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Kohonen Feature Map Associative Memory with Area Representation for Sequential Patterns

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Abstract—In this paper, we propose a Kohonen feature map associative memory with area representation for sequential patterns. This model is based on the Kohonen feature map associative memory with area representation and the Kohonen feature map associative memory for temporal sequences. The proposed model can learn sequential patterns successively, and has robustness for damaged neurons. We carried out a series of computer experiments and confirmed that the effectiveness of the proposed model.

1. Introduction

Recently, neural networks are drawing much attention as a method to realize flexible information processing. In the field of neural networks, although a lot of models have been proposed, their learning and recall processes are divided, and therefore they need all information to learn in advance.

However, in the real world, it is very difficult to get all information to learn in advance, so we need the model whose learning process and recall process are not divided. As such model, some models have been proposed[1]–[4]. However, their storage capacities are small because their learning algorithm is based on the Hebbian learning.

On the other hands, the Kohonen Feature Map (KFM) associative memory [5] has been proposed. Although the KFM associative memory is based on the local representation, it can learn new patterns successively[6], and its storage capacity is larger than that of models in refs.[1]–[4]. It can deal with auto and hetero associations and the associations for plural sequential patterns including common terms[7]. Moreover, as the model which has robustness for damaged neurons, the KFM associative memory with area representation[8] has been proposed. The area representation[9] is an intermediate representation of the local representation and the distributed representation. In the area representation, one concept is expressed by the winner neurons and some neurons located adjacent to the winner neuron.

In this paper, we propose a Kohonen Feature Map associative memory with area representation for sequential patterns which has the robustness for damaged neurons. The proposed model is based on the KFM associative memory for temporal sequences[7] and the KFM associative memory with area representation[8].

2. KFM Associative Memory for Temporal Sequences

Here, we explain the conventional KFM associative memory for temporal sequences[7] which is used in the proposed model. In the model, an association for sequential patterns which have common terms is realized by using recurrent difference vectors.

2.1. Learning Process

Let $\boldsymbol{Y}^{(k,1)} \rightarrow \boldsymbol{Y}^{(k,2)} \rightarrow \cdots \rightarrow \boldsymbol{Y}^{(k,t_k)}$ be the kth temporal sequence to be stored, where t_k shows the length of the kth sequence. Then, the learning vectors $\{\boldsymbol{X}^{(k,t)}\}_{k=1,\cdots,p}$ are defined as follows:

$$\boldsymbol{X}^{(k,t)} = \begin{pmatrix} \boldsymbol{Y}^{(k,t)} \\ \boldsymbol{0} \end{pmatrix} + \begin{pmatrix} \boldsymbol{0} \\ \boldsymbol{Y}^{(k,t+1)} \end{pmatrix} \qquad (t = 1, \cdots, t_k - 1). \tag{1}$$

In the sequential learning algorithm for the KFM associative memory for sequential patterns, the connection weights are learned as follows:

(1) The initial values of weights are chosen randomly and the recurrent difference vector is set to $\boldsymbol{y}_i = \boldsymbol{0}$.

(2) The recurrent difference vector of the neuron $\boldsymbol{i}$ in the Map Layer is calculate.

$$\boldsymbol{y}_i(n,t) = (1-\beta)\boldsymbol{y}_i(n,t-1) + \beta(\boldsymbol{X}^{(k,t)} - \boldsymbol{W}_i(n,t)) \tag{2}$$

where $\beta (0.5 < \beta < 1)$ is the weighting factor determining the effect of the earlier difference vectors and the new input vector in the computation of $\boldsymbol{y}_i(n,t)$, and n is the number of learning iterations.

(3) The winner neuron $\boldsymbol{r}$ whose recurrent difference vector $\| \boldsymbol{y}_i(n,t) \|$ is minimum is found.

