Synthesis of Neural Associative Memories for Artificial Vision Systems by Fuzzy Image Segmentations

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Abstract: - A design procedure of neural associative memories to be used for robot vision systems is developed, which fits in the capabilities both of discrete-time cellular neural networks (DTCNNs) and fuzzy logic. The choice of this kind of neural networks is motivated by their architecture, suitable for storing images, and their locally connected structure, which is effective for the hardware implementation of the designed memories. In particular, fuzzy logic has been used for mapping original images into binary segmented ones, which can be stored into this kind of neural associative memory, due to the fact that the discrete-time cellular neural networks hardware realization cannot agree with the 256 gray levels of natural images and with their strongly nonlinear hystograms. The necessary storage capacity is guaranteed for the associative memory by imposing the conditions which assure the asymptotic stability for the segmented images to be memorized. The performance of the designed memory is then investigated by testing its error correction capability.

Key words:- Discrete-Time Neural Networks, Fuzzy Logic, Cellular Neural Networks, Neural Associative Memories

1 Introduction

In the field of robotics image processing in real time is imperative, as it usually provides the information necessary for the execution of robot tasks. Since a robot makes its decisions and acts on the basis of image analysis, irrespective of any consequence, the results of a recognition process required from a robot must possess a greater safety with respect to traditional pattern recognition techniques. Furthermore, artificial vision in automatic units needs to be pursued by considering the extraction of information specifically required for a robot to carry out its job. This implies that vigorous constraints in object matching have to be applied by means of suitable techniques.

Taking into account the step sequence to be followed by any robot vision system for carrying out an object matching procedure, it can be noted that, after detecting images by means of proper signal sensors, these images have to be transformed, so as to extract the relevant features. Object matching can be obtained for automatic units by exploiting memories properly designed to store and compare the reference images with the detected ones.

On the basis of these considerations, in this paper a design procedure of discrete-time cellular neural networks (DTCNNs) for associative memories to be used in robot vision systems is developed, which fits in the capabilities both of cellular neural networks and fuzzy logic.

The choice of cellular neural networks [1] is motivated by their attractive architecture, which proves adequate for image storing [2, 3] and their structure characterized by local connections, which could lead to an effective hardware implementation of the designed networks. However, since the hardware realization cannot agree with the 256 gray levels of natural images and their strongly nonlinear hystograms, difficulties arise in determining proper and reliable image segmentations. In this paper an attempt is made to overcome this drawback by adopting fuzzy encoding procedures in the course of the image segmentation [4-6] to map original images into binary segmented ones, more easily storable into a cellular neural network behaving as an associative memory. The required storage capacity of the associative memory is obtained by imposing the conditions for assuring that each segmented image corresponds to an asymptotically stable equilibrium point of the network [3]. An example concerning with the recognition of industrial tools, handled by a robot in an assembly line, is illustrated and the performance of the corresponding designed memory is evaluated by testing its error correction capability.

2 Fuzzy encoding procedure

The proposed fuzzy technique enables to segment original 256-level images $\boldsymbol{P} = [p_{ij}]$ into binary segmented images $\boldsymbol{F} = [f_{ij}]$ which can be easily stored in a DTCNN with a two-level output function. A proper fuzzification procedure, based on the analysis of the histograms of the given images [5], is therefore developed to define two fuzzy subsets adequate to describe their semantic content as industrial tools to be used by a robot. In particular, it can be observed that the domain of gray level values between 0 and 255 is quantized into two semi-overlapped input fuzzy subsets (X_1 = Object, X_2 = Background) as:

$$X_1 = \{X_1\,(p_{ij}) = m(p_{ij}, X_1) \mid 0 \le p_{ij} \le p_2\}$$
$$X_2 = \{X_2\,(p_{ij}) = m(p_{ij}, X_2) \mid p_1 \le p_{ij} \le p_3\}$$

with $p_1 \le p_2 \le p_3 \le 255$. The quantities $m(p_{ij}, X_k)$ denote the value of the membership function for each pixel and can range from 0 to 1. Triangular shapes have been chosen for the fuzzy subsets. Since the fuzzy subsets X_k are semi-overlapped and satisfy the condition

$$X_1(p_{ij}) + X_2(p_{ij}) \le 1 \qquad \forall p_{ij}$$

they are called max-t orthogonal [5].

