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Brief Papers

Associative memory network and its hardware design

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ABSTRACT

In order to improve the performance of the conventional associative memory network, a novel associative memory network composed of input layer, computing layer, associative layer and output layer is proposed. An improved Hebb learning rule is designed for the associative network to perform the associative memory of strong correlation and multi-valued sample patterns. The associative memory can be performed by the associative network in only one forward calculation. The hardware circuit of the network can be designed by simple devices to ensure its parallel computation ability and meet the real-time requirement. Simulation results show that the network has better associative performance than conventional associative network in the binary patterns associative memory, it can store and associate strong correlation sample patterns, and it can retrieve the distortion multi-valued sample patterns with 40% noise correctly.

1. Introduction

Associative memory is an important cognitive function in artificial intelligence, which is also an important research area in the neural network field [1–4]. Associative memory can be applied in the field of pattern recognition, image process and others [5–8]. It is content addressable memory referring to brain-like devices for storing prototype patterns such that the stored patterns can be retrieved with the recalling probes or cues that contain information about the contents of the patterns [9].

The earlier studies on the associative memory focus mostly on the binary patterns. Many associative networks, such as Hopfiled neural network, bidirectional associative memory (BAM) neural network, chaotic neural network, and so on, are proposed to improve the associative performance [10–14].

As the research developing, it has been recognized that the research on associative memory of multi-valued patterns has very important practical value and theoretical significance. But comparatively, the research achievements on the multi-valued associative memory are quite rare [15]. If the binary associative network is used to resolve multi-valued associative problem, the structure of networks will become more complex, and the associative performance will degrade seriously [16]. Therefore, the multi-valued associative memory is one of the hotspots in the research of associative memories at present.

Based on the Hebb rule, an improved learning rule which can be applied to perform multi-valued associative memory is proposed in this letter. Using this learning rule, a novel associative network is constructed. In addition, the hardware circuit of the network is designed by some common devices. The numerical simulations are done, and the associative performances of the proposed associative memory network are deeply analyzed.

In Section II, the associative memory network based on the improved Hebb rule is given, and the working process and performances of the network are analyzed. In Section III, the hardware design of the associative network is shown by the circuit diagram. In Section IV, various associative memory examples are given by the numerical simulations. A brief conclusion is given in Section V.

2. Novel associative memory network based on improved Hebb rule

The conventional Hebb rule can only store binary patterns, so most of Hopfield associative memory networks cannot do the associative memories for the multi-valued patterns. In this letter, a new learning rule based on the Hebb rule for not only binary patterns but also multi-valued patterns is proposed, and the corresponding associative network is constructed to perform the associative memories for binary patterns, strong correlation patterns, and multi-valued patterns.

Let the network store M sample patterns, and each sample pattern contains N elements. Each element takes value in P constants. That is, set the M stored pattern as A_1, A_2, …, A_M, where

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$A_i=[a_i^1, a_i^2,\ldots, a_i^N]$, and $a_i^j \in \{b_1, b_2,\ldots, b_P\}$. Because the associative memory belongs to the pattern recognition category, the sequence numbers of the stored patterns are used as the output of the associative network. A heteroassociative network is designed to perform the associative memory. The structure of the associative network is shown in Fig. 1.

The associative network contains four layers. The first layer is the input layer composed of N neurons, which correspond to the N elements of the input pattern. The second layer is the computing layer composed of $(N^2-2N)/2$ neurons, which form a triangular matrix. The plan of the second layer is shown in Fig. 2.

The neurons in the computing layer have only two states: excitement and inhibition. All the solid neurons are on the top right corner, which are organized as the computing layer. And the dotted neurons $h_{i\ j}$, $(i \geq j)$, are non-existent, or these dotted neurons are always inhibition, and their output are invariably zero. Each solid neuron in the second layer connects with two neurons in the first layer. For instance, the neuron $h_{i\ j}$, $(i<j)$, in the second layer connects with the neurons x_i and x_j in the first layer. All the dotted neurons and solid neurons form a $N \times N$ square matrix $\boldsymbol{H}$ together.

$$H=\begin{bmatrix} H_1^{\mathrm{T}} & H_2^{\mathrm{T}} & \ldots & H_N^{\mathrm{T}} \end{bmatrix}=\begin{bmatrix} h_{11} & h_{12} & \ldots & h_{1N} \\ h_{21} & h_{22} & \ldots & h_{2N} \\ \ldots & \ldots & \ldots & \ldots \\ h_{N1} & h_{N2} & \ldots & h_{NN} \end{bmatrix} \tag{1}$$

Where, the symbol "T" is the transpose operation of the vector, and H_i^{T} is a column vector as follows:

$$H_i^{\mathrm{T}}=\begin{bmatrix} h_{i1} & h_{i2} & \ldots & h_{iN} \end{bmatrix}^T, i=1,2,\ldots,N \tag{2}$$

