The Sixteenth International Symposium on Artificial Life and Robotics 2011 (AROB 16th '11),
B-Con Plaza, Beppu,Oita, Japan, January 27-29, 2011

Signal transmission in multilayer asynchronous neural networks

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Abstract: It is believed that common input to nearby neurons leads to their synchronous spiking. However, recent studies have shown that recurrent neural networks can generate an asynchronous state characterized by low mean spiking correlations despite substantial amounts of shared input. The asynchronous state is generated by the interaction of excitatory and inhibitory populations, which is called active decorrelation. Here, we investigate the advantage of the active decorrelation on signal transmission in multilayer neural networks. The results of numerical simulations show that the active decorrelation is suitable for transmission of rate code because it can suppress the layer-by-layer growth of correlation.

Keywords:Neural Networks, Asynchronous States, Active Decorrelation.

1 Introduction

It is thought that brains process information by the temporal and spatial patterns of neuronal firing. Previous studies showed that synchronous firing plays functional roles such as binding information. However, a recent experiment [1] has shown that the correlation of neuronal firing in monkey's V1 is extremely low, and a theoretical study[2] has proposed the mechanism that can generate an asynchronous state although neurons share a large amount of input. The asynchronous state is generated by the effect of balanced excitatory and inhibitory populations, which is called active decorrelation. In this study, we investigate the advantage of the active decorrelation for information processing by numerical simulations. We investigate how the active decorrelation improves transmission of rate code in multilayer neural networks.

2 Methods

2.1 Model Description

As mentioned earlier, we consider multilayer neural networks that transmit rate code (see Fig. 1). This network structure corresponds to the hierarchical organization in the real brains. For example, visual information is transmitted through retina, LGN, V1, V2, and so on. Although it is known that brains send top-down signals to process information effectively, here, we do not consider such feedback connections for simplicity.

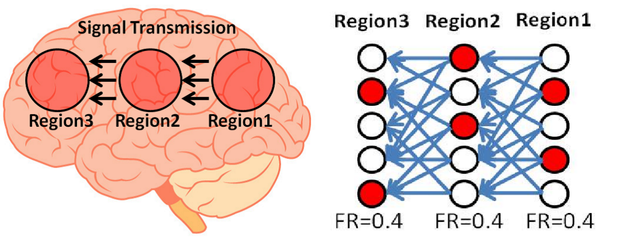

Figure 1: Transmission of rate code in a multilayer network. FR, firing rate.

2.1.1 Neuron Model

Here, we use McCulloch-Pitts model[3], which is the simplest and popular neuron model. The model outputs 1 if the sum of input from other neurons exceeds the threshold . If not, it outputs 0. The model's equation can be described as follows:

$$x_i(t+1) = 1[\sum_j w_{ij} x_j(t) - \ ], \quad (1)$$

where w_{ij} is the conection strength from jth neuron to ith one, is the threshold, and 1[u] is the step function:

$$1[u] = \begin{cases} 1 & (u \geq 0) \\ 0 & (u < 0) \end{cases} . \quad (2)$$

2.1.2 Network

The network architecture of our model is shown in Fig. 2. X is external input consisting of excitatory neurons, E denotes an excitatory population, and I denotes an inhibitory population. The number of neurons in each populations is N=1000, and neurons are connected with probability p=0.2. The layers correspond to the regions in Fig. 1. The inter-layer connections of the model in Fig. 2 are only from excitatory populations because it is known anatomically that axons of excitatory neurons are longer than those of inhibitory neurons. Axons mean a part of neurons which play a role of connection. Detail of parameter settings are the same to the Renart's study[2].

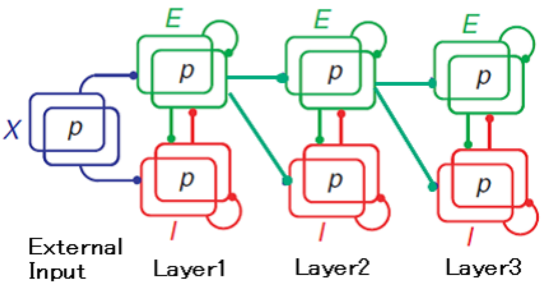

Figure 2: Schematic of the network architecture.

2.2 Evaluation

2.2.1 Rate Code

Rate code is one of the important information representations in brains. In this study, we consider mean firing rate that is the number of firing neurons divided by the population size. So the range is [0,1]. In other words, a neuronal population represents one scalar value. Here, we investigate the efficiency of transmission of rate code signals when the active decorrelation works effectively (active decorrelation ON) and when it does not (active decorrelation OFF).

