

## Optimizing Opto-Electronic Cellular Neural Networks Using Bees Swarm Intelligent

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### Abstract

This paper presents an application of Bees algorithm to the optimization of cellular neural network for opto-electronics design, where cellular neural networks bees are a large – scale nonlinear analog circuit which processes signals in real time. It is made of massive cells, which communicate with each other directly only through its nearest neighbors. Each bee cell is made of a linear capacitor, a nonlinear voltage controlled current source, and a few resistive linear circuit elements with photo diode and photo-detector for connections. In this paper application of bee cellular neural networks in pattern recognition is presented with its opto-electronic circuit design. It is found the real opto-electronic arrays, with all their deficiencies are able to learn and perform various processing tasks well.

**Keywords:** Neural Networks, Swarm Intelligent, Optical Electronics

### أفضلية التمثيل الالكتروضوئي للشبكات العصبية الخلوية باستخدام ذكاء النحل

#### الخلاصة

يقدم البحث تطبيق ذكاء النحل في تصميم وتدريب الشبكات العصبية الخلوية، حيث تعتبر دوائر لا خطية تنفذ العمليات في الزمن الفعلي. تتكون الشبكات العصبية الخلوية للنحل من مجموعة من الخلايا العصبية متصلة مع بعضها من خلال الاتصال المباشر فقط لكل خلية عصبية مع جارها الأقرب المحيط بها ويكون التمثيل المكافئ للخلية الخلوية الالكتروضوئية للنحل من متسعة ومصدر فولتية لا خطي معتمد على مصدر تيار ومجموعة من المقاومات الخطية وطريقة توصيل الخلايا العصبية الخلوية للنحل مع المحيطة بها تكون ضوئية باستخدام الداويد الضوئي والمتحسس الضوئي. تم في هذا البحث تطبيق الشبكات العصبية الخلوية للنحل بعد تمثيلها الكتروضوئياً في مجال تميز الأنماط وان هناك مجالات متعددة للتطبيق طالما هذه الشبكات لديها القدرة على التعلم لتنفيذ العمليات المعقدة.

### 1-Introduction

Swarm intelligence has become a research interest to many research scientists of related fields in recent years. the swarm intelligence defined as “any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies” [1]. The viewpoint on social insects alone such as termites, bees, wasps as well as other different ant species.

However, the term swarm is used in a general manner to refer to any restrained collection of interacting agents or individuals.

The classical example of a swarm is bees swarming around their hive; nevertheless the metaphor can easily be extended to other systems with a similar architecture. An ant colony can be thought of as a swarm whose individual agents are ants. Similarly a flock of birds is a swarm of birds. An immune system is a

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swarm of cells and a molecule as well as a crowd is a swarm of people [2]. Particle Swarm Optimization (PSO) Algorithm models the social behavior of bird flocking or fish schooling [3].

A key element of most neural network systems is the massive number of weighted interconnections (synapses) used to tie relatively simple processing elements (neurons) together in a useful architecture [4, 5]. The inherent parallelism and interconnection capability of optics make it a likely candidate for the implementation of the interconnection process.

Hardware implementations of artificial neural networks have been tried in electronics and optics. A desired configuration is a semiconductor chip, which includes a huge number of artificial neurons and interconnections. However, reported Si VLSI contained only several tens of neurons in a chip, since a wide area was occupied by complicated variable interconnections. Thus a simpler variable interconnection is expected [6, 7].

A novel class of information-processing system called cellular neural networks has been presented. Like neural network, it is a large-scale nonlinear analog circuit, which processes signals in real time. It is made of a massive aggregate of regularly spaced circuit clones, called cells which communicate with each other directly only through its nearest neighbors [8-9].

Cellular neural networks share the best features of both worlds; its continuous time feature allows real time signal processing found wanting in the digital domain and its local interconnection feature makes it tailor made for VLSI implementation [10].

In this paper some theoretical results concerning the dynamic range and the steady-state behavior of cellular neural networks have been presented. As well as a proposed opto-electronic circuit that implement the cellular neural networks will be described for pattern recognition application.

## 2- Behavior of Honey Bee Swarm

The minimal model of forage selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers and the model defines two leading modes of the behavior: the recruitment to a nectar source and the abandonment of a source:-

**i) Food Sources:** The value of a food source depends on many factors such as its proximity to the nest, its richness or concentration of its energy, and the ease of extracting this energy. For the sake of simplicity, the “profitability” of a food source can be represented with a single quantity [1].

**ii) Employed foragers:** They are associated with a particular food source which they are currently exploiting or are “employed” at. They carry with them information about this particular source, its distance and direction from the nest, the profitability of the source and share this information with a certain probability.

**iii) Unemployed foragers:** They are continually at look out for a food source to exploit. There are two types of unemployed foragers: scouts, searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and establishing a food source through the information shared by employed foragers. The mean number

of scouts averaged over conditions is about 5-10% [1].

The exchange of information among bees is the most important occurrence in the formation of the collective knowledge. While examining the entire hive it is possible to distinguish between some parts that commonly exist in all hives. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources takes place in the dancing area. This dance is called a waggle dance as shown in Fig.1.

In order to understand the basic behavior characteristics of foragers better, let us examine Fig. 2. Assume that there are two discovered food sources: A and B. At the very beginning, a potential forager will start as unemployed forager. That bee will have no knowledge about the food sources around the nest. There are two possible options for such a bee:

i) It can be a scout and starts searching around the nest spontaneously for a food due to some internal motivation or possible external clue (S on Fig. 2).

ii) It can be a recruit after watching the waggle dances and starts searching for a food source (R on Fig.2).

After locating the food source, the bee utilizes its own capability to memorize the location and then immediately starts exploiting it. Hence, the bee will become an "employed forager". The foraging bee takes a load of nectar from the source and returns to the hive and unloads the nectar to a food store. After unloading the food, the bee has the following three options:

i) It becomes an uncommitted follower after abandoning the food source (UF).

ii) It dances and then recruits nest mates before returning to the same food source (EF1)

iii) It continues to forage at the food source without recruiting other bees (EF2).

