Efficiency Improvements for Fuzzy Associative Memory

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Abstract. FAM is an Associative Memory that uses operators of Fuzzy Logic and Mathematical Morphology (MM). FAMs possess important advantages including noise tolerance, unlimited storage, and one pass convergence. An important property, deciding FAM performance, is the ability to capture contents of each pattern, and associations of patterns. Standard FAMs capture either contents or associations of patterns well, but not both of them. In this paper, we propose a novel FAM that effectively stores both contents and associations of patterns. We improve both learning and recalling processes of FAM. In learning process, the associations and contents are stored by mean of input and output patterns and they are generalised by erosion operator. In recalling process, a new threshold is added to output function to improve outputs. Experiments show that noise tolerance of the proposed FAM is better than standard FAMs with different types of noise.

Keywords: Fuzzy Associative Memory, Noise Tolerance, Pattern Associations.

1 Introduction

Bidirectional Associative Memory (BAM) models store pattern associations and can retrieve desired output patterns from noisy input patterns. FAM is an Associative Memory that uses operators of Fuzzy Logic and Mathematical Morphology (MM). FAMs have three important advantages over traditional BAMs, which are noise tolerance, unlimited storage, and one pass convergence. Thanks to those advantages, FAMs have been widely applied in many fields such as image processing and optimization. Some standard FAMs [9,12,14] effectively store pattern associations by using the ratio of input pattern to output pattern. As a result, they do not store the content of patterns. Others [7,5,2,14] store the content of output patterns or some representative values, which means the associations of pattern pairs are not included.

In this paper, we propose a new standard FAM that can store both the content of patterns as well as pattern associations. Our FAM is improved in both learning and recalling process. In learning process, the associations and the contents are stored by the mean of input and output patterns, and they are generalized

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by erosion operator of Mathematical Morphology. In recalling process, a new threshold is added to the output function to improve recalled results. We have conducted experiments in face recognition and pattern recognition with three types of noise to confirm the effectiveness of our model.

The rest of the paper is organized as follows. Section 2 summarizes related work. In the section 3, we describe our novel FAM. Section 4 presents our experiments to show the advantages of the proposed FAM.

2 Related Work

Studies of FAMs can be divided into two categories: developing new models, and applying them into applications. In the first category, researchers mainly apply operators of Fuzzy Logic and MM to store pattern associations. The input and the association matrix are used to compute the output.

Kosko [7] used the minimum of input and output pattern to store the association and generalized them by dilation operator. A fuzzy implication operator was used to present associations by Junbo et al. [5]. Generalizing patterns was performed by erosion operator. The FAM set of Fulai [2] and some of Sussner [14] were similar to Junbo's FAM, in which the difference was only the output function. After that, Fulai and Tong proposed a way to add/delete a pattern pair [3]. These FAM, however, weakly presented the associations of patterns as they stored only input or output pattern for showing the association of each pattern pair.

Ping Xiao et al. [9] designed a model that applied the ratio of input to output patterns for the associations. Erosion operator was used for generalizing the associations. Wang and Lu [12] proposed a set of FAM that used division operator to describe the associations and erosion/dilations for generalizing the associations. Some FAMs of Sussner [14] used fuzzy implication to show the association and used s-norm operator in the output function. A threshold was added to the output function to improve weak outputs. Because of using the difference between input and output pattern for storing, the content of patterns was not presented in these FAMs.

An intuitive FAM that based on Junbo's model was proposed by Long et al. [8]. This FAM was added a complement value of each element of patterns and associative matrices. Valle and Sussner modified implicative FAMs tomake them be able to work with integer values by replacing values in [0,1] with values in [0,1,...,L] [15]. Other researchers focused on the stability of FAMs, the conditions for perfectly recalling stored patterns, and how to transform a given FAM to new FAMs [18,10,17,1].

In the second category, working with uncertain data is the reason why novel FAMs has been used in many fields such as pattern recognition, control, estimation, inference, and prediction. There are some typical examples of each field. Sussner and Valle used the implicative FAMs for face recognition [14]. Kim et al. predicted Korea stock price index [6]. Shahir and Chen inspected the quality of soaps on-line [11]. Wang and Valle detected pedestrian abnormal behaviour [16]. Sussner and Valle predicted the Furnas reservoir from 1991 to 1998 [13].

3 Our Approach

3.1 Design of the Proposed FAM

Because previous FAMs only effectively store the content or the associations, so some useful information from patterns is lost. Thus, the ability of recall is limited. We propose a novel FAM that stores both the content and the associations of patterns better. Furthermore, we propose a new threshold for the output function which can improve the noise tolerance.

Assuming that our FAM stores **p** pattern pairs, $(A_1, B_1), (A_2, B_2), ..., (A_p, B_p)$ in the general weight matrix $\mathbf{W}$. The k^{th} pair is represented by the vectors $A^k = (A_1^k, ..., A_m^k)$ and $B^k = (B_1^k, ..., B_n^k)$.

