# A Cellular Fuzzy Associative Memory for Image Fuzzification in Robot Vision Systems

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*Abstract:* In this paper a Cellular Fuzzy Associative Memory containing fuzzy rules for bidimensional image fuzzification in robot vision systems is developed. This cellular processor constitutes a subsystem of a CNN-based architecture which can store both bidimensional patterns and the rules to process them. After establishing the fuzzy rules characterizing the Fuzzy Associative Memory, a CNN behaving as an associative memory is properly synthesized to store them. A numerical example is reported to show how the synthesized Cellular FAM can process bidimensional patterns for industrial object matching analyses.

*Key words:* Image Fuzzy Coding for Restoration, Cellular Neural Networks, Robot Vision Systems

## 1. Introduction

It is well known that in robot vision systems satisfactory performances are required for pattern recognition processes to assure safety to the applications themselves. On this proposal, the specific extraction of information needed for object matching analyses implies vigorous constraints which have to be satisfied by means of suitable techniques. At present, a great attention is focused on methods based on fuzzy encoding procedures [1-3], which offer the advantage of an approach to processing uncertainty similar to human experts' ones. In particular, an image processing problem can be formulated by an expert as a sequence of local rules, or it might be prespecified by a set of given input-output pairs. In both cases, an adequate object matching analysis needs the presence of memories properly designed to store and compare reference images with detected ones.

For this purpose, in recent years the design of Cellular Neural Networks (CNNs) has revealed successful for image processing applications [4-6] due to their lattice structure adequate for storing particular memory vectors such as bidimensional patterns [7-9]. In [9] a first approach has been made to design CNNs with bipolar output functions able to store 256-gray images by considering the presence of a pre-processor to segment original natural images in a less number of gray levels before storing them into a CNN-based memory. Difficulties often arise in determining an adaptive threshold encoder capable of providing the required segmentations. On the basis of these considerations, a Fuzzy Associative Memory (FAM), which enables to fuzzify bidimensional patterns in such a way to be easily segmented and stored in a CNN-based system, is synthesized by adopting a fuzzy encoding procedure based on the fuzzy Possibility/Necessity Technique reported in [2]. Successively, a Cellular Neural Network is designed to behave as a memory to store the designed FAM. In this way, the above mentioned preprocessor is a CNN itself, behaving as a FAM which involves the fuzzification rules. The recovered capabilities of the designed memory are illustrated and discussed by means of a numerical example, concerning with the fuzzification of 256-level images of industrial tools, which can be easily segmented and stored into a CNN with a two-level output function.

## 2. Fuzzy Associative Memory

In this section a Fuzzy Associative Memory is developed as the preprocessing stage of the CNN-based system considered in this paper. In fig.1 the block diagram of the proposed system is illustrated.

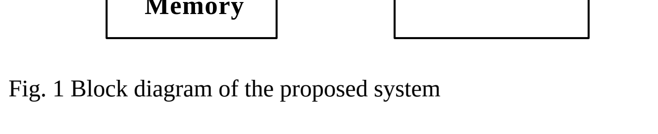



Fig. 1 Block diagram of the proposed system

The proposed system enables to transform 256-gray images into bipolar ones, which are more easily storable into a Discrete Time Cellular Neural Network, behaving as a memory in a stereovision 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, which, as it is well known, can be classified as belonging to the Object/Background class [8]. In an analogous way, the domain of output values between –1 and 1 has been quantized into two output fuzzy subsets called Dark and Light. In particular, the fuzzy rules which provide the mapping from original images (input) into fuzzified ones (output) can be expressed as:

IF $p_{ij} \in$ Object THEN $f_{ij} \in$ Dark

IF $p_{ij} \in$ Background THEN $f_{ij} \in$ Light (1)

where $p_{ij}$ and $f_{ij}$ denote the gray level of the (i,j)-th pixel in the original image and in the fuzzified one, respectively. As stated by Theorem 2 in [10], the reported fuzzy rules can be encoded into a single Fuzzy Associative Memory (FAM) by determining a weight matrix **M** based on the max-bounded-product (max-⊗) composition. The block diagram of the proposed fuzzy system is reported in the following figure.

