BSCHS (2008-13-2-04)
[Original Article]

Biomedical Soft Computing and Human Sciences, Vol.13, No.2, pp.27-34 (2008)

Associative Memory with Pattern Analysis and Synthesis by a Bottleneck Neural Network

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(received 28 September 2007, revised and accepted 28 November 2007)

Abstract: We propose a new associative memory to improve its noise tolerance and storage capacity. Our underlying model is an improved multidirectional associative memory (IMAM), which uses autoassociative bottleneck neural networks to remove noise in its input, i.e., analyze patterns. IMAM has inefficient storage capacity and low noise tolerance due to a correlation matrix representing association. One of our basic ideas is to replace a correlation matrix with a multilayer perceptron (MLP), which has better learning and generalization capability. Moreover, we introduce two improvements. One is to add intermediate elements into MLP to improve its performance. The other is to use outputs of hidden layers in a five-layer bottleneck neural network. These outputs include information on synthesis of a key pattern from compressed information in the middle layer. To evaluate the proposed approaches, we compared three types of associative memory: associative memory with a bottleneck neural network and MLP (AM/B-M), AM/B-M with intermediate elements (AM/B-I), and AM/B-I with synthetic outputs (AM/B-IS). 10-by-10 images of Latin alphabet are used as patterns for association. In a case of association between 78 non-injective pattern pairs with 10% noise, our proposed AM/B-IS is better than AM/B-M by more than 40% in pattern recalling ratio.

Keywords: Associative memory, bottleneck neural network, multilayer perceptron, intermediate element, noise tolerance

1. Introduction

An associative memory stores information in a decentral style as a pattern and retrieve desired information from a partial information [1,2]. Early associative memories use correlation matrix for association of patterns representing a concept or image. Associatron [3], Hopfield associative memory (HAM) [4,5], and Bidirectional associative memory (BAM) [6] are classified into that type. These conventional associative memories deal with one-to-one association because of simplicity. However, it is clear that human beings have association between a key item and multiple associated items. Then we should discuss a model of one-to-many association to realize human-like association. One-to-many associative memories have been proposed. One of them is Multidirectional Associative Memory (MAM) [7]. MAM is an improved BAM to realize one-to-many association. MAM has a drawback that recall probability decreases in case of an input pattern with much noise. Then Improved MAM (IMAM) [8]with bottleneck neural networks has been proposed to remove noise. The above mentioned associative memories use correlation matrix. Associative memory using correlation matrix has a problem that its storage capacity is low due to crosstalk noise.

The goal of this paper is to propose a new type associative memory to improve its noise tolerance and storage capacity and to evaluate it. Our approaches are to replace correlation matrix with a multilayer neural network and to use analytic and synthetic information of an input pattern through a bottleneck neural network. A multilayer neural network for heteroassociation stores pairs of patterns without crosstalk due to a hidden layer. However, associative memory using a general multilayer neural network is low in storage capacity since its learning capability is not so high. Associative memory can be improved by increasing performance of a multilayer neural network. A further improvement is that analysis and synthesis of information are introduced into associative memory. It is considered that analytic and synthetic information is effectively used in association in human's thinking. Then it is expected that both a focused concept and its superordinate/subordinate information are used for a recollection process and that large storage capacity,

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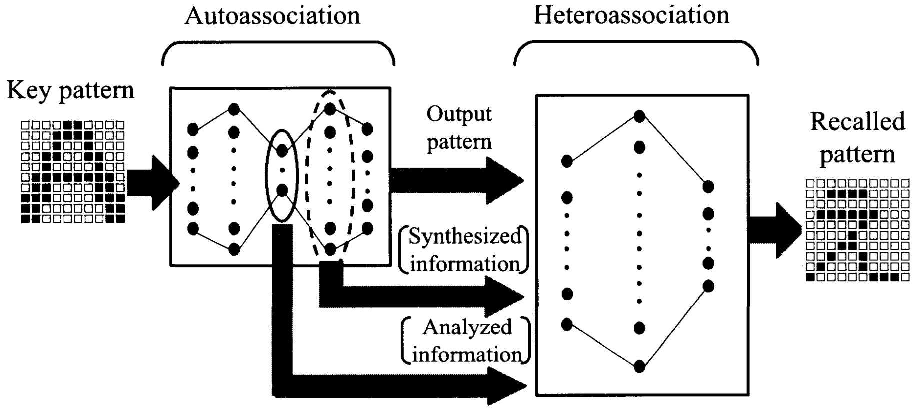