It is important to note that not all bees start foraging simultaneously. The experiments confirmed that new bees begin foraging at a rate proportional to the difference between the eventual total number of bees and the number of present foraging.

### 3. The Bees Algorithm

This section summary the main steps of the Bees Algorithm. The algorithm requires a number of parameters to be set, namely: number of scout bees (nsb), number of sites selected for neighborhood search (out of n visited sites) (spt), number of top-rated (elite) sites among m selected sites (e), number of bees recruited for the best e sites (nep), number of bees recruited for the other (m-e) selected sites (nsp), the initial size of each patch (ngh) (a patch is a region in the search space that includes the visited site and its neighborhood), and the stopping criterion. The algorithm starts with n scout bees randomly distributed in the search space. The fitness of the sites (i.e. the performance of the candidate solutions) visited by the scout bees are evaluated in step 2.

In step 4, the m sites with the highest fitness's are designated as "selected sites" and chosen for neighborhood search. In steps 5 and 6, the algorithm searches around the selected sites, assigning more bees to search in the vicinity of the best e sites. Selection of the best sites is

made according to the fitness associated with them. Search in the neighborhood of the best e sites – those which represent the most promising solutions - are made more detailed. As already mentioned, this is done by recruiting more bees for the best e sites than for the other selected sites. Together with scouting, this differential recruitment is a key operation of the Bees Algorithm.

In step 6, for each patch only the bee of highest fitness value is selected to form the next bee population. In nature, there is no such restriction. This restriction is introduced here to reduce the number of points to be explored. In step 7, the remaining bees in the population are placed randomly around the search space to scout for new potential solutions.

At the end of each iteration, the colony has two parts to its new population: representatives from the selected patches, and scout bees assigned to conduct random searches. These steps are repeated until a stopping criterion is met [2].

*Pseudo code of the basic Bees Algorithm.*

1. Initialize population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met)
  - //Forming new population.
4. Select sites for neighborhood search.
5. Recruit bees for selected sites (more bees for best e sites) and evaluate fitness's.
6. Select the fittest bee from each patch.
7. Assign remaining bees to search randomly and evaluate their fitness's.
8. End While

### 3-1 Architecture of Bees Cellular Neural Networks

The basic unit of Bees Cellular Neural Networks (BCNN) is called a cell. The structure of cellular neural networks is similar to that found in cellular automata namely any cell in a cellular neural network is connected only to its neighbor cells. The adjacent cells can interact directly with each other. Cells not directly connected together may affect each other indirectly because of the propagation effects of the continuous-time dynamics of cellular neural networks. An example of a two-dimensional cellular neural network is shown in Fig.3. Consider an M x N cellular neural network, having M x N cells arranged in M rows and N columns. We call the cell on the ith row and jth column C (i, j). The r-neighborhood of a cell (i, j), in a cellular neural network is defined by [9].

$$N_r(i, j) = \{C(k, l) \mid \max\{|k - i|, |l - j|\} \leq r\} \quad I \in k \in M; \quad I \in l \in N \quad \dots(I)$$

Where r is a positive integer number. Fig.4 shows 3 neighborhoods of the same cell with r = 1, 2 and 3 respectively.

### 4- Electronic Implementation of BCNN's

The basic circuit unit of BCNN's is called cell that contains linear and nonlinear circuit elements, which typically are linear capacitors linear resistors, linear and nonlinear controlled sources, and independent sources as shown Fig.5.

The node voltage  $V_{xij}$  of C (i, j) is called the state of the cell. The node voltage  $V_{uij}$  is called the input of C (i, j) and is assumed to be a constant with magnitude less than or equal to

1. The node voltage  $V_{yij}$  is called the output.

Applying KCL and KVL, the circuit equations of a cell are easily derived as follows [9]:-

Output equation:-

$$V_{yij}(t) = \frac{I}{2} \left( |V_{xij}(t) + I| - |V_{xij}(t) - I| \right) \quad \dots(2)$$

Where M rows and N columns.

Input equation: -

$$V_{uij} = E_{ij} \quad 1 \leq i \leq M, 1 \leq j \leq N \quad \dots(3)$$

Where  $E_{ij}$  is independent voltage source. Constraint conditions:-

$$\left\{ \begin{array}{l} |V_{xij}(0)| \leq 1, \\ |V_{uij}| \leq 1 \end{array} \right\} \quad \dots(4)$$

$$1 \leq i \leq M; 1 \leq j \leq N$$

the only nonlinear element in each circuit cell is a voltage controlled current source:-

$$I_{yx} = \frac{I}{R_y} F(V_{xij}) \quad \dots(5)$$

With characteristic  $F(.)$  as shown in Fig.6

The value of the circuit elements can be chosen to between  $1k\Omega$  and  $1M\Omega$  for  $R_x$  and  $R_y$  and  $CR_x$  is the time constant of dynamics of the circuit and is usually chosen to be  $10^8 - 10^{-5}$  sec.

### 5- Optoelectronic Implementation Of BCNN

Analog opto-electronic hardware implementation of neural network has been focus of attention for several reasons. Primary among these is that the opto-electronic or photonic approach combines the better of two worlds: the massive interconnectivity and parallelism of optics and the flexibility, high gain, and decision making capability offered by

electronics. For the above reason a proposed opto-electronic circuit that performs the BCNN task is illustrated in this section.

Fig.7 shows how these already-efficient analog networks could be improved by using opto-electronics for image processing applications the input to each cell is light from one pixel of an image, so that the entire array can receive a processed data in parallel. On detection, this light is turned into a photocurrent, which flows into its nearest neighbor cells.

In other word, light from an image pixel falls on each cell sending photo-current into a summation circuit and to the entire cell's nearest neighbors. Each cell also sends output as feedback into its nearest neighbors. The opto-electronic cell circuit is shown in Fig.8.