A fuzzy transformation from input fuzzy sets to output fuzzy sets is established by generating fuzzy rules to relate these fuzzy subsets to the following output ones:

$$Y_1 = \{Y_1\,(f_{ij}) = 0 \mid i, j = 1,..., 256\} \qquad \text{Black}$$
$$Y_2 = \{Y_2\,(f_{ij}) = 255 \mid i, j = 1,..., 256\} \qquad \text{White}$$

In particular, the fuzzy rules which provide the mapping from original images (input) to segmented ones (output) can be expressed as:

IF $p_{ij} \in X_1$ THEN $f_{ij} \in Y_1$
IF $p_{ij} \in X_2$ THEN $f_{ij} \in Y_2$

where $\boldsymbol{F} = [f_{ij}]$ is the generic binary segmented output image. As stated by Theorem 2 in [5], the above reported fuzzy rules can be encoded in a single fuzzy associative memory (FAM) weight matrix by using the max-bounded-product (max-$\otimes$) composition as follows:

$$\boldsymbol{M} = \max_k\, [X_k^T(p_{ij}) \otimes Y_k(f_{ij})] \qquad k = 1, 2$$

All encoded fuzzy rules can be recalled using max-t composition, since the input fuzzy subsets X_k are normal and max-t orthogonal to each other [5].

3 Synthesis of Discrete-Time CNNs for Associative Memories

3.1 Model and stability analysis of Discrete-Time Cellular Neural Networks

The model of an n-cell rectangular DTCNN can be expressed in vector form as [3]:

$$\boldsymbol{u}(k+1) = \boldsymbol{T}\,\boldsymbol{v}(k) + \boldsymbol{I} \qquad (1a)$$
$$\boldsymbol{v}(k) = \boldsymbol{g}(\boldsymbol{u}(k)) \qquad (1b)$$

where $\boldsymbol{u} = [u_1,...,u_n]^T \in R^n$ is the state vector, $\boldsymbol{v} = [v_1,...,v_n]^T \in R^n$ is the output vector, $\boldsymbol{I} = [I_1,...,I_n]^T \in R^n$ contains the current sources values and $\boldsymbol{g} = [g,...,g]^T \in R^n$, where the function $g: R \to R$ is a continuous, and piecewise linear output function in the form

$$g(u) = (|2u+1| - |2u+1|)/2 \qquad (2)$$

The sparse matrix $\boldsymbol{T} = [T_{ij}] \in R^{n \times n}$ is the interconnection matrix, which takes into account the local connection property of the cellular neural network architecture.

Any point $\boldsymbol{u_0} \in R^n$ is said to be an equilibrium point of (1) if [1, 3]

$$\boldsymbol{u_0} = \boldsymbol{T}\,\boldsymbol{g}(\boldsymbol{u_0}) + \boldsymbol{I} \qquad (3)$$

Moreover, it can be proved that the suggested model assures the asymptotic stability of any equilibrium point of system (1), which is a necessary condition to generate an associative memory. In the proposed design, each binary segmented image has to constitute an equilibrium point of the DTCNN.

3.2 Synthesis of Neural Associative Memories based on DTCNNs

The segmented images derived from the fuzzy encoding procedure constitute the set of memories $\boldsymbol{v}^i$, $i = 1,...,m$, to be stored in the memory, each $\boldsymbol{v}^i$ corresponds to an equilibrium point $\boldsymbol{u}^i$ of (1) if and only if

$$\boldsymbol{u}^i = \boldsymbol{T}\,\boldsymbol{v}^i + \boldsymbol{I} \qquad i = 1,..., m \qquad (4)$$

where $\boldsymbol{u}^i = [u_1^i, u_2^i, ..., u_n^i]^{\mathrm{T}} \in R^n$ and $\boldsymbol{v}^i = [v_1^i, v_2^i, ..., v_n^i]^{\mathrm{T}} \in R^n$. Equation (4) can then be rewritten in compact form as:

$$\boldsymbol{U} = \boldsymbol{T}\,\boldsymbol{V} + \boldsymbol{I'} \qquad (5)$$

where $\boldsymbol{V} = [v^1, v^2, \ldots, v^m] \in R^{n \times m}$, $\boldsymbol{I'} = [\boldsymbol{I}, ..., \boldsymbol{I}] \in R^{n \times m}$ and $\boldsymbol{U} = [u^1, u^2, \ldots, u^m] \in R^{n \times m}$.

Our objective consists in determining the matrices $\boldsymbol{T}$ and $\boldsymbol{I'}$ so that the constraint (5) is satisfied. To this purpose, some matrices have to be defined:

$$\boldsymbol{R} = [\boldsymbol{V}^{\mathrm{T}} \,|\, \boldsymbol{J}\,] \in R^{m \times (n+1)}$$

$$\boldsymbol{w}_k = [T_{k1}, T_{k2}, ..., T_{kn} \,|\, I_k] \in R^{1 \times (n+1)}$$

$$\boldsymbol{U}_k = [u_k^1, u_k^2, \ldots, u_k^m] \in R^{1 \times m} \quad k = 1, ..., n$$

where $\boldsymbol{J} = [1, 1, ..., 1]^{\mathrm{T}} \in R^{m \times 1}$.