Fig. 1. A schematic diagram of proposed associative memory (AM/B-IS)

high noise tolerance and advanced association can be realized. A bottleneck neural network is used to incorporate analysis and synthesis of information into associative memory. Ueki et al. showed that analysis and synthesis of facial expressions are achieved through learning of an identical mapping of the expressions in a five-layer bottleneck neural network [9]. It is expected to increase performance of associative memory by using outputs in hidden layers of a bottleneck neural network.

In our previous work [10,11], we have proposed a new type of associative memory with a multilayer neural network and information analysis/synthesis. However, the previous work dealt with injective pattern pairs, which means that mapping of a key pattern and a recalled pattern is injective. This paper presents evaluation of the proposed associative memory with non-injective pattern pairs as well as evaluation of effects with a multilayer neural network and analysis/synthesis information in storage capacity and noise tolerance [12]. Non-injective pattern pairs are more complex than injective pattern pairs because the former has pairs of different key patterns and a same recalled pattern. We demonstrate the proposed associative memories through association of letter image patterns such as Latin alphabet, hiragana, and katakana.

2. An associative memory with a bottleneck neural network

Our proposed associative memory with a bottleneck neural network is shown in Fig. 1. Improvements of this associative memory from IMAM are listed as follows.

- A correlation matrix in IMAM for heteroassociation is replaced with a three-layer multilayer neural network to increase storage capacity and noise tolerance.
- A bottleneck neural network in autoassociation and a multilayer neural network in heteroassociation have intermediate elements between their layers to increase performance of these neural networks.
- Analyzed/synthesized information in a bottleneck neural network is used in heteroassociation to increase recall performance.

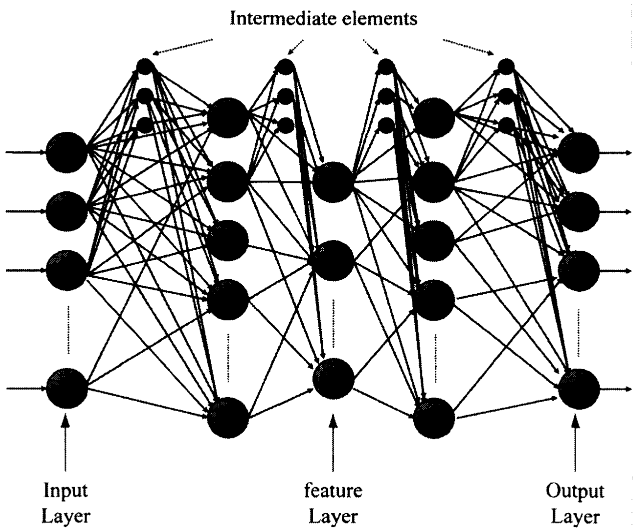

Fig. 2. A bottleneck neural network with intermediate elements in autoassociation

In storage process, first, a bottleneck neural network learns autoassociation, and then a multilayer neural network learns heteroassociation. In recall process, an input is sent to a bottleneck neural network, and then an output which is the same as the input is generated due to autoassociation. A bottleneck neural network removes noise in an input. And analyzed/synthesized information are generated from the third and forth layers. A multilayer neural network for heteroassociation recalls a learned pattern from outputs and analyzed/synthesized information of a bottleneck neural network for autoassociation.

2.1. A bottleneck neural network in autoassociation

In a bottleneck neural network, the number of nodes in a hidden layer is less than the number of an input layer and an output layer. A bottleneck neural network has function of information compression in virtue of its structure [13].