The third layer in Fig. 1 is the associative layer composed of M neurons, which correspond to the M stored patterns. The second layer and the third layer are fully connected by the weights $\{w_{ij,k}\}$. All the weights connected with the k-th neuron in the third layer form a $N \times N$ square matrix $\boldsymbol{W}_k$ together as:

$$W_k=\begin{bmatrix} W_{1,k}^{\mathrm{T}} & W_{2,k}^{\mathrm{T}} & \ldots & W_{N,k}^{\mathrm{T}} \end{bmatrix}=\begin{bmatrix} w_{11,k} & w_{12,k} & \ldots & w_{1N,k} \\ w_{21,k} & w_{22,k} & \ldots & w_{2N,k} \\ \ldots & \ldots & \ldots & \ldots \\ w_{N1,k} & w_{N2,k} & \ldots & w_{NN,k} \end{bmatrix} \tag{3}$$

Where, $W_{i,k}^{\mathrm{T}}$ is a column vector as follows:

$$W_{i,k}^{\mathrm{T}}=\begin{bmatrix} w_{i1,k} & w_{i2,k} & \ldots & w_{iN,k} \end{bmatrix}^T, i=1,2,\ldots,N \tag{4}$$

Because neurons h_{ij} $(i \geq j)$ are non-existent, the weights $w_{ij,k}$ $(i \geq j)$ are also non-existent, which are all set to zero. Therefore, the weight matrix $\boldsymbol{W}_k$ is also an upper triangular matrix.

The fourth layer is the competitive output layer, which outputs the associative result.

The learning algorithm of the network is mainly used to design the connection weights between the second layer and the third layer. In this letter, a new learning algorithm based on the Hebb rule is proposed. The design principle of Hebb rule is that when the two neurons become excited simultaneously the weight between them will be strengthened. In order to perform multi-valued associative memory, Hebb rule is improved and generalized as: when the two neurons' states are same, the weight between them is strongly connected (the weight value is 1), otherwise the weight between them is disconnected (the weight value is 0). Therefore, the connection weight $w_{ij,k}$ between the neuron h_{ij} in the second layer and the k-th neuron in the third layer can be designed according to the stored patterns as follows:

$$w_{ij,k}=\begin{cases} 1, \text{ if } a_k^i=a_k^j \text{ and } i<j \\ 0, \text{ otherwise} \end{cases} \tag{5}$$

The input pattern is put into the input layer of the associative network to do the associative memory. When the sates of the i-th and j-th neurons in the input layer are same, the state of the neuron h_{ij} in the second layer will be excited. Otherwise, the state

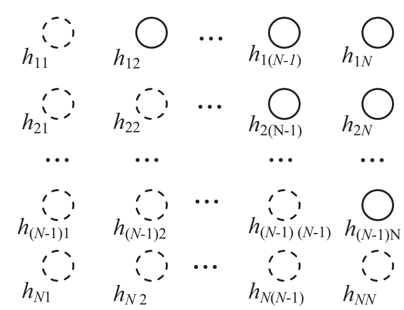

Fig. 2. The plan of the second layer.

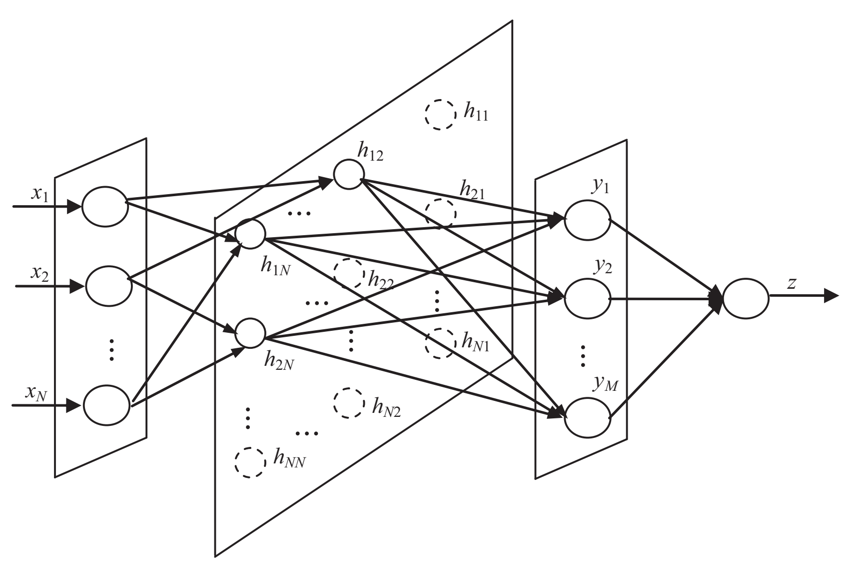

Fig. 1. The structure of the associative memory network.