The basic bee cell circuit consists of three parts, which are the weight cells, a current summing part and an output part. The weight part acts as a synaptic connection in which connection polarity and strength are controlled by gate voltage  $V_{g1}$  and  $V_{g2}$  of nMOS FET's Q1 and Q2. For excitatory connection  $V_{g1}$  is high and  $V_{g2}$  low; then Q1 is on and Q2 is off. For inhibitory connection  $V_{g1}$  is low and  $V_{g2}$  high; then Q1 is off and Q2 is on.

The photo current  $I_{ij}$  is generated in the bi-directional photo diode (PD). The excitatory connection (+1) and inhibitory connection (-1) were realized for  $V_{g1} > 3.2$  v and  $V_{g2} = 0$  and  $V_{g1} = 0$  and  $V_{g2} > 1.4$  v respectively. Thus photocurrents from each cell were summed in the current summing part. When the summed value was larger than the threshold value  $V_{th}$  the LED in the output part emitted the optical output to other

cells. When the summed current was less than the threshold value, no optical output was emitted to other cells. We introduce the circuit analysis by using Matlab program as shown in Fig.9 that give the relationship between the difference input voltage and the output current by using the following equation: -

$$I_{ij} = I_{pd} \times \tanh\left(\frac{k(V_{g1} - V_{g2})}{2}\right) \quad \dots(6a)$$

$$I_{ij} \propto T_{ij} V_j \quad \dots(6b)$$

$$T_{ij} = V_{g1} - V_{g2} \quad \dots(6c)$$

For excitatory connection,  $V_{g1}$  is large than  $V_{g2}$  ( $T_{ij} \mathbf{f} 0$ ) and for inhibitory connection  $V_{g1}$  is smaller than  $V_{g2}$  ( $T_{ij} \mathbf{p} 0$ ). The linear range of  $T_{ij}$  values was about -0.1 to +0.1 Volt.

The second proposed design of opto-electronic cell of CNN is shown in Fig.10, where each cell is composed of an input summing port, a nonlinear transfer device, and an output port [11].

In an opto-electronic system, a differential pair of detectors is operated as the input to the neuron, signals with positive (excitatory) weights arrive at one detector, and signals with negative (inhibitory) weights arrive at the other detector.

These detectors sum up the intensity of each optical signal arriving at the cell. The cell's activation function is electronically applied to the detected signal to produce an output signal. The output signal drives either an optical source (or pair of sources) as shown in Fig.10 that uses a pair of laser diodes to encode the cell's output signal.

## 6- Computer Simulation of a Simple BCNN

The flow chart shown in Fig. 11 illustrate BCNN program. In this section, a very simple example will be illustrated how the BCNN described in section 4 works. The BCNN for this example is store three patterns as shown in Fig.12 that is network size is 4x4. Consider a pattern No.1, as shown in Fig. 13. This pattern is a 4x4 pixel array with each pixel values  $P_{ij} \in [-1,+1]$  for  $1 \leq i, j \leq 4$ .

Assume that the pixel value -1 corresponds to a white background, the pixel value +1 corresponds to a black object point value, and the pixel values between -1 and +1 correspond to the gray values. The pixel classification problem is to classify each pixel of the pattern into two or more classes. For any neighborhood system let: -

$$R_y(i, j; i-1, j-1) = 0$$

$$R_y(i, j; i-1, j) = 1k\Omega$$

$$R_y(i, j; i-1, j+1) = 0$$

$$R_y(i, j; i, j-1) = 1k\Omega$$

$$R_y(i, j; i, j) = 2k\Omega$$

$$R_y(i, j; i, j+1) = 1k\Omega$$

$$R_y(i, j; i+1, j-1) = 0$$

$$R_y(i, j; i+1, j) = 1k\Omega$$

$$R_y(i, j; i+1, j+1) = 0$$

$$R_y(i, j; i-1, j-1) = 0$$

$$C = 10^{-9} F; \quad R_x = 1k\Omega; \quad I = 0$$

$$R_x(i, j; k, l) = 0 \text{ for } C(k, l) \in N_r(i, j)$$

The dynamic equations of the bee cellular neural network corresponding to the above parameters are given by equation 2 and equation 7: -

$$\frac{dV_{xij}(t)}{dt} = 10^6 \begin{bmatrix} -V_{xij}(t) + 2V_{yij}(t) + V_{yij-1}(t) \\ +V_{yi-1j}(t) + V_{yi+1j}(t) \\ +V_{yij+1}(t) \end{bmatrix} \dots(7)$$

It is convenient to recast the right-hand side of equation 7 into symbolic form:-

$$\frac{dv_{xij}(t)}{dt} = -10^6 v_{xij}(t) + 10^6 \begin{bmatrix} 1 \\ 1 & 2 & 1 \\ 1 \end{bmatrix} * v_{yij}(t) \dots(8)$$

To study the transient behavior of equation (7), let us apply an initial voltage  $V_{xij}(0)$  across the capacitor of each cell  $C(i,j)$ . Each initial voltage may be assigned any voltage between -1 and +1, however the input patterns can have multiple gray levels, provided that their corresponding voltage satisfies equation (4).

The Mat lab circuit simulator is used to obtain transient response, the initial condition specified in the array of Fig. 13a. The state variables of the circuit,  $V_x$ , at  $t=5$  micro-sec. Are shown in Fig.13b. The maximum absolute value of the state variables at  $t=5$  micro-sec is equal to 6, approximately. The corresponding outputs,  $V_y$ , at  $t= 5$  micro-sec are shown in Fig.13c. Observe that all output variables assume binary values, either +1 or -1.

