Evaluation of Spiking Neural Network Performance based Interconnection Scheme

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Abstract-- In this paper, a new spiking neural network architecture based Ellias Grossberg model is proposed and different connection schemes that investigate the synchronization performance is provided. The synchronization time and the network neurons correlation are used as a measure of the network performance. An example of a pattern recognition problem is used to illustrate the proposed connection schemes. Results on the English character recognition are presented. Any of the proposed connection schemes may be used to design artificial neural networks for scene segmentation, figure ground segregation and object recognition.

1. Introduction

Due to its critical importance for computer vision, scene segmentation has been studied quite extensively. Many techniques have been proposed in the past [2], [5]. Despite these techniques, as pointed out by Haralick and Shapiro [15], there is no underlying theory of image segmentation, and the techniques tend to be ad hoc and emphasize some aspects while ignoring others. Compared to the traditional techniques for segmentation, the oscillatory correlation approach offers many unique advantages. The dynamical process is inherently parallel. While conventional computer vision algorithms are based on descriptive criteria and many ad hoc heuristics.

The human cerebral cortex has more than 10^{10} neurons, and there are probably ten times that number in the nervous system as a whole. Each neuron receives 1,000 to 100,000 synapses, and each neuron transmits to correspondingly large number of neurons in its neighborhood. This is why a salient aspect of neurons is their incredibly large number [6]. The ability to extract salient sensory features from a perceived scene or sensory field, and group them into coherent clusters, or objects, is a fundamental task of perception. These abilities are essential for figure/ground segregation, object segmentation, and pattern recognition. There are two forms of sensory segmentation: peripheral segmentation, which is based on the correlation of local qualities within a pattern, and central segmentation, which is based on prior knowledge about patterns. As the techniques for single object recognition become more advanced the need for efficient segmentation of multiple objects grows, since both natural scenes and manufacturing applications of computer vision are rarely composed of a single object [1]-[3].

The number of possible linkages between multiple objects grows combinatorially when these objects have many features. The feature-binding problem is the problem of correctly bound together these features to form an object. Theoretical considerations of brain functions suggest temporal correlation of neural activity as a representational framework for perceptual grouping [3], [6], and [7]. In the correlation theory of Von der Malsburg and Schneider [8], features are linked through temporal correlation in the firing patterns of different neurons. A natural implementation of temporal correlation is the use of neural oscillators, whereby each oscillator represents some feature (may be just a picture element, or a pixel) of an object. In this scheme, each segment (object) is represented by a group of oscillators that are synchronized (phase-locked) at a certain time. Different groups whose oscillations are synchronized at different times represent different objects.

In Figure 1 we show various topological conventions represent patterns of connection among neurons. Forward convergence and divergence of connections with continuous distributions are found in many areas of the cortex [10] as shown in Figure 1 (a) and (b). Neural population does not exist merely because of the large number of neurons driven by common input in parallel shape as in Figure 1 (d). Feedback interactions among various cortical neurons which yield cooperative activity is shown in Figure 1 (e)-(h).

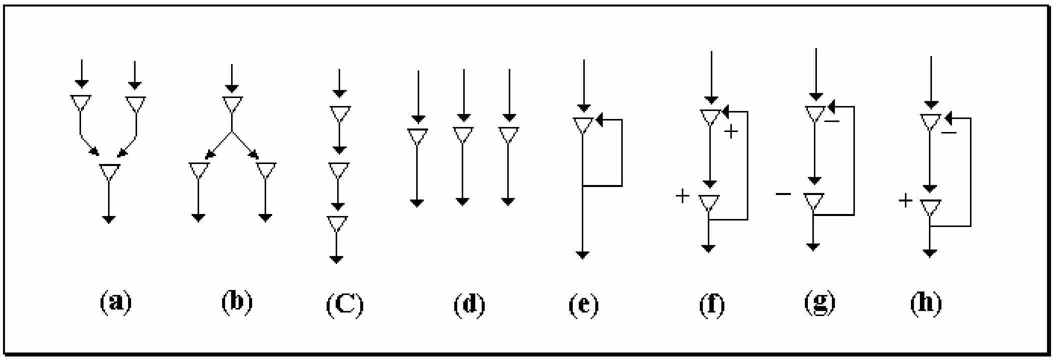


Figure 1. the topological conventions represent patterns of connection among neurons. (a) Convergence (b) Divergence (c) Series (d) Parallel (e) Auto feedback (f) Positive excitatory feedback (g) Positive inhibitory feedback (h) Negative feedback. (figure from freeman [1975], courtesy of Academic press)[10].