The design of our FAM is presented in the following processes:

Learning Process Consists of Two Steps:

Step 1: Learn the association of patterns (A^k, B^k) by their mean values to store both the contents and the associations of patterns more clearly.

$$W_{ij}^k = \frac{1}{2}(A_i^k + B_j^k) \tag{1}$$

Step 2: Generalize the associations of patterns and store in the general weight matrix W.

$$W_{ij} = \bigwedge_{k=1}^{p} W_{ij}^k \tag{2}$$

Recalling Process is Executed as Follows

We use a new threshold for the output function. The threshold is used in case current output is much different from training output. That means the current output is equal to threshold when it is smaller than the minimum of training outputs. Models of Sussner [14] used a threshold that is the minimum of the training output patterns while our threshold is an arithmetic mean. Therefore, the ability of output correcting of Sussner's FAMs is lower than our model. The reason is that the ratio of minimum/maximum to the mean is smaller than the ratio of minimum/maximum to the minimum.

Our threshold is formulated as:

$$\theta_j = \frac{1}{p}\sum_{k=1}^{p} B_j^k \tag{3}$$

The summary of the current input and the general weight matrix is formulated by dilation operator. Then it is compared to the threshold. If it is smaller than the threshold then the current output is equal to the threshold, otherwise the current output is equal to it. Therefore, output Y is recalled from an input X by the equation:

$$Y_j = \bigvee_{i=1}^{m} X_i.W_{ij} \vee \theta_j \tag{4}$$

3.2 Discussion

To improve efficiency, our FAM employs arithmetic mean in both input and output functions. Thus, we name it MIOFAM (Mean Input and Output FAM).

MIOFAM has three important advantages over standard FAMs. First, it has unlimited capacity because of storing patterns in a single matrix. Second, recalling process performs in an iteration, which reduces computation and converges in only one pass. Finally, we expect to increase the noise tolerance ability because of the improvement in both learning and recalling process. In addition to the known advantages of FAM, MIOFAM is easy to understand and implement. As a result, we expect that our MIOFAM will perform well in different applications under harsh conditions.

4 Experiments

We have conducted three experiments with four image sets. FAMs are tested in the hetero-association mode since it is more general than the auto-association mode. The first experiment is face recognition from distorted inputs. The second and last experiment are pattern recognition from in-complete inputs and "salt & pepper" noise.

To prove the effectiveness, our novel FAM is compared to standard FAMs. Standard FAMs which are selected for comparison, are models of Kosko [7], Junbo et al. [4], Fulai and Tong [2], Ping Xiao et al. [9], Wang and Lu [12], and Valle and Sussner [14]. We choose best model of each set of FAM to compare. These FAMs and proposed FAM are similar to both learning and recalling process. Therefore, we only compare the noise tolerance of FAMs.

We use the peak signal-to-noise ratio (PSNR) to measure quality between the training and an output image. The higher the PSNR, the better the quality of the output image. PSNR is computed by the following equation:

$$PSNR = 40log_{10}\frac{R^2}{MSE} \tag{5}$$

where R is the maximum fluctuation in the input image data type. Working with grey-scale images, value of R is 255. MSE represents the cumulative squared error between the training and an output image. MSE is formulated by the following equation:

$$MSE = \frac{\sum_{M,N}(I_1(m,n) - I_2(m,n))^2}{M * N} \tag{6}$$

where M and N are the number of rows and columns in the input images. I_1, I_2 are the output and the training image.

4.1 Experiment 1: Face Recognition from Distorted Inputs

We choose the faces database of AT & T Laboratories Cambridge[1] including 40 people. Figure 1 shows some typical patterns in this experiment.

[1] Avaliable at: `http://www.uk.research.att.com/facedatabase.htm`

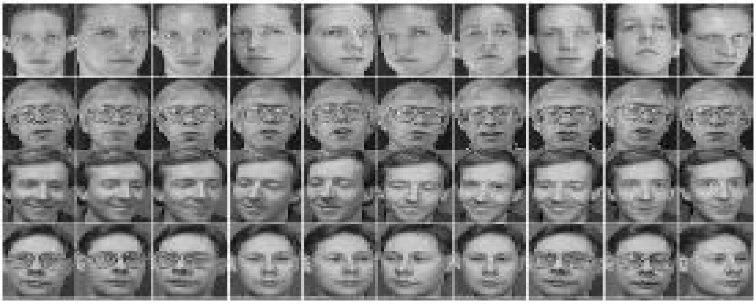

Fig. 1. Typical patterns for face recognition

There are 10 images for every person in the database, including one normal image and nine distorted images. Normal images are used to train and the distorted images are noisy inputs for experiments. Noisy inputs are made from the training images by rotating faces, changing position of light source, wearing glasses,...The size of each image is 112x92 pixels. We rescale the original images to 23x19 pixels. Figure 2 shows PSNR of models in Experiment 1. The results show that our FAM improves noise tolerance from 4% to 36 % comparing to standard FAMs.