The transient behavior of one cell  $C(2,2)$  is shown in Fig.14 since it would take much space to display the transient of the entire circuit. The initial value of the state variable is equal to +1, and the value at  $t= 5$  micro-sec is equal to 2.02. The maximum value of  $V_{x22}(t)$  is equal to 3 at  $t= 0.8$  micro-sec. This is because the state variable is kept above 1 during the entire transient regime. For our current example,

equivalently, the stable cell equilibrium states of an inner cell circuit  $C(2,2)$  are the solution  $v_{xij}$  of the dc cell circuit equations obtained by replacing all capacitors by open circuits; namely,

$$v_{xij} = 2v_{yij} + v_{yi-j} + v_{yi+j} + v_{yij-1} + v_{yij+1} \dots (9)$$

Under the conditions:

$$|v_{xkl}| \geq 1, \quad 1 \leq k, l \leq 4 \dots(10)$$

$$|v_{ykl}| = 1, \quad 1 \leq k, l \leq 4 \dots(11)$$

Substituting condition equation 11 into dc equation 9 and using the  $F(\cdot)$  function defined by:-

$$F(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$$

Then obtain:-

$$v_{xij} = 2F(v_{yij}) + F(v_{yi-j}) + F(v_{yi+j}) + F(v_{yij-1}) + F(v_{yij+1}) \dots(12)$$

Furthermore, since

$$F(v_{yij}) = F(v_{xij}), \text{ it follows that:-}$$

$$v_{xij} - 2F(v_{xij}) = F(v_{yi-j}) + F(v_{yi+1}) + F(v_{yij-1}) + F(v_{yij+1}) \dots(13)$$

Observe that the right-hand side of equation 13 can only assume five possible values; -4, -2, 0, 2, 4. It follows that the corresponding values that can be assumed by the state variables  $v_{xij}$  are -6, -4, (-2 or 2), 4, and 6. It follows from the above analysis that each inner cell circuit for our present example can have only six possible stable cell equilibrium states; namely, -6, -4, -2, 2, 4, and 6.

Fig. 15 show the error of 4x4 BCNN for 2 iterations to train pattern No.1 and 22 iterations to trained neural networks the stored patterns.

### 7- Discussions & Conclusions

Hardware implementation of Bees Cellular Neural Network (BCNN) is necessary to take full advantage of this parallel analog computer paradigm. In order to envision large-scale application of BCNN as fast and inexpensive image processing devices, it is desirable to build large arrays of cells, so as to have one cell per pixel.

The study in this paper can perform parallel signal processing in real time for BCNN. The computer simulation is used to illustrate some dynamic properties of simple BCNN. Opto-electronic circuits that perform BCNN were also proposed here. The opto-electronic implementation that presented in this paper has the advantages over the analog circuit in that the input and output are realized optically on the circuit in full parallel fashion, by implying light-sensing and emitting devices integrated in each cell, this leads to large scale integration in a small semiconductor chip and to low power dissipation.

The opto-electronic BCNN circuit was simulated successfully by using Multisim and Matlab programs. Analog opto-electronic hardware implementation of neural network combines the best of two worlds: the massive interconnectivity and parallelism of optics and the flexibility, high gain, and decision making capability offered by electronics. However, in the absence of suitable fully optical decision-making devices, the capabilities of the opto-electronic approach remain quite attractive and could in fact remain competitive with other

approaches when one considers the flexibility of architectures possible with it. This paper concentrates therefore on the opto-electronic and gives a proposed circuit for BCNN and give selected example of simple image at very high speed.

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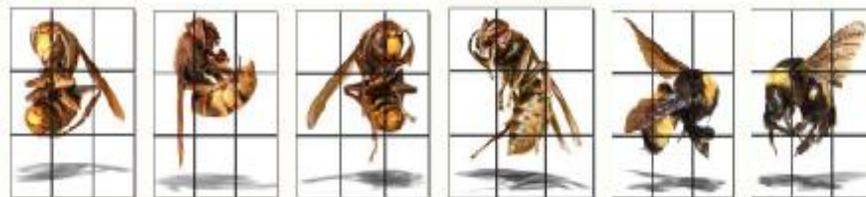


Figure (1) The waggle dance of Bees [1]

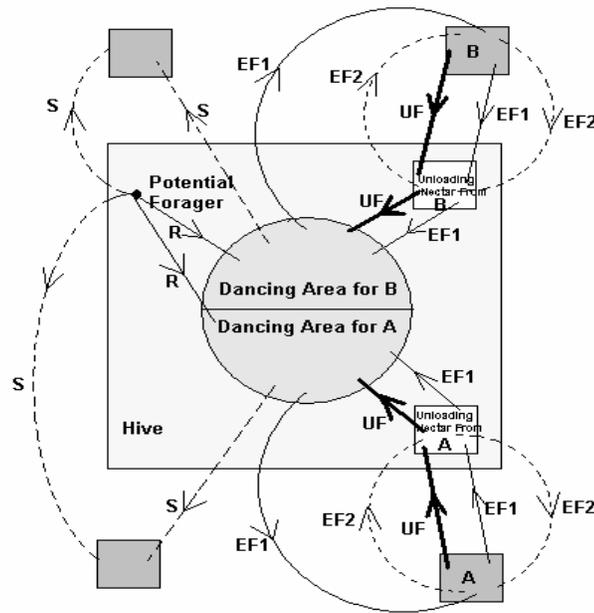


Figure (2) The behavior of honey bee foraging for nectar [2].

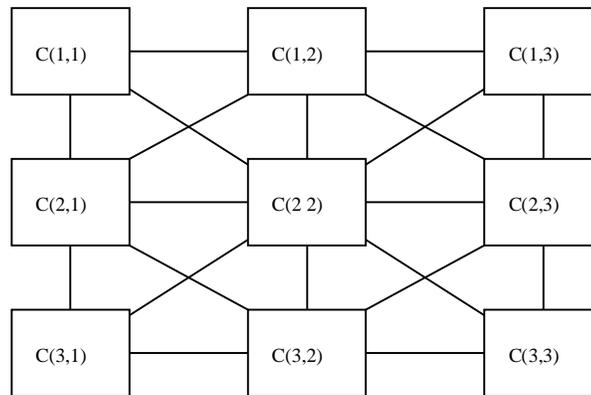


Figure (3) A two dimensional Bees cellular neural network size 3x3.

