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Improving learning rule for fuzzy associative memory with combination of content and association

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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 content of each pattern, and association of patterns. Existing FAMs capture either content or association of patterns well, but not both of them. They are designed to handle either erosive or dilative noise in distorted inputs but not both. Therefore, they cannot recall distorted input patterns very well when both erosive and dilative noises are present. In this paper, we propose a new FAM called content-association associative memory (ACAM) that stores both content and association of patterns. The weight matrix is formed with the weighted sum of output pattern and the difference between input and output patterns. Our ACAM can handle inputs with both erosive and dilative noises better than existing models.
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1. Introduction

Associative memories (AMs) store pattern associations and can retrieve desired output pattern upon presentation of a possibly noisy or incomplete version of an input pattern. They are categorized as auto-associative memories and hetero-associative memories. A memory is said to be auto-associative if the output is the same as the input. On the other hand, the memory is considered hetero-associative if the output is different from the input. The Hopfield network [1] is probably the most widely known auto-associative memory at present with many variations and generalizations. Among different kinds of associative memories, fuzzy associative memories (FAMs) belong to the class of fuzzy neural networks, which combine fuzzy concepts and fuzzy inference rules with the architecture and learning of neural networks. Input patterns, output patterns, and/or connection weights of FAMs are fuzzy-valued. Working with uncertain data is the reason why FAMs have been used in many fields such as pattern recognition, control, estimation, inference, and prediction. For example, Sussner and Valle used the implicative FAMs for face recognition [2]. Kim et al. predicted Korea stock price index [3]. Shahir and Chen inspected the quality of soaps on-line [4]. Wang and Valle detected pedestrian abnormal behaviour [5]. Sussner and Valle predicted the Furnas reservoir from 1991 to 1998 [2].

Kosko's FAM [6] in the early 1990s has initiated research on FAMs. For each pair of input X and output Y, Kosko's FAM stores their association as the fuzzy rule "If x is X then y is Y" in a separated weight matrix called FAM matrix. Thus, Kosko's overall fuzzy system comprises several FAM matrices. Therefore, the disadvantage of Kosko's FAM is very low storage capacity. In order to overcome this limitation, different improved FAM versions have been developed that store multiple pattern associations in a single FAM matrix [7–10]. In Chung and Lee's model [7] which generalizes Kosko's one, FAM matrices are combined with a max-t composition into a single matrix. It is shown that all outputs can be recalled perfectly with the single combined matrix if the input patterns satisfy certain orthogonality conditions. The fuzzy implication operator is used to present associations by Junbo et al. [9], which improves the learning algorithm for Kosko's max–min FAM model. By adding a threshold at recall phase, Liu has modified Junbo's FAM in order to improve the storage capacity [10]. Recently, Sussner and Valle has established implicative fuzzy associative memories (IFAMs) [2] with implicative fuzzy learning. This can be considered as a class of associative memories that grew out of morphological associative memories [11] because each node performs a morphological operation. Sussner and Valle's models work quite well in auto-associative mode with perfect input patterns, similar to other improvements of Kosko's model. However, these models suffer much from the presence of both erosive and dilative noises.

In binary mode, many associative memory models show their noise tolerance capability from distorted input based on their own mathematical characteristics [10,2]. For example, models

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using maximum operation when forming the weight matrix are excellent in the presence of erosive noise (1 to 0) while the models using minimum operation are ideal for dilative noise (0 to 1) [11]. On the other hand, models with maximum operation cannot recover well patterns with dilative noise and models with minimum operation cannot recover well patterns with erosive noise. In grey scale or fuzzy valued mode, even though existing models can recover main parts of the output pattern, noisy parts of the input pattern affect seriously to the recalled output pattern. Threshold is probably the most effective mechanism so far to deal with this problem. However, the incorrectly recalled parts in the output are normally fixed with some pre-calculated value based on the training input and output pairs. Clearly, there are two main ways to increase noise tolerance capability of the associative memory models, which are recovering from the noise and reducing the effect of the noise. Existing models concentrate on the first way. The work in this paper is motivated from the second way, which is how to reduce the effect of noisy input patterns to the recalled output patterns. We propose our work based on the implicative fuzzy associative memories [2], which also belong to the class of morphological associative memories [11]. Instead of using only rules to store the associations of the input and output patterns, we also add a certain part of the output patterns themselves in the weight matrix. Depending on the ratio of association and content of output patterns in the weight matrix, the effect of noise in the distorted input patterns onto the recalled output patterns can be reduced. Obviously, incorporating the content of the output patterns would influence the output selection in the recall phase. However, the advantages from the tradeoff are worth to consider. We have conducted experiments in recalling images from the number dataset and the Corel dataset with both erosive and dilative noises to confirm the effectiveness of our model when dealing with noise.

