Fuzzy Associative Memories for Bidimensional Pattern Segmentation in CNN-based Systems

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Abstract: - In this paper a design procedure of Fuzzy Associative Memories containing fuzzy rules for bidimensional pattern segmentation in CNN-based systems is developed. A Fuzzy Necessity/Possibility Technique is considered for these memories to provide binary segmented images adequate to be stored into cellular neural networks for object matching analysis. Simulation results are reported to show the capabilities of the proposed method.

Key-Words: - Neural Networks, Fuzzy Associative Memories, CNN-based Systems

1.Introduction

In pattern recognition processes satisfactory performances are required for industrial applications to assure safety to the applications themselves. In particular, the specific extraction of information needed for object matching implies vigorous constraints which can be satisfied by means of suitable techniques. Among these techniques, an adequate object matching can be obtained by exploiting memories properly designed to store and compare the reference images with the detected ones. For this purpose, in recent years the design of Cellular Neural Networks (CNNs) has revealed successful both for their attractive architectural feature of local connections and for their structure adequate for storing particular memory vectors such as bidimensional patterns [1]. These aspects lead to an efficient hardware implementation of the corresponding designed networks [2]. In addition, if CNNs with multilevel output functions are used, the designed networks reveal able to store gray level images [3]. However, it should be noted that, since the hardware complexity rapidly increases with the number of the gray levels of the images to be stored, until now and in so far as the authors are aware, rare attempts have been made to design CNNs with bipolar output functions able to store natural images characterized by 256 gray levels.

A different approach could consist in using an encoder to segment each original natural image in a less number of gray levels before storing it into a CNN-based system. Unfortunately, due to the fact that natural images generally present strongly nonlinear hystograms, obvious difficulties arise in determining an adaptive threshold encoder capable of providing the required segmentations. On the basis of these considerations, in this paper a design procedure of Fuzzy Associative Memories is developed, with the aim of solving the above mentioned problem, that is, thresholding images in such a way to be easily storable in a CNN-based system [4].

The idea is based on the observation that, as is well known, a fuzzy encoding rule can easily map crisp inputs into crisp outputs [5,6] and more rules satisfying certain properties can be included into a single Fuzzy Associative Memory (FAM) [7] which behaves as a fuzzifier. In this paper a FAM based on the fuzzy Possibility/Necessity Technique developed by Pedrycz et al. in [6] is designed to map the crisp values of gray-levels into proper fuzzy subsets characterized by fuzzy membership functions, which provide a measure of the degree of similarity of each crisp value to each fuzzy subset. The FAM is synthesized in such a way to involve contemporary the fuzzy rules which map each original image into a segmented one. The recovered capabilities of the designed memory are illustrated and discussed by means of a numerical example, concerning with the segmentation of 256-level images of industrial tools into binary ones, which can be easily stored in a CNN with a two-level output function.

2. Fuzzy encoding procedure

In this work a Fuzzy Associative Memory has been developed as reported in figure 1.

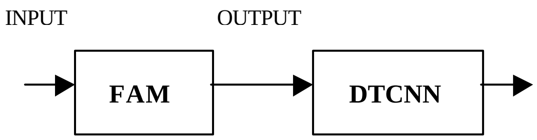


Figure 1: Block diagram of the proposed architecture

The proposed system enables to transform original 256-levels images into binary segmented ones more easily storable into a Discrete-Time Cellular Neural Network (DTCNN), which behaves as a memory in an industrial artificial vision system. A proper fuzzification procedure is developed to define two fuzzy subsets adequate to describe the semantic content of patterns such as images of industrial tools. These images can be classified as belonging to the Object/Background class. In particular, it can be observed that the domain of gray level values between 0 and 255 can be quantized into two overlapped input fuzzy subsets A_1 and A_2 corresponding to Object and Background, respectively, and defined as follows:

$$A_1=\{A_1(p_{ij}) = m_{A1}(p_{ij}) \mid 0 \le p_{ij} \le p_2\}$$
$$A_2=\{A_2(p_{ij}) = m_{A2}(p_{ij}) \mid p_1 \le p_{ij} \le p_3\}$$

with $0 \le p_1 \le p_2 \le p_3$, being p_{ij} the pixel of the original image whose indices are i and j. The quantities $m_{Ak}(p_{ij})$ denote the value of the membership function for each pixel and can range from 0 to 1. Right-angled triangular shapes have been chosen for the fuzzy subsets, such that:

$$m_{A1}(p_{ij}) + m_{A2}(p_{ij}) \le 1 \qquad \forall p_{ij}$$

as visualized in Fig.2.

