtaining particular results. The package contains many different learning rules and synaptic stabilization methods, including variants of Hebbian learning(Linsker, 1986; MacKay and Miller, 1994; Erwin and Miller, 1998), BCM(Bienenstock et al., 1982; Intrator and Cooper, 1992; Blais et al., 1999), and ICA(Hyvarinen and Oja, 1997; Blais et al., 1998).

2 Examples

The following are a few examples of simulation results using the package. Other than the very large network simulations, each of these simulations can be easily run in real time, with modifications performed on-the-fly. These are just examples of the *many* possibilities of the package.

Figure 1 shows a simulation of monocular deprivation in a natural scene environment, using a BCM neuron. The dynamics of the modification threshold can be observed as the responses of the closed eye falls. Figure 2 is a reproduction of a result from Erwin and Miller(Erwin and Miller, 1995), where a neuron develops both orientation selectivity and ocular dominance in a correlation-based environment. The package allows the user to see the principle components of this environment (to compare with the final weight configurations), and warns the user when the correlation function specified is not positive-definite. Figure 3 shows an example network simulation of 400 neurons in a moving natural image environment, developing direction selectivity. A couple of different types of response maps are shown. Figure 4 provides a low-dimensional example of ICA, in an input environment, composed of 2-dimensional vectors chosen from a rotated Laplace distribution. Although such an environment is not directly applicable to biology or real data, the package can handle higher-dimensional data easily, and such low dimensional data can be used for educational purposes.

3 Conclusions

These examples touch on the huge flexibility of the package. What is unique about this package is the ease with which parameters can be changed on-the-fly, and that the range of environments available is very large. This is the first example of high-dimensional correlation-based approaches being compared side-by-side with high-dimensional natural image approaches to visual development. *Plasticity* provides an environment with which comparisons between different rate-based theories can be performed on the same test-bed. The package is currently being expanded to include spike-based plasticity, which will allow for the first time a comparison between rate-based and timing-based theories of synaptic plasticity.

4 Space Requirements and Special Notes

For this demo, a large monitor or small projection device is necessary, to connect to a laptop I will be bringing.

Due to my teaching constraints, I cannot arrive on the 9th of December. Any other day, from the 10th to the 14th, is fine. I appreciate your consideration of this special request.

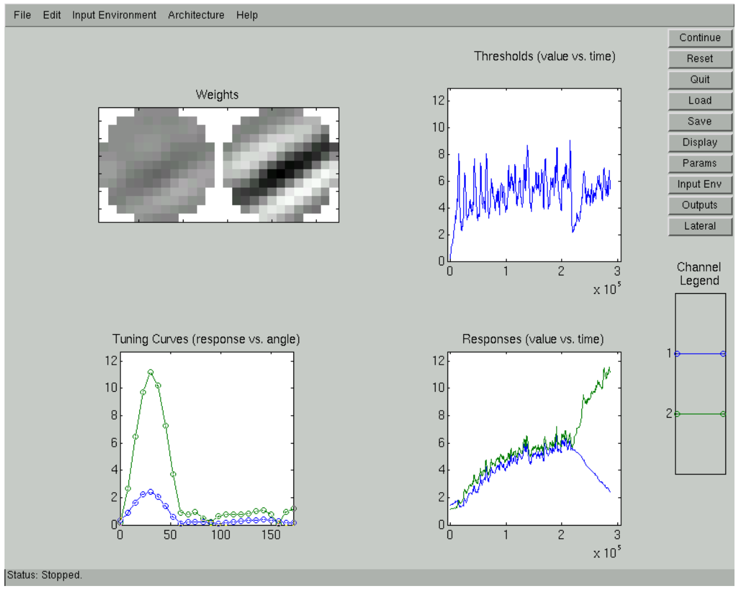

Figure 1: Example BCM (Bienenstock, Cooper, Munro 1982) simulation of monocular deprivation in a natural scene environment. The dynamics of the modification threshold can be observed (upper right), and the responses to the deprived eye can be seen to drop (lower right).