The rest of the paper is organized as follows. Section 2 presents background on fuzzy associative memory models. We also present in this section motivational analysis for our work. In Section 3, we describe in detail our model. Section 4 presents analysis on the properties of the proposed model and experiments to illustrate these properties.

2. Background and motivation

2.1. Fuzzy associative memory models

The objective of associative memories is to recall a predefined output pattern given the presentation of a predefined input pattern. Mathematically, the associative memory can be defined as a mapping G such that for a finite number of pairs $\{(A^\xi, B^\xi), \xi = 1, \ldots, k\}$:

$$G(A^\xi) = B^\xi. \tag{1}$$

The mapping G is considered to have the ability of noise tolerance if $G(A'^\xi)$ is equal to B^ξ for noisy or incomplete version A'^ξ of A^ξ. The memory is called auto-associative memory if the pattern pairs are in the form of $\{(A^\xi, A^\xi), \xi = 1, \ldots, k\}$. The memory is hetero-associative if the output B^ξ is different from the input A^ξ. The process of determining G is called *learning phase*, and the process of recalling B^ξ using G with the presentation of A^ξ is called *recall phase*. When G is described by a fuzzy neural network, and the patterns A^ξ and B^ξ are fuzzy sets for every $\xi = 1,\ldots,k$, the memory is called fuzzy associative memory (FAM).

The very early FAM models are developed by Kosko in the early 1990s [6], which are usually referred as max–min FAM and max-product FAM. Both of them are single layer feed-forward artificial neural networks. If $W \in [0,1]^{mn}$ is the synaptic weight matrix of a max–min FAM and if $A \in [0,1]^n$ is the input pattern, then the output pattern $B \in [0,1]^m$ is computed as follows:

$$B = W \circ_M A, \tag{2}$$

or

$$B_j = \bigvee_{i=1}^{n} W_{ij} \wedge A_i \quad (j = 1 \ldots m). \tag{3}$$

Similarly, the max-product FAM produces the output

$$B = W \circ_P A \tag{4}$$

or

$$B_j = \bigvee_{i=1}^{n} W_{ij}.A_i \quad (j = 1 \ldots m). \tag{5}$$

For a set of pattern pairs $\{(A^\xi, B^\xi) : \xi = 1, \ldots, k\}$, the learning rule used to store the pairs in a max–min FAM, which is called correlation-minimum encoding, is given by the following equation:

$$W = B \circ_M A^T \tag{6}$$

or

$$W_{ij} = \bigvee_{\xi=1}^{k} B_j^\xi \wedge A_i^\xi \tag{7}$$

Similarly, the learning rule for the max-product FAM called correlation-product encoding is given by $W = B \circ_P A^T$.

Chung and Lee generalized Kosko's model by substituting the max–min or the max-product with a more general max-t product [7]. The resulting model, called generalized FAM (GFAM), can be described in terms of the following relationship between an input pattern A and the corresponding output pattern B:

$$B = W \circ_T A \quad \text{where } W = B \circ_T A^T, \tag{8}$$

and the symbol $\circ_T$ denotes the max-C product and C is a t-norm. This learning rule is referred as correlation-t encoding.

For these learning rules to guarantee the perfect recall of all stored patterns, the patterns $A_1, \ldots, A_k$ must constitute an orthonormal set. Fuzzy patterns $A, B \in [0,1]^n$ are said max-t orthogonal if and only if $A^T \circ_T B = 0$, i.e. $T(A_j, B_j) = 0$ for all $j = 1, \ldots, n$. Consequently, $A^1, \ldots, A^k$ is a max-t orthonormal set if and only if the patterns A^ξ and A^η are max-t orthogonal for every $\xi \neq \eta$ and A^ξ is a normal fuzzy set for every $\xi = 1, \ldots, k$. Some research focused on the stability of FAMs and the conditions for perfectly recalling stored patterns are [11–14].

Based on Kosko's max–min FAM, Junbo et al. [9] introduced a new learning rule for FAM which allows for the storage of multiple input pattern pairs. The synaptic weight matrix is computed as follows:

$$W = B \circledast_M A^T \tag{9}$$

where the symbol $\circledast_M$ denotes the min-I_M product.

Liu proposed a model, which is also known as the max–min FAM with threshold [10]. The recall phase is described by the following equation:

$$B = (W \circ_M (A \vee c)) \vee \theta. \tag{10}$$

The weight matrix $W \in [0,1]^{mn}$ is given in terms of implicative learning and the thresholds $\theta \in [0,1]^m$ and $c = [c_1, \ldots, c_n]^T \in [0,1]^n$ are of the following form:

$$\theta = \bigwedge_{\xi=1}^{k} B^\xi \tag{11}$$

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