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AUTOASSOCIATIVE NEURAL NETWORK USING CGH FOR NEURONS INTERCONNECTION

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ABSTRACT: One of the most promising implementation of artificial neural networks is optoelectronic implementation. Optical interconnections are useful for neural networks as far as one can take advantage of the special potential of 3D connection through free space. This paper presents an autoassociative memory built for graphic pattern recognition. Neurons interconnections are considered to be implemented optically by computer generated holograms (CGH). The network functioning was simulated on computer and the paper presents a CGH layout for neuron interconnections.
Keywords: autoassociative memory, optical interconnections, computer generated holograms.

1. INTRODUCTION

During last ten years the fields of optoelectronic and neural networks were characterized by a great dynamics with remarkable results, very useful for human society progress. The two fields are characterized by a great amount of parallelism of processes. This paper intends a theoretical survey of the using of optoelectronic techniques in the implementation of artificial neural networks, especially in that concern the interconnections between neurons. The paper will detail the problems dealing with: autoassociative memories, 3D interconnection by CGH, the design of CGH for interconnecting the artificial neurons.

Some of the fundamental demands for the implementation technologies of neural networks are:

- The used technology must allow the achievement of neurons with non-linear transfer functions;
- Also it have to allow a great amount of connectivity between neurons, possible total connectivity;
- The interconnection of neurons must be realized by variable weights, which will be settled during training process;
- The implementation technology must provide answer times suitable for the field of application of the neural network.

From the functioning point of view, the neural networks have two important features:

- The non-linear processing of information at the neuron level;

- The large volume and the height degree of parallelism of neurons interconnections.

While the non-linear processing is easier to accomplish with electronic devices, the interconnections are more efficient if they are optically made. Therefore in electronics-photonics competition, each area has its advantages and disadvantages. Optics has the advantages of large bandwidth, parallelism, electromagnetic noise immunity etc. Still it does not provide isolation between input and output like electronic circuits and problems in handling photons spots may occur. This is why most approaches use a hybrid system, composed of optical and electronic devices in order to implement neural networks. This kind of optoelectronic system is shown in figure 1.

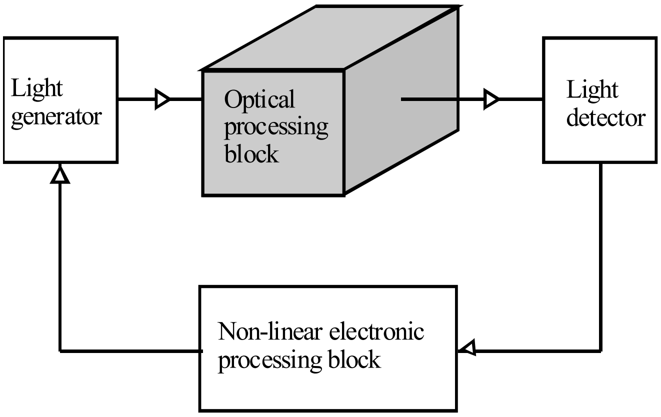

Fig. 1. Block diagram of an optoelectronic system

2. THE ARTIFICIAL NEURAL NETWORK MODEL

In this section we=ll briefly introduce the main theoretical elements concerning associative memories and recurrent neural networks, elements that will be used in section 4 in order to build an associative memory for signature recognition.

We=ll call ›pattern= a multidimensional vector with real components. An associative memory is a system that accomplishes the association of p pattern pairs $\xi^\mu \in R^n$, $\zeta^\mu \in R^m$, (μ=1, 2,..., p) so that when the system is given a new vector $\mathbf{x} \in R^n$ such as

$$d(x,\xi^i) = \min_j d(x,\xi^j) \qquad (1)$$

the system responds with ζ^i; in (1) d(**a**,**b**) is the distance between patterns **a** and **b**.

The pairs (ξ^i, ζ^i), (i= 1,2,... p) are called prototypes and the association accomplished by the memory can be defined as a transformation Φ: $R^n \times R^m$ so that $\zeta^i = \Phi(\xi^i)$. The space $\Omega \subset R^n$ of input vectors **x** is named configuration space and the vectors ξ^i, (i=1,2,...,p) are called attractors or stable points. Around each attractor, there is a basin of attraction B_i such that $\forall\, \mathbf{x} \in B_i$, the dynamics of the network will lead to the stabilization of (ξ^i, ζ^i) pair. For the autoassociative memory $\xi^i = \zeta^i$, (i=1,2,...,p) and if some vector **x** is nearest ξ^i, then $\Phi(\mathbf{x})=\xi^i$. In section 4 we will use for graphic pattern recognition a neural network whose model is presented below. Let=s consider the single-layer neural network built from totally connected neurons, whose states are given by $x_i \in \{-1,1\}$, i=1,2,... n, (fig.2). We denote: $\mathbf{W}=[w_{ij},: 1\le i, j\le n]$ the weights matrix, $\boldsymbol{\theta}=[\theta_1,$