Auto-feedback scheme is not commonly found in the human cortex because of two reasons. First, there is a very little chance that the axon collaterals of a neuron will end on the same neuron itself not one of the other thousands in the surround neighborhood. Second, if a neuron inhibit or excite itself, it will end up to its own refractory period. In artificial neural networks (ANNs), auto-excitation is commonly used in a non-biological way to compensate ANNs as a first order ordinary differential equation (ODE) and the omission of the explicit terms for synaptic and dendritic cable delays.
There are three main classes of feedback: cooperative, competitive, and negative. In cooperative feedback one excitatory pool excites another, which re-excites the first one as in Figure 1 (f). In population, this mutual excitation tends to couple neurons to fire more or less together.

Recently, a cooperative feedback largely ignored by biologists since it was recognized by its instability and regenerative feedback. This was exemplified by the mechanism of potential action which failed to grasp the utility of mutual excitation as a mean for coordinating the activity of neurons. In many publications, authors has combined the interest of long distance excitatory connections with research in neural networks. For example, Anderson et al. [1977], Amari [1977], Grossberg [1973] and others. According to these studies we concluded that a fully connected neural network is not an efficient solution because of the large number of neurons involved.

In this paper our goal is to explore the performance of a simple network design using Ellias Grossberg model with a variety of connection schemes taking into consideration the time of synchronization as a measure of network performance. The performance of the developed network structure will be tested in two cases. First; the isolated English characters for single object recognition. Second; the connected Arabic word as a multiple object recognition. The simulated models in this paper will perform computation based on connections and oscillatory dynamics. The organizational simplicity renders our model particularly feasible for very large scale integration (VLSI) implementation. Also continuous dynamics allow real time processing, desired by many engineering applications. We plan to show that it is possible to use oscillatory correlation as a methodology to solve the binding problem in consistent with the time of synchronization for each pattern group.

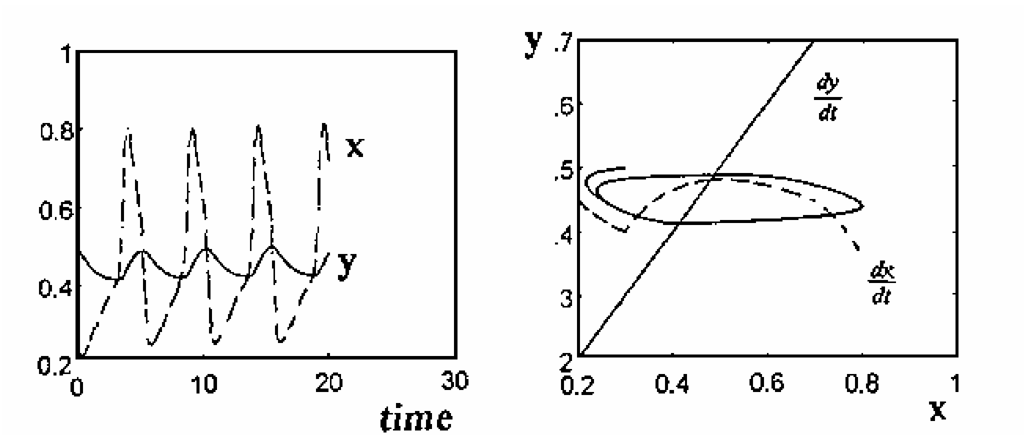
2. Model Identification

In this work, we used the Ellias-Grossberg model for our study. This model has many major advantages over other neural network models. It is simple, has a fast speed of synchronization compared to other types of neural network models, it is ease for control and also stable [9]. The model with a single oscillator is defined in its simplest form as a feedback loop between an excitatory unit and an inhibitory unit [7]. The ODE that describe the model is given as follows:

$$\frac{dx}{dt} = -Ax + (B - x)\{C[x - \Gamma]^{+} + I\} - Dx[y - \Gamma]^{+} \qquad (1)$$

$$\frac{dy}{dt} = E(x - y) \qquad (2)$$

where $(s)^{+} = \max(s, 0)$. The variable x represents the potential of an excitatory cell governed by a nonlinear shunting equation. y represents the potential of an inhibitory cell governed by a linear equation. The values of the equation parameters are given as A=1, B=1, C=20, D=33.3, Γ=0.5 and the range of I is between 0.2 and 1.0. E in equation (2) governs the relative time scales of x and y and represents the relative rate at which the inhibitory inter-neuron tracks the firing rate of the excitatory cell. The value of E govern the domain of the relaxation regime and the sinusoidal behavior activities. Figure 2 shows the results of a single oscillator.



