Comparing Neurophysiological Measurements of Simulated and Real Brains

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Abstract

The paper presents the comparison of simulated brains with real brains by means of statistical properties of neurophysiological measurements. Two neural models are selected to build a simulated column of the primary visual cortex. The first simulation uses classical neuron models, the second uses more complex neural assembly models that perform computations by using emerging spatio-temporal firing patterns. The comparison indicates that the second, more complex model produces results that are more similar to the recordings from real brains.

Key words: chaos; cortex model; neural networks; neurophysiological comparison

1 Introduction

There are several neuron and neural assembly models [3]. An important issue is to investigate to what extent these models produce similar results to real brains in simulated natural conditions. Such evaluations can provide the basis for selection of models for more detailed investigations.

Here we analyse two simulated cortical columns. The first simulated cortex uses classical model neural networks (e.g. [5]). The neurons have simple tuning curves, enabling them to select local features of the stimulus, and they interact to select the global properties of the incoming information (e.g., edges in the visual input). The second model is built by neural networks that use spatio-temporal activity patterns to process information [1]. We made simulated single electrode recordings and surface EEG recordings from both model columns. The results were compared to similar measurements from real brains.

The rest of the paper is structured as follows. We present the neural network models in Section 2. The data measurements are discussed in Section 3. The comparison of the simulation data with the real data is presented in Section 4. The paper is closed by the conclusion section.

2 Simulation methods

Here we describe the two neural network models. In both cases we built a simulated cortical column of the visual cortex.

2.1 Classical neural network model

Classical neural network models of the cortex build on idealized neuron models characterized by a tuning curve that represents the activty (e.g., firing rate) of the neuron in response to various input stimuli that are comparable by some appropriate metric (e.g., the orientation of short bars).

The model cortical column is made up of many excitatory neurons with similar tuning curves [6]. The model also contains a set of inhibitory neurons that mediate lateral inhibition, lateral excitation being performed by the excitatory neurons. The layered structure of the model column is presented in Figure 1.

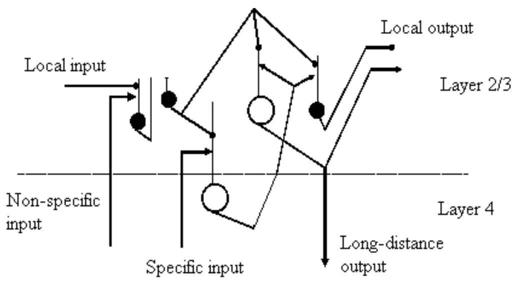

Fig. 1. The classic neural network model of a cortical column structure

2.2 Sierpinski network model

Experimental evidence suggests that neural activity patterns play an importan role in neural information processing [2]. Consequently, in order to reproduce more faithfully the operations of biological neural networks we consider models that simulate such behavior, i.e., computation by actvity patterns of neurons. One such model is the Sierpisnki neural network [1] that contains a mixture of excitatory and inhibitory neurons organized in a particular network architecture. The structure of the Sierpinski network is presented in Figure 2.

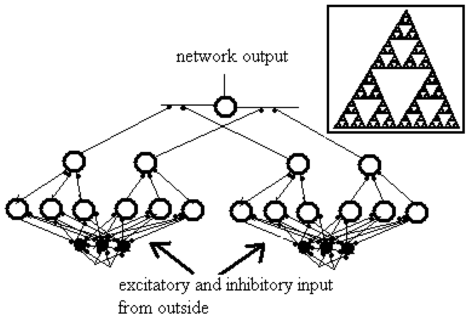

Fig. 2. The Sierpinski neural network. Inset shows a Sierpinski triangle.

The bottom layer of the sub-networks is formed by three pairs of excitatory neurons and three inhibitory neurons. This excitatory-inhibitory complex is organized such that at any time only one pair of excitatory neurons is spiking together with one of the inhibitory neurons. The pair of the active excitatory neurons is selected randomly. The two neurons in the upper layer of the sub-networks integrate the output of the excitatory-inhibitory complex, and send excitatory output to the top neuron of the network. The top neuron detects the coincident firing of the sub-network output neurons. The temporal output pattern of the sub-networks can be respresented as a Sierpinski triangle (see inset in Figure 2) [1], and the output of the top neuron of the network represents the number of intersections between the triangles of the sub-networks. The behavior of the top neuron can be characterized by a Sierpinski tuning curve [1].

The second cortical column model is built by Sierpinski neural networks together with additional inhibitory neurons that mediate the lateral inhibition. The layered structure of the Sierpinski cortical column is presented in Figure 3.

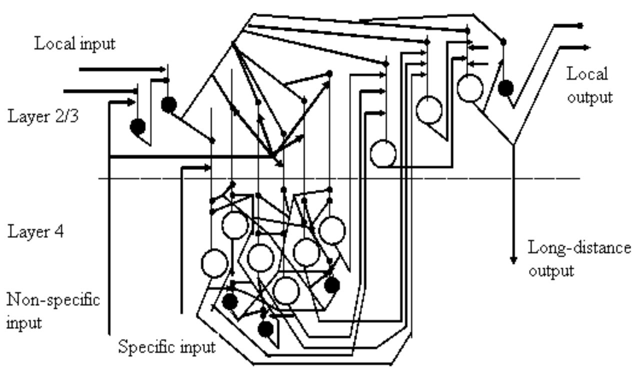

Fig. 3. The Sierpinski model of the cortical column structure

3 Data measurement

In this section we present the data that we used to do the comparison of the models with the real brain. We considered single electrode recordings and surface EEG measurements.