Equation (5) then becomes:

$$\boldsymbol{R}\,\boldsymbol{w}_k^{\mathrm{T}} = \boldsymbol{U}_k^{\mathrm{T}} \qquad k = 1, ..., n \qquad (6)$$

Equation (6) has to be solved taking into account the constraints dictated by the DTCNN structure in the synthesis procedure and defining a matrix $\boldsymbol{S} = [S_{ik}] \in R^{n x n}$ as follows:

$S_{ik} = 1$ if the k-th cell belongs to the same r-neighbourhood of the i-th cell;
$S_{ik} = 0$ otherwise ($i = 1, ..., n$; $k = 1, ..., n$).

Now, a matrix $\boldsymbol{R}_{rk} \in R^{m x h_k}$ can be obtained from the matrix $\boldsymbol{R}$ by eliminating those columns the indices of which correspond to the zero elements in the k-th row of $\boldsymbol{S}$. Moreover, a vector $\boldsymbol{w}_{rk}$ can be defined as the vector obtained from $\boldsymbol{w}_k$ by eliminating its zero elements. Thus, from (6) it results:

$$\boldsymbol{R}_{rk}\,\boldsymbol{w}_{rk}^{\mathrm{T}} = \boldsymbol{U}_k^{\mathrm{T}} \qquad k = 1, ..., n \qquad (7)$$

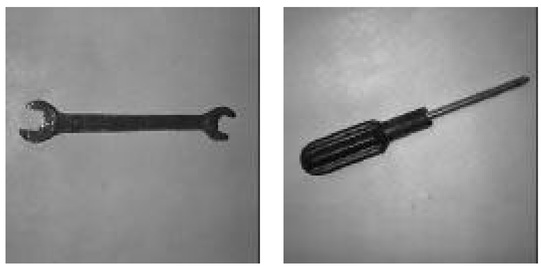
From (7) it follows:

$$\boldsymbol{w}_{rk}^{\mathrm{T}} = \boldsymbol{R}_{rk}^{+} + \boldsymbol{U}_{kj}^{\mathrm{T}} \qquad k = 1, ..., n \qquad (8)$$

where $\boldsymbol{R}_{rk}^{+}$ denotes the pseudo-inverse of $\boldsymbol{R}_{rk}$ [3]. The synthesis procedure concludes by expanding the vector $\boldsymbol{w}_{rk}^{\mathrm{T}}$ with zero elements until the vector $\boldsymbol{w}_k^{\mathrm{T}}$ is obtained.

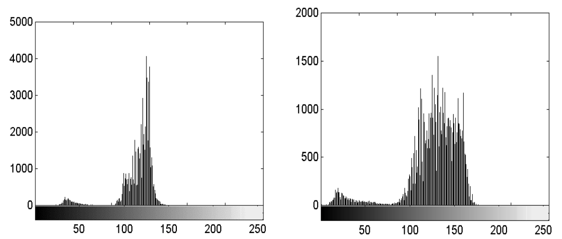
4 Numerical example

In this example a (256x256)-cell DTCNN with the neighbourhood reported in [1] ($r = 1$) is designed to store natural images of industrial tools, as shown in Fig.1. These images are composed of 256x256 pixels, each pixel being capable of assuming a gray level value between 0 and at most 255, as visualized in their hystograms reported in Fig.2.



(a) (b)

Fig.1 – Natural images of industrial tools to be handled by a robot



(a) (b)

Fig.2–Hystograms of the images reported in Fig.1

In particular, it can be observed that the domain of gray level values ranges from 0 to 161. The gray level values used to establish the membership function have been estimated from the original image hystograms [4] as equal to $p_1 = 56$, $p_2 = 80$, $p_3 = 161$. Accordingly, the two following semi-overlapped fuzzy subsets (see Fig. 3) are obtained:

$B = \{p_{ij} \mid 0 \leq p_{ij} \leq 80\}$ Background
$O = \{p_{ij} \mid 56 \leq p_{ij} \leq 161\}$ Object