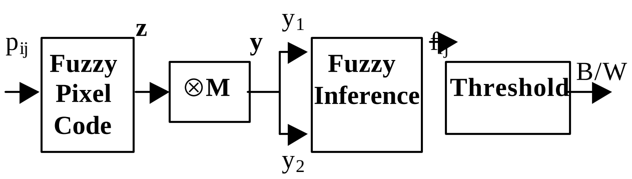



Fig.2 – Block diagram the proposed fuzzy system

From this diagram it can be observed that each pixel $p_{ij}$ can be firstly codified by adopting the PN model introduced in [2], where each pixel can be represented with a vector $\mathbf{z} \in \mathbf{R}^4$ as follows:

$$\mathbf{z} = [\ P(p|m_{A1}) \quad N(p|m_{A1}) \quad P(p|m_{A2}) \quad N(p|m_{A2})\ ] \quad (2)$$

with

$$P(p|m_{A1}) = m_{A1}(p_{ij});\ N(p|m_{A1}) = m_{A1}(p_{ij});$$
$$P(p|m_{A2}) = m_{A2}(p_{ij});\ N(p|m_{A2}) = m_{A2}(p_{ij}) \quad (1)$$

This vector can recall a vector $\mathbf{y} = [y_1\ y_2]$ by means of an operation of max bounded-composition with a matrix **M** such that [10]:

$$\mathbf{y} = \mathbf{z} \otimes \mathbf{M} \quad (2)$$

In particular, the elements $y_1$ and $y_2$ give information about the "firing" of the first rule and of the second one, respectively. Successively, the two outputs $y_1$ and $y_2$ are inferred with the well known method of the "center of gravity" [1] to obtain a fuzzy value $f_{ij}$ for each pixel such that:

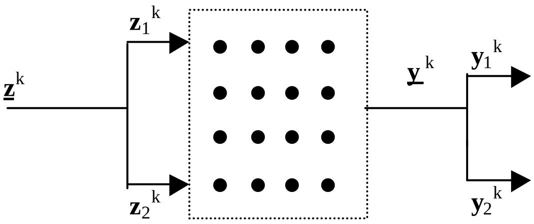
$$f_{ij} = (-y_1 + y_2) / (y_1 + y_2) \quad (3)$$

The generic fuzzified variable y coincides with the output of the inference block reported in Fig.2. Then the values of this variable y are thresholded for each fuzzified image using the method reported in [11] with the aim of obtaining the corresponding bipolar image to be stored.

## 3. Synthesis of a Robust CNN for a Fuzzy Associative Memory

It is well known that CNNs behaving as associative memories have to be synthesized on the basis of an assigned training set, which is formed by the patterns the memory has to store [7]. In this paper, these patterns correspond to the fuzzy rules which constitute the FAM. For this purpose, let the matrix **M** be the (4x2)-matrix which can codify the described FAM system. More in detail, each input $\mathbf{z}^k$ is associated to an output vector $\mathbf{y}^k = \mathbf{z}^k \otimes \mathbf{M}$, where $\mathbf{z}^k \in \mathbf{R}^4$, $\mathbf{y}^k \in \mathbf{R}^2$, k = 1, …, 256.
From conditions (1) it can be noticed that the first two components and the second two ones of the vector $\mathbf{z}^k$, respectively, have identical values. For this purpose, the 4-element vector $\mathbf{z}^k$ can be defined as $\mathbf{z}^k=[z_1^k\ z_1^k\ z_2^k\ z_2^k]$ and its generic component can assume 256 fuzzy values in [0, 1] corresponding to the number of gray levels of original images. Each element needs to be converted into an 8-bit bipolar vector $\mathbf{z}_i^k \in \{-1,1\}^8$, i=1, 2, to be usefully considered as an input to the CNN. It should be noted that the components of the output vector $\mathbf{y}^k$ can assume only two fuzzy values corresponding to the firing of the outputs Dark and Light, respectively. As a consequence, only two bipolar eight-bit vectors $\mathbf{y}_1^k$ and $\mathbf{y}_2^k$ are required to describe the vector $\mathbf{y}^k$.
Being the input vector $\underline{\mathbf{z}}^k = [\mathbf{z}_1^k\ \mathbf{z}_2^k] \in \{-1, 1\}^{16}$ and the output vector $\underline{\mathbf{y}}^k=[\mathbf{y}_1^k\ \mathbf{y}_2^k] \in \{-1, 1\}^{16}$, respectively, k = 1,…, 256, a CNN behaving as an associative memory containing the 256 coupled patterns $(\underline{\mathbf{z}}^k, \underline{\mathbf{y}}^k)$ can be designed by considering the algorithm reported in [7]. It can be observed that the CNN to be synthesized has to contain the fuzzy rules, which are completely identified by the matrix **M**. The architecture of the proposed CNN-based system is shown in detail in the following figure.