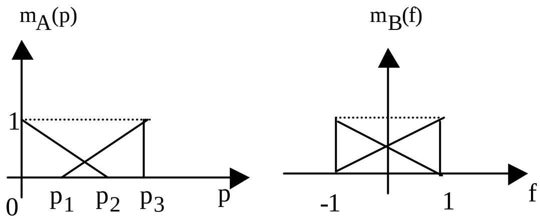


Figure 2: Membership functions

Since A_1 and A_2 satisfy this condition, they are called max-t orthogonal. In an analogous way, the domain of output values between –1 and 1 has been quantized into two similar output fuzzy subsets B_1 and B_2 (B_1 = Black, B_2 = White). In particular, the fuzzy rules which provide the mapping from original images (input) into segmented ones (output) can be expressed as:

IF $p_{ij} \in A_1$ THEN $f_{ij} \in B_1$
IF $p_{ij} \in A_2$ THEN $f_{ij} \in B_2$

where f_{ij} denotes the (i,j) pixel in the final segmented image. The architecture of the corresponding proposed CNN-based system is illustrated in Fig.3, and its blocks are described in detail in the following.

As stated by Theorem 2 in [7], the reported fuzzy rules can be encoded in a single fuzzy associative memory (FAM) by determining a weight matrix **M** based on the max-bounded-product (max-⊗) composition as follows:

$$\mathbf{M} = \max\,[\mathbf{a_1} \otimes \mathbf{b_1},\ \mathbf{a_2} \otimes \mathbf{b_2}]$$

where

$$\mathbf{a_1} = [\ m_{A1}(0)\ \ m_{A1}(p_1)\ \ m_{A1}(p_2)\ \ m_{A1}(p_3)]$$
$$\mathbf{a_2} = [\ m_{A2}(0)\ \ m_{A2}(p_1)\ \ m_{A2}(p_2)\ \ m_{A2}(p_3)]$$
$$\mathbf{b_1} = [\ m_{B1}(-1)\ \ m_{B1}(1)]$$
$$\mathbf{b_2} = [\ m_{B2}(-1)\ \ m_{B2}(1)]$$

The matrix **M** encodes the two fuzzy rules that can be recalled using max-t composition, since fuzzy sets A_1 and A_2 are normal and max-t orthogonal to each other.

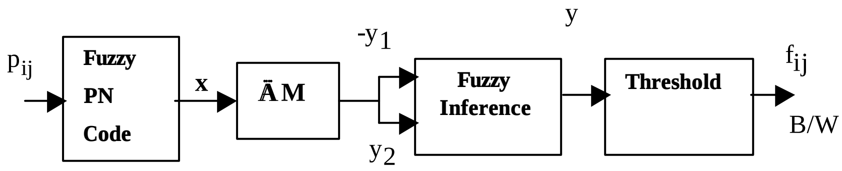


Figure 3: Block diagram of the proposed CNN-based system

3. Synthesis of Fuzzy Associative Memories

Taking into account the PN model introduced in [6], each pixel, codified through the above mentioned model, is represented with a vector **x** = [x_1 x_2 x_3 x_4] as follows:

$$\mathbf{x} = [P(p|m_{A1})\ \ N(p|m_{A1})\ \ P(p|m_{A2})\ \ N(p|m_{A2})]$$

that is,

$$\mathbf{x} = [m_{A1}(p_{ij})\ \ m_{A1}(p_{ij})\ \ m_{A2}(p_{ij})\ \ m_{A2}(p_{ij})]$$

This vector recalls a vector **y** of rules by means of a max-bounded composition with **M** such that:

$$\mathbf{y} = [-y_1\ y_2] = \mathbf{x} \otimes \mathbf{M}$$

where y_1 gives information about the "firing" [5] of the first rule, y_2 gives information about the "firing" of the second one. Successively, the two outputs y_1 and y_2 are infered with the so called method of the "center of gravity" to obtain a single variable y. The value of this final variable

$$y = (-y_1 + y_2) / (y_1 + y_2)$$

is then thresholded using the method reported in [8], for each fuzzified image. The generic fuzzified image coincides with the output of the inference block reported in Fig.3.