(a) **(b)**

Figure 2. Relaxation oscillation obtained for Ellias-Grossberg model. (a) Waveforms for inhibitory cell (solid curve) and excitatory cell (dashed curve), (b) Phase portrait, limit cycle and Nullclines [8].

3. Simulation of the Ellias-Grossberg Model

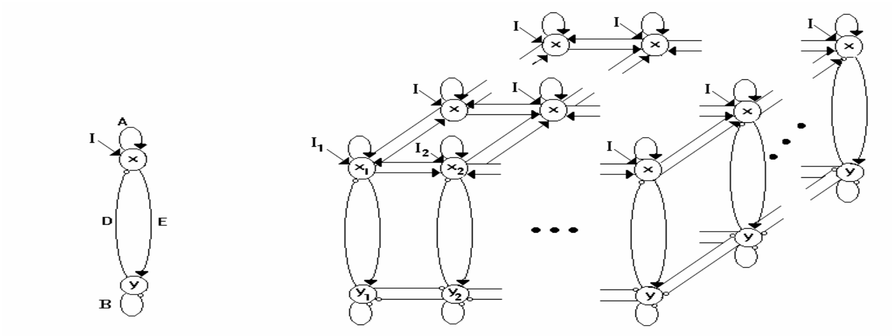
The fundamental aspect of system perception is to bind spatially separate sensory features essential for object identification, segmentation of different objects, and figure ground segregation [13], [14]. It was found that locally coupled neural oscillators can yield global synchronization. Using the Ellias-Grossberg Model, we simulated two-dimensional network of 10x22 oscillators with different connection schemes as shown in Figure 3. At the beginning the network connections were implemented in three different cases. They are 4, 8 and all nearest neighbors in the excitatory layer cells. This was done assuming that the inhibitory cells are connected only to their coupled Excitatory cells.

The network was designed with simultaneous connections of the Excitatory and inhibitory layers. For the modified model, the i th oscillator was governed by equations (1) and (2), where x and y were replaced by x_i and y_i respectively. The nearest neighbor coupling was generated by adding the terms described in equations (3) and (4) to equations (1) and (2), respectively.

$$\xi\,\alpha(B-x_i)\{\sum_{k\in Ni}[x_k-\Gamma]^+\} \quad .... \qquad (3)$$

$$\xi\,\gamma(B-y_i)\{\sum_{k\in Ni}[y_k-\Phi]^+\} \quad .... \qquad (4)$$

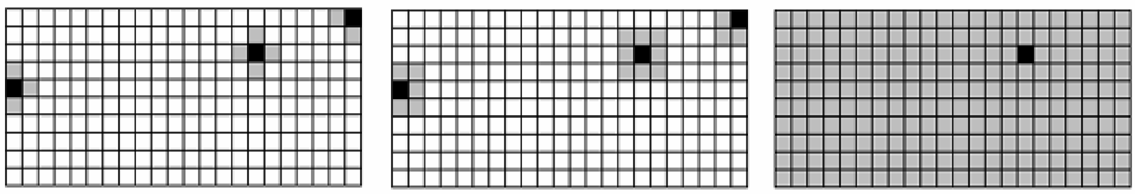
Equation (3) and (4) governs the Excitatory coupling term and the inhibitory coupling term, respectively. α is the Excitatory coupling strength, γ is the inhibitory coupling term, ϕ is the inhibitory threshold level, *N(i)* is the set of the adjacent oscillators that connect to oscillator I. ζ is a scaling factor calculated based on the number of connected neighbors.



(a) **(b)**

Figure 3. A diagram showing the interactions between the excitatory and inhibitory units in a 2-D network of oscillators.

