A Novelty Detector Using a Network of Integrate-and-Fire Neurons

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Abstract. Information in the nervous system has often been considered as being represented by simultaneous discharge of a large set of neurons. We propose a learning mechanism for neural information processing in a simulated cortex model. Also, a new paradigm for pattern recognition by oscillatory neural networks is proposed. The relaxation time of the oscillatory networks is used as a criterion for novelty detection.

1 Introduction

Representation of information in the nervous system has often been considered as being contained in simultaneous discharge of a large set of neurons. How does a neural system use that kind of information representation while performing learning and pattern recognition ? Recent studies on nonlinear cooperative complex dynamics in neural systems provided various kinds of models that described the cooperative behavior such as synchronization and chaos. In [6], Thiran and Hasler present a valuable overview on this approach. Hayashi [2] present an interesting characteristic of an oscillatory network: a limit cycle near a memory pattern (memory retrieval with ambiguous fluctuation) for an input closed to it, and a chaotic orbit wandering among memory patterns (autonomous search) for an input far from them. It is not easy to identify dynamical behavior. Stassinopoulos and Bak [5] propose a self-organizing model with a capability to interact with the surrounding environment. Self-organizing behavior arises by interaction between non-fixed threshold neurons and by feedback from environment. Although the model displays a rich dynamical behavior, it is still not clear how to associate patterns to the network's states. Dayhoff [1] proposes a learning mechanism that allows a Hopfield network having a rich dynamic behavior including fixed point, limit cycle and chaotic attractors. She also shows that the network can have many attractors and it overcomes the limitation of the original Hopfield model. However, we still do not know how to associate patterns to these behaviors, in other words, how to apply this network model for recognition problems. In fact, we need a way to manipulate the chaotic behaviors.

Hill and Villa [3] developed neural models to study the spatiotemporal pattern generation properties in a simulated "cortical neural network". The model uses integrate-and-fire neurons as elementary units. Furthermore, the topology is inspired from that of layer IV in the cortex. Although this model helps to observe the evolution of spatiotemporally organized activity in a simulated cortex, the learning rule is not yet proposed. In this paper, we propose a learning mechanism for neural information processing in the simulated cortex model. Along with the learning mechanism, we propose a new paradigm for pattern recognition by oscillatory neural networks. The relaxation time of oscillatory behavior was used as a criterion for novelty detection.

2 Neuronal Model

Our neuron model was inspired from the integrate-and-fire neuronal model proposed by Hill and Villa [3] with refractory period and post-synaptic potential decay. The state of the neuron at time t, is deterministically modeled by a control potential, U as:

$$S_i(t) = \begin{cases} 0 & \text{if } (t - t_{spike}) < \rho, \\ \mathcal{H}[U_i(t) - \theta] & \text{otherwise,} \end{cases} \tag{1}$$

where $\mathcal{H}$ is the Heaviside function defined as $\mathcal{H}[x] = 1$ for $x > 0$ otherwise $\mathcal{H}[x] = 0$. The value t_{spike} represents the last firing time for unit i. The value ρ denotes the absolute refractory period. Refractoriness corresponds to the period following the production of a spike or action potential, during which the cellular biochemical mechanisms cannot generate another signal, regardless of the strength of the stimulation. The control potential is defined as the integration of all afferent postsynaptic potential at time t:

$$U_i(t+1) = \sum_i C_{ij} S_j(t) + U_i(t) + s_i \tag{2}$$

where the indices i and j indicate the units, C is the connection strength, and s is the input signal.