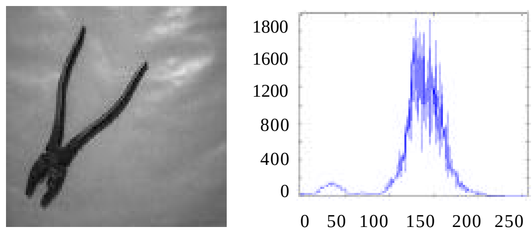
Each pixel contains a gray level value, belonging to the Object set, or to the Background one, respectively, with a degree of membership given by $F_1 = m_{A1}(p_{ij})$ and $F_2 = m_{A2}(p_{ij})$, respectively.

Cellular Neural Networks working as associative memories can be synthesized on the basis of an assigned training set which contains the patterns the memory has to store. Let matrix **M** be the (4x2)-matrix which can codify the described FAM system, where each input **x** is associated to a numerical output vector $\mathbf{y} = \mathbf{x} \otimes \mathbf{M}$, with $\mathbf{x} \in \mathbf{R}^4$, $\mathbf{y} \in \mathbf{R}^2$.

It can be observed that the synthesized FAM memory contains the matrix **M**.

4. Numerical example

In this example the segmentation of an image, representing an industrial tool, is illustrated. This image, which is shown in Fig.4(a) is composed of 256 x 256 pixels, each pixel being capable of assuming a gray level value between 0 and 255, as visualized in its strongly nonlinear hystogram reported in Fig.4(b).



(a) (b)

Figure 4 : Original image (a) and its hystogram (b)

The gray level values used to establish the antecedent membership functions have been estimated equal to p_1=95, p_2=160 and p_3=255. These values give the optimal results, referring to the degree of overlapping of the corresponding fuzzy sets. This choice leads to :

$$\mathbf{a_1} = [\ m_{A1}(0)\ m_{A1}(95)\ m_{A1}(160)\ m_{A1}(255)]$$

$$= [\ 1\ 0.4063\ 0\ 0]$$

$$\mathbf{a_2} = [\ m_{A2}(0)\ m_{A2}(95)\ m_{A2}(160)\ m_{A2}(255)]$$

$$= [\ 0\ 0\ 0.4063\ 1]$$

$$\mathbf{b_1} = [\ m_{B1}(-1)\ m_{B1}(1)] = [\ 1\quad 0\ ]$$

$$\mathbf{b_2} = [\ m_{B2}(-1)\ m_{B2}(1)] = [\ 0\quad 1\ ]$$

In this case the matrix **M** which encodes the two fuzzy rules that can be recalled using max-t composition is

$$\mathbf{M} = \begin{pmatrix} 1 & 0 \\ 0.4063 & 0 \\ 0 & 0.4063 \\ 0 & 1 \end{pmatrix}$$

After processing the image with the synthesized FAM, the obtained hystogram is reported in Fig.5.

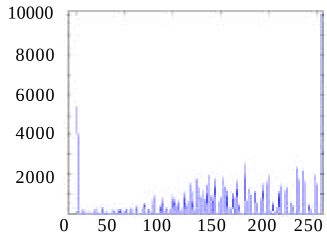


Figure 5. Hystogram of the fuzzified image

The binary image resulting from segmentation is reported in Fig. 6.

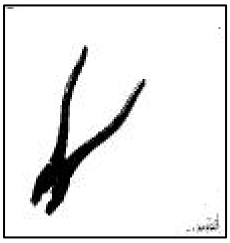


Figure 6: Segmentation result

It can be observed that the synthesized FAM provides segmented images where objects can be well distinguished from the background.

5.Conclusions

In this paper a design procedure of Fuzzy Associative Memories containing fuzzy rules for bidimensional pattern segmentation in industrial applications has been developed. The considered Fuzzy Necessity/Possibility Technique provides binary segmented images adequate to be memorized in CNN-based systems. Simulation results have shown the capabilities of the proposed method.

Acknowledgement

This work was partly supported by the Ministero dell'Università e della Ricerca Scientifica and partly by the Politecnico di Bari .

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