For a broad range of initial conditions and coupling strengths we found that two-dimensional arrays of relaxed oscillators can be synchronized more rapidly than it could happen for arrays of sinusoid oscillators with the same coupling and initial condition [14]. It is important to realize that the absolute rates of synchronization depend on the values of the coupling strength. Using the relaxation model at a moderate coupling strength (e.g. α=0.10, γ=0.10 [16-17]), the nearest neighbor networks will always approached in few cycles. It is uncommon to reach this synchrony criterion in less than 30-40 cycles.



(a) (b) (c)

Figure 4. Basic Architecture of the network structure. The Oscillators are arranged in 2-D grid, The oscillator located at the black site is connected only to the oscillators on adjacent stripped squares. Note that we do not use periodic boundary conditions.

The diagram shown in Figure 4 (a) describes how each oscillator is connected to its four immediate neighbors except on the boundaries with no wrap-around used. In Figure 4 (b) each oscillator is connected only to its eight immediate neighbors except on the boundaries with no wrap-around used. In Figure 4 (c) each oscillator is connected to all the network oscillators.

An image composed of four patters was used as a test pattern mapped to a 10X22 network as shown in Figure 5. If a square is entirely covered by the input, the corresponding oscillator receives an external input; otherwise, the oscillator receives no external input. We have chosen an Arabic connected characters to show the ability of the network to concurrent segmentation and recognition in short time compared to other networks [2], [4] and [11].

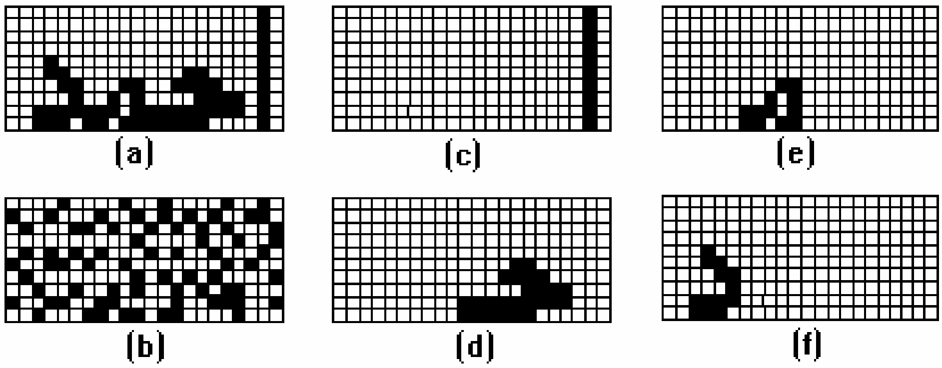


Figure 5. Four objects were arbitrary selected: ا ، ح ، م and د; those form the word "احمد". These patterns were simultaneously presented to the networks as shown in (a) Fig's (b) - (f) show the instantaneous activity of the networks at various stages of dynamic evolution.

4. Results on Two Layer Network

Several experiments were implemented with different parameter settings for the two case studies with the given test patterns. These parameter settings were used along with ϕ=0.5, α=γ=0.2. ζ was chosen based on the number of connected neighbors. The applied input I was 0.8 for the nodes receiving external input and 0.0 for the rest. Random values ranging from 0.0 to 0.5 were used as the initial values for the inhibitory and excitatory action potential voltage.

According to our experiments, it was found that changing the initial values does not affect the time of synchronization but affects the first part of the resulting traces. In Figure 6 we show the results for the same initial values in all cases using the above described values of parameter setting. The oscillators receiving no external input were excluded from the display in Figure 6 for the characters ا ، ح ، م and د. The activities of the oscillators simulating each object are combined into a single trace near the end of its figure.

Table 1 shows the simulation time for each connection scheme. From the table we can see that the simulation time in the case of two layer ANNs is not twice the time needed for the single layer ANNs in all cases. That is because of the simplicity of the inhibitory cell equation compared to the excitatory cell equation.

Connection Scheme	**No. of Iterations to synchronize**	**Complexity**	**Simulation Time (min.)**
4 E	**46**	**C_n + 1C**	**3**
4 E + 4 I.	**20**	**C_n + 2C**	**5**
8 E	**42**	**C_n + 2C**	**4**
8 E + 8 I.	**18**	**C_n + 4C**	**7**
All E.	**35**	**C_n + 55C**	**17**
All E + All I.	**15**	**C_n + 110C**	**31**

Table 1. Simulation Results, where E is an Excitatory Neighbor, I is an Inhibitory Neighbor, C_n is the original differential equations complexity and C is the complexity overhead due to the interconnections.