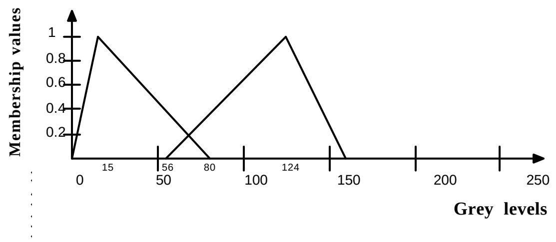


Fig.3 – Membership functions

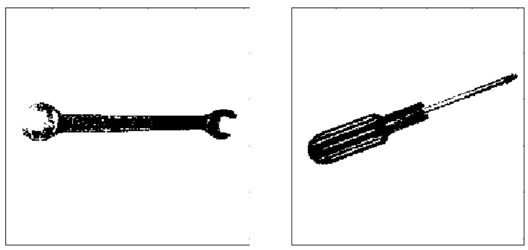


Fig.4 – Binary segmented images

In Fig.4 the fuzzified images have been reported. Then, these images have been submitted to the DTCNN to be trained as asymptotically stable memory vectors. The DTCNN error correction capability has been successively investigated by submitting several noisy images to the designed memory. In Fig.5(a) a noisy image, obtained by adding a spatially distributed gaussian noise $\boldsymbol{N}(m, s)$ with $m = 0$ and $s^2 = 20$, is visualized. The DTCNN output image is recovered in fourteen steps and is shown in Fig.5(b)-(d). It can be noted that the image visualized in Fig.5(d) is identical to the one reported in Fig.4. Other different noisy images ($\boldsymbol{N}(0, 5)$ and $\boldsymbol{N}(0, 25)$) have been submitted to the DTCNN and, accordingly, the recovered images have been obtained in eight and seventeen steps, respectively. It can be observed that the designed DTCNN is able to recover quite satisfactorily the memorized images also when $s^2 = 25$.

5 Conclusions

In this paper a synthesis procedure of neural associative memories for artificial vision systems based on DTCNNs has been developed via a fuzzy encoding procedure. The fuzzy encoding technique enables the designed network to store natural images. A satisfying error correction capability has been found for the designed memory

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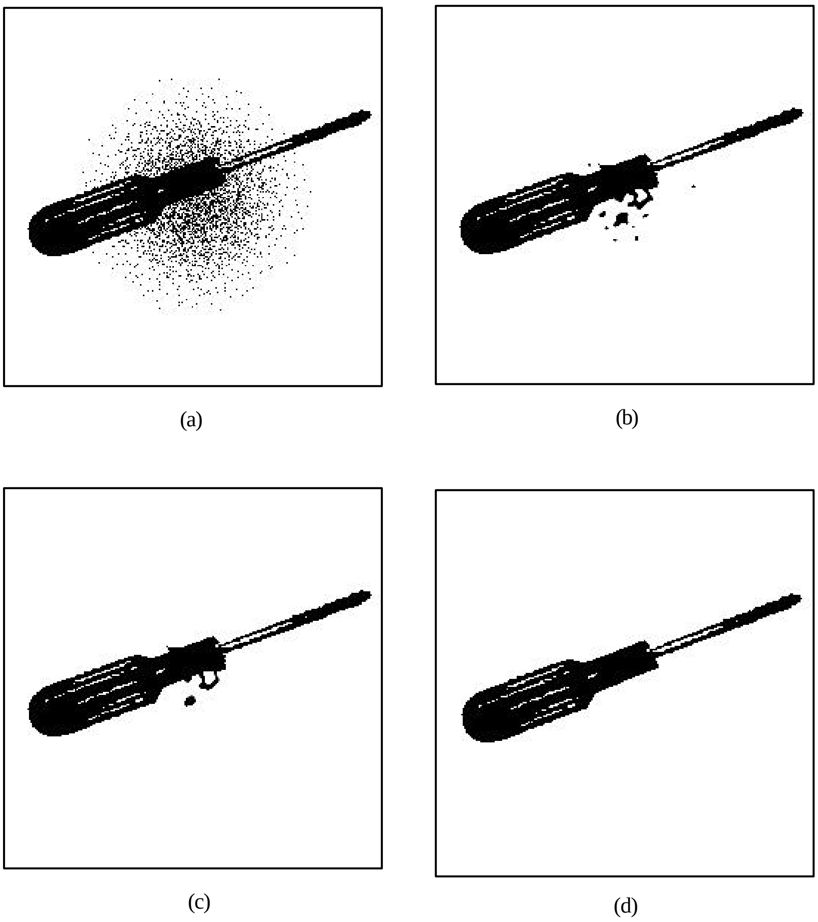

Fig.5 – Evolution of a selected noisy pattern: (a) submitted noisy image; (b) output at step 4; (c) output at step 8; (d) final output at step14.