(4) The connection weight except those of fixed neurons are updated by

$$\boldsymbol{W}_i(n,t+1) = \boldsymbol{W}_i(n,t) + H(d_{\boldsymbol{i}})\alpha(n)h_{ri}\boldsymbol{y}_i(n,t) \tag{3}$$

where $\boldsymbol{H}(d_{\boldsymbol{i}})$ is given by

$$\boldsymbol{H}(d_{\boldsymbol{i}}) = \tanh(d_{\boldsymbol{i}}/\varepsilon). \tag{4}$$

(5) (2)~(4) are iterated until $t = t_k - 1$. This accomplishes the learning of the kth temporal sequence on time. Then, for the next iteration, the recurrent difference vector is reseted as $\boldsymbol{y}_i = \boldsymbol{0}$. The obtained weights are inherited in the next iteration.

$$\boldsymbol{W}_i(n+1,1) = \boldsymbol{W}_i(n,t_k) \tag{5}$$

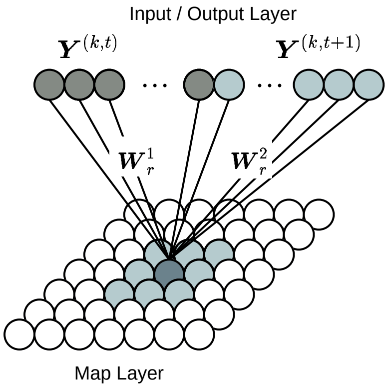


Figure 1: Structure of Proposed Model.

(6) (2)~(5) are iterated until $n = n_{max}$. Then, the weights of $t_k - 1$ winner neurons selected in the final iteration.

(7) (2)~(6) are repeated for all k.

Since the KFM associative memory for temporal sequences is learned by using weights fixed and semi-fixed neurons, it can store a new temporal sequence without retraining previously learned temporal sequences.

2.2. Recall Process

In the recall process, the pattern $(\boldsymbol{Y}^{(k,1)}, \boldsymbol{0})^T$ is applied to the Input/Output Layer. Namely, the left part of the Input/Output Layer receives an input vector and the corresponding output is recalled in the right part. When an input is given, the winner neuron is found by using min[$\| \boldsymbol{y_i}(n,t) \|$].

The output in the Input/Output Layer $\boldsymbol{O}$ is given by

$$\boldsymbol{O} = \mathrm{sgn}(\boldsymbol{W_r}) \tag{6}$$

$$\mathrm{sgn}(u) = \begin{cases} 1, & \text{if } u \geq 0 \\ -1, & \text{if } u < 0 \end{cases} \tag{7}$$

3. KFM Associative Memory with Area Representation for Sequential Patterns

Here, we explain the proposed KFM associative memory with area representation for sequential patterns. The proposed model is based on the conventional KFM associative memory for temporal sequences[7] and the KFM associative memory with area representation[8].

3.1. Structure

Figure 1 shows the structure of the proposed KFM associative memory with area representation for sequential patterns. As seen in Fig.1, the proposed model has two layers; (1) Input/Output Layer and (2) Map Layer, and the Input/Output Layer is divided into two parts.

3.2. Learning Process

The learning process of the proposed model is based on the conventional learning algorithm for the KFM associative memory for temporal sequences. However, in the proposed model, the following $H(d_{\boldsymbol{i}})$ is used in Eq.(3) instead of Eq.(4).

$$H(d_{\boldsymbol{i}}) = \frac{1}{1 + \exp(-(d_{\boldsymbol{i}} - D)/\varepsilon)} \tag{8}$$

In this equation, $d_{\boldsymbol{i}}$ is the Euclid distance between the neuron $\boldsymbol{i}$ and the nearest weights fixed neuron in the Map Layer, D is the constant and ε is the steepness parameter of the function $H(d_{\boldsymbol{i}})$.