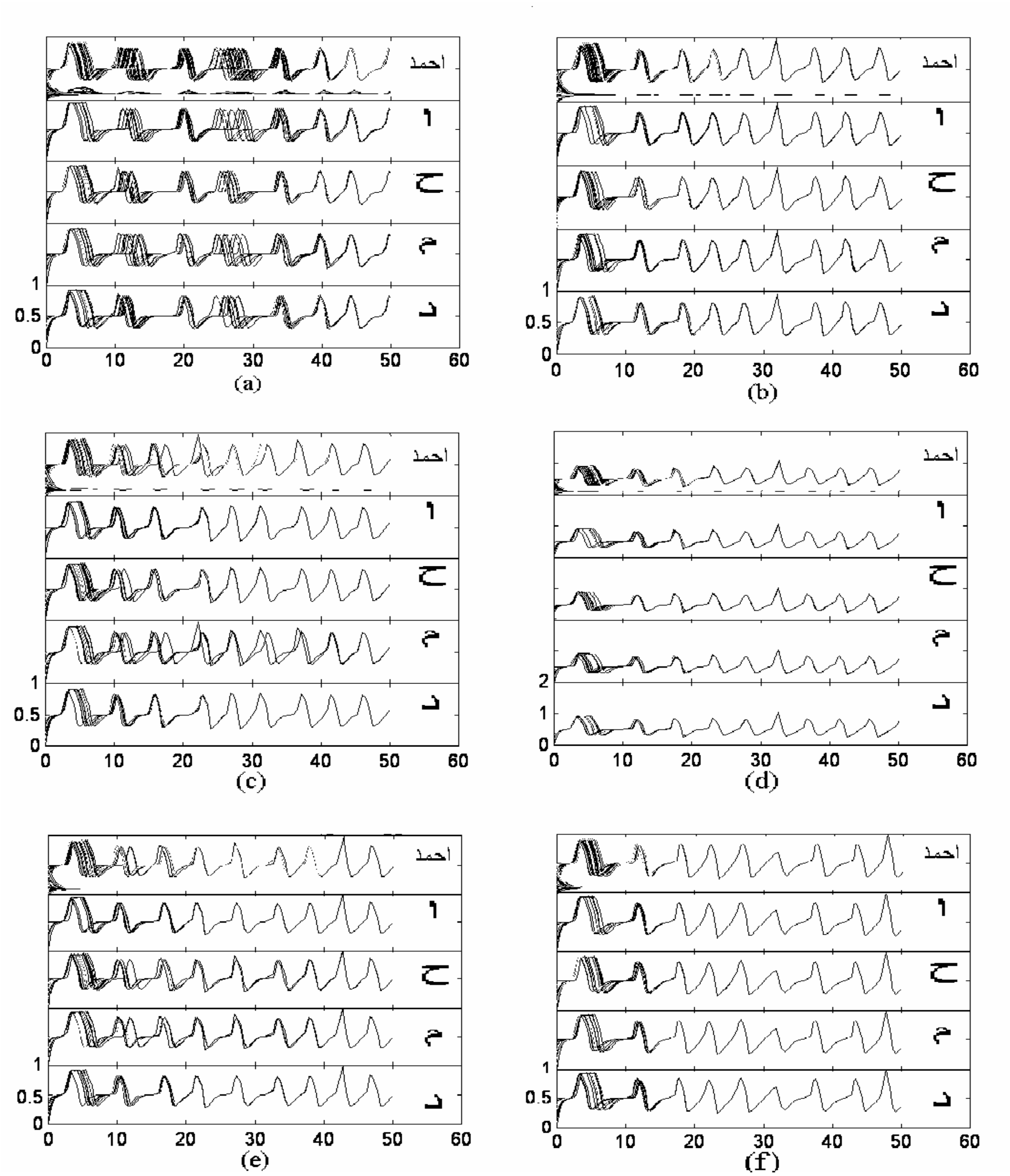


Figure 6. Traces show the combined temporal activities of the oscillator blocks representing the whole word and its four patterns respectively. (a), (c) and (e) Each Excitatory cell is connected to its 4, 8, and all immediate neighbors except for the boundaries,` no connections in the inhibitory layer and no warp-around is used. (b), (d) and (f) Each Excitatory and Inhibitory cell is connected to its 4, 8, and all immediate neighbors except for the boundaries and no warp-around is used.