2.2.2 Correlation

We evaluate whether the system is in synchronous states or in asynchronous states by calculating correlation of neuronal activities in each layer. The correlation is calculated as follows:

$$r_{ij} = \frac{\sum_{t=1}^{T}(\mathbf{E}_i(t)-\overline{\mathbf{E}}_i)(\mathbf{E}_j(t)-\overline{\mathbf{E}}_j)}{\sqrt{\sum_{t=1}^{T}(\mathbf{E}_i(t)-\overline{\mathbf{E}}_i)^2}\sqrt{\sum_{t=1}^{T}(\mathbf{E}_j(t)-\overline{\mathbf{E}}_j)^2}}, \qquad (3)$$

where r_{ij} is the correlation between ith neuron and jth neuron, $\mathbf{E}$ is the time series of neuronal activities represented by 1 (firing) and 0 (rest). $\overline{\mathbf{E}}_i$ means the time average of $\mathbf{E}_i(t)$. We consider the average of r_{ij} over all the pairs in a population as the correlation of the population.

2.2.3 Time Response

Vreeswijk et al.[4] mentioned that the response time of the population rates is shorter than the time constant of single neurons in the balanced state. Here, we check the phenomenon by changing the firing rate of external input m_X according to a sine curve and measuring the lag of the peaks of population rates between layers.

3 Simulation Results

3.1 Transmission of Rate Code

The response against sine input is shown in Fig. 3. Each line means each layer's firing rate. The active decorrelation is ON in Fig. 3 (A) and OFF in Fig. 3 (B). We change the parameter , which is the relative time constant of inhibitory neurons against excitatory ones, to switch between active decorrelaion ON and OFF. is set to 1 in Fig. 3 (A) and 2 in Fig. 3 (B). The system transmits rate code clearly when the active decorrelation is ON.

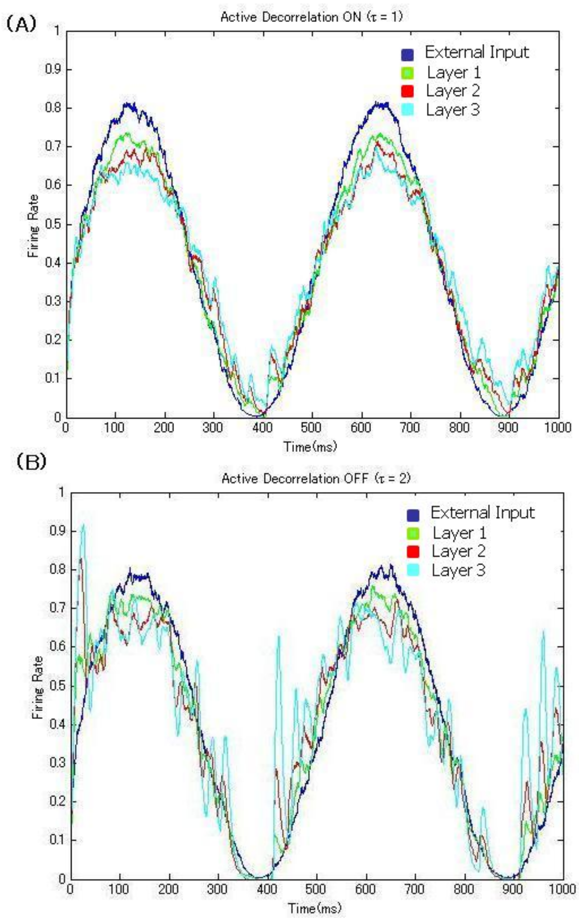

Figure 3: Time series of the firing rate of each excitatory population in response to a sinusoidal input.

The correlation and raster plots are shown in Fig. 4 where external input m_X is fixed to 0.1 to check whether the active decorrelation creates an asynchronous state. The blue dots in Fig. 4 represent neuronal firing. Vertical stripes mean synchronous firing of neurons. You can see that layer 3 is in a highly synchronous state when the active decorrelation is OFF. The active decorrelation suppresses the layer-by-layer growth of correlations, and it is suitable for transmission of rate code.