3.3. Recall Process

When the pattern $\boldsymbol{X}$ is given, the output of the neuron i in the Map Layer $x_i^{map}(t)$ is given by

$$x_i^{map}(t) = \begin{cases} 1, & \text{if } \| \boldsymbol{y_i}(t) \| < \theta^{map} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$\boldsymbol{y_i}(t) = (1-\beta)\boldsymbol{y_i}(t-1) + \beta(\boldsymbol{X} - \boldsymbol{W_i}) \tag{10}$$

where θ^{map} is the threshold of the neuron in the Map Layer.

The output of the neuron k in the Input/Output Layer $x_k^{in}(t)$ is given by

$$x_k^{in}(t) = \frac{1}{\sum_i x_i^{map}} \sum_{i:x_i=1} W_{ik}. \tag{11}$$

Table 1: Experiment Conditions.

initial value of α	α_0	0.1
initial value of σ	σ_i	0.5
final value of σ	σ_f	3.0
steepness parameter	ε	0.01
weighting coefficient	β	0.70
coefficient for threshold of neurons in Map Layer	a	0.01
constant (semi-fixed area)	D	3
threshold of neurons in Input/Output Layer	θ^{in}	0
upper limit of learning iterations	n_{max}	500

4. Computer Experiment Results

In this section, we show the computer experiment results to demonstrate the effectiveness of the proposed KFM associative memory with area representation for sequential patterns.

Table 1 shows the experiment conditions.

4.1. Recall Result

Two sequential patterns including a common term shown in Fig.2 were memorized in the proposed model which has 800 neurons in the Input/Output Layer and 400 neurons in the Map Layer. Figure 3 shows association results when "lion" or "cat" was given as an initial input. In Fig.3(a), "lion" was given to the network as an initial input, the area representation corresponding to the input pattern was formed in the Map Layer, and then "lion" and "crow" were recalled. In the next step, "crow" was given to the network, the area representation corresponding to "lion→crow" was formed in the Map Layer, and then "crow" and "monkey" were recalled. In the same way, when "monkey" was given, "duck" was recalled, and when "duck" was given, "penguin" was recalled. Fig. 3(b) shows the association result when "cat" was given. Although the stored two sequential patterns have "monkey" as a common term, in the case when "lion→crow→monkey" were recalled and the case when "cat→dog→monkey" were recalled, the proposed model formed different area representations when "monkey" was given. As a result, after "lion→crow→monkey" were recalled, the proposed model recalled "duck", and after "cat→dog→monkey" were recalled, the proposed model recalled "mouse". From these result, we confirmed that the proposed model can recall the sequential patterns including common terms correctly.

4.2. Storage Capacity

Here, we examined the storage capacity of the proposed model. Figures 4 and 5 show the storage capacities of the proposed model. In these experiments, the temporal sequences composed of 4 random patterns were memorized in the proposed model composed of 800 neurons in the Input/Output Layer and 400/800 neurons in the Map Layer. Figures 4 and 5 show that the storage capacity of the proposed model depends on the number of neurons in the Map Layer and the number of learning iterations.

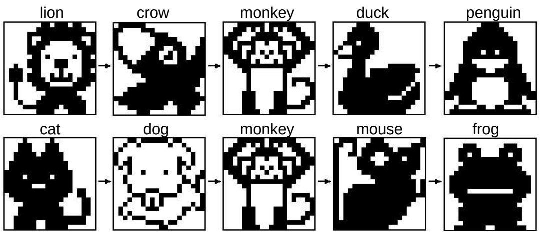
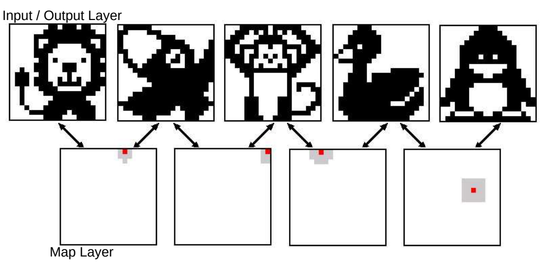
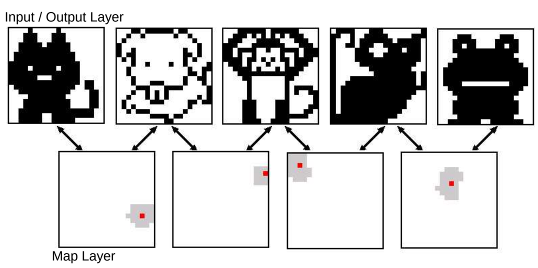


Figure 2: Stored Sequential Patterns including Common Term.