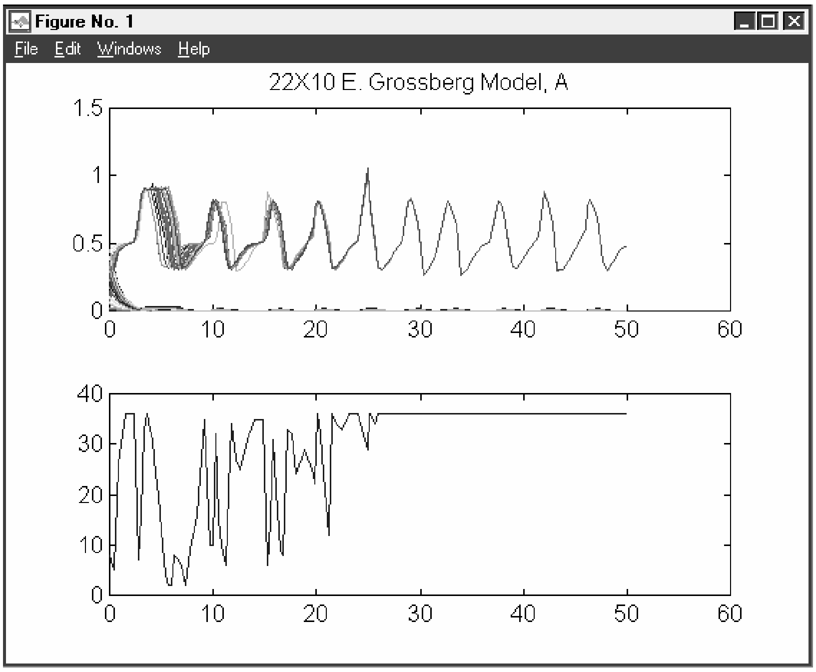


Figure 7. The upper traces show the combined temporal activities of the oscillator blocks representing the character 'A'. Each Excitatory cell is connected to its 4 immediate neighbors except for the boundaries, no connections in the inhibitory layer and no warp-around is used. The Lower trace is the temporal Correlation output.

Character	No of Iterations to Sync.	No of Correlated Neurons	Character	No of Iterations to Sync.	No of Correlated Neurons
A	26	35	N	42	54
B	38	52	O	18	40
C	67	30	P	28	38
D	29	42	Q	31	42
E	47	33	R	32	50
F	72	28	S	27	34
G	44	39	T	43	26
H	32	43	U	23	38
I	22	20	V	23	34
J	54	25	W	35	60
K	36	40	X	39	39
L	28	24	Y	23	30
M	40	62	Z	57	34

Table 2. Results according to the application of English characters (Simple font, size 8). The second column shows the time taken by the network to synchronize for the corresponding characters in the first column, the third column gives the no. of correlated neurons for the applied character, then the last column shows the suggestion of error with in range of two for any of the time of synchronization or the number of correlated neurons.

Table 2. shows the result in the English character recognition case. We use English characters with font of size 8 applied to a network structure of 22x10 Ellias-

Grossberg neurons. The correlation function was computed using the number of synchronized neurons at each simulation step and measures the time of synchronization. The value of the correlation function reached its maximum at the synchronization point then remains constant as long as the network remains synchronized. The time of synchronization can be optimized in each case using genetic approaches [18-19].

5. Three Layer Network

A section of the mammalian cortex reveals a clear laminar structure in the vertical direction, whereas the connectivity is isotropic in the tangential plane. The layered structure is reflected in the vertical range of the dendritic and axonal arborization of pyramidal cells. That is, the afferent and efferent connectivity is layer-dependent. Ascending projections tend to terminate in layer IV (granular layer), whereas feedback connections from higher areas usually project to infragranular and supragranular layers, avoiding layer IV. These findings suggest a complicated pattern of vertical signal flow.

