Novelty Detection Based on Relaxation Time of a Network of Integrate-and-Fire Neurons

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Abstract

We propose a neural network model inspired from a simulated cortex model. Also, a new paradigm for pattern recognition by oscillatory neural networks is presented. The relaxation time of the oscillatory networks is used as a criterion for novelty detection. We compare the proposed Neural Network with Hopfield and back-propagation networks for a noisy digit recognition task. It is shown that the proposed network is more robust. This work could be a possible bridge between nonlinear dynamical systems and cognitive processes.

1 INTRODUCTION

The processing or the recognition of non stationary noisy process with Neural Networks is a challenging and yet unsolved issue. Most of the contemporary pattern processing or recognition techniques assume that the pattern or the time series to be recognized are stationary. Furthermore, in real life applications, the information is most of the time corrupted, partial or noisy (image, speech, etc.). Therefore, the pattern recognizers have also to be robust.

Among the many neural network works that are reported in the literature, we can find neural networks with complex behavior or dynamics. These networks are sometimes called 'chaotic neural networks' by some authors. We are interested in evaluating neural networks with complex dynamics as potential recognizer systems of non stationary noisy processes. In the present work we propose an oscillatory network and we evaluate here the system on a noisy limited task.

Representation of information in the nervous system has often been considered as being contained in simultaneous discharges 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 provide various kinds of models that describe the cooperative behavior such as synchronization and chaos (Buonomano and Merzenich (1995), Destexhe (1994), Brown et al. (1996), Brunel (1994), Burkitt (1994), Matsuno (1994), Wang (1995)). Especially, Thiran and Hasler (1996) give a valuable overview on some principles for information storage and retrieval based on oscillations in dynamical systems.

Synfire chains have been proposed as a mechanism for neural information processing in the cortex by Abeles (1982). Hertz and Prugel-Bennette (1996) investigated whether synfire chains can be formed through a biologically plausible self-organizing mechanism. They proposed a network model of cortical neurons capable of learning synfire chains by introducing a Hebbian learning mechanism. However, this type of network is unstable against the formation of long synfire chains. Hill and Villa (1995, 1997) 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 neural network model that allows to study neural information processing in the cortex. The network model has the architecture inspired from that of layer IV in the cortex. Learning is based on a rewarding feedback mechanism. The system dynamics and the self-organizing process exhibit robustness against highly noisy input patterns. Along with the neural network model, we present a new paradigm for pattern recognition by oscillatory neural networks. The relaxation time of oscillatory behavior is used as a criterion for novelty detection. When input is similar to one of learned patterns, the network takes a very short time to go to an equilibrium state. In contrast, when input is different from any learned patterns, the network takes a long time to go to an equilibrium state.

2 NEURONAL MODEL

Our neuron model is inspired from the integrate-and-fire neuronal model proposed by Hill and Villa (1995) 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:

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

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 potentials at time t:

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

where the indices i and j indicate the units, C_{ij} is the connection strength, and s_i is the input signal.

In order to introduce the influence of the firing frequency into the neuron's behavior, we add 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, equation (2) becomes

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

Self-reference at local level is also used in our network model to increase the potential of self-organization of the network. The input signal is maintained until the network reaches a stable state. However, one can construct systems where the input signal is presented to the system at a short instant then disappears. In our model, the presenting time of an input signal is a variable parameter. It is demonstrated by experiments that the network is more robust when the input signal is maintained during a reasonable time. Also, the fact that input signal is maintained creates an interference between the input signal and all dynamical states of the network. It is somewhat a temporal summation at local level.

3 LEARNING WITH REWARDING FEEDBACK MECHANISM

The idea is inspired from the work of Stassinopoulos and Bak (1994) by which a global feedback signal is used as a rewarding feedback mechanism to stabilize the self-organizing activity of the network. In a fashion analogous to the behaviorist techniques used in the training of animal, the network is introduced with a set of external signals each of which rewards a specific action. The system learns to recognize all signals and choose the corresponding rewarding action. Learning and retrieving are two aspects of the same dynamical process. In the following, we apply this learning mechanism to the our neural network model.