(a) "lion"



(b) "cat"

Figure 3: Association Result.

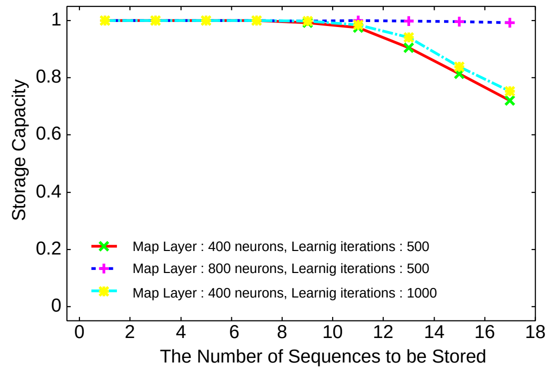


Figure 4: Storage Capacity.

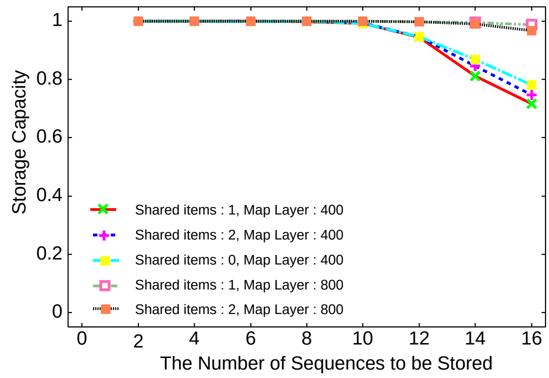


Figure 5: Storage Capacity (including Common Terms).

4.3. Noise Reduction Effect

Here, we examined the noise reduction effect of the proposed model.

Figure 6 shows an association result of the proposed model which memorized the sequential patterns shown in Fig.2 when a noisy input was given. As shown in Fig.6, the proposed model could recall patterns correctly from noisy input.

Figure 7 shows the noise sensitivity of the proposed model. In this experiment, we used the proposed model which has 800 neurons in the Input-Layer and 400 neurons in the Map-Layer and 5 temporal sequences composed of 4 random binary patterns were stored. Figure 7 shows the average of 100 trials. In Fig.7, the result in the conventional KFM associative memory for temporal sequences are shown for reference. As shown in Fig.7, the proposed model has the robustness for noisy input.

4.4. Robustness for Damaged Neurons

Here, we examined the robustness for damaged neurons of the proposed model.

Figure 8 shows an association result of the proposed model which memorized the sequential patterns shown in Fig.2 when some neurons in the Map Layer were damaged. As shown in Fig.8, the proposed model could recall patterns correctly when some neurons in the Map Layer were damaged.

Figure 9 also shows the robustness for damaged neuron of the proposed model. In this experiment, n% of the neurons in the Map Layer were damaged randomly. Figure 9

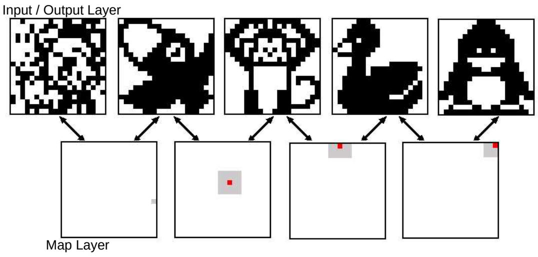


Figure 6: Association Result for Noisy Input.