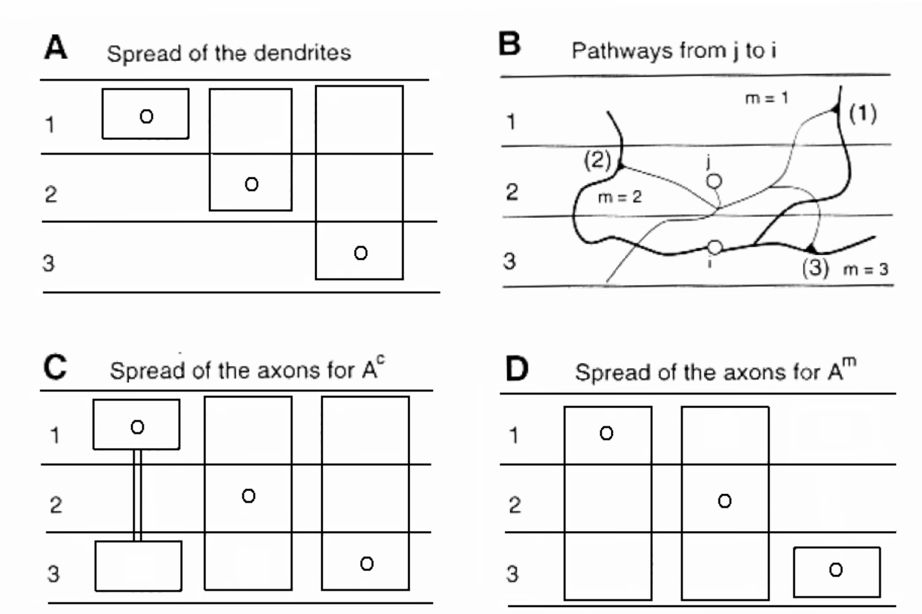


Figure 8. Structure of the layered network. (A) The dendrites of a neuron in layer l (l=1, 2, 3 from the left to right). (B) Different pathways between two neurons may exist and result in different delays. (C) and (D) the spread of the axons for the proposed different connection schemes.

In this section, the question of signal flow in the cortex is related to the problem of existence (or nonexistence) of collective 30-50 Hz oscillations, which have been observed in cat and monkey visual cortex. Coherent oscillations with zero phase-lag have been detected within one column between different layers, cells exhibiting oscillatory responses being located primarily in supra and infragranular layers rarely in layer IV. This synchronized activity could be a mechanism for feature linking, acting as a temporal label and thus solving the problem of global object perception. Ursula Fuents, Raphael Ritz, Wolfram Gerstner, and J. Leo Van Hemmen have developed a model of the layered cortical structure in order to study signal flow in a

small slab of cortex (e.g., a hypercolumn of 1-mm diameter). They focus on the question whether collective oscillations (if they occur at all) are restricted to a single layer or whether they are spread out vertically over the full hypercolumn.
In this section we provide the results for a model developed using three ANNs layers, each layer contains N pairs of neurons. The upper layer (layer 1) represents the cortical supragranular layers, whereas the lower layer (layer 3) represents the infragranular layers. Layer 2 corresponds to the cortical input layer IV. Reducing the number of layers from six to three is suggested by common interareal connections. A uniform distribution of 3N neurons into three layers is not far from reality since one can conclude from experimental results on cell densities and thickness of layers.

In our experiment, we are assuming full connectivity of the neurons in each layer. This will lead to isotropic tangential structure, consistent with the known homogeneous wiring structure in the tangential plane of a small cortical slab. The dendritic and axonal arborization, which is layer-dependent, was considered as shown in Figure 8. Given the axonal and dendritic branching pattern, a connection scheme between layers has to be defined. One can assume that there is a synaptic connection whenever a dendrite of one-neuron touches an axon of another neuron.

The following assumption was assumed: given neuron i in layer l ($1\leq l \leq 3$) and neuron j in layer k ($1\leq k\leq 3$), there is a connection from neuron j to neuron I in each layer which is passed or reached by both axons of neurons in layer k and dendrites of neurons in layer l (see figure 8 (b)).

6. Multi-Layer Network Simulation

We simulated a network of two layers based on our single oscillator model. The above connection scheme between layers was used. Eight neighbor connections between cells in the same layer were used. The output from the two layers is reported in Figure 9 which shows that the output is improved from layer one to layer two. Therefore, we are expecting more improvement in the third layer. We note that, the simulation for the network with two layers takes about 60 times the simulation of one layer. The improvement achieved was in the synchronization time (i.e. the number of cycles). This is why we recommend the use of connections in the inhibitory layer only with one layer network. This will provide the same result in less time as proved before.