Fig.3 Cellular Fuzzy Associative Memory




The vector $\underline{\mathbf{z}}^k = [\mathbf{z}_1^k \;\; \mathbf{z}_2^k] \in \mathbf{R}^{1\text{x}16}$ is the input for a CNN working as a bipolar associative memory, whereas the output vector is $\underline{\mathbf{y}}^k = [\mathbf{y}_1^k \; \mathbf{y}_2^k]$.

In this paper the class of rectangular Cellular Neural Networks reported in [7] is considered, where a synthesis procedure of a CNN to behave as a heteroassociative memory is accurately formulated. Following the procedure reported in [7] it is possible to compute the matrices **T** and **B**, where the matrix **T** is a symmetric matrix and the matrix **B** is an upper triangular one. Furthermore, a robustness analysis has been developed by considering perturbations terms on both the matrices **T** and **B** to take into account the existence of parameter variations **DT** and **DB** when implementing the memory. By choosing proper values of $\alpha$ in the synthesis procedure, it can be concluded that the network dynamics moves towards the desired output patterns even in the presence of parameter deviations.

## 4. Numerical example

In this example the capabilities of a CNN synthesized to behave as a Fuzzy Associative Memory have been illustrated by considering its performance on the fuzzification of a 3D-image, representing an industrial tool. In the (256x256)-image shown in Fig.4(a), each pixel can assume a gray level value between 0 and 255, as visualized in its strongly nonlinear hystogram reported in Fig. (b).

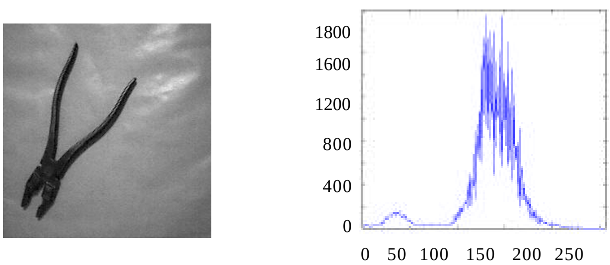



Fig.4 . Original image (a); its hystogram (b).

Right-triangular membership functions have been chosen for both the antecedent fuzzy subset and the consequent one. The gray level values used to establish the antecedent membership functions have been estimated equal to $p_1$=0, $p_2$=95 and $p_3$=160 and $p_4$=255. These values give the optimal results, referring to the degree of overlapping of the corresponding fuzzy sets.

It has been considered a neighbourhood r=1 for the synthesized CNN which behaves as a FAM. The robustness analysis for the (16x16)-matrices **T** and **B** has been developed by considering $\pm$ 10% parameter variations with respect to their nominal values, being the bias vector **I** a (16x1)-null vector. The matrix **M** and the considered templates are:

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

$$\mathbf{DT} = \begin{pmatrix} 0.1 & 0.1 & 0.1 \\ 0.1 & 0.9 & 0.1 \\ 0.1 & 0.1 & 0.1 \end{pmatrix} \quad \mathbf{DB} = \begin{pmatrix} 0.1 & 0.1 & 0.1 \\ 0 & 0.9 & 0.1 \\ 0 & 0 & 0.1 \end{pmatrix}$$

After processing the image with the synthesized Cellular Fuzzy Associative Memory, the image resulting from fuzzification and its hystogram are reported in Fig. 5.