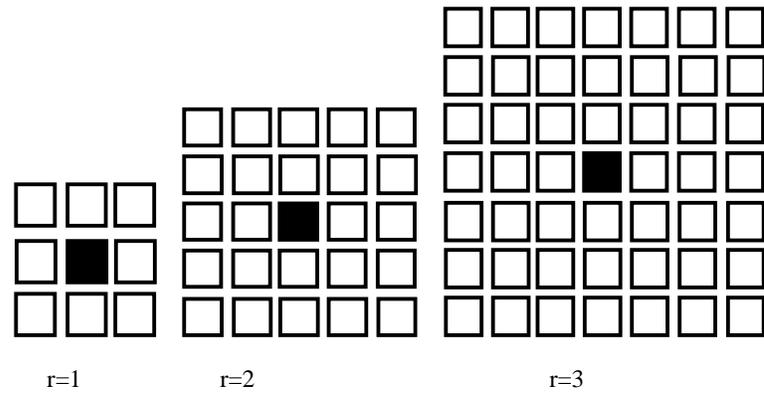


Figure (4) The neighborhood of bee cell C (i, j) for r=1, r=2, r=3.

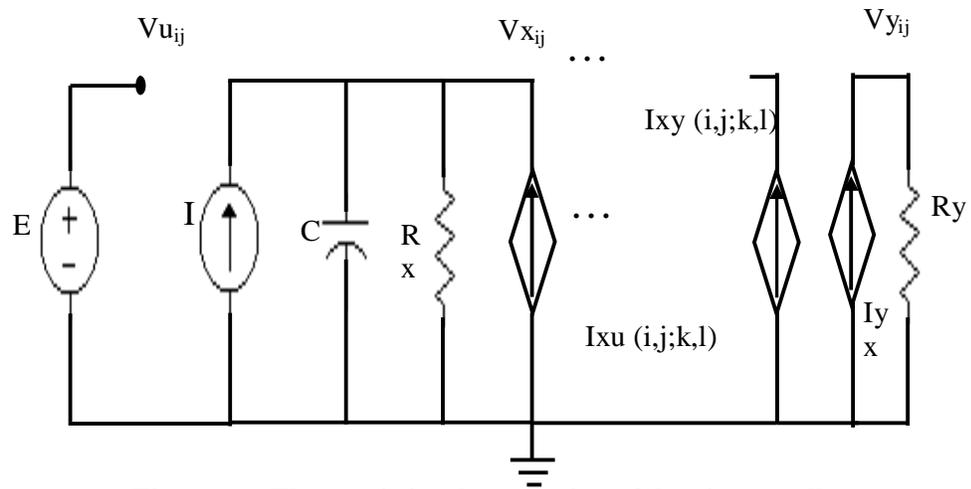


Figure (5) Electronic implementation of bee inner cell circuit.

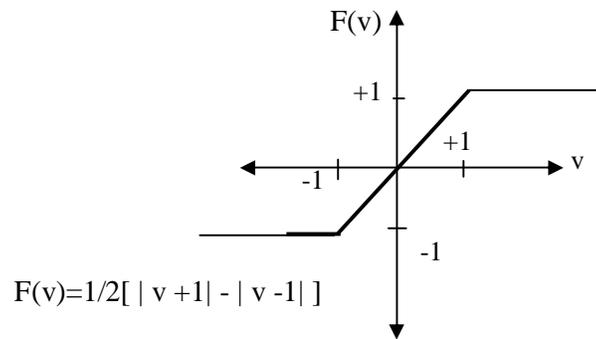


Figure (6) The characteristic of the nonlinear controlled source [8].

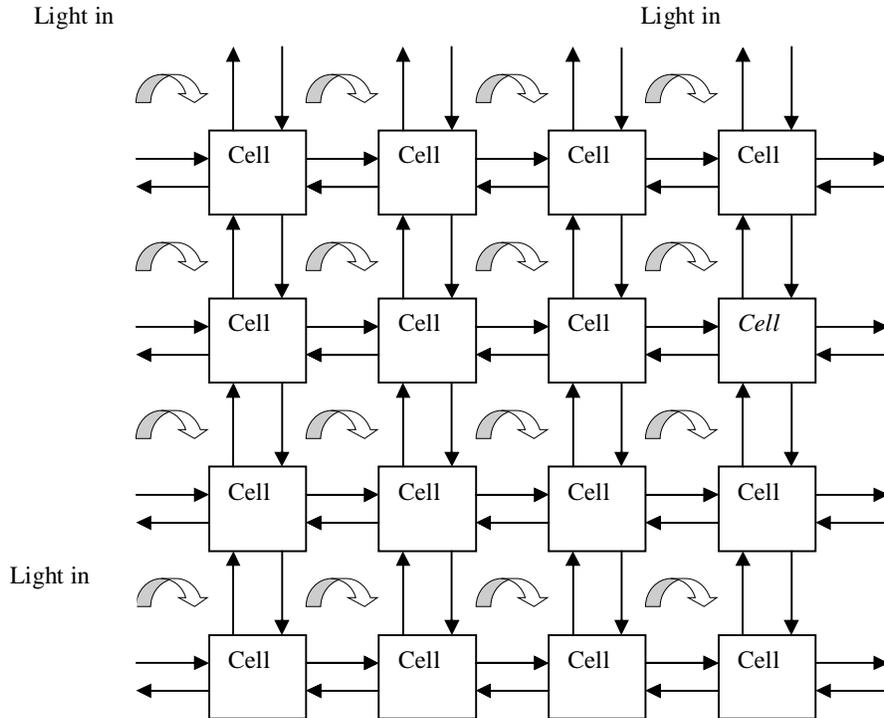


Figure (7) Photonics BCNN architecture.