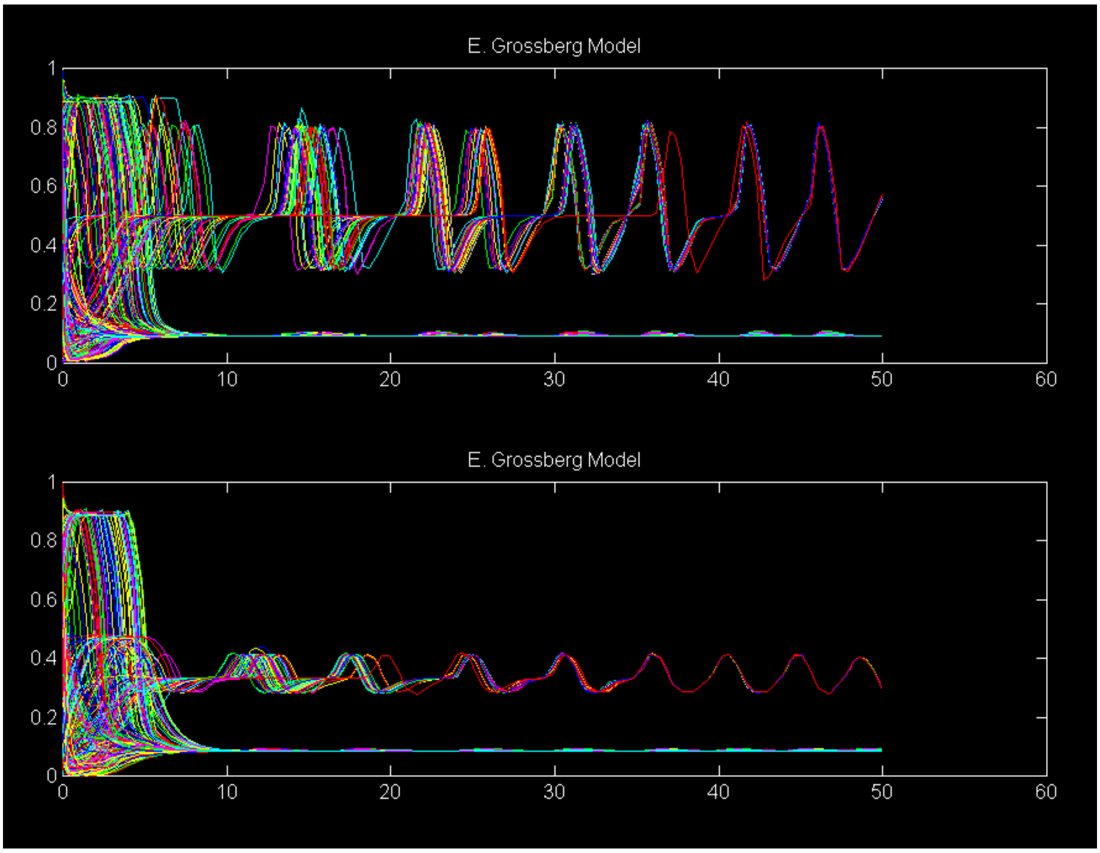


Figure 9. The two-layer network output. The upper traces show the combined temporal activities of the oscillator blocks of the first layer representing the whole word, while the lower traces show the combined temporal activities of the oscillator blocks of the second layer representing the whole word.

7. Conclusion

In this paper, a neural network architecture based Ellias Grossberg model was developed. Different connection schemes that investigate the synchronization performance was employed to study various connection of two and three layer network. The synchronization time was used as a measure to compute the developed network performance. Example of pattern recognition problem was used to illustrate the advantageous of the proposed idea. From this study, we can assure that local connections can yield global synchronization. Global synchronization can be achieved for all connection schemes and number of connected neighbors starting with four. The more fully architectures, relaxation arrays continues to enjoy the synchronization advantages. Inhibitory layer connections achieved remarkably improvement in the network performance. Introducing extra layers to the network improve the output performance with the price of extra simulation time which can be optimized using genetic approaches.

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