The network architecture is inspired from an over-simplified model of cortical layer IV (Hill & Villa (1995, 1997)). 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. Excitatory and inhibitory neurons can have different neighboring radius. The rewarding feedback mechanism is implemented based on the firing activity of a set of neurons that are defined as output neurons. Output neurons are randomly chosen from the population of excitatory neurons (Figure 1). The output signal is the firing state of the set of output neurons. For each input signal, the network's action is considered successful if one or more neurons belonging to the set of output neurons are firing. If the network's action is successful, the feedback signal is positive. Thus, every neuron who is firing is reinforced with a positive feedback signal (+1). Otherwise, if the action is unsuccessful the feedback signal is negative and every firing neuron is reinforced with a negative feedback signal (-1).

In other words, if the network's action, stimulated by an input signal, is successful, all connections of firing neurons are reinforced, whether or not they participated in creating a successful action; if the action is unsuccessful, the connections of firing neurons are weakened. For updating the connection weights, the Hebbian updating rule is applied in this network model. Let h be the feedback signal (h = +1 or -1), the following equation is used to update the connection weights between a pair of neurons:

$$C_{ij}(t+1) = C_{ij}(t) + \alpha C_{ij}(1 - C_{ij}) S_i(t) S_j(t) h(t) \quad (4)$$

where α is the learning rate.

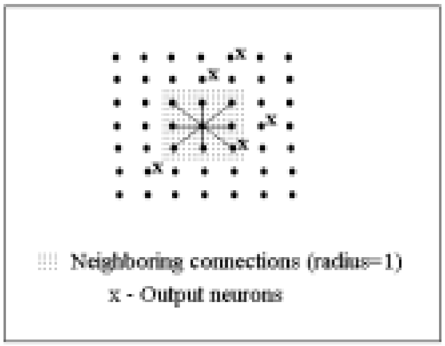

Figure 1. The architecture of the neural network.

In our work, we try to integrate the dynamics of firing activity of neurons and the interactivity between neurons. In fact, the input of each neuron is not only a spatial combination but implicitly a temporal combination of firing activity too. Along with a combination created by the feedback control signal, the network model has a spatiotemporally complex combination of signals. We hopefully think that the comlex dynamics of the network can help to catch and to manipulate the dynamics of input signals.

4 NOVELTY DETECTION

4.1 Novelty detection based on relaxation time

The proposed network model is a non linear dynamical system. How can the evolution of non linear 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 systems so that they can be applied to pattern recognition. We observed from simulating experiments that the dynamical network can reach a stable state very quickly if the input signal has already been seen. From this observation, we have proposed a new paradigm for novelty detection by oscillating network models (Ho & Rouat (1997)). The paradigm is comprised of two phases:

+ *Learning phase*: the network with randomly initialized connection strengths is trained with learning 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 present examples of this 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 Figure 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 [Figure 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 neighborhood radius is 2 for excitatory neurons and 1 for inhibitory neurons. The pattern image is positioned at the center of the network plane. Every neuron which is covered by the pattern image will receive input signal, even if it had been chosen as output neuron. Other neurons which are not covered by the pattern image will not receive any input signal (It means that input signal for these neurons is set to 0).

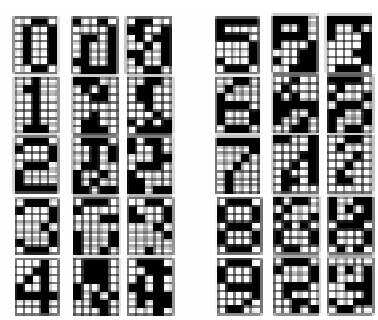

Figure 2. Patterns of 0-9 digits with 20% noise.

4.2 Experiment 1: Learning digit patterns [0-4]

4.2.1 Novelty detection by the network model

The digit patterns from 0 to 4 are used to train the network. Each pattern is presented sequentially to 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 the network stimulated by the patterns 0-4 are 332, 266, 347, 11 and 307 iterations respectively.

After learning phase, we use either the noisy versions of learning 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 has been "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 pattern. In contrast, the network has a significant long relaxation time (271 or 170 iterations) when the testing patterns have never been 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). Note that the network used in this experiment has a 7x7 dimension. It seems here that it can memorize about 5 patterns, i.e. 0.1N where N is the number of neurons of the network.

Table 1. Relaxation time of the proposed network trained on 'clean' 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	170	271	271
Noisy version 1	11	11	11	11	11	271	271	170	271	11
Noisy version 2	11	11	11	271	11	271	271	11	271	271

4.2.2 Comparison with a Hopfield network

Hopfield networks are interesting from a theoretical standpoint and can be used for classification. Therefore, comparing with them may give readers a view about the data set as well as about our model. We use the Hopfield network implemented in the MATLAB package (Demuth and Beale (1996)). Hopfield networks can act as vector categorization networks. Input vector are used as the initial conditions to the network, which recurrently updates until it reaches a stable output vector. This type of network may be used to store the exemplars or training patterns.

We use the same training pattern set (digits [0-4]) and testing pattern set (digit [0-9]) as in the previous test. We tried the Hopfield network with several dimensions: 35, 49 and 81 neurons. The network has an error rate of 27% (8/30), 23% (7/30) and 23% (7/30) respectively. We report in Table 2 the recognition result of the Hopfield network with 49 neurons. Indeed, this network has the same dimension as our network model.

Table 2. Novelty detection using a Hopfield network trained on 'clean' digits [0-4] and tested on digits [0-9].

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	y	y	y	y	y	n	y	y	y	y
Noisy version 1	y	y	y	y	n	y	y	y	y	n
Noisy version 2	y	y	y	n	n	n	y	y	y	n

'y' indicates that the pattern is correctly classified by the network. Otherwise, 'n' indicates that the pattern is not correctly classified. The unlearned patterns are considered being correctly classified if their corresponding recall patterns are differents from the learned patterns.

4.2.3 Comparison with a backpropagation network

Multilayer networks with the backpropagation learning are most widely used as pattern recognizers in the field. This comparison might let readers gain further understanding about our model and the nature of pattern data in this paper. Multilayer networks under the standard generalized delta rule with momentum (Eberhart & Dobbins (1992)) are used for our experiments.

The same training [0-4] and testing [0-9] pattern sets are used with backpropagation networks. Regarding the data set, a network with one input layer (35 neurons), one hidden layer and one output layer (5 neurons) is chosen. We tried the network with the hidden layer having 3, 5 and 10 neurons respectively. The network has an error rate of 30% (9/30), 27% (8/30) and 30% (9/30). Table 3 presents novelty detection result by the backpropagation network with the hidden layer comprising 5 neurons.

Based on the experiment on learning 'clean' digit patterns [0-4], we conclude that our model made the smallest error rate of 10% while the Hopfield and back-

Table 3. Novelty detection using a backpropagation network trained on 'clean' digits [0-4] and tested on digits [0-9].

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	y	y	y	y	y	n	y	y	n	y
Noisy version 1	y	y	y	y	y	y	y	y	n	n
Noisy version 2	y	y	y	y	y	n	y	n	n	n

'y' indicates that the pattern is correctly classified by the network. Otherwise, 'n' indicates that the pattern is not correctly classified.

propagation network made the error rate of 23% and 30% respectively.

4.3 Experiment 2: Learning digit patterns [5-9]

4.3.1 Novelty detection by the network model

One of the weak points of neural networks is that their recognition performance is effectively changed when they are trained by different input sets. In order to examine our network model, other test based on the initial training on digits [5-9] and testing on digits [0-9] was also performed. Simulation conditions are the same as in previous test. Oscillation times of the network stimulated by these patterns are 223, 340, 368, 313 and 11 iterations respectively during 'training'. Results are reported in Table 4. The network has more recognition mistakes than previous test with an error rate of 30% (9/30).

Table 4. Relaxation time of the proposed network trained on 'clean' digits [5-9] and tested on [0-9].

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	11	11	286	11	168	11	11	11	11	11
Noisy version 1	281	168	286	169	168	281	11	11	11	281
Noisy version 2	11	281	286	11	168	168	169	11	11	11

4.3.2 Comparison with a Hopfield network

We also performed novelty detection using the Hopfield network with several dimensions: 35, 49 and 81 neurons. The network has an error rate of 40%(12/30), 43% (13/30) and 40% (12/30) respectively. Novelty detection results using the Hopfield network with 49 neurons are reported in Table 5.

Table 5. Novelty detection using a Hopfield network trained on 'clean' digits [0-4] and tested on digits [0-9].

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	n	y	n	n	y	y	y	y	y	y
Noisy version 1	n	y	n	y	y	y	n	y	n	n
Noisy version 2	y	y	y	n	y	y	n	n	n	n

'y' indicates that the pattern is correctly classified by the network. Otherwise, 'n' indicates that the pattern is not correctly classified. The unlearned patterns are considered being correctly classified if their corresponding recall patterns are differents from the learned patterns.

4.3.3 Comparison with a backpropagation network

We performed novelty detection using the network with the hidden layer comprising 3, 5 and 10 neurons respectively. The network made an error rate of 33% (10/30), 30% (9/30) and 37% (11/30). Novelty detection results using the network with the hidden layer comprising 5 neurons are reported in Table 6.

Table 6. Novelty detection using a backpropagation network trained on 'clean' digits [5-9] and tested on digits [0-9].

Patterns	0	1	2	3	4	5	6	7	8	9
Original version	y	y	n	n	y	y	y	y	y	y
Noisy version 1	y	n	n	y	y	y	y	y	n	y
Noisy version 2	n	y	y	n	y	y	n	n	y	y

'y' indicates that the pattern is correctly classified by the network. Otherwise, 'n' indicates that the pattern is not correctly classified.

With the experiment on learning 'clean' digit patterns [5-9], our network model has the same error rate of 30% as the backpropagation network while the Hopfield network has the error rate of 40%.

5 CONCLUSION

Our neural network model is a result of an attempt to associate non linear dynamical systems with neural networks in order to treat spatiotemporal patterns. A new paradigm for pattern recognition by non linear systems is presented in this study. This paradigm is based on a criterion that is the time of oscillation of the network when a pattern is introduced into it. In other words, the relaxation time is 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 neural network model with capability against noise as well as spatiotemporal transformation. However, theoretical analysis is still left as a future work. Ongoing works are investigating the use of this kind of network model for recognition of temporal sequences. Preliminary experiments show that the network has ability to perform recognition of temporal sequences.

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REFERENCES

[1] Abeles M. (1982). Local Cortical Circuits. An Electrophysiological Study. Spring-Verlag.

[2] Buonomano Dean V., & Merzenich Michael M. (1995). Temporal Information Transformed into a Spatial Code by a Neural Network with Realistic Properties. *Science*, Vol. 267, 1028-1030.

[3] Brown Guy J. et al. (1996). Are Neural Oscillations the Substrate of Auditory Grouping ? . *Workshop on the Auditory Basis of Speech Perception*, Keele University (UK), 174-179.

[4] Burkitt Anthony N. (1994). Attractor Neural Networks with Excitatory Neurons and Fast Inhibitory Interneurons at Low Spike Rates. *Network: Computation in Neural Systems*, UK, 5, 437-448.

[5] Brunel Nicolas (1994). Dynamics of an attractor neural network converting temporal into spatial correlations. *Network: Computation in Neural Systems*, UK, 5, 449-470.

[6] Demuth H. & Beale M. (1996). Neural Network Toolbox for Use with MATLAB, *The Math Works Inc.*

[7] Destexhe Alain (1994). Oscillations, complex spatiotemporal behavior and information transport in networks of excitatory and inhibitory neurons. *Physical Review E*, Vol. 50, No. 2.

[8] R. C. Eberhart, R. W. Dobbins. (1992). Neural Netwroks PC Tools: a practical guide. Academic Press. San Diego, USA.

[9] Hertz .J, Prugel-Bennette A. (1996). Learning Short Synfire Chains by Self-Organization. *Neural Computation in Neural Systems*, UK, 7, 357-363.

[10] Hill S., & Villa A. (1997). Dynamic transitions in global network activity influenced by the balance of excitation and inhibition. *Network: Computation in Neural Systems*, UK, Vol. 8, 2, 165-184.

[11] Hill S., Villa A. (1995). Global Spatiotemporal Activity Influenced by Local Kinetics in a Simulated "Cortical" Neural Network. *Workshop on Supercomputing in Brain Research*, World Scientific, 371-375.

[12] Ho T.V., Rouat J. (1997). A Novelty Detector Using a Network of Integrate and Fire Neurons. To appear in *Proceeding of the 7th Int. Conf. on Artificial Neural Networks*, Lausanne, Switzerland, 8-10 Oct. 1997.

[13] Matsuno .Tet al. (1994). Periodic Signal Learning and Recognition in Coupled Oscillators. *Journal of Physical Society of Japan*, Vol. 63, No. 3, March, 1194-1204.

[14] Stassinopoulos D., Bak P. (1994). Self-organization in a Simple Brain Model. *Proc. of WCNN'94*, San Diego, Jun, Vol. 1, pp. 4-26.

[15] Thiran P., Hasler M (1996). Information storage using stable and unstable oscillations: an overview. *Int. Journal of Circuit Theory and Applications*, Vol. 24, 57-67.

[16] Wang D., & Terman D. (1995). Locally Excitatory Globally Inhibitory Oscillatory Networks. *IEEE Transactions on Neural Networks*, 6: 283-286.