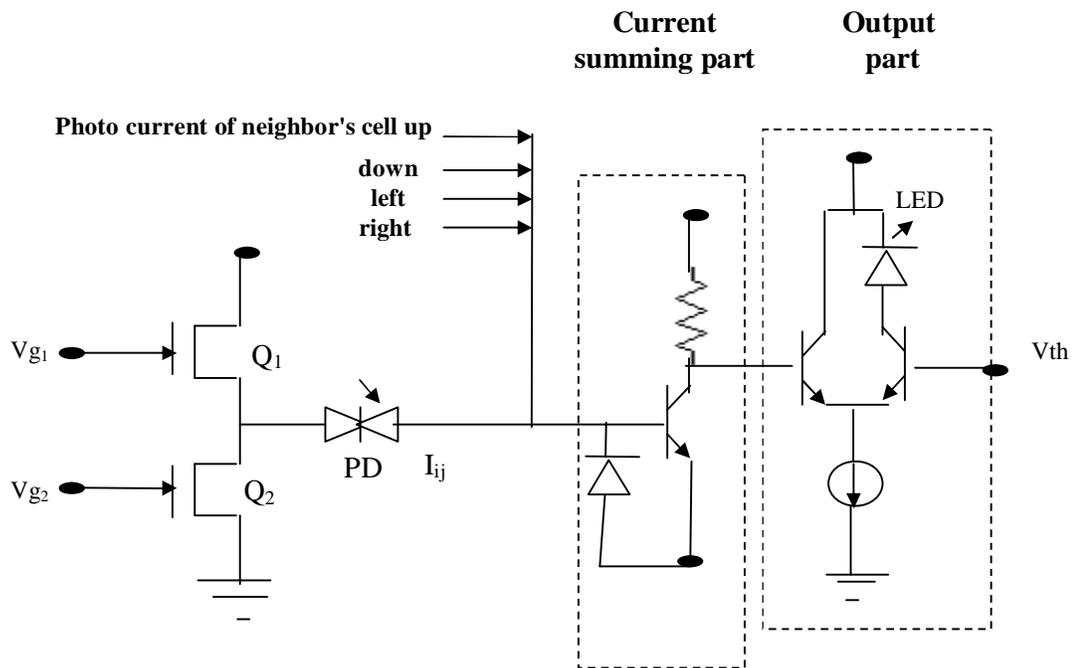


Figure (8) The proposed opto-electronic bee cell.

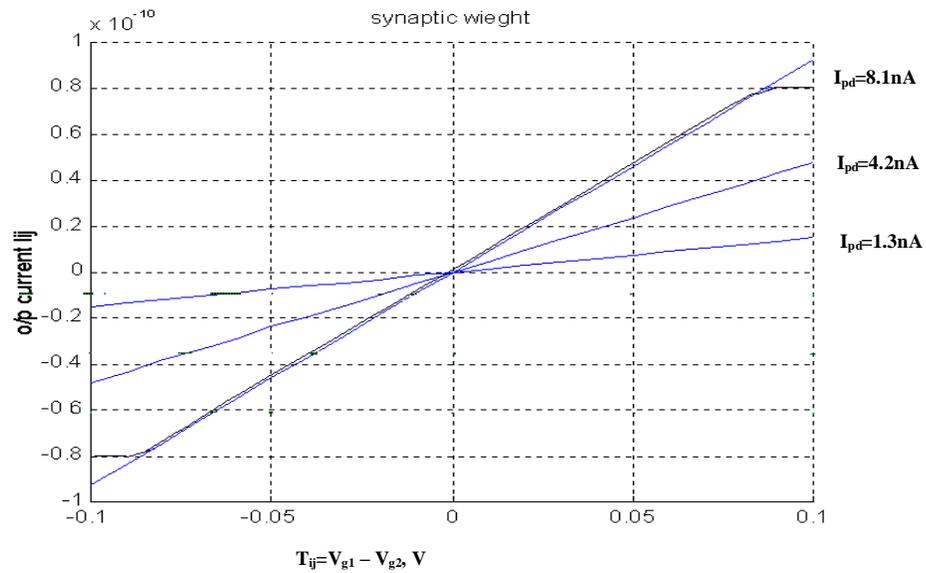


Figure (9) Simulation of optoelectronic synaptic weight

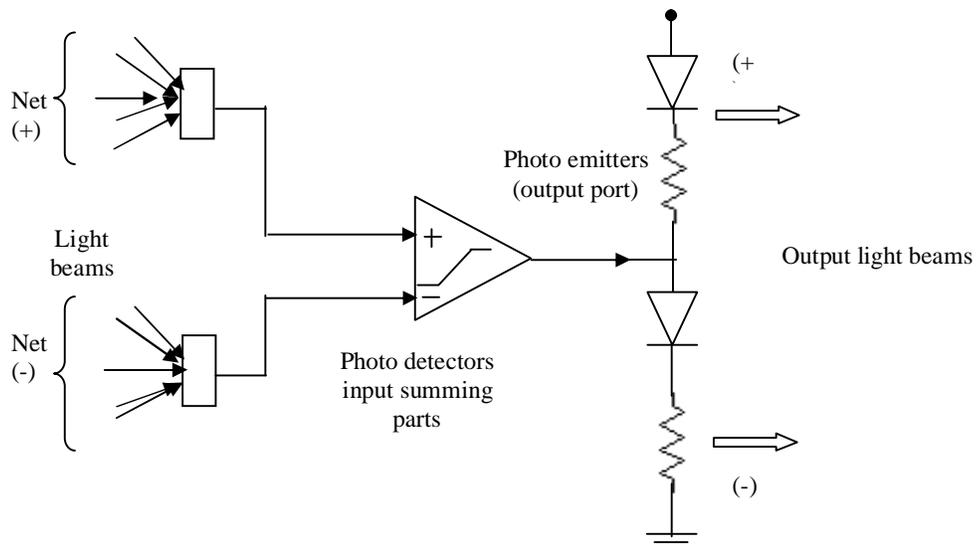


Figure (10) (10) Prototype opto-electronic bee cell constructed from detectors and emitters.