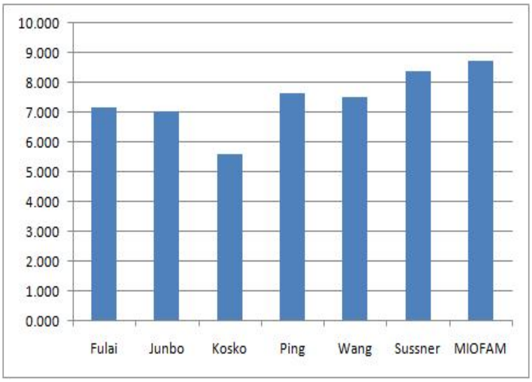

Fig. 2. PSNR of FAMs for face recognition from distorted inputs

4.2 Experiment 2: Recognition Applications from Incomplete Inputs

We select three image sets which include many groups of images, namely, human, animal, house, radar image, car, and thing. The first set contains 48 images of the grey-scale image database (CVG) of the Computer Vision Group, University of Granada, Spain[2] with six groups of images. The second set has 50 animal images

[2] Avaliable at: `http://decsai.ugr.es/cvg/wellcome.html`

Fig. 3. Some typical images of data sets.
(a), (b), (c) show CVG, CAR, ANIMAL datasets.

(ANIMAL) with many species from 50 Amazing Animals in the shared database of Torrentz in EU. The last set includes 48 images (CAR) of car features, which are selected from Corel database. Images are rescaled from 512x512, 1920x1080, 384x256 to 21x21, 23x19, 24x16 respectively. Figure 3 shows some typical images of the three datasets.

Normal images are used to create the training set and the test set is made from the training images by deleting parts of images. Figure 4 shows PSNR of FAMs in Experiment 2. This experiment shows that MIOFAM is better than standard FAMs in all datasets. Especially, our FAM achieves significant improvement in ANIMAL set (22.3% comparing to FAMs of Fulai, the second best FAM).

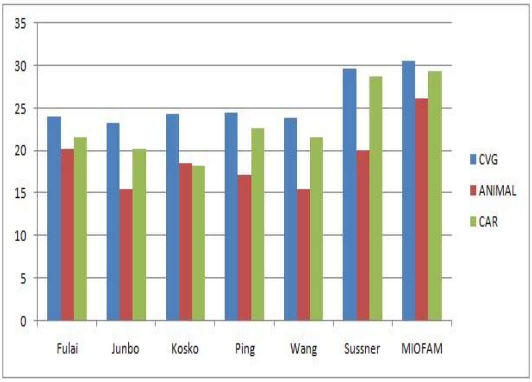

Fig. 4. PSNR of FAMs for pattern recognition from incomplete inputs

4.3 Experiment 3: Pattern Recognition from "Salt & Pepper" Noise

We use the same three image sets in Experiment 2. Noisy images are made from the training images by adding "salt & pepper". Figure 5 shows PSNR of FAMs

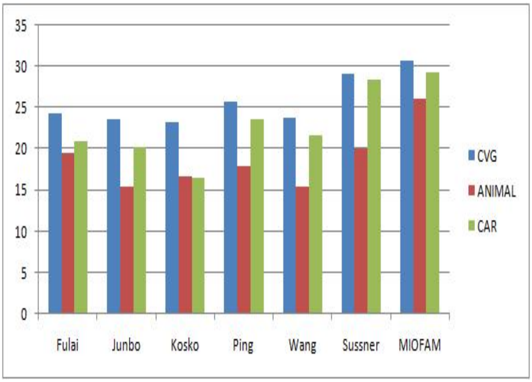

Fig. 5. PSNR of FAMs for pattern recognition from "salt & pepper" noise

in Experiment 3. Again, MIOFAM performs better than all other FAMs. In the ANIMAL dataset, our FAM tolerates noise 23.2% better than the second best FAM, FAMs of Sussner.

5 Conclusion

In this paper, we proposed a new FAM - the MIOFAM - that captures both content and associations of patterns. Our FAM improves both learning and recalling process by using arithmetic mean. While still possessing vital advantages of standard FAMs, the MIOFAM has better noise tolerance and is easy to construct. We have conducted three experiments in face recognition and pattern recognition to prove the efficiency of the proposed FAM. The obtained results show that MIOFAM is better than standard FAMs in experiments with three types of noise. Especially, our FAM performs much better than standards FAMs in one dataset, the ANIMAL dataset. This hints that our improvement in capturing pattern content and associations can be extremely effective. Our further work would investigate further into this direction, such as measuring the diffusion in pattern content and association to confirm that hypothesis.

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