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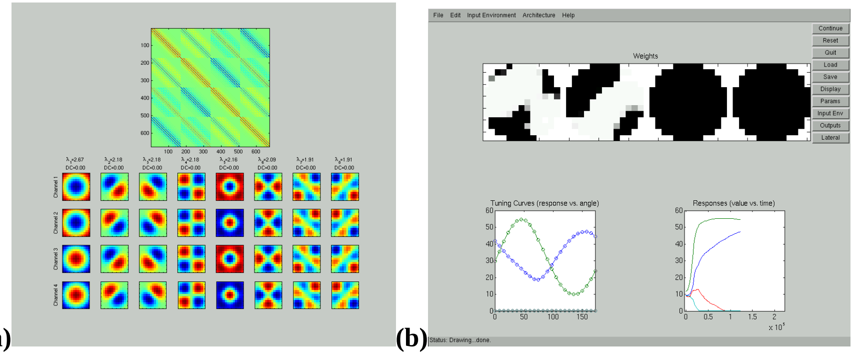

(a) **(b)**

Figure 2: Example simulation of ocular dominance and orientation selectivity, as described in Erwin and Miller 1995. (a) The correlation matrix is used to generate environment vectors, which are then used in the simulation. (b) The weights and responses indicate that the left eye weights (left two channels) are dominant and that the ON and OFF channels are opposite and oriented, leading to a cell which expressed ocular dominance and orientation selectivity.

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Acknowledgments

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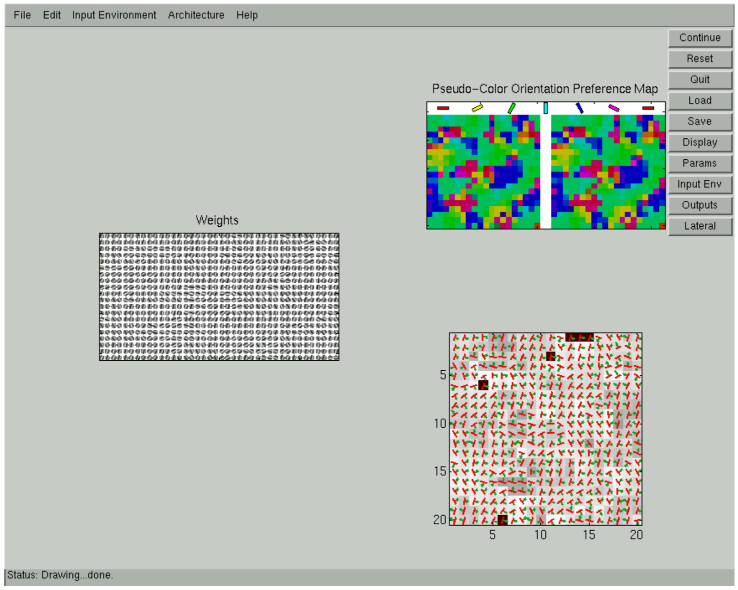

Figure 3: Example network simulation of BCM neurons in a moving natural image environment, developing direction selectivity. The left shows the weights for the lagged and non-lagged channels in each neuron. Upper right shows a pseudo-color orientation map and the lower right shows a direction/orientation map.

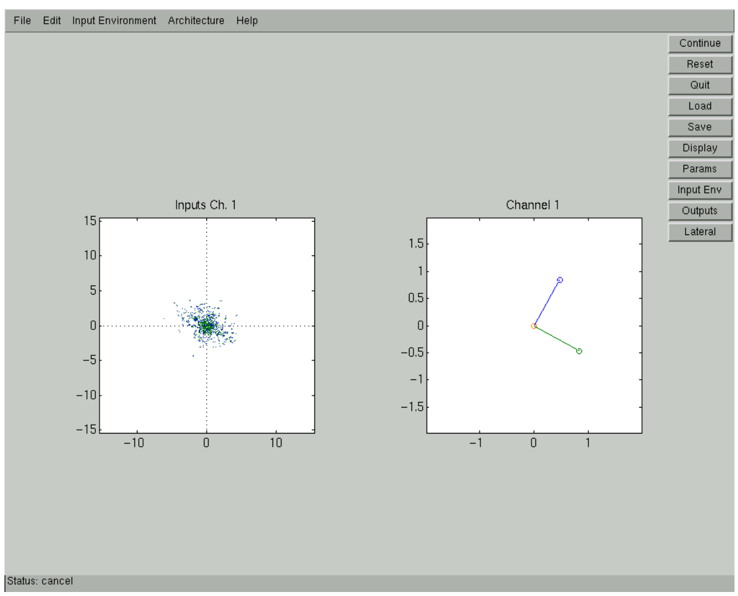

Figure 4: Example low-dimensional simulation of two neurons using the Kurtosis energy function and an orthogonalization constraint to find the independent components as in Hyvarinen and Oja 1997. The left is the input environment, composed of 2-dimensional vectors chosen from a rotated Laplace distribution. The right shows the weight vectors after convergence.