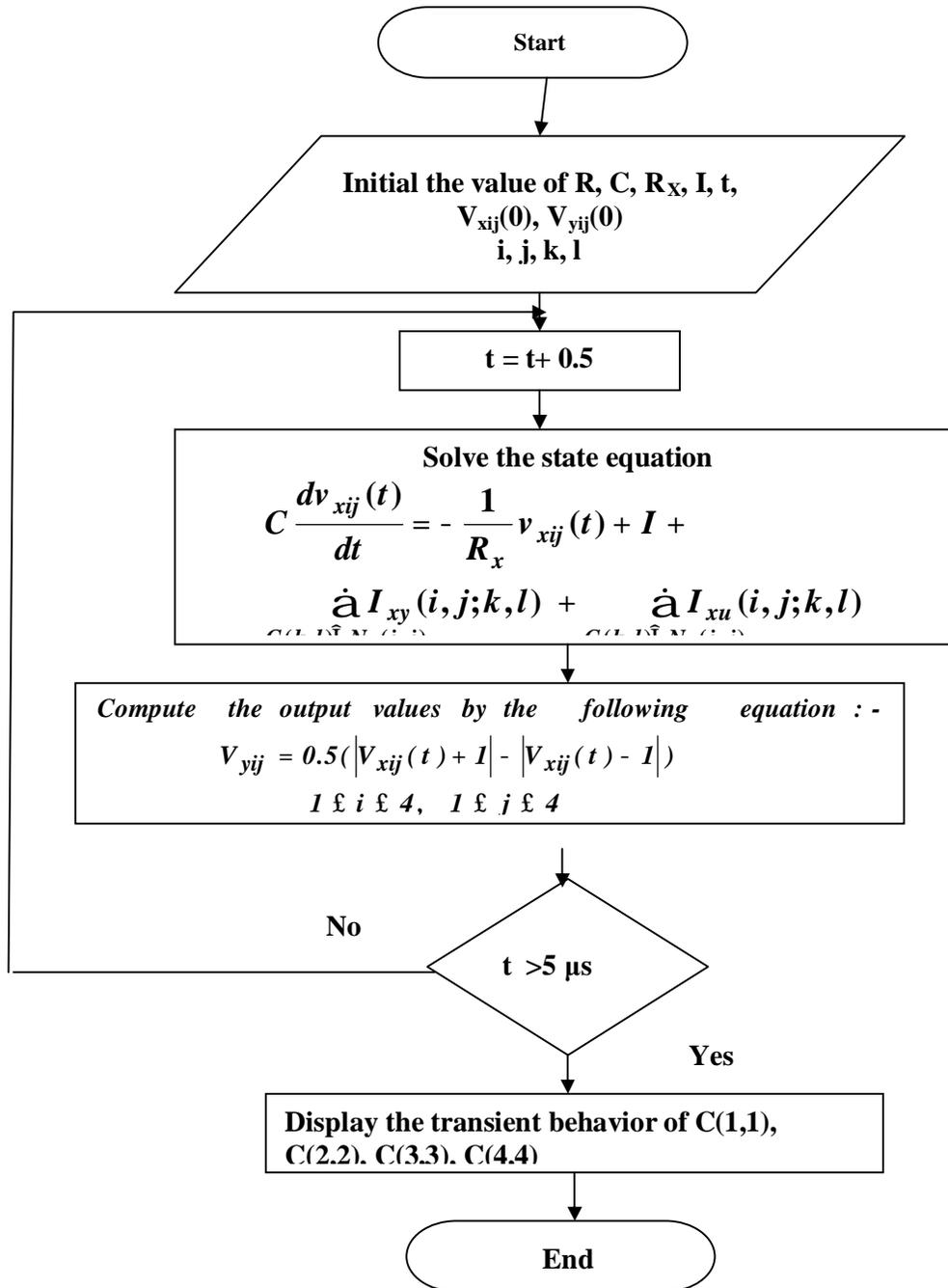


Figure (11) The flow chart of BCNN Matlab program.

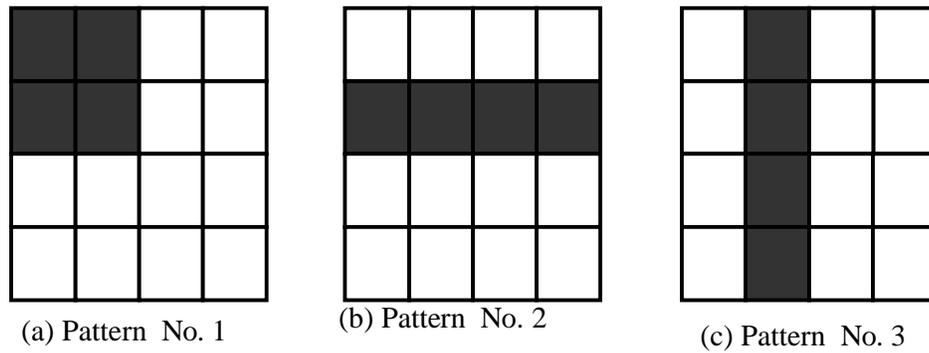


Figure (12) The three stored patterns of a 4x4 BCNN.

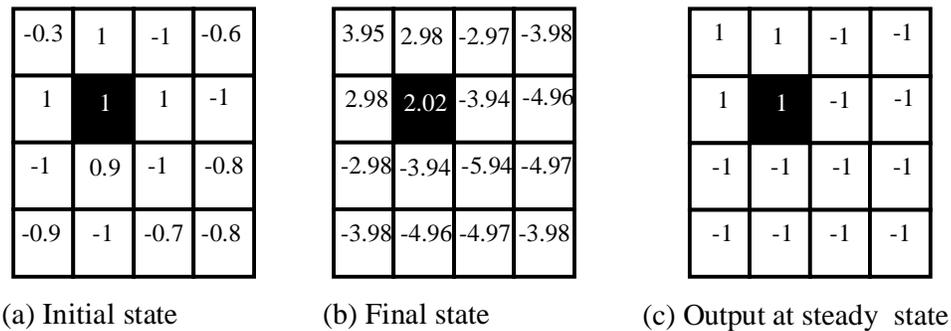


Figure (13) Computer simulation result of stored pattern No.1 using Mat lab for 2 iterations.