In order to introduce the influence of the firing frequency into the neuron's behavior, we added a variable firing frequency factor f to the neuron model. Simulating experiments showed that this factor has a strong influence in the neuron's behavior. Thus, the equation (2) becomes

$$U_i(t+1) = \sum_i C_{ij} S_j(t) + U_i(t) + s_i + f_i. \tag{3}$$

3 Network Architecture

The network architecture was inspired from an oversimplified model of cortical layer IV [3]. This model defines a single two-dimensional sheet of excitatory and inhibitory neurons with recurrent connections. The layer consists of two populations of neurons interspersed within the plane. These neurons are positioned according to a space-filling pseudo-random Sobol distribution. Each neuron has a set of interconnections chosen according to a square neighborhood, centered at the neuron itself and with a radius depending on whether the neuron is excitatory or inhibitory. From this topology, we can say that this model uses an interactivity at local level to create a self-organizing evolution. Here, we want to modify the model by introducing an interactivity at global level with a global inhibitor (Fig. 1). By this approach, we can create an interactivity between all neurons in the network. The global inhibitor is actually a trigger whose state is either active, i.e. firing, or inactive depending on a control mechanism. The control mechanism is based on a threshold for the total number of of firing neurons. Whenever the number of firing neuron at a time t is above the threshold, the global inhibitor fires and it generates a negative feedback signal to every neuron in the network. Otherwise, if the number of firing neurons is below th threshold, the global inhibitor generates a positive feedback signal. Thus, the global inhibitor plays a role of regulating neuron activity at global level. With a feedback signal h, the equation (3) becomes:

$$U_i(t+1) = \sum_i C_{ij} S_j(t) + U_i(t) + s_i + f_i + h(t). \tag{4}$$

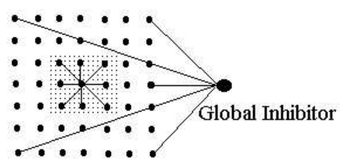

Fig. 1. The architecture of the neural network

4 Learning Rule

The learning rule, that modifies the coupling strengths, is widely used in many kinds of neural network models. In our model, there are two kinds of coupling: one is between neighboring neurons and the other is between the global inhibitor and all neurons. The Hebbian rule was used as updating rule for the coupling weights. The following equation is used for the coupling weights between a pair of neurons:

$$C_{ij}(t+1) = C_{ij}(t) + \alpha C_{ij}(1 - C_{ij}) S_i(t) S_j(t) \tag{5}$$

where α is the learning rate. The coupling weights between each neuron and the global inhibitor are updated according to:

$$G_i(t+1) = G_i(t) + \beta G_i(t)(1 - G_i(t)) S_i(t) h(t) \tag{6}$$

where G_i is the coupling weight of the neuron i, β is the update rate and h is the feedback signal from the global inhibitor.

Learning phase starts when the network is stimulated by an input signal. The network begins to oscillate. At each instant, the coupling weights of a neuron are updated if this neuron fires. It receives also a feedback signal. The later is either negative or positive depending on if the number of firing neuron is above or below the threshold of firing neurons. The network is considered to reach a stable state when its local coupling weights do not change anymore or they change in a very small given range. When the network reaches a stable state, the learning phase terminates.

5 Novelty Detection by this Model

The proposed network model is a non linear dynamical system. How can the evolution of dynamical systems be associated with the execution of cognitive tasks ? We need to find a paradigm that can be used to characterize dynamical evolution inside the system so that it can be applied to pattern recognition. We observed from simulating experiments, we have observed that the dynamical network can reach a stable state very quickly if the input signal has already been seen. From this observation, we propose a new paradigm for novelty detection by this network model. The paradigm is comprised of two phases:

+ *Learning phase*: the network with randomly initialized connection strengths is trained by training patterns. It reaches an equilibrium state after learning.

+ *Novelty detection phase*: patterns are introduced to the trained network. The network reaches an equilibrium state after a relatively small number of iterations if these patterns have been learned before. Otherwise, it takes a long time for the network to reach an equilibrium state. Based on the relaxation time, novelty detection can be done by our neural network model.