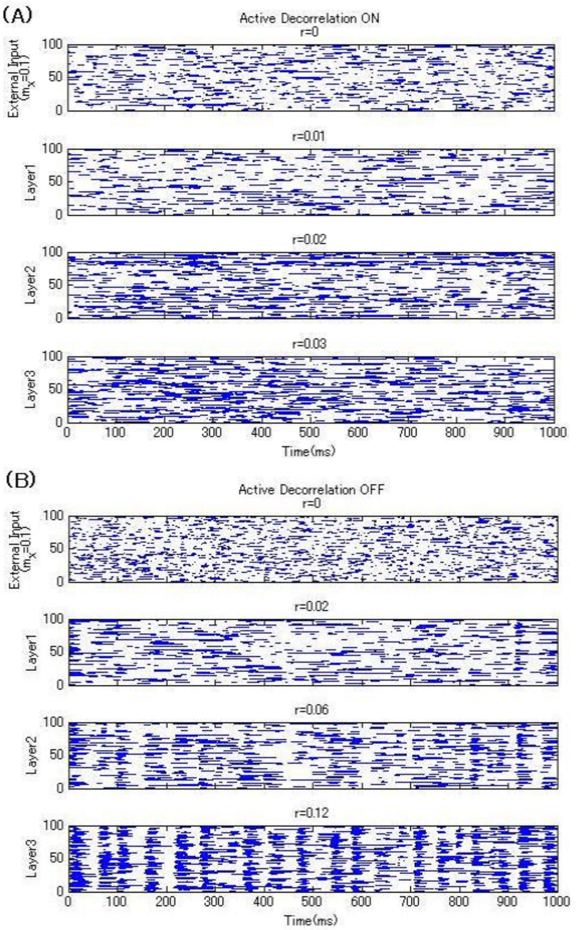

Figure 4: Raster plots and the correlations of neuronal firing in multilayer networks.

By carefully checking Fig. 3 and Fig. 4, you can find some features. In Fig. 3(A), the rough profile of the sine curve is transmitted well but the correct values are not. For example, the peaks of the firing rates are about 0.8 in external input, 0.7 in layer 1, 0.65 in layer 2 and 0.60 in layer 3. It is thought that the values of the firing rates decay because of the deviation from linearity in the input-output relationship, as shown in Fig. 5.

The intersection is about 0.5 in Fig. 5. It is the equilibrium point because signals converge to the intersection when they are transmitted through layers repeatedly. It is easy to check if the intersection is stable or not. We denote the value of the intersection as a and the response curve of layer 1 as f. Here, a is about 0.5, and f is the red line

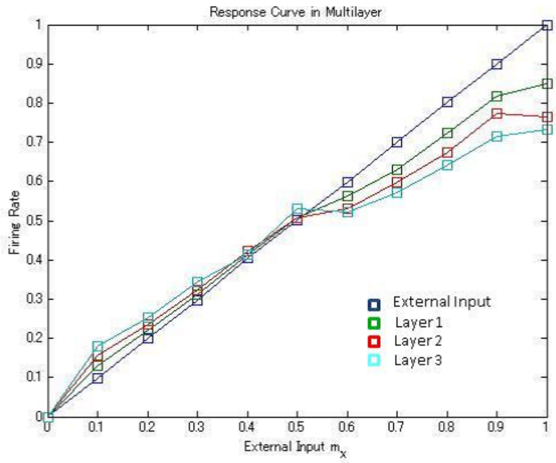

Figure 5: Firing rates in excitatory populations against external input. The active decorrelation is ON.

in Fig. 5. If $f'(a) > 1$, a is an unstable fixed point, and the firing rate converges to 0 or 1 depending on the initial condition. If $f'(a) < 1$, a is a stable fixed point, and the firing rate converges to a. For the above reason, the only perfect linear system can transmit rate code in infinite layers, and such a perfect one can not exist. So what we can do for good transmission of rate code is to make the response curve closer to linear one. This problem of response curves between layers has been mentioned by Litvak[5].

In this paper, we have shown two problems to transmit rate code in multilayer networks. One is the layer-by-layer increase of correlation. The other is the nonlinearity in the response curves. We have shown that the former problem can be resolved by the active decorrelation.

3.2 Time Response

We investigate another advantage of the active decorrelation—time response. As the frequency of external

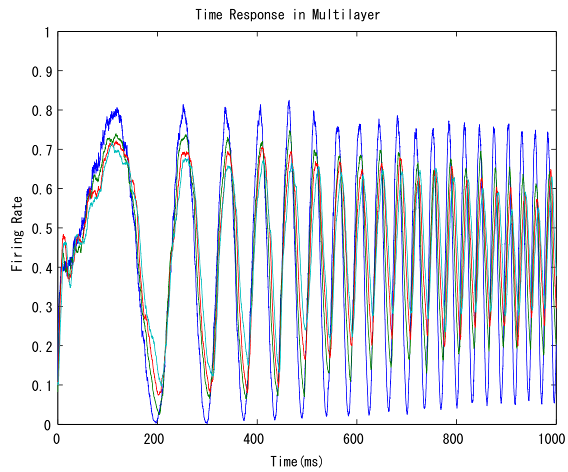

Figure 6: Responses to a sinusoidal input with increasing frequency. The active decorrelation is ON.

input m_X increases in Fig. 6, the time lag becomes apparent. You can see the lag is several milliseconds between successive layers in Fig. 7 which is an enlarged view of Fig. 6. In this model, the time constant of one excitatory neuron is 10 ms, so the populations track the signal changes quickly as compared with the time constant. A previous study[4] has shown theoretically that such a quick tracking occurs in balanced states. The study showed that the lag decreases in proportion to $1/\sqrt{K}$, where K is the number of connections per neuron. We have shown that such a quick tracking also occurs in multilayer networks.

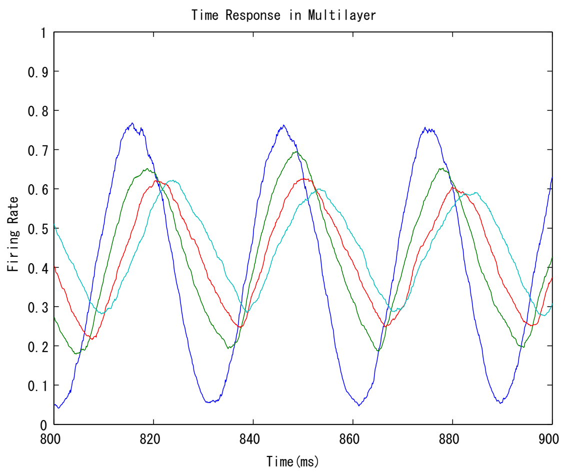

Figure 7: An enlarged view of Fig. 6 in the range from 800 to 900 ms.

3.3 Characteristic Frequency

Another point that we can find from Fig. 3 and Fig. 4 is that a synchronous network has a characteristic frequency. In Fig. 4(B), synchronous firing which is represented as vertical stripes is observed in layer 3, and it seems to be periodic. We set external input to various frequencies in the situation of active decorrelation "OFF" (= 2) to check its periodicity. An interesting phenomenon like sympathetic vibration is observed in Fig. 8. It is not observed against higher frequencies. So we can conclude that the network with the active decorrelation OFF has a characteristic frequency. It can play a role as oscillator in vivo. Further parameter analysis would be required to check whether the phenomenon occurs broadly.

4 Conclusion

We have investigated the advantage of the active decorrelation for transmission of rate code in multilayer neural networks. However, the active decorrelation seems incompatible with other codes such as temporal code. So it can be thought that the brains use both synchronous and asynchronous states depending on the situation and areas of the

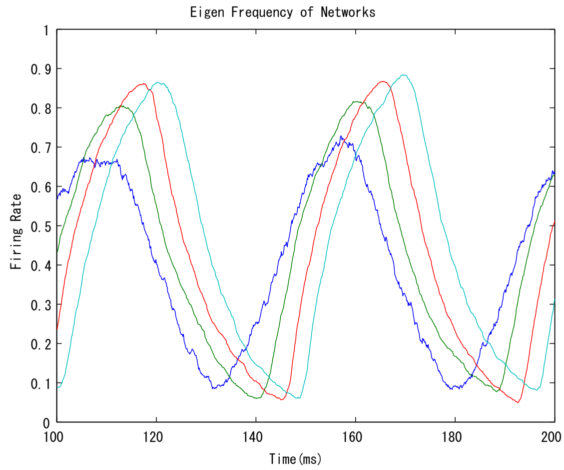

Figure 8: Sympathetic vibration in a synchronous network. The active decorrelation is OFF.

brain. We have also observed the existance of characteristic frequencies in synchronous networks. The networks seem to have a range of resonant frequencies, and it is our future problem to check the generality of the phenomenon.

Acknowledgements

This research is partially supported by the FIRST program, Grant-in-Aid for Scientific Research (A) (20246026) and Grant-in-Aid for JSPS Fellows (21·937) from JSPS.

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