3.1 Real data

The single electorde recordings represent the activity of multi-units in macaque primary visual cortex [4]. The EEG recordings represent single channel data of 64-electrode surface EEG measured on the visual cortex of cats [7]. Twenty recordings were considered in both cases. Figure 4 shows examples of the real data.

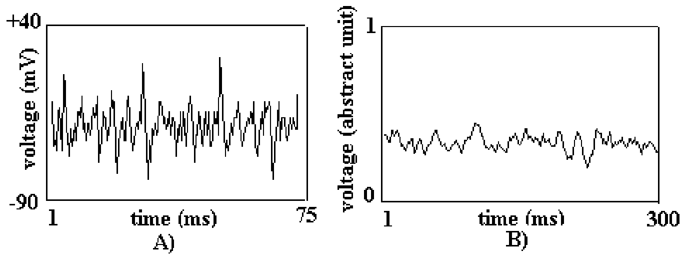

Fig. 4. Brain recordings: A) single electrode recording from macaque visual cortex; B) surface EEG recording from cat visual cortex.

3.2 Simulation data

We simulate the electrophysiological measurements for the model columns. To calibrate the time of the simulations we matched the average spike time spans to the average time spike times of the real data. In all cases we made 20 recordings with different randomized intial conditions.

For the single electrode recordings we selected a point in layer 4 of the model column and measured the variation of the axonic signal of all neurons situated in a relatively close neighbourhood of the simulated electrode tip. We summed the axonic signals considering a distance dependent weighting of the individual signals. For the EEG recordings we considered the dendritic signals in the whole simulated column. We summed the signals with distance dependent weighting. Figure 5 shows examples of the simulated data.

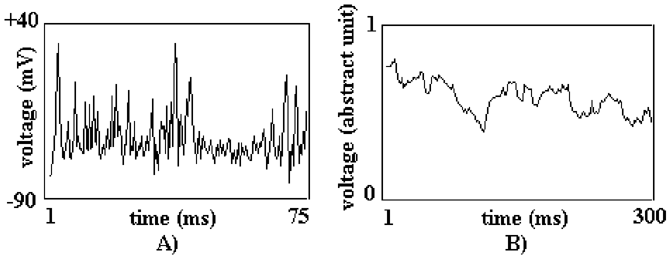

Fig. 5. Simulated brain recordings: A) single electrode recording from layer 4 of the classical model; B) surface EEG recording from the Sierpinski model.

4 Comparison

We compared the time and frequency structure of the real and simulated data, by comparing the autocorrelation and Fourier coefficients of the data series. The means and standard deviations of the coefficients were calculated for each data type. The mean values were compared with the t-test.

The results of the comparison of autocorrelation coefficients for single electrode recordings are shown in Figure 6. In this case the majority of the Fourier coefficients were situated in the 5% confidence interval of the real values for both models. The results show that the Sierpinski model data are more similar to the real data in terms of the autocorrelation structure than the data from the classical model.

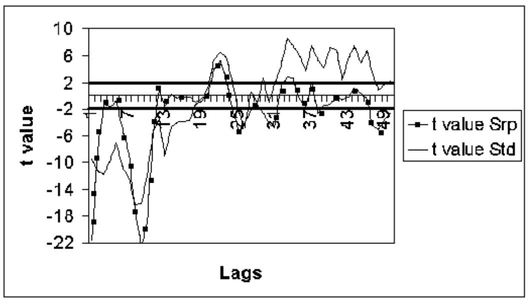

Fig. 6. The comparison of the single electrode recordings: Srp stands for the Sierpinski model, Std stands for the classical model. The graphs show how significantly the autocorrelation coefficients of the simulated data series differ from those of the real data series. The horizontal thick lines show the 5% signficance boundaries.

The results of the Fourier coefficient comparison for surface EEG recordings are presented in Figure 7. These results indicate that in these terms there is not very much difference between the two models. In terms of autocorrelation coefficients both models show significant difference from the real data for almost all coefficients.

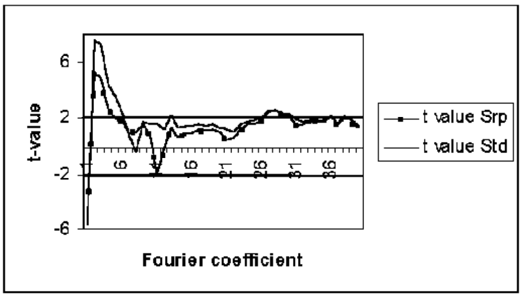

Fig. 7. The comparison of the surface EEG recordings: Srp stands for the Sierpinski model, Std stands for the classical model. The graphs show how significantly the Fourier coefficients of the simulated data series differ from those of the real data series. The horizontal thick lines show the 5% signficance boundaries.

5 Conclusions

We analyzed two neural network models to see to what extent can they produce realistic simulated electrophysiological measurements. The comparison shows that the Sierpinski model performs slightly better than than the classical model. The results suggest that more realistic activity pattern - based models may lead to even better fits with the real data.

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