In the following, we show an example of ths paradigm to novelty detection by our neural network model. A set of 0-9 digits is used as a pattern set in this paper. As seen in Fig. 2, each digit pattern is coded by using a 7x5 binary pixel matrix. In order to test the robustness of the network, a set of noisy patterns obtained from the original patterns is also used. The noisy patterns are created by adding a certain amount of noise to the original pattern images [Fig 2., right]. In other words, given an amount of noise (by percentage), a number of pixels in the patterns are changed. The pixels are randomly chosen with a uniform probability distribution. As in this experiment, with a 20% of noise, 7 pixels in each 7x5 pixel image have their value changed. Though the pattern images used herein are binary images, our network can manipulate analog images (i.e. real numbers can be manipulated by the network). For the experiments in this paper, we used a 7x7 dimension network with 70% population being excitatory neurons and the remaining 30% being inhibitory neurons. The pattern image is positioned at the center of the network plane.

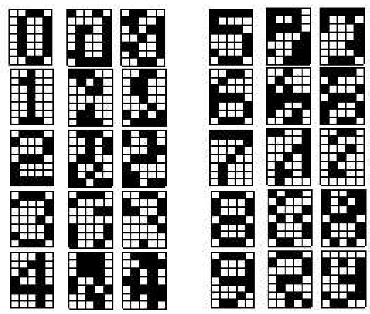

Fig. 2. Patterns of 0-9 digits with 20% noise

The digit patterns from 0 to 4 are used to train the network. The pattern is presented sequentially into the network. The network oscillates and reaches an equilibrium state. When the network reaches a stable state, a new pattern is fed into it. In this experiment, the set of 5 patterns (0-4 digits) is presented to the network only one time. Oscillation times of patterns 0-4 are 351, 290, 321, 11, 307 iterations respectively. Note that oscillation time of the network is often dependent on the sequence of training data. After learning phase, we use either the noisy versions of learned patterns or a set of "never seen" patterns (5-9 digits) to test the ability of novelty detection of the network. According to the proposed paradigm, we use the relaxation time (in term of number of iterations) of the network during testing phase as a criterion to decide whether a pattern is "seen" or "never seen" by the network. A short relaxation time means that the pattern has been seen before. Otherwise, the pattern has never been seen before. Table 1 shows that the network has a short relaxation time (11 iterations) when the testing patterns are either the learned patterns or the noisy patterns of the learned patterns. In contrast, the network has a significant long relaxation time (271 or 162 iterations) when the testing patterns have never seen before. The network made recognition mistakes on 3 patterns (noisy version 2 of patterns 3, 7 and noisy version 1 of pattern 9), i.e. with an error rate of 10% (3/30).

In order to examine the network's performance, another test based on the initial training on digit [5-9] and testing on digits [0-4] was also done. During training, oscillation times of patterns 5-9 are 183, 132, 148 11 and 11 iterations respectively. The testing result is given in Table 2. The network made more recognition mistakes than previous test with an error rate of 23% (7/30). Ongoing works are focues to improve recognition performance of the network. In addtion, theoretical analysis is left as a future work.

6 Conclusion

A new paradigm for pattern recognition by non linear systems is proposed in this study. This paradigm is based on a criterion that is the time of oscillation of the network when a pattern is injected into it. In other words, the relaxation time is

Table 1. Relaxation time of the network trained on digits [0-4] and tested on [0-9]

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	11	11	11	11	11	271	271	162	271	271
Noisy version 1	11	11	11	11	11	271	271	162	271	11
Noisy version 2	11	11	11	271	11	271	271	11	271	271

Table 2. Relaxation time of the network trained on digits [5-9] and tested on [0-9]

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	11	152	153	11	143	11	11	11	11	11
Noisy version 1	153	152	153	11	152	153	11	11	11	153
Noisy version 2	11	153	153	11	143	11	11	11	11	11

used to decide whether a pattern has ever been seen before. A short relaxation time implies that the pattern has been already seen. Otherwise, a long relaxation time implies that the pattern has never been seen. This paradigm allows us to develop novelty detection systems based on the proposed network model with capability against noise as well as spatiotemporal transformation.

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