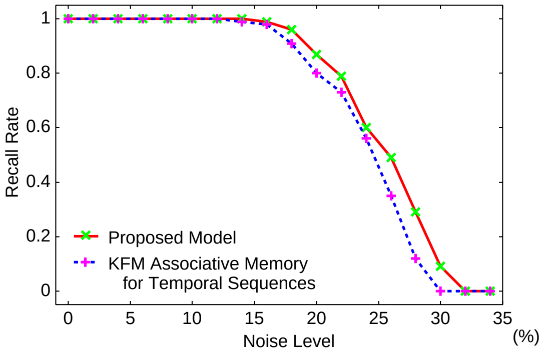


Figure 7: Noise Reduction Effect.

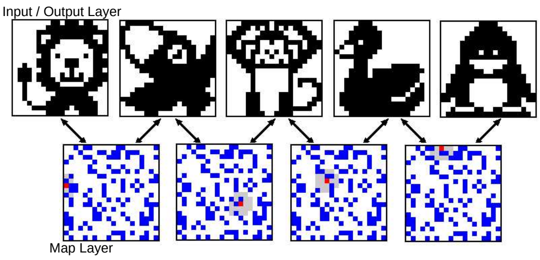


Figure 8: Association Result for Damaged Neurons.

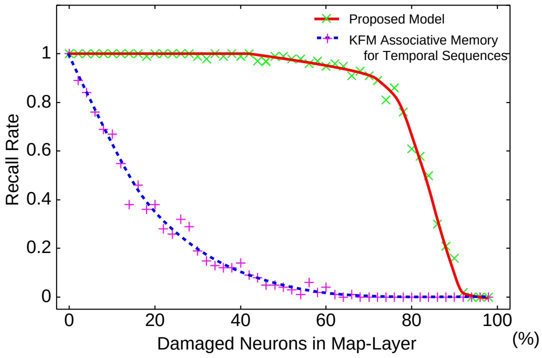


Figure 9: Robustness for Damaged Neurons.

shows the average of 100 trials. In this figure, the results of the conventional KFM associative memory for temporal sequences were also shown.

From these result, we confirmed that the proposed model has robustness for neuron damages.

4.5. Relation between Length of Common Terms and Recall Rate

Here, we examined the relation between the length of common terms and the recall rate. In this experiment, we used the proposed model which has 800 neurons in the In-

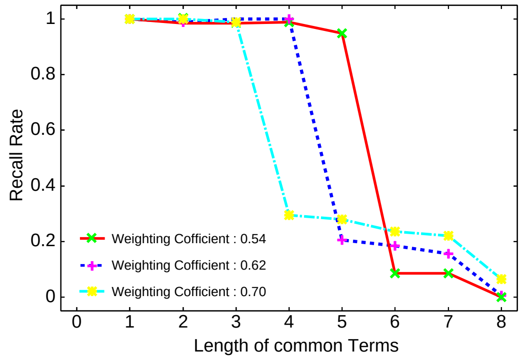


Figure 10: Relation between Length of Common Terms and Recall Rate

put/Output Layer and 400 neurons in the Map Layer and 2 temporal sequences composed of 10 random patterns were memorized. Figure 10 shows the relation between the length of common terms and the recall rate. Figure 10 shows that the weighting coefficient effects the recall rate of the proposed model.

5. Conclusion

In this paper, we have proposed the Kohonen Feature Map associative memory with area representation for sequential patterns. The proposed model is based on the KFM associative memory for temporal sequences[7] and the KFM associative memory with area representation[8]. We carried out a series of computer experiments and confirmed that the proposed model has following features.

(1) It can learn sequential patterns successively.

(2) It can deal with binary sequential patterns including common terms.

(3) It has large storage capacity.

(4) It has robustness for noisy input.

(5) It has robustness for damaged neurons.

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