Synchronous Dynamics in Realistic Neural Networks and Possible Mechanisms of Selective Memory

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Abstract

Our previous studies have shown that the realistic neural network in a certain parameter domain can produce a synchronous "burst-like" behavior induced by a random impulse input in a narrow window of discharge rate. It has been suggested that the RNN might play a role of a recognition element that selectively produces a synchronous activity in response to relevant stimuli. In the present study, this hypothesis was tested in computer simulations. Static part of the interneural connections (long-term memory of the RNN) has been shaped up using the Hebbian rule. Various sets of images (from 1 to 4 per set depending upon an experimental condition) have been fed into the memory of the 2D RNN. The following results were obtained. If one stimulus is memorized, its presentation induces a burst-like behavior in which the stimulus is recalled by bursts. Further, if several (up to 4) stimuli are memorized, the presentation of the superposition of these stimuli to the RNN produces a complex burst-like behavior in which separate memories are extracted in separate bursts. These data enable us to suggest that the RNN can be used for separation of object against background.

Introduction

During the last few decades a vast amount of empirical knowledge has been obtained in neuroscience indicating existence of temporal coding of sensory information in the cortex (for review see [1], [2]). The temporal coding is manifested in synchronous oscillations of impulse activity of neurons and local field potentials induced by stimuli in frequency band about 40 Hz. The functional role of this kind of activity is still unclear. The main hypothesis shared by a majority of investigators suggests that temporal correlation of neuronal discharges may serve to bind a distributed neuronal activity into unique representation.

The idea of distributed nature of information processing in the brain appeared in 60th and was associated with holographycal representation of information [3], [4]. In the modern neuroscience the distributed nature of information processing received a new experimental and theoretical support. The attempt to build up a theory of parallel distributed processing on the basis of modern neuroscience has been made in the 80th [5], [6].

In this paper, a realistic neural net (RNN) is suggested to implement some of the features of temporal coding in the cortical areas.

Description of RNN

The realistic neural net is based upon neurophysiological data concerning neuronal membrane dynamics and synaptic short-term plasticity (for more detail see [7]-[10]). It consists of 2D array of neurons interconnected with each other via dynamical synaptic connections. Each unit *i* of the net is characterized by a time-varying potential $P_i(t)$ that changes according to the following equation:

(1) $\mathrm{P}_\mathrm{i}(t+1)=0$ and $N_i(t+1)=1$, if $P_i(t)>\Theta$

(2) $N_\mathrm{i}(t+1)=0$ and $\mathrm{P}_\mathrm{i}(t+1)=(1-\alpha)\mathrm{P}_\mathrm{i}(t)+\sum_{j\neq i} W_{ij}(t)N_j(t)+S_i(t)$, if $\mathrm{P}_\mathrm{i}(t)<\Theta$

Short term alterations of interneural connections $W_{ij}(t)$ are described by two different presynaptic processes: ***depression*** - a decrease of connection efficiency after spiking of the presynaptic neuron, and ***potentiation*** - an increase of efficiency after spiking of the presynaptic neuron. Each of above mentioned processes decays with different time constant, thus providing a complex dynamic of connection efficiency. A linear approximation of the synaptic weight is defined as follows:

(3) $W_{ij}(t)=\left(X_{ij}^{(1)}(t)+X_{ij}^{(2)}(t)+K\right)W_{ij}^{(0)},$

where $X_{ij}^{(1)}$ describes the synaptic potentiation, $X_{ij}^{(2)}$ describes the synaptic depression and K represents the constant part of the synaptic strength. $X_{ij}^{(1)}(t)$ and $X_{ij}^{(2)}(t)$ are defined as follows:

(4) $X_{ij}^{(1)}(t+1)-X_{ij}^{(1)}(t)=a_1X_{ij}^{(1)}(t)+b_1N_j(t)$

(5) $X_{ij}^{(2)}(t+1)-X_{ij}^{(2)}(t)=a_2X_{ij}^{(2)}(t)+b_2N_j(t)$

Where it is supposed that $a_1<0$, $a_2<0$, $b_1>0$, $b_2<0$ and $a_{1,2}<<\alpha$ that reflects the suggestion that a potential changes much more quicker than a synaptic strength does. The matrix $W^{(0)}$ mimics a long-term memory of the RNN - a static part of interneuronal connections. Prior studying the dynamics of the RNN, a set of M stimuli $\left\{\xi_i^{(m)}\right\}_{m=1}^{M}$ was fed into long-term memory. The matrix $W^{(0)}$ was defined according to the Hebbian rule:

(6) $W_{ij}^{(0)}=\sum_{m=1}^{M}\xi_i^{(m)}\xi_j^{(m)},$

where summation is made over all stimuli $\left\{\xi^{(m)}\right\}$.

On the next step, the dynamics of the RNN elicited by the superposition of the memorized stimuli $\sum_{\forall m} \xi_{ii}^{(m)}$ was studied. According to neurophysiological observations, the external stimuli were simulated as random and independent impulse trains fed into corresponding neurons of the net. They were defined as follows:

(7) if $\nu \le P_{st}$ then $S_i(t) = \sum_{\forall m} \xi_i^{(m)}$ else $S_i(t) = 0$

where ν is a random value from the unit interval and P_{st} is positive constant which defines spatial frequency of the trains.

Noisy impulse trains of certain frequency P_{ns} and amplitude A_{ns} were added to the above mentioned stimuli, thus simulating a noise in the nervous system.

Results of computer simulation and discussion

Computer simulations of the model were performed on IBM PC. The membrane potential and impulse activity of neurons of the RNN were sequentially computed according to equations (1-7). Impulsation of neurons of the RNN at each instance *t* was visualized on the computer screen together with dynamics of averaged (across all neurons) discharge rate, potential and synaptic weight. Computer experiments were carried out with 1, 2, 3 and 4 external stimuli. Examples of two of these stimuli are presented in Fig.1.

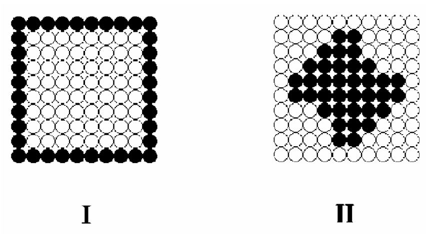

Fig.1: View of two stimuli that were implemented into the long-term memory and used as a source of the external random trains entered to the network. The set of parameters was as follows: a_1=b_1=0, a_2=-0.1, b_2=-0.9 and K=0.5. Amplitudes of both of the stimuli were the same and equal to 0.55. Amplitude of noise was chosen to be equal 0.24. Spatial frequencies of stimuli and noise were the same and equal to 0.5, that is, on each step approximately half of the neurons have been receiving the external input.

The parameters of the model were chosen on the basis of the previous studies. The exact values of the parameters, used in the present computer experiments, are shown in legend to Fig.2. It should be stressed here that these parameters were chosen from the certain domain of parameter space, which defined a burst-like behavior of the RNN.

The results of one of computer experiments are presented in Fig.2. One can see that neurons of the RNN does not fire randomly (note that they receive a stochastic input), but produce bursts. The most striking feature of the behavior was that almost each burst matched one of the memorized stimuli (marked by **I** and **II** in Fig.2). Rare bursts (only few percents) corresponded to superposition of the stimuli (marked by **I+II** in Fig.2).

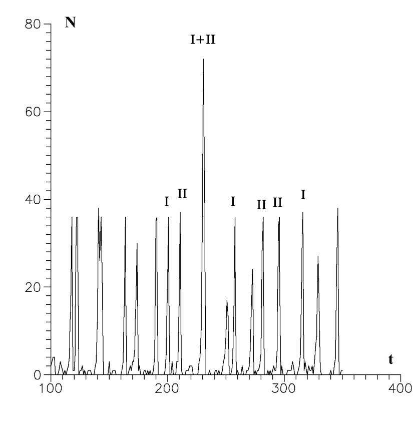

Fig.2: Plot of spike activity *N(t)* of the network. Bursts correspondent to one or another stimulus are noted by the same roman number as the very stimuli in Fig.1.