..., $\theta_n]^T \in R^n$ the thresholds vector, $\mathbf{x}\,(t)=[x_1(t), \ldots x_n(t)]^T \in \{-1,1\}^n$ the network state vector. The evolution in time of the network is described by the following dynamic equation [5]:

$$x_i(t+1) = \mathrm{sgn}[\sum_{j=1}^{n} w_{ij} x_j(t) - \boldsymbol{\theta}_i] \quad i = 1,2,\ldots,n \qquad (2)$$

with the convention:

$$\sum_{j=1}^{n} w_{ij} x_j - \boldsymbol{\theta}_i = 0\,, \;\; x_i(t+1) = x_i(t) \qquad (3)$$

where :

$$\mathrm{sgn}(x) = \begin{cases} 1 \text{ if } x > 0 \\ -1 \text{ if } x < 0 \end{cases} \qquad (4)$$

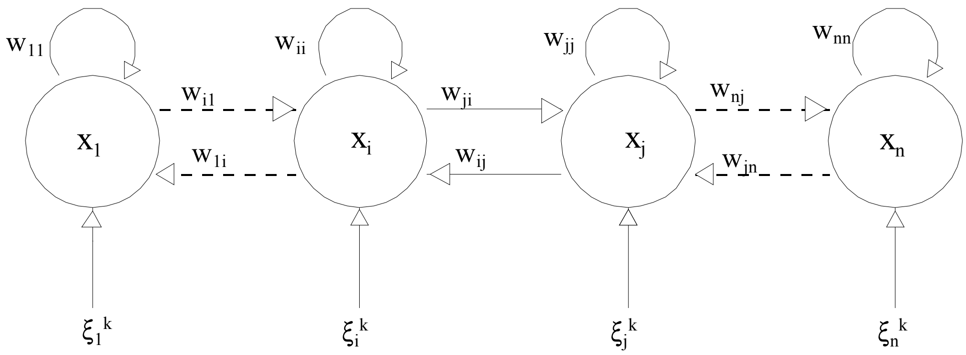

Fig. 2. Single layer recurrent neural network

In many situations we may give up the neural network threshold θ_i and we=ll do this whenever it doesn’t affect the results. For the autoassociative memory described in this paper, the weight matrix **W** will be built as follows:

Given a set of n-dimensional prototype vectors $\mathbf{X}=[\boldsymbol{\xi}^1, \boldsymbol{\xi}^2, \ldots, \boldsymbol{\xi}^p]$, we establish the synaptic matrix **W** and the threshold vector $\boldsymbol{\theta}$, so that the prototype vectors become stable points for the associative memory, that is:

$$\xi^i = \mathrm{sgn}(W\,\xi^i - \theta)\; i = 1,2,\ldots,p \qquad (5)$$

where the sgn function is applied to each component of the argument.

Several classical rules for determining the weights matrix proved successful in time: the ›Hebb= rule, the projection rule, the delta projection rule (the gradient method)

3. OPTICAL INTERCONNECTIONS OF ARTIFICIAL NEURONS

The implementation of optical interconnections that benefit of the advantage of parallelism and speed is connected to the development of parallel computers and optical telecommunication systems. Facing the electronic connections, the optical ones have greater speed and noise immunity. Also, they can be used at different levels of computing: in local area networks, between processors, between processors and memories, between a system planes, between devices on a plane and between the components of a chip.

Into one ideal system every element is connected to the others. In reality, depending on the concrete problem and the technological and economical constraints, one use only partially interconnections. Depending on application, it is necessary to use one special type of interconnections:

- In optical digital computers is necessary one to one connectivity;
- In analogue processing or in systolic or cellular implementations are needed regularly interconnections, invariant to spatial shift;
- In neural networks, the strength of connection depends on neuron; the connectivity is dense and usually is non-uniform.

Optical interconnections can be realized in free space, by optical fiber or by integrated optical guides. This kind of interconnections are useful for neural networks as far as one can take advantage of the special potential of 3D connection through free space. This involves the organizing of the neurons layer in 2D configurations (planar), where the optical interconnections realize the desired links between the two planes. A certain connection also materializes the synaptic weight corresponding to neuron j from input plane and neuron i from output plane (fig. 2). The interconnection network accomplishes the following function:

$$\beta(k, l) = \sum_{ij} T_{ijkl}\alpha(i, j) \qquad (6)$$

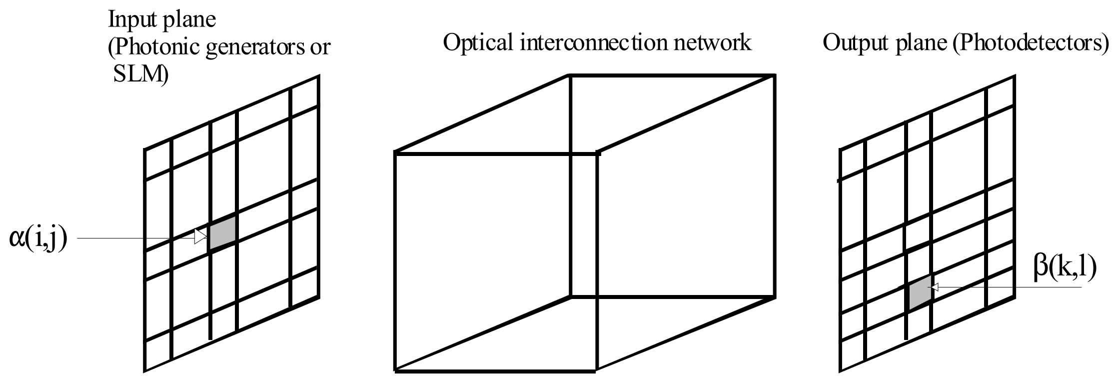

Fig. 3. Optical interconnection of two neural plans

In order to connect the two-neuron planes one may use computer-generated holograms (CGH), which, by light waves diffraction, assure the desired connections. Due to the fact that generally the connections differ from neuron to neuron, the interconnection system will be a spatial variant system, each point from the input plane being connected differently to the output plane.

4. COMPUTER GENERATED HOLOGRAMS (CGH)

There are a lot of types of holograms, which are identified by the modality of realization or the way the object wave is registered or rebuilt. There is a category of holograms, synthesized with the help of the computer and the information registered is the result of a process of codification and quantification and not the result of a physical process of interference. These are called synthetically or computer generated holograms (CGH-Computer Generated Holograms). These are optic diffractive elements in which the diffractive structure was determined on a computer by a mathematical description of the wave front to be obtained or by a sampling of this one.

The synthesis of a CGH comprises more steps that could be synthesized as follows [4], [5], [6]:

- computation of the amplitude complex distribution in hologram plan from the specification of the image to be retraced.
- codification of the complex amplitude as a real, non-negative function
- description (display) of the transmittance obtained at the previous item on an adapted device.
- the transfer of the transmittance on an optical material, by photo-reduction in the view of generation of the properly hologram.

The steps above mentioned are displayed in figure 4.

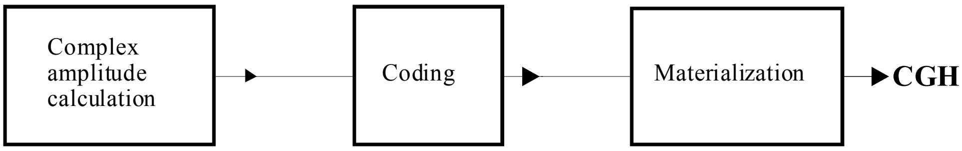

Fig. 4. The main steps in CGH processing. Source [7], p. 29

Next we will consider the case of *Fourier amplitude holograms*

5. EXPERIMENTAL RESULTS

We attempted the design an example of interconnection CGH. We considered a very simple recurrent network, designed to recognize the graphical patterns in figure 5. The network was organized as a plan of 16x16 neurons. In our approach it is necessary a CGH for every neuron, to achieve the interconnection of this neuron to all other neurons in network. We calculated only one interconnection CGH, from neuron (1,1) to the other neurons in network. The method used was “detour phase”, with no error correction. Because the amplitude dynamic range resulted after Fourier transform was too great, we compressed this dynamic range. The resulting layout is displayed in figure 6. We developed our own applications to design autoasociative memories and also to design CGH starting by interconnection matrix. Using our simulator (SIMREC) we theoretically studied the influence of implementation errors on the memory behavior.

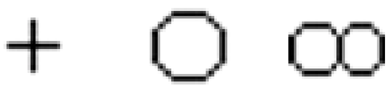

Fig. 5. Graphical patterns used as prototypes

6. CONCLUSIONS

The interconnections of optoelectronic neuron by means of CGH seem to be a useful solution to satisfy the necessity of dense connectivity. There are, nevertheless, several problems due to the spatial variant interconnection and to diffraction efficiency.

Other problems appear as consequences of errors which can appear in the realization of CGH and in optical set-up. The simulations [2] have shown diminished performances of the auto associative memory as a result of the random weights deviations from the correctly computed values. For the statistical parameters used above the performances' degradation is relatively small, which proves certain insensitivity to those deviations. Therefore, the memory appears quite robust, not only in what the noise contained by the patterns to be recognized is concerned, but also in relation with the random weights deviations.

This aspect is to be elucidated in further studies. It would also be useful to determine quantitatively the contribution of the errors to the deviation of actual weights from accurate ones, in order to state realistic requests for the hardware implementation of the auto associative memory.

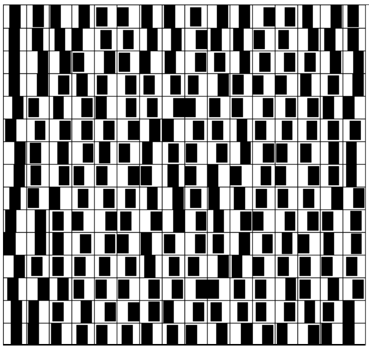

Fig. 6. Layout of CGH connecting neuron (1,1) to the other neurons

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