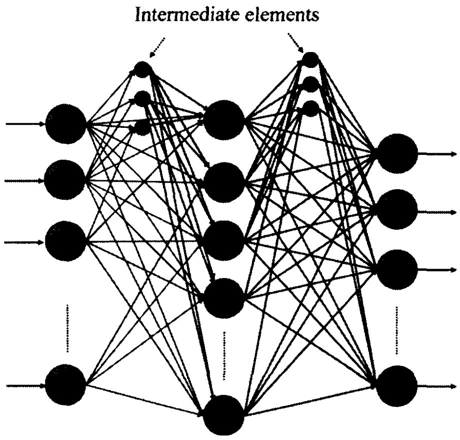

Fig. 3. A multilayer neural network with intermediate elements in heteroassciation

A bottleneck neural network learns an identical mapping, which means that an input is the same as an output. In a central layer, information compression proceeds since its layer is mall. In other word, that is feature extraction. Then, in precedent half of a bottleneck neural network, analysis of input information is carried out to extract features. In the subsequent half, synthesis of output information from the features is carried out. A bottleneck neural network can remove noise from input information through feature extraction. These functions of a bottleneck neural network contribute to increase noise tolerance of associative memory.

2.2. A multilayer neural network with intermediate elements

A general multilayer neural network with a back-propagation learning algorithm is not so high to learn a large dataset. To improve learning capability, a multilayer neural network with intermediate elements has been proposed in [14-16]. As shown in Figs. 2 and 3, a layer of intermediate elements are added between original layers. An intermediate element extracts hidden information from output in a precedent layer and sends it to a subsequent layer. An intermediate element increases learning capability of the neural network. The literatures [13-15] show that learning capability of a multilayer neural network with intermediate elements increases in comparison with a neural network without them.

A multilayer neural network with intermediate elements is applied to neural networks in both autoassociation and heteroassociation. It is expected to increase recall performance of associative memory due to increase learning capability of neural network by intermediate elements.

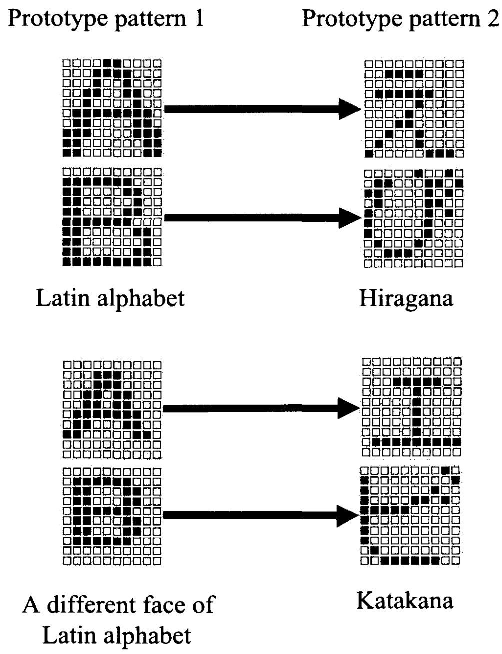

Fig. 4. Injective pattern pairs

2.3. Application of analyzed/synthesized information in a bottleneck neural network to heteroassociation

As shown in Fig. 1, outputs in the third and fourth layers of a bottleneck neural network are sent to a neural network in heteroassociation. As mentioned in Section 2.1, the third layer output represents compressed information. We call this output analyzed information. The fourth layer output includes information to generate a key pattern from analyzed information. We call such output synthesized information. When a key pattern is given with much noise, a bottleneck neural network may be not able to remove noise sufficiently. In this case, compound association by using not only the output in a bottleneck neural network but also analyzed/synthesized information facilitates heteroassociation and increases recall performance because analyzed/synthesized information has less effect on noise and the compound association compensates information lost by noise.