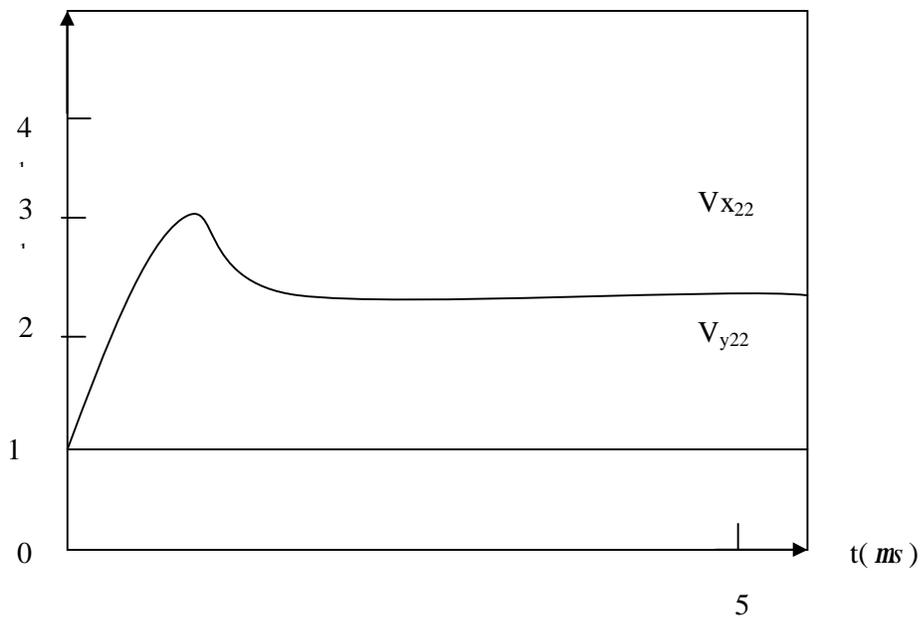
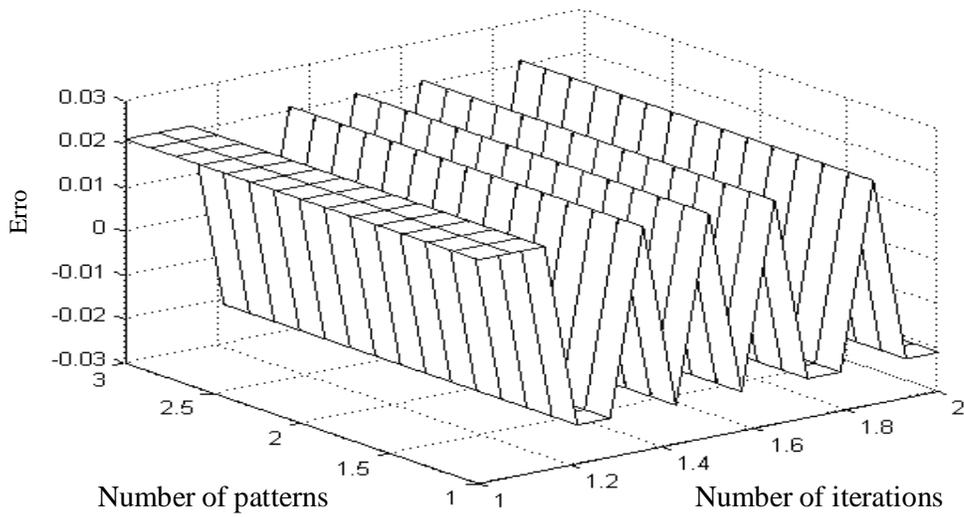
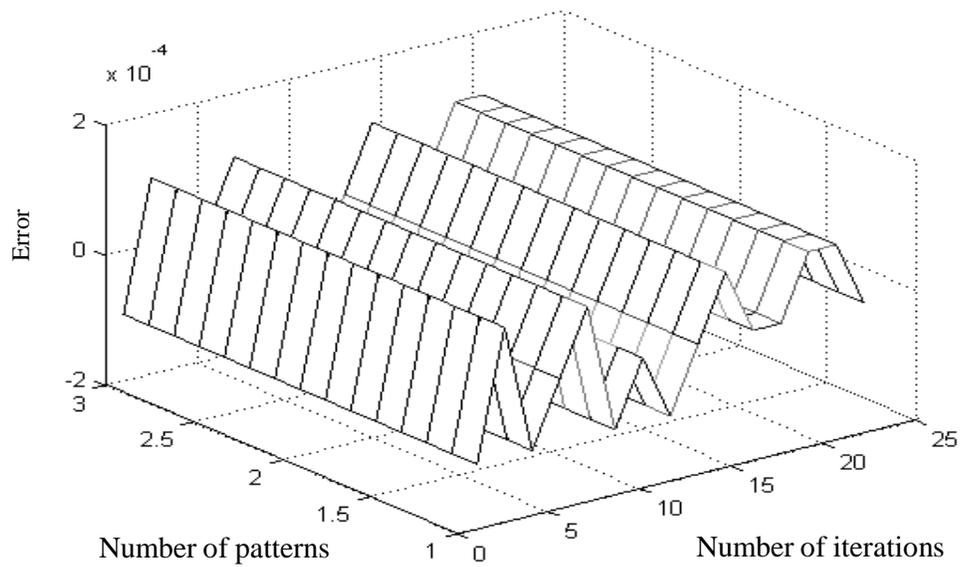


Figure (14) Transient waveforms of Bee cell circuit C(4,4) for cell C(2,2) only.



(a)



(b)

Figure (15) The error of the 4x4 BCNN a-the number of iterations is (2). b-the number of iterations is (22).