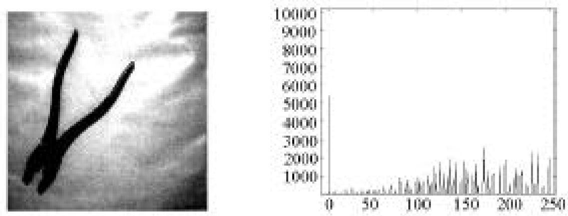



Fig.5 Fuzzified image and its hystogram.

From this figure it can be noticed that the fuzzified image can be segmented in an easier way with respect to the original one before being stored in a CNN-based memory.

## 5. Conclusions

In this paper a Cellular Fuzzy Associative Memory containing fuzzy rules for bidimensional pattern fuzzification in stereovision systems has been designed. The required rules have been adequately codified and stored in a CNN behaving as an associative memory. A numerical example for industrial object matching analysis has been reported.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### *References*


[1] B. Kosko, *Neural Networks and Fuzzy Systems*, Prentice Hall, 1996.

[2] W. Pedrycz, J. Bezdek, R.J. Hathaway, G. W. Rogers, ‘Two Nonparametric Models for Fusing Heterogeneous Fuzzy Data‘, *IEEE Trans. on Fuzzy Systems*, vol. 6, no.3, 1998, pp.411-424.

[3] F.L. Chung, J.C. Duan, 'On Multistage Fuzzy Neural Network Modeling', *IEEE Trans. on Fuzzy Systems*, vol. 8, no. 2, April 2000, pp. 125-142.

[4] L.O. Chua, ‘CNN: A Vision of Complexity‘, *Int. J. of Bifurcation and Chaos*, vol. 7, no. 10, pp.2219-2425, 1997.

[5] M. Brucoli, D. Cafagna, L.Carnimeo, ‘Design of Cellular Associative Memories for Robot Vision via a Fuzzy Image Segmentation‘, *Proc. of ECCTD’99*, Aug. 29-Sept. 2, Stresa, Italy, 1999, pp. 1171-1174.

[6] R. Dogaru, P. Julian, L. O. Chua, 'A Robust and Efficient Universal CNN Cell Circuit using Simplicial Neuro-Fuzzy Inferences for Fast Image Processing', *Proc. of the 2001 IEEE Sym. on Circuits and Systems (ISCAS01*), 6-9 May 2001, Sydney, Australia, pp.493-496.

[7] M. Brucoli, L.Carnimeo,G.Grassi ‘Heteroassociative Memories via Cellular Neural Networks‘, *Int. J. Circuit Theory & Appl.*, vol. 26, 1998, pp.231-241.

[8] M. Brucoli, D. Cafagna, L. Carnimeo, 'On the Performance of CNNs for Associative Memories in Robot Vision Systems ', *Proc. of the 2001 IEEE Sym. on Circuits and Systems (ISCAS01),* 6-9 May 2001, Sydney, Australia.

[9] L.Carnimeo, A.Giaquinto, 'Fuzzy Associative Memories for Bidimensional Pattern Segmentation in CNN-based Systems', Proc. of the *Int. Conf. on Fuzzy Sets and Fuzzy Systems (FSFS02),* 12-14 Feb. '02, Interlaken, Switzerland.

[10] Fu-Lai Chung, T. Lee, ‘On Fuzzy Associative Memory with Multiple-Rule Storage Capacity ‘, *IEEE Trans. on Fuzzy Systems,* vol. 4 , no. 3, Aug. 1996, pp. 375-384.

[11] X. Yang and P.S. Toh, 'Adaptive Fuzzy Multilevel Median Filter', *IEEE Trans. on Image Processing,* vol.4, no. 5, May 1995, pp. 680-682.