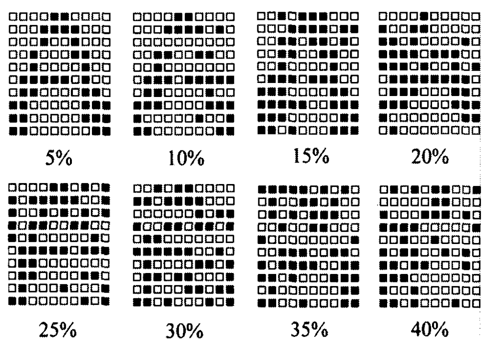

Fig. 5. Patterns with noise

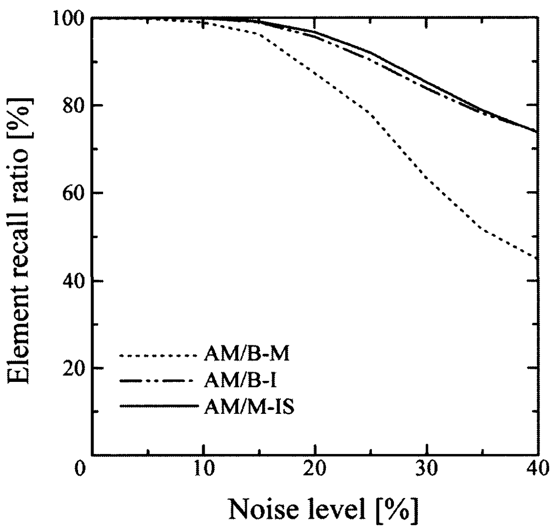

Fig. 6. Element recall ratio in case of 26 injective pattern pairs

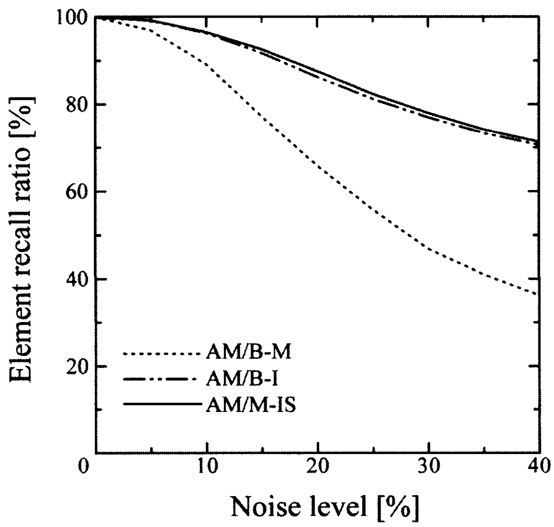

Fig. 8. Element recall ratio in case of 52 injective pattern pairs

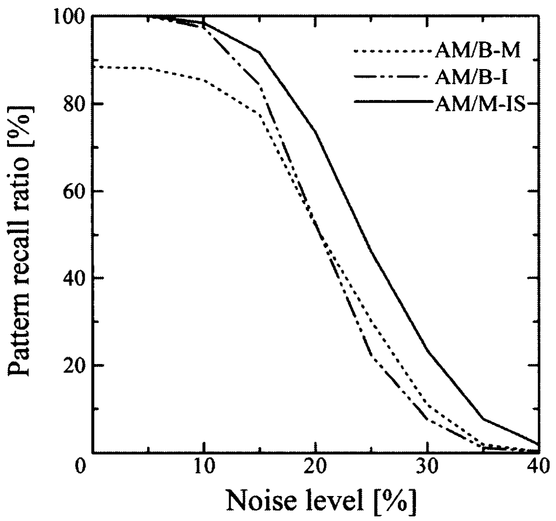

Fig. 7. Pattern recall ratio in case of 26 injective pattern pairs

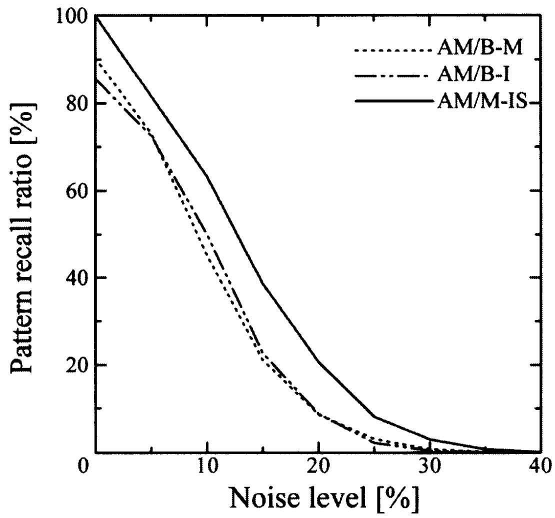

Fig. 9. Pattern recall ratio in case of 52 injective pattern pairs

3. Experiments

To evaluate effects of intermediate elements and analyzed/synthesized information, three types of associative memory with a bottleneck neural network are prepared as follows.

- Associative memory with a multilayer neural network in heteroassociation (AM/B-M)
- Associative memory with a multilayer neural network with intermediate elements in heteroassociation (AM/B-I)
- AM/B-I using analyzed/synthesized information (AM/B-IS)

AM/B-IS is our proposed associative memory. These types of associative memories are compared through association of injective or non-injective patterns pairs in view of storage capacity and noise tolerance. We deal with association of letter image patterns, i.e., 10-by-10 pixel image of Latin alphabet with variable face.

3.1. Association of injective pattern pairs

A bottleneck neural network in autoassociation is situated in the same condition between the three types of associative memories. A five-layer (100-150-20-150-100) neural network is used for autoassociation. The neural network in AM/B-I and AM/B-IS has 10 intermediate elements between each layer and its subsequent layer. In AM/B-M and AM/B-I, a three-layer (100-300-100) neural network is used for heteroassociation. In AM/B-IS, another three –layer (270-300-100) neural network is used for heteroassociation. A heteroassociation neural network in AM/B-I and AM/B-IS has 45 intermediate elements between each layer and its subsequent layer.

Our used injective prototype patterns are shown in

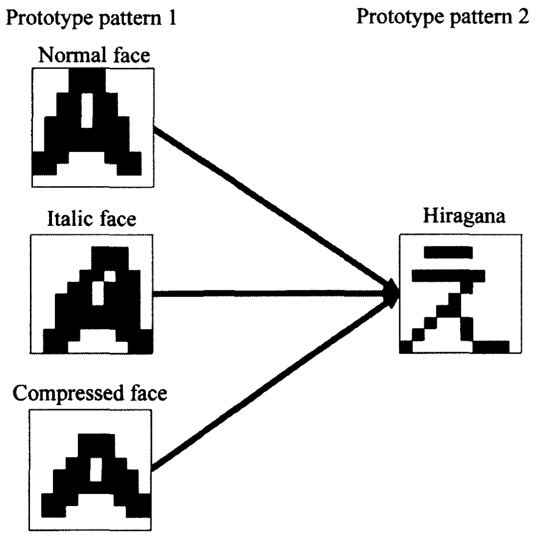

Fig. 10. Non-injective pattern pairs

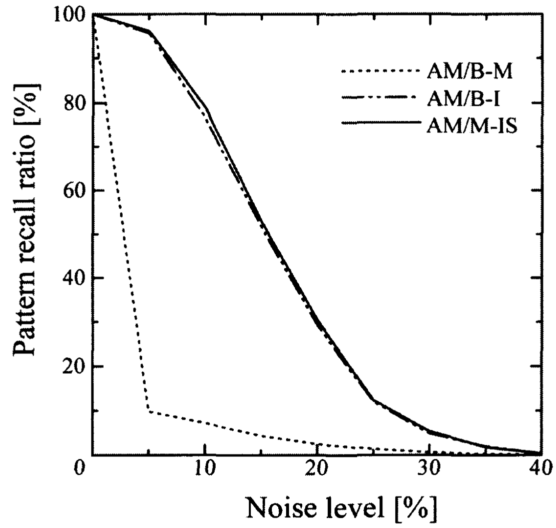

Fig. 12. Pattern recall ratio in case of 52 non-injective pattern pairs

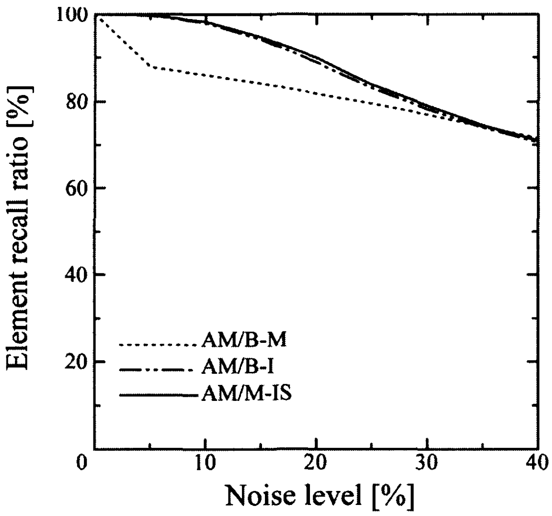

Fig. 11. Element recall ratio in case of 52 non-injective pattern pairs

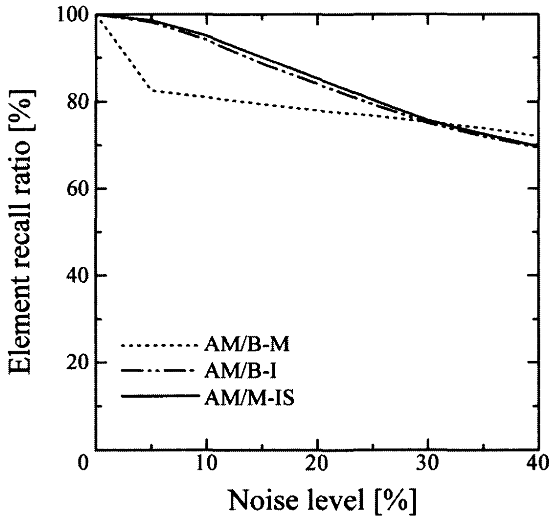

Fig. 13. Element recall ratio in case of 78 non-injective pattern pairs

Fig. 4. Two sets of prototype patterns with different number of pairs are used to evaluate storage capacity. The prototype pattern set with 26 pairs consists of Latin alphabet (uppercase) for input and hiragana for output. Prototype pattern 1 is defined as a key pattern, which is given to a bottleneck neural network. Prototype pattern 2 is defined as a recalled pattern, which is a desired pattern generated by heteroassociation. The set with 52 pairs consists of Latin alphabet with two different faces for input and hiragana and katakana for output. A prototype pattern represents a 100 dimensional vector composed of +1 (black) and -1 (white), which is generated from 10-by-10 pixel image. Analog outputs in heteroassociation are converted into +1 or -1 for performance evaluation.

To increase recall performance, when an output of an autoassociation neural network is positive, the corresponding input to heteroassociation is set to be +1. When the output is negative, the input to heteroassociation is -1.

Learning cycles of neural networks in both autoassociation and heteroassociation is 40,000. Optimal learning rate in each network is decided through a preliminary experiment and used to evaluate performance of the three types of associative memory.

To evaluate noise tolerance, patterns shown in Fig.5 are prepared. Patterns with noise are made by inverting pixels with a certain ratio in random. Noise level is defined as ratio of inverting pixels and all pixels. Noise level ranges from 5% to 40% by 5%. 40 different patterns with same noise level in a prototype pattern are prepared for statistical evaluation.

As performance indices, element recall ratio and pattern recall ratio are used. Element recall ratio is defined as ratio of right recall pixels and all pixels

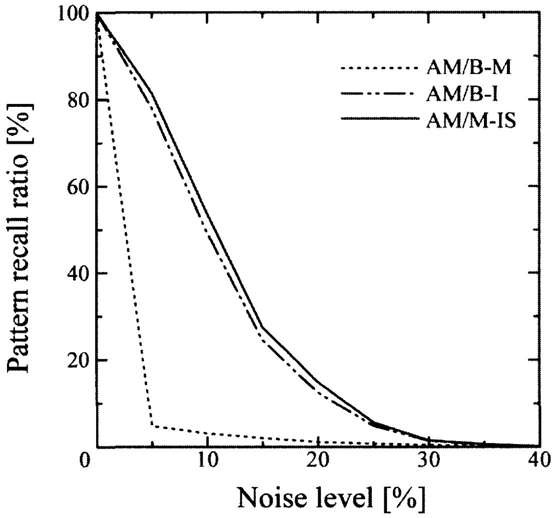

Fig. 14. Pattern recall ratio in case of 78 non-injective pattern pairs

through all patterns. Pattern recall ratio is defined as ratio of right recall patterns in which all recall pixels are right in a pattern and all patterns. These performance indices are statistically calculated through many-time trials because of dealing with noise tolerance and randomness of initial weights.

Experimental results are shown in Fig. 6 to 9. In all the experiments, AM/B-IS is the best. In the case of association of 52 pairs, AM/B-IS keeps higher pattern recall ratio by approximately 10% at noise level 10% than AM/B-M and AM/B-I. In particular, AM/B-M becomes worse in the case of patterns with much noise. Therefore, AM/B-IS has better storage capacity and noise tolerance.

3.2. Association of non-injective pattern pairs

Our used non-injective prototype patterns are shown in Fig. 10. Two sets of prototype patterns with different number of pairs are used to evaluate storage capacity. The prototype pattern set with 52 pairs consists of Latin alphabet with Arial font face and its italic face for Prototype pattern 1 (input) and hiragana for Prototype pattern 2 (output). The set with 76 pairs consists of Latin alphabet with three different faces (Roman, italic, vertically 10% compressed) for Prototype pattern 1 and hiragana for Prototype pattern 2. The number of learning cycles is 20,000. Other experimental settings are the same as Section 3.1.

Experimental results are shown from Fig. 11 to 14. AB/M-IS is best among all the experiments. In comparison with previous experiments in Section 3.1, AM/B-M becomes much worse but AM/B-I becomes better. It is clear that AM/B-M has a problem of storage capacity and noise tolerance because pattern recall ratio of AM/B-M is lower by more than 40% at noise level 10% than the others. However, difference between AM/B-I and AM/B-IS is very small. As shown in the Fig. 14 in case of 78 pairs, the difference is larger than Fig. 12 in the case of 52 pairs. Then when the number of association pairs increases, AM/B-IS may be much better than AM/B-I.

3.3. Discussion

From experimental results of AM/B-M, only replacing a correlation matrix with a multilayer neural network can not improve storage capacity and noise tolerance. Storage capacity and noise tolerance are improved by using both intermediate elements and analyzed/synthesized information by a bottleneck neural network in autoassociation. AM/B-M without them has low noise tolerance because its recall performance largely decreases for even 5% noise as shown in Fig. 11 to 14. Therefore, introducing of intermediate elements and analyzed/synthesized information is useful to associative memories.

Effects on intermediate elements have already evaluated in [11-13]. Recall performance of our proposed associative memory increases due to improvement of a neural network in heteroassociation with intermediate elements.

From Figs. 7 and 9 in association of injective pattern pairs, analyzed/synthesized information contributes to recall performance of our proposed associative memory (AM/B-IS). However, in association of non-injective pattern pairs, difference of recall performance between AM/B-IS and AM/B-I, which does not use analyzed/synthesized information, is small as shown in Figs. 12 and 14. The reason is that recall performance in association of non-injective pattern pairs (Fig. 12) is better than association of injective pattern pairs (Fig. 9). Therefore, we should evaluate association of non-injective pattern pairs with large volume of dataset to verify effects on analyzed/synthesized information.

4. Conclusions

We proposed a new type of associative memory with a bottleneck neural network to enhance recall performance and evaluated through association of letter image pattern. Different from conventional associative memory, a correlation matrix in heteroassociation was replaced with a multilayer neural network to increase storage capacity and noise tolerance. To improve the performance of neural networks, intermediate elements were introduced. Analyzed/synthesized information from a bottleneck neural network in autoassociation was introduced to increase performance in heteroassociation because it includes features of input information. We demonstrated experiments on association of injective or non-injective pattern pairs of 10-by-10 letter pixel images of Latin alphabet with three types of associative memory to evaluate effects on intermediate elements and analyzed/synthesized information. Our proposed associative memory with intermediate elements and analyzed/synthesized information was better in pattern recall ratio than associative memory with them. For example, our proposed associative memory was better by more than 40% in pattern recalling ratio than the others in association of 78 non-injective pattern pairs with 10% noise. We showed that introducing intermediate element and analyzed/synthesized information improve associative memory in storage capacity and noise tolerance.

In future work, we will accurately evaluate associative memory by using a large dataset and other kinds of data.

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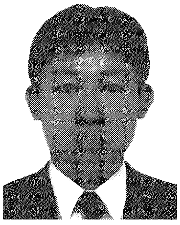

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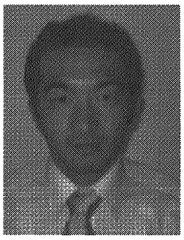

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