Prerequisites for emergence of burst-like behavior are as follows. First, the synaptic strength $W^{(0)}$ should be strong enough to provide "a positive feedback". Namely, the synaptic potential which is produced by discharge of a neuron should be larger than the membrane potential which the neuron "loses" after its discharge. Second, the synaptic depression should be also strong enough to provide "a negative feedback". Namely, the synaptic strength should decrease effectively after neuronal discharge. A competition of these two feedback can lead to burst-like behavior. It should be noted, that the burst-like behavior can be produced in a rather small range of input frequency. This frequency should not be too small because otherwise the input is not able to initiate an avalanche. On the other hand, this frequency should not be too big because otherwise the depression would dominate in the competition.

Application of learning procedure (the Hebbian rule, in this paper) leads to strengthen of synaptic weights which in turn leads to establishing a positive feedback, and, consequently, to producing burst-like behavior. This behavior can be induced only by appropriate stimuli or their parts. Bursts occur at random intervals. Interestingly, that when a superposition of memorized stimuli is presented each burst corresponds to a separate image.

Summary

The bursts produced by our model can be considered as oscillations that incorporate a synchronous activation of neurons corresponding to a memorized stimulus. Similar synchronous activity was observed in the visual cortex and olfactory system [1], [2]. Our studies enable us to suggest that a synchronous activity could be responsible for extraction of traces from memory. Moreover, if two images are presented simultaneously, memories of these objects are not superposed but are rather extracted independently (at the corresponding time scale). This characteristics of the RNN can explain the phenomenon of extraction of object against background.

References

[1] Engel A.K., Konig P., Kreiter A.K., Schillen T.B., Singer W. (1992) "Temporal coding in the visual cortex: new ideas on integration in the nervous system", *Trends in Neuroscience*, Vol. **15**, No.6

[2] Freeman W.J. (1990) "On the Problem of Anomalous Dispersion in Chaoto-Chaotic Phase Transitions of Neural Masses, and Its Significance for the Management of Perceptual Information in Brains", **in:** *Synergetics of Cognition*, **eds.:** H.Haken and M.Stadler, Springer-Verlag Berlin, Heidelberg. Vol. **45**

[3] Pribram, K.H. (1971). Languages of the brain: Experimental paradoxes and principles in neuropsychology. Englewood Cliffs, NJ: Prentice-Hall.

[4] Barret, T.W. (1969). The cortex as interferometer: The transmission of amplitude, frequency, and phase in cortical structures. *Neuropsychologia*, **7**, pp. 135-148.

[5] Hopfield, J.J. (1982) *Proc. Natl. Acad. Sci. USA* **79**

[6] McClelland, J.L., Rumelhart, D.E.& Hinton, G.E. (1986) "The appeal of parallel distributed processing" **In:** *Parallel Distributed Processing. Explorations in the microstructure of cognition.* **Eds.:** J.L. McClelland, D.E.Rumelhart & the PDP Research Group, Vol.1: Foundations. Cambridge, MA/London, U.K., A Bradford Book, The MIT Press: pp.30-44.

[7] Kropotov, Ju.D., Pakhomov, S.V. (1981) *Fizeologiya Cheloveka*, vol.7, p.152 (in Russian)

[8] Kropotov, Ju.D., Pakhomov, S.V. (1983) *Fizeologiya Cheloveka*, vol.9, p.787 (in Russian)

[9] Kropotov, Ju.D., Pakhomov, S.V. (1984) *Fizeologiya Cheloveka*, vol.10, p.813 (in Russian)

[10] Mardanov K., Pismak Yu., Potyagailo A. (1996) "General Properties of Realistic Neural Network Dynamics.", *Mathl.